Catastrophic risks and insurance in farm-level decision making

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Abstract

Catastrophic risks can cause severe cash flow problems for farmers or even result into their bankruptcy. To cope with catastrophic risks farmers need to apply risk management strategies. Insurance is a frequently used instrument to cover catastrophic risks. The main goal of the research is to analyse the actual farmer's behaviour (descriptive approach) and to model the impact of catastrophe insurance purchase (prescriptive approach). Concerning insurance decisions to cope with catastrophic risks, the impact of farmer personal and farmer characteristics is important to consider. In this research, the impact of farmer's personal risk characteristics on catastrophe insurance purchase was mainly addressed. These characteristics are the farmer's personal risk perception and his risk attitude.

The descriptive approach evaluated the impact of farm and farmer personal characteristics on actual insurance purchase in arable farming as well as in dairy farming. The first part of the descriptive analysis focused on the purchase of several general types of insurance (i.e., damage, disability, health and liability insurance and a combination of previous insurance covers). In the second part, more specific insurance covers were analysed (hail, storm, brown rot, hail-fire-storm insurance for buildings, disability insurance, and insurance against epidemic animal disease outbreaks). The results showed that farm and farmer's personal characteristics (including risk perception and risk attitude) had a significant impact on actual (catastrophe) insurance purchase.

In the prescriptive analysis, the decision making problem describing how arable farmers can cope with catastrophic yield risks was modelled. The analysis focused in more detail on risk perception and risk attitude. For this purpose the results obtained from single-crop two-state risk models were compared with the results obtained from multi-crop multi-state models (utility-efficient portfolio approach). The preferred options whether the decisions to insure and not to insure in terms of utility accounted either for farm income or terminal wealth. The analysis showed that if a farmer makes decisions only in terms of an income-based utility function he is more prone to purchase catastrophe insurance. Those decision-makers who perceived that a risk would relatively seldom occur were less inclined to insure and self-insurance would be preferable. However, if insurance decisions are made only on the basis of the single-crop two-state approach, they may differ from portfolio results because of alternative risk reducing options such as a diversification are not taken into account.

Keywords: risk perception, risk attitude, catastrophic risk, insurance, farm characteristics, farmer personal characteristics, utility-efficient programming, arable farming, dairy farming

Preface

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Victor Ogurtsov Almere 2008, January

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Chapter 1 General Introduction

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1.1 General introduction of the problem

Farming is a risky business. For example, arable farmers are exposed to meteorological events, such as hail, storm, drought, frost, heavy precipitation, excessive heat, and crop diseases such as brown rot, which may result in potential damage to crops (Langeveld et al., 2003). In dairy farming, epidemic diseases, such as FMD (foot-and-mouth disease) and BSE (bovine spongiform encephalopathy), cause severe economic losses (Huirne et al., 2003).

The examples presented above can be regarded as catastrophic risks. Catastrophic risks are the events with low probability of occurrence (rare events) leading to major and typically irreversible losses with potentially adverse impact on business results (Chichilnisky, 2000; Vose, 2001). Rarity and severity are typically associated with catastrophic risks: the more severe a risk, the rarer it usually will tend to be, and vice versa (Frohwein et al., 1999).

To cope with catastrophic risks farmers need to apply risk management strategies. Insurance is a frequently used instrument to cover catastrophic risks (Pritchet et al., 1996). Concerning insurance decisions to cope with catastrophic risks, the impact of farmer personal and farm characteristics is important (Mishra and Goodwin, 2003; Sherrick et al., 2004). Farm characteristics refer to the general conditions a farm operates such a size, input use, operational results and financial structure. The main farmer personal characteristics affecting catastrophe insurance decisions that need to be evaluated are the farmer's risk perception and his risk attitude.

Risk perception is a subjective statement of risk by decision-makers, it is more like the mental interpretation of a risk, decomposed as the chance of a loss occurring and the magnitude of the loss (Hardaker et al, 2004; Smidts, 1990). Likewise risk perception, risk attitude plays an important role in understanding the decision-maker's behaviour. Risk attitude deals with the decision-maker's interpretation of the risk and how much (s)he dislikes the outcomes resulting from the risk (Pennings et al., 2002). According to Dillon and Hardaker (1993), risk attitude is defined as the extent to which a decision-maker seeks to avoid risk or is willing to face risk. As most farmers are commonly assumed to be risk-averse (Hardaker et al., 2004). A farmer who is risk-averse is willing to give up some expected return to reduce a risk.

The impact of both farm and farmer personal (including risk perception and risk attitude) characteristics on catastrophe insurance purchase can be analysed by either descriptive or prescriptive approach. Descriptive analysis refers to how farmers actually make insurance decisions. In this approach, the impact of farm and farmer personal characteristics can be analysed by econometric models on basis of actual insurance purchase decisions.

Alternatively, prescriptive analysis indicates how catastrophe insurance decisions should be made according to a set of well-known criteria. The merit of insuring catastrophic agricultural risks cannot be assessed without considering stochastic dependency between farming activities (Hardaker et al., 2004). For this purpose the catastrophe insurance decisions need ideally to be taken in a prescriptive whole-farm portfolio context. Within this framework both expectations and preferences of the farmer need to be considered but are difficult to ascertain.

1.2 Objectives of the research

The impact of farm and farmer personal characteristics affecting catastrophe insurance purchase is the central issue in this research. The main goal of the research is to analyse the actual farmer's behaviour concerning catastrophes (descriptive analysis) and to model the impact of catastrophe insurance purchase (prescriptive analysis). The research objectives are the following:

- To describe the methods that analyse risk perception and risk attitude to model decisions to cope with catastrophes (Chapter 2);
- To analyse actual purchase of all-risk insurance and specific types of insurance (Chapter 3);
- To analyse the relationship between purchase of catastrophe insurance and risk perception and risk attitude (Chapter 4);
- To model the economic impact of catastrophes (Chapter 5);
- To model the purchases of catastrophe insurance in a partial and whole-farm context (Chapter 6).

The research is mainly focused on arable farming with some comparative examples in dairy farming. More details on research objectives are provided in the following section.

1.3 Overview of the research

In Figure 1 a schematic overview of the thesis is presented. There are three main input modules: 1) literature, 2) data set of the Farm Accountancy Data Network (FADN) and 3) a questionnaire. The empirical analysis part is presented in the second column and comprises regression models of actual insurance purchase. Subsequently two types of normative approaches are applied: utility-efficient programming (UEP) and two-state risk modelling (see third column). The last column represents the main results in line with chapter-structure of the thesis. The connection between the modules is indicated with three different links, i.e. 1) literature, 2) empirical data and results, and 3) results of normative modelling.

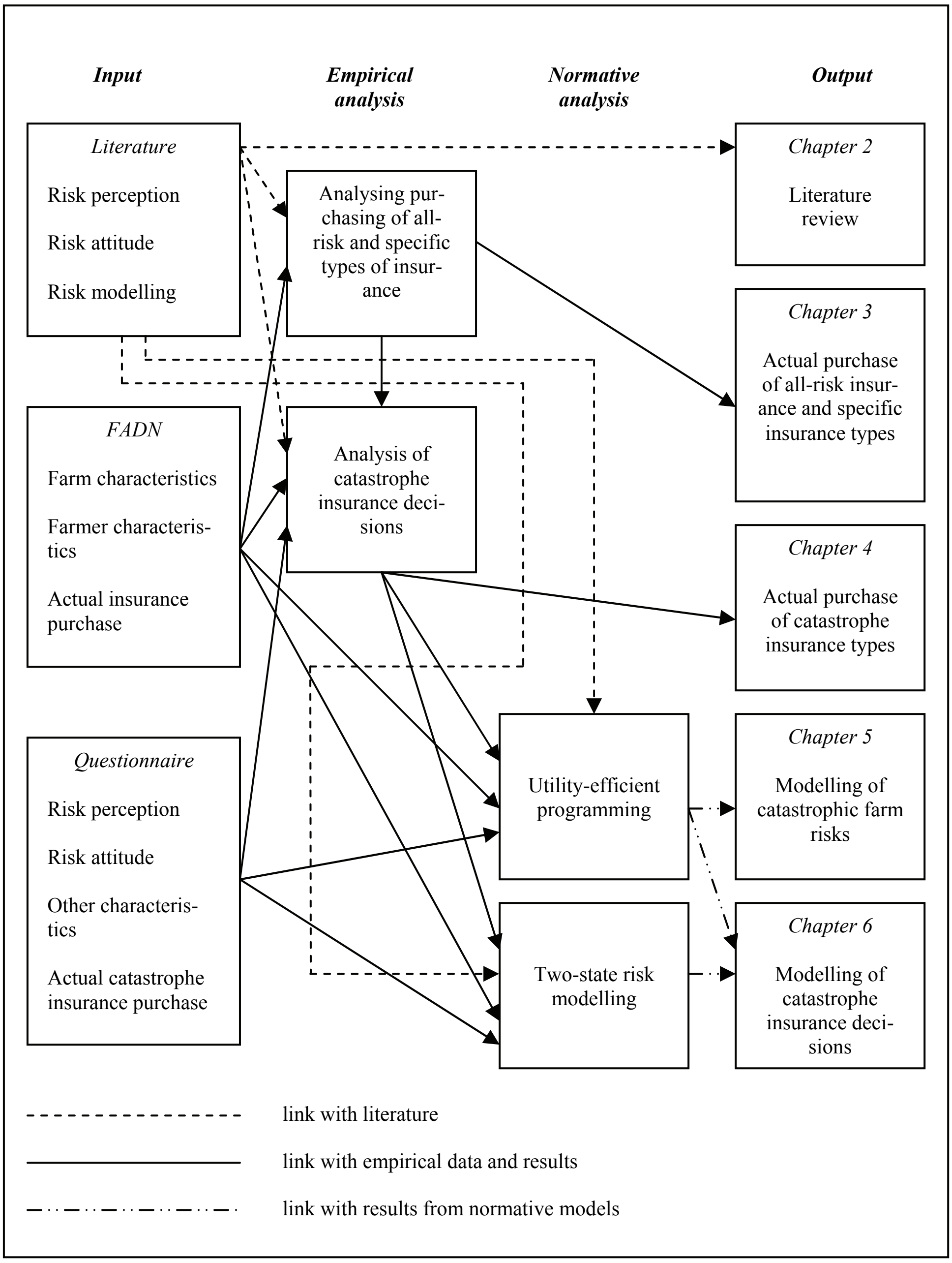

Figure 1. **Schematic overview of the thesis with key concepts of each module**

In order to study the main goal of the research, it is important to define which methods of risk perception, risk attitude and modelling are applicable to support the farmer's goal. A literature overview elaborating on specific methods dealing with risk perception, risk attitude and risk modelling, is presented in *Chapter 2*.

Chapter 3 provides a broader perspective of characteristics that influence actual purchase of insurance. The analysis is focused on the several general types of insurance such as damage, disability, health and liability insurance. An aggregate coverage (so-called whole-farm insurance) is analysed as well. To estimate the impact that diversification has on insurance purchase, two farming systems are analysed. Hereto the decisions made by arable farmers, having usually diversified set of activities, are compared to the decisions made by dairy farmers which business is usually highly specialised. The analysis is restricted mostly to the farm characteristics.

Based on the findings from the previous chapter, *Chapter 4* analyses actual purchase of specific catastrophe insurance types by arable farmers in comparison to the actual catastrophe insurance decisions made by dairy farmers. Beside farm characteristics, the analysis estimates the impact of farmer specific characteristics, including risk perception and risk attitude, on the purchase of catastrophe insurance.

Chapter 5 evaluates different approaches accounting for the stochastic dependency between different crops to incorporate catastrophes on the basis of sparse data. The risk analysis compares the approaches of multivariate normal distribution (MVN) and multivariate kernel density estimation procedure (MVKDE) applying the joint distributions of crop yields and prices. For this purpose, on the basis of statistical tests, the simulated data is tested on the appropriateness to represent the available sparse data. The applicability of different distribution assumptions is estimated in the whole-farm portfolio optimisation approach.

Chapter 6 estimates the impact of catastrophe insurance purchase in the domains of annual income and final wealth. The analysis compares the applicability of simplistic risk models accounting for two states of nature and portfolio optimisation models. In the two-state risk models, the decision to purchase catastrophe insurance is evaluated in the context of two states of nature - no catastrophe and presence of a catastrophe. For this purpose the elicited catastrophic risk perceptions are used in the model. Alternatively, the performance of catastrophic risk insurance is estimated in whole-farm portfolio context incorporating the abundance of states of nature (generated by joint distributions of crop yields and prices) updated with elicited risk perceptions.

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Chapter 1

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Chapter 2 Assessment and modelling of catastrophic risk perceptions and attitudes in Dutch farming: A review

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Abstract

Catastrophic risks result in high losses in agriculture. To cope with those losses farmers need to apply risk management strategies to balance their profits and risks. Therefore risk assessment and risk modelling is important to support farm-level decision making. This paper 1) reviews the techniques to elicit risk perception and risk attitude, and 2) describes how the simultaneous impact of risk perception and risk-attitude could be accounted for in risk programming models. Although inherent to catastrophic risks, objective data are sparse and eliciting subjective data are likely to be flawed; the review showed that the negative impact resulting from catastrophes cannot be ignored without compromising the optimal decision.

Keywords: catastrophe, risk perception, risk attitude, risk modelling, farmer

2.1 Introduction

Farming is typically a risky business (Hardaker et al., 2004). Facing a risk implies a possibility of losing property or income (Pritchet et al., 1996). Farm risks can be of financial and business nature. Financial risk refers to the method of financing. Business risk of a farmer is related to production, personal, price and institutional risk (Hardaker et al., 2004). Particularly severe business and financial risks or their combinations can constitute a catastrophic risk at farm level.

Generally defined, a catastrophic risk is a low-probability (rare) event leading to major and typically irreversible losses with adverse impact on business results (Chichilnisky, 2000; Vose, 2001). Catastrophic risks in agriculture can cause severe cash flow problems or even result in bankruptcy. For example, livestock farmers can be exposed to epidemic diseases such as FMD (foot-and-mouth disease), BSE (bovine spongiform encephalopathy) and CSF (classical swine fever), or be injured and not able to continue farming (Hartman et al., 2004; Huirne et al., 2003). In arable farming, the potential crop damage of crop production can be caused by extreme meteorological events such as hail, precipitation, drought, storm and frost (Langeveld et al., 2003).

Farmers need to manage catastrophic risks somehow. This can be done by applying risk management strategies, such as insurance, diversification, self-insurance, forward contracting. In decision analysis, the models should take the farmer's perception of specific risk and risk attitude into account.

Many researchers modelling risk prefer to deal with objective probabilities and impact (i.e. Bouma et al., 2005; Ermoliev et al., 2000a, b; Johnson-Payton et al., 1999; Melnik-Melnikov and Dekhtyaruk, 2000; Pradlwarter and Schueller, 1999). Contrary to this, risk perception, is a subjective statement of risk by decision makers, their degree of believe. Risk perception is more like the mental interpretation of risk, decomposed as the chance to be exposed to the content and the magnitude of the risk (Hardaker et al., 2004; Pennings, 2002; Senkondo, 2000; Smidts, 1990).

Like risk perception, risk attitude plays an important role in understanding the decision maker's behaviour. Risk attitude is a personal characteristic and deals with the decision-maker's interpretation of the risk and how much (s)he dislikes the outcomes resulting from the risk (Pennings, 2002). According to Dillon and Hardaker (1993), risk attitude is the extent to which a decision maker seeks to avoid risk (i.e. risk aversion) or prefers to face risk (i.e. risk preference). According to reasonable asset integration assumptions, a farmer would view losses or gains from specific risks as being equivalent to changes in wealth (Hardaker et al., 2004). Therefore, although risk attitude is not affected by specific catastrophic risk, it does affect the decisions to cope with catastrophes.

Table 1. **Methods used and their advantages and disadvantages with catastrophic risks**

Method	Advantages	Disadvantages with catastrophic risks	Sources with examples
1. Risk elicitation			
Risk perception elicitation			
Direct method	High descriptive power, generated scale variables.	No probabilities derived	Smidts (1990); Pennings (1998); Senkondo (2000); Van Asseldonk et al. (2002).
Strength of conviction	Main distributional parameters are derived.	Problems to derive low probabilities.	Smidts (1990); Pennings (1998); Senkondo (2002).
Risk perception of catastrophic risks	Avoids judgemental biases	Biases still possible	Weinstein et al. (1996); Kunreuther et al. (2001)
Risk attitude elicitation and estimation			
Direct method	High descriptive power, generated scale variables.	No risk attitude coefficients derived.	Smidts (1990); Pennings (1998); Senkondo (2000); Ganderton et al. (2000); Van Asseldonk et al. (2002).
ELCE[1]	Fifty-fifty chance situations easy to evaluate.	Fifty-fifty chance situations are not relevant.	Smidts (1990); Pennings (1998); Senkondo (2000); Torkamani (2005).
Econometric models	Inferences about degree of aversion are obtained.	Strong assumptions of models, specification errors.	Antle (1989); Bar-Shira (1997); Oude Lansink (1999); Gardebroek (2002).
2. Risk modelling			
Stochastic simulation			
MCS[1]	The most commonly used method	Can underestimate tail of the distribution	Ermoliev et al. (2002a, b); Kobzar (2006)
Latin Hypercube	All segments of the distribution are considered, including a tail.	n.a.[2]	Lien et al. (2006); Richardson et al. (2006)
Farm risk programming			
QRP[1] and MOTAD[1]	Only mean and variance required	Only quadratic form of utility function, normality assumptions.	Kobzar (2006); Lien et al. (2006)
UEP[1]	Any form of utility function and joint probability distribution.	More sensitive to input data	Lien and Hardaker (2001); Torkamani (2005); Acs (2006); Kobzar (2006); Flaten and Lien (2007)

[1] ELCE = equally likely certainty equivalent; MCS = Monte Carlo simulation; QRP = quadratic risk programming; MOTAD = minimisation of total absolute deviation; UEP = utility-efficient programming.
[2] n.a. = not appropriate

Many risk modelling studies are devoted only to either objective or subjective (i.e. risk perception) probabilities, while the impact of risk attitude is usually omitted from the context (i.e. Cummins and Mahul, 2003; Bouma et al., 2005; Ermoliev et al., 2000a,b; Johnson-Payton et al., 1999; Kunreuther et al., 2001; Melnik-Melnikov and Dekhtyaruk, 2000; Pradlwarter and Schueller, 1999). Examples of studies combining risk perception and risk attitude simultaneously include Pennings (1998), Senkondo (2000) and Smidts (1990). Quantitative modelling studies focusing specifically on agricultural catastrophic risks that combine risk perception and risk attitude are, however, hardly available at all as best we can determine.

Concerning catastrophic risks, there are some challenging problems with respect to the data. Data on catastrophes are inevitably skewed (non-symmetric), and major problems are inherent in proper estimation of low probabilities in the downside tail (i.e., Ganderton et al., 2000; Hardaker et al, 2004; Kunreuther et al., 2001). Therefore, the properties of tail estimation need to be explicitly accounted for.

This paper reviews the methods of risk perception and risk attitude elicitation, and methods of risk modelling combining risk perception and risk attitude towards the agricultural decisions to cope with catastrophic risks in one framework. The central question is to what extent standard methods are appropriate to accommodate catastrophic risks.

The paper is structured as follows. First the standard methods of risk perception and specific issues on catastrophic risks are reviewed. In the next section, the subjective expected utility theory with its limitations and risk attitude elicitation techniques are discussed. Then the methods of combining risk perception and risk attitude for catastrophic risk modelling are described. Hail, which is a typical catastrophic risk for a farmer, is used as an example. The paper finishes with the main findings with respect to modelling of catastrophic risks.

2.2 Risk perception methods

In this section the standard direct method, strength of conviction method and specific issues on elicitation of catastrophic risk perceptions are reviewed. Their main advantages and disadvantages are presented in Table 1 and for each method the implication for the hail example is addressed.

Hail is a typical catastrophic risk on an arable farm, since it occurs very irregularly in time and space and can have a serious adverse impact on the farm business as a result of damage of several crops. In general, crop damage can be categorised into 1) destruction of the entire or part of the crop, resulting in yield losses depending on the percentage of crops destroyed; 2) mechanical damage to the plants, such as defoliation, breakage or bruising of the stems and 3) reduced quality of the product resulting in a downgrading and therefore lower prices (Van Asseldonk et al., 2002). Concerning hail, the insurance strategy is very commonly adopted in Dutch agriculture. Dutch insurers have defined spatially separated hail-risk prone locations for outdoor crops, in which premiums for coastal regions are lower than those for interior regions. A maximal discount of 65% of the base premium rate can be obtained at coastal regions versus no discount at highly prone locations (Van Asseldonk et al., 2002). The average annual hail insurance premiums for a main crop such as wheat constitute 0.625% of the insured sum, for sugar beet - 1.75%, potatoes for industry and consumption - 0.75%, and rye - 0.65% (Anonymous, 1999).

Occurrence of hail has a low probability, but a high negative impact. That can be seen in the annual levels of loss ratio (total indemnities paid plus administration costs divided by total premiums collected) of insurance companies. If a loss ratio is 100%, there is an offsetting Euro of premiums collected for every Euro of indemnities. A loss ratio lower than 100% indicates high profits for the insurer, whereas a loss ratio higher than 100% implies that the indemnities paid are higher than the premiums collected. On average, in the Netherlands the loss ratio of hail insurance for arable farming, horticulture and bulb-growing is around 50-100%, while in adverse years with catastrophes it can be much higher than 100%.

2.2.1 Standard methods of risk perception measurement

In the *direct method*, risk perception can be measured by conducting a questionnaire with straight questions about risk perception. Many studies were conducted with this method to measure risk perceptions (i.e. Pennings, 1998; Senkondo, 2000; Smidts, 1990; Van Asseldonk et al., 2002). Such a questionnaire can include socio-economic and psychological statements, perhaps helping to explain risk perception of farmers. In the example of hail, farmers can place their subjective expected probability of hail occurrence on a 7-point Likert scale. In a similar way, questions can be asked about the magnitude of a loss after hail occurs. The direct measurement procedure does not define a subjective absolute probability distribution; rather it estimates probability and outcomes in relative terms (Smidts, 1990). Nevertheless, this method is of use, if scores from the Likert scales are able to be combined with known probabilities.

The *strength of conviction method* involves elicitation of several points of the subjective cumulative distribution function. The probability distribution function is then fitted to these points. Thereafter main parameters (mean, median, standard deviation and skewness) can be derived from the distribution. The method is called indirect, because the measures of central tendency and variation are indirectly derived from the probability distribution function (Smidts, 1990). Examples of studies conducting the strength of conviction method include Pennings (1998), Senkondo (1990) and Smidts (1990). For the hail example, the strength of conviction method can be applied by eliciting several points of the subjective cumulative distribution function. However, with only several points, the probability in the tail of the distribution may be inadequately estimated. If probability of hail is very low, it is hard to estimate the downside tail of the distribution, because people have problems in interpreting low probabilities (Kunreuther, 2002; Kunreuther et al., 2001). The knowledge of farmers about subjective probability and impact is usually bounded. Farmers may overestimate the quality of data on risk and their ability to perceive risk and mistake their real exposure of risk. Hence, the evaluation of catastrophic risk perception from probability distribution by standard strength of conviction method to elicit probabilities may not be appropriate (Desvousges et al., 1998; Hagihara, 2002).

2.2.2 Specific issues on elicitation of catastrophic risk perception

Difficulties in risk perception elicitation frequently occur in catastrophe situations since there is often a lack of data (Ekenberg et al., 2001). When a decision-maker moves from events with considerable historical and scientific data to those where there is greater uncertainty and ambiguity, there is a much greater degree of discomfort in assessing risk perception (Kunreuther, 2002). But if the number of data increases, subjective probability changes and degree of conviction concerning the subjective probability likely increases and the value of subjective probability may closely coincide with the objective probability determined by experts. Hence, if the degree of conviction of the subjective probability is not very high, the subjective probability and the choice based on it may change because of the additional data (Hagihara, 2002). Kunreuther et al. (2001) and Weinstein et al. (1996) conducted studies where they could handle different psychological biases concerning the elicitation of risk perception of catastrophic risks, which are explained below.

Psychological biases affecting risk perceptions of catastrophic risks

Risk perceptions can be over- or underestimated due to judgmental biases such as availability heuristic, vividness, denial and evaluability.

The *availability* heuristic is the most relevant one for dealing with catastrophe events. Decision-makers estimate the likelihood of an event by the ease with which they can imagine or recall past instances of the event. In case where the information on an event is conspicuous, many people will tend to overestimate the probability of the event occurring (Kunreuther, 2002). For instance, the farmer's subjective probability of hail occurring typically increases when this event recently took place.

A cousin of availability bias in decision making process is *vividness*. Vividness refers to how concrete or imaginable the event is, although occasionally it can have other meanings. Sometimes vividness refers how emotionally interesting or how exciting something is. Farmers are affected more strongly by vivid information than by pallid, abstract, or statistical information. In this respect vividness can increase the perceived probability of a catastrophe event (Plous, 1993). The power of vivid information is widely appreciated by persuaders. In agriculture it can be an insurance company convincing a farmer that a probability of hail at his farm is high, or that a nearby farmer has already bought a specific type of catastrophe insurance or has already been exposed to a catastrophe event.

Farmers may also tend to *deny* extremely negative outcomes. In this respect farmers will tend to overestimate (is more probable) positive events and underestimate (is less probable) the negative ones (Plous, 1993). Therefore, hail as a negative example can be underestimated. The notion of *evaluability* is also important for a decision making process with respect to low probabilities. Most people feel that small numbers can easily be dismissed, large numbers get their attention (Kunreuther, 2002).

Expressions to improve risk perceptions of catastrophic risks

This section deals with ways how to elicit probabilities for catastrophic risks from farmers, taking into account the psychological biases. For a decision-maker it is usually easier to elicit risk perception for catastrophic risks if the likelihood is depicted in ratios to other risks (e.g., the probability of hail is one half of a specific traffic accident probability). It is more reasonable to present the probabilities in a time interval (i.e. for a farmer a probability of hail once in 75 years is more readily imaginable than a probability of 0.013 per year). Weinstein et al. (1996) found that reframing the probability of an event as the time interval during which a single event is expected can affect risk perceptions in comparison to framing one-year events. It is also evident that the absolute probability in this case seems to be perceived as a very small number close to zero (Kunreuther, 2002).

Small probabilities will not be readily evaluable by farmers in the absence of context information. Farmers need comparison scenarios that are located on a probability scale and evoke their own feelings about risk. As farmers are provided with increasingly useful context information, the probabilities become more and more evaluable, which results in well-developed risk perceptions (Kunreuther et al., 2001). For easier understanding of a hail probability, a farmer could be provided with additional context information that could include the recent history of hail with its consequences in different regions, probabilities of related risks such as storm or heavy rain, the speed of wind, temperature, etc.

2.3 Subjective expected utility theory

In this section, the subjective expected utility (SEU) theory is presented, and the focus is on its components such as the SEU model, estimation and elicitation of risk attitude coefficients, forms of utility functions and stochastic dominance. As in the previous section, the hail risk of an arable farmer will be used as an example.

2.3.1 SEU model

The SEU hypothesis states that utility of a risky prospect is the decision-maker expected utility for that prospect, meaning the weighted average of the utilities of outcomes (Hardaker et al., 2004). When the probabilities of outcomes are discrete, the expected utility model can be formulated in the following way (Smidts, 1990):

$$U(A_i) = \sum_{j=1}^{J} p_i(x_j) \cdot u(x_j) \tag{1}$$

Where A_i – is an alternative from a set of alternatives $A = (A_i;\ i = 1,2, \ldots, I)$;

x_j – is an outcome from a set of outcomes $X = (x_j;\ j = 1,2, \ldots, J)$;

$p_i(x_j)$ – is a probability from a set of probabilities $P = (p_i(x_j);\ i = 1,2, \ldots, I;\ j = 1,2, \ldots, J)$ of outcome x_j with alternative A_i;

$U(A_i)$ – is expected utility of alternative A_i;

$u(x)$ – is utility of outcome x_j.

In case of continuous probabilities, the SEU model is formulated as follows:

$$U(A_i) = \int f_i(x) \cdot u(x)dx \qquad (2)$$

Where $f_i(x)$ – is a probability distribution of outcomes x resulting from choosing of alternative A_i;

$u(x)$ – is utility function of outcomes x.

In the hail example, SEU should focus on the probability distribution of yields, where the hail risk is incorporated in the tail of the probability distribution.

A decision-maker can be a risk-lover (i.e. risk preference), risk-averse or risk-neutral. Risk attitude can be seen from the shape of the expected utility function. The utility function is concave when a decision-maker is risk-averse, convex in case of risk preference and linear when a decision-maker is risk-neutral. Most farmers are risk-averse as decision-makers (Hardaker et al., 2004). As can be seen from the formulas (1) and (2), the SEU model integrates risk perception and risk attitude.

2.3.2 Risk attitude coefficients

The degree of risk aversion is measured by the risk aversion coefficients. The following standard risk attitude coefficients are used: coefficient of absolute risk aversion, coefficient of relative risk aversion and coefficient of partial risk aversion (for details see Hardaker et al., 2004). The most relevant is the Arrow-Pratt absolute risk aversion coefficient *Ra* that is calculated as follows:

$$Ra = -\frac{U^{(2)}(w)}{U^{(1)}(w)} \qquad (3)$$

Where $U^{(2)}(w)$ - is the second derivative of utility function of wealth;

$U^{(1)}(w)$ - is the first derivative of utility function of wealth;

w – is a farmer's wealth.

Note that in formula (3) the outcome argument $\boldsymbol{x}$ from formulas (1) and (2) is introduced by argument w (wealth), however other outcome measures such as income can be substituted for wealth here (Hardaker et al., 2004, p.100). The second risk aversion coefficient that is often used in decision analysis is the relative risk aversion coefficient *Rr*. There is a mathematical relationship between *Ra* and *Rr*:

$$Rr=Ra\cdot w \tag{4}$$

Anderson and Dillon (1992) developed a rough classification of decision makers on the basis of *Rr*. According to this classification, for a risk-averse farmer the coefficient of relative risk aversion varies from 0.5 to 4, typically about 1, with the following meanings: 0.5 – hardly risk-averse at all, 1.0 – somewhat risk-averse (normal), 2.0 – rather risk-averse, 3.0 – very risk-averse, 4.0 – almost paranoid about risk (Hardaker et al., 2004). In decision analysis, *Rr* is usually taken as a basis to calculate *Ra* as in the formula (2). *Ra* and *Rr* are usually used for the wealth measures[1] of utility function. Coefficient of partial risk aversion assigned for the measures of gains or losses, or sometimes income, is rarely used in decision analysis.

2.3.3 Risk attitude estimation, elicitation and stochastic dominance

Risk attitude coefficients can be either elicited or estimated. The following alternatives are described – the direct method, equally likely certainty equivalent (ELCE) method and econometric models. The advantages and disadvantages of three methods are presented in Table 1.

Direct method

Like risk perception, risk attitude can be elicited by a direct method, for example, by straight questions in a questionnaire. The direct measurement procedure, however, does not lead to the estimation of the risk attitude coefficients. Instead, the inferences about risk attitude (aversion) can be derived.

A questionnaire can include socio-economic and psychological Likert statements, characterising the farmers' risk attitudes (i.e. Ganderton et al., 2000; Pennings, 1998; Senkondo, 2000; Smidts, 1990; Van Asseldonk et al., 2002). In a simple way, risk attitude can be asked as a linear variable measured on a 5-point or 7-point scale (i.e. Ganderton et al., 2000). Some studies elicited 'relative' risk aversion of a farmer, where a farmer was compared to the average farmers/persons in the group (i.e. Pennings, 1998; Van Asseldonk

[1] In case of failure of asset integration assumptions, these coefficients are calculated on the basis of income measure (for details see Hardaker et al. (2004)

et al., 2002). A group of farmers was asked to state their degree of risk attitude. A questionnaire used several statements on a 5-point or 7-point scale characterising risk attitude of a farmer compared to the average farmer in the sector. Then the average score per farmer and per group were calculated. After comparing of individual and group average scores, farmers were labelled 'less-risk-averse' or as 'more-risk-averse'.

Estimation of risk attitude from observed economic behaviour by econometric models

In the studies by Antle (1989), Bar-Shira et al. (1997), Gardebroek (2002) and Oude Lansink (1999), risk attitude in a form of absolute, relative or partial risk aversion coefficient was estimated from observed economic behaviour based on the assumption that farmers act more or less consistently with the SEU theory. The models are based on assumptions about the nature of the production and decision environment, including the structure of attitudes and perceptions about the associated uncertainty (risks).

Hardaker et al. (2004) showed two weaknesses of this approach. The first one is related to the strong assumption that the analyst and farmers share the same view of uncertainty farmers can face. It particularly concerns the fact that the probabilities based on historical series of observations of key uncertain phenomena are the same probabilities that farmers use in decision making. The second one refers to specification errors that can be represented by econometric models. The reality can be far more complex than the assumptions made, and therefore the effects of the specification errors will be rolled into the estimates of risk aversion, making the reliability of results doubtful.

ELCE

ELCE method is widely used to elicit the utility function of von Neumann-Morgenstern. The examples of the studies conducted include Pennings (1998), Senkondo (2000), Smidts (1990) and Torkamani (2005).

Suppose, there is a risky prospect with discrete payoffs $x_1, x_2, ...x_m... x_{n-1}, x_n$ with corresponding probabilities $p_1, p_2 ...p_m... p_{n-1}, p_n$ summing to 1. In using the ELCE method, the first step in dealing with preferences is to find a certainty equivalent (CE) for a hypothetical 50/50 lottery with the best outcome x_n (having utility of 1) and worst possible outcome x_1 (with utility of 0) of the decision problem as the two risky consequences. CE is the maximum sure payment the farmer would be willing to accept (pay) rather than face the risk

(Hardaker et al., 2004); this value x_m is higher than x_1 and lower than x_n. Then the expected utility for the CE of x_m is calculated.

The next step is to find the CE with its corresponding expected utility for other points between x_1 and x_n. Suppose, then we calculate CE for the points between x_1 and x_m. After the CE between the points x_1 and x_m is found, then the expected utility of this outcome is calculated as a weighted average of utilities for x_1 (that is 0) and x_m (that is known after the first step) and their probabilities of 50%. In a same way, the CEs and expected utilities can be calculated for other points. This process of establishing of utility points is continued until sufficient number of CEs is elicited to plot the utility function. The details on ELCE method can be found at Anderson et al. (1977) and Hardaker et al. (2004). The advantage of ELCE is that it is based on the ethically neutral probabilities of 0.5 (Hardaker et al., 2004; Smidts, 1990). People find 50:50 risky prospects much easier to conceptualise than prospects with other probability ratios (Hardaker et al., 2004).

In a way presented above, several attempts have been made to elicit utility functions to put SEU hypothesis to work in the analysis of risky alternatives in agriculture. The results were, however, often unconvincing (Anderson and Hardaker, 2002; Hardaker et al., 2004; King and Robison, 1984; Smidts, 1990).

One disadvantage of the expected utility approach is its complexity. The elicitation of CEs and subjective probability distributions is judged as fairly difficult and quite time-consuming, requiring an active role of an interviewer. However, taking into account the limitations, the results found may be even more surprising and unconvincing (Hardaker et. al, 2004; Smidts, 1990). There is evidence that the functions obtained are vulnerable to interviewer's bias and to bias from the way the questions are framed to elicit CEs (Hardaker et. al, 2004).

Concerning catastrophes, one problem arises in the estimation of the worst outcome and the CE between the worst outcome and other points. The ease of method is 50/50 equally likely outcomes. However, for catastrophic risks having very low probabilities, it would be more difficult to assign the states 'there is' and 'there is no' catastrophic hail risk by 50/50 prospects. Morgenstern (1979), one of the founders of standard SEU theory, recognised the limited applicability of expected utility in elicitation of risk aversion coefficients, when probabilities were extremely low (Chichilnisky, 2000; Ekenberg et al., 2001; Ganderton et al., 2000; Kruse and Thompson, 2003).

Forms of utility functions

The utility functions, elicited in a way presented above, need to have a mathematical form to derive risk aversion coefficients. However, there are some existing functional forms based on the properties of risk aversion. The elicited utility function then can be tested whether it fits the existing functional form.

The most commonly used functional forms are based on the constant absolute risk aversion (CARA) and the constant relative risk aversion (CRRA) (Hardaker et al., 2004). The extensively used in decision analysis is the negative exponential function on the basis of CARA. CARA means that preferences among risky choices are unchanged if all outcomes are multiplied by a positive constant absolute risk aversion coefficient. The exponential function takes the following form:

$$U = 1 - exp(-Ra \cdot w),\ Ra>0,\ w>0 \tag{5}$$

The exponential function has numerical problems for large values of wealth, which is why this function is only applicable when the risky prospect is small compared to the total farm's wealth. In the case of catastrophic risks such as hail, when the risky prospect may result in substantial changes in wealth, CRRA is more applicable. While *Ra* declines as wealth increases (i.e. decreasing absolute risk aversion), it is less probable that *Rr* is affected by changes in wealth. Logarithmic and power utility functions are based on CRRA properties. The power function based on CRRA properties takes the following form:

$$U = \left[\frac{1}{\left(1 - Rr\right)}\right] w^{(1-Rr)},\ w>0 \tag{6}$$

In case when the relative risk aversion coefficient equals one, the power utility function is undefined, and therefore the logarithmic function can be used. It takes the following form:

$$U = ln(w),\ w>0 \tag{7}$$

The other commonly used functional forms are expo-power, polynomial-exponential, quadratic and hyperbolic absolute risk aversion (HARA) utility functions (Hardaker et al., 2004; Richardson, 2006). The described functional forms are widely used in risk modelling that will be presented further.

2.4 Stochastic dominance

The SEU theory, however, remains the appropriate theory for *prescriptive* assessment of risky choices (Hardaker et al., 2004). To avoid the problems of SEU theory with respect to risk attitude elicitation, methods of stochastic dominance have been developed.

First the concept of first-degree stochastic dominance (FSD) was presented by Hadar and Russell (1969). According to FSD, it is possible to order alternatives for decision-makers (preferring more wealth to less) with absolute risk aversion coefficient with respect to wealth between the bounds minus and plus infinity (King and Robison, 1984).

Thereafter the concept of second-degree stochastic dominance (SSD) was introduced by Hanock and Levy (1969). SSD assumes that the decision-makers are not risk preferring (i.e. risk neutral and risk-averse), so that absolute risk aversion bounds were between zero and plus infinity.

Stochastic dominance with respect to a function was introduced by Meyer (1977) and allows for tighter restriction on risk aversion levels between lower and upper bounds. Hardaker et al. (2004) applied stochastic efficiency with respect to a function (SERF), providing alternatives in terms of CEs as a measure of risk aversion over a definite range on the basis of rough classification of relative risk aversion coefficients developed by Anderson and Dillon (1992) presented earlier. Several studies have been conducted by SERF assuming this range of relative risk aversion coefficients (i.e. Acs, 2006; Kobzar, 2006; Lien and Hardaker, 2001; Torkamani, 2005). The SERF is widely used in risk modelling that will be shown in the following section.

2.5 Risk modelling

For applicability of catastrophic risk modelling, the methods of stochastic simulation and farm risk programming are reviewed. For details concerning advantages and disadvantages see Table 1. Again the example of hail risk is used for applicability in risk modelling.

2.5.1 Stochastic simulation

Stochastic simulation is often applied to generate a sample of outputs recognising risky inputs (Richardson, 2006). Stochastic models are used to analyse ‘what-if’ questions about a real system. The method is sufficiently flexible to allow the incorporation of complex relationships between variables and hence to mimic aspects of complex real systems in agriculture (Hardaker et al., 2004).

A large number of distributions can be used for simulation of inputs. For catastrophic risks such as hail, the distributions are not symmetric around the mean and skewed (Kruse and Thompson, 2003). The examples of parametric distributions that deal with catastrophes are Poisson, gamma, exponential, negative binomial, Weibull and extreme value distributions (Johnson-Payton et al., 1999; Vose, 2001). Alternatively, besides parametric distributions, also non-parametric distributions can be accommodated for stochastic simulation of catastrophes. One of them is the kernel density estimation (KDE) procedure, where the estimates of the probability at a given point depend on a pre-selected probability density that is specified by different kernel functions and subjective extreme points are added (for details see Richardson, 2004; Richardson et al., 2006).

In complex systems with more than one activity, as in farming, the stochastic dependency is always present. For example, crop yields tend to be positively correlated in that a good year for one crop also often suits other crops, and vice versa. Similarly, prices for several kinds of farm products tend to move together, depending on general economic conditions (Hardaker et al., 2004). Ignoring stochastic dependency between risky prospects in farm planning can be seriously misleading. In modelling of catastrophic risks, the standard approach to accommodate stochastic dependency is the multivariate kernel density estimation (MVKDE) procedure, which is based on historical correlations between yields and prices (Richardson et al., 2006). A more sophisticated approach to account for stochastic dependency is using copula (joint or multivariate distribution) functions. Compared to MVKDE, which deals with historical correlation coefficients between variables, the correlation in copulas is a fixed parameter and is specified by the choice of copula function (for details see Venster and Carpenter, 2001). The approaches KDE and copulas have a limited use, however, since they are hampered due to scarcity of data. The functions need more data points for their justification on a statistical basis, but on the other hand, it is what the decision maker or expert believes that really counts.

The procedure Monte Carlo Simulation (MCS) is widely used in stochastic simulation studies for the generation of outputs given risky inputs (i.e. Ermoliev et al., 2000a, b; Kobzar, 2006). The risky inputs are specified by a probability distribution function. Then in a simulation (generation) of outcome values, a number of data points used from an input probability distribution function needs to be specified. A number of data points specifying an input distribution can also be called a number of iterations. Each iteration produces one possible outcome of a system, a so-called state of nature. During a simulation, MCS randomly selects data points (values) from probability distributions.

MCS is also extensively used for the modelling of catastrophic risks (Ermoliev et al., 2000a, b). However, the possible drawback of the MCS is that it samples a greater percent of the random values from the area about the mean and there is a chance that it under samples the tails. When MCS is used it is recommended that a large number of iterations to be used to minimise the effect of under sampling the tails of probability distributions. However, when there is a large tail of the distribution (highly skewed), even a very large number of iterations may fail to produce sufficient values in the tail of the data to accurately represent the area of interest (Richardson, 2006; Vose, 2001).

As one of the ways to capture the downside tail of the distribution, the Latin Hypercube simulation procedure can be applied. Latin Hypercube simulation is the late version of MCS. This procedure significantly reduces a number of iterations compared to MCS. Latin Hypercube segments the distribution into a number of intervals and makes sure that at least one value is randomly selected from each interval. The number of intervals therefore equals the number of iterations, and in this respect this simulation technique ensures that all areas of the probability distribution are considered for simulation (Richardson, 2006). The examples of the simulation studies on the basis of Latin Hypercube sampling include Lien et al. (2006) and Richardson et al. (2006).

2.5.2 SERF

In stochastic simulation models of catastrophic risks, risk perception and risk attitude can be incorporated by SERF method introduced before. SERF has the advantage that it can assume all types of utility function forms presented. As stated before, SERF is applicable when risk attitude coefficients (preferences) are unknown so that a whole range of relative risk aversion coefficients developed by Anderson and Dillon (1992) is used. Then for each level of risk aversion the result in a form of CE is calculated. If a number of decisions is limited, the discrete alternatives can be compared by CEs, so that a strategy with highest CE over a range of risk aversion coefficients dominates other strategies. SERF can be applied for simple discrete examples, such as bearing hail risks by the farmers themselves or transferring the risk by purchasing insurance with basic options instead.

However, in case of more complex decisions or when the decisions are not discrete (such as allocation of several crops), stochastic model based on SERF have its limitations.

SERF will be more appropriate for simple insurance decisions as presented before, but it will not account for the fact that once the decision to insure is made, it will affect other decisions such as a change in the production plan**.** Such complex decisions had better be modelled by farm risk programming models, which use the same range of relative risk aversion coefficients developed by Anderson and Dillon (1992).

2.5.3 Farm risk programming

Contrary to stochastic simulation models, risk programming methods are used to optimise an objective function subject to a set of constraints at farm level. Usually a set of activities is optimised to maximise/minimise the objective function. The outputs from stochastic simulation models can be used in farm risk programming as inputs (i.e. yield or net farm income per 1 of 500 possible states of nature with equal probability). Methods of risk programming often applied to deal with risk perception (or probabilities and impact) and risk attitude (a range of risk aversion coefficients by Anderson and Dillon (1992) are utility-efficient programming (Hardaker et al., 2004), quadratic risk programming (Markowitz, 1952; Freund; 1956) and minimisation of total absolute deviation (Hazell, 1971). Suppose a farmer has a hail risk and operates with three crops - wheat, potatoes and sugar beet, the available land has to be optimally allocated among these crops.

Utility-efficient programming

Utility-efficient programming (UEP) has a goal function to maximise the expected utility of a risky prospect. UEP operates with all functional forms presented above, and therefore can handle changes in wealth by power utility function that is applicable to catastrophic risks. UEP is highly applicable in risk programming and includes examples such as Acs (2006), Flaten and Lien (2007), Kobzar (2006), Lien and Hardaker (2001) and Torkamani (2005). UEP model is formulated in the following way (Hardaker et al., 2004):

maximise $E[U]=pU(z, R)$, R varied (8)

Subject to

$$A\,x <= b \quad (9)$$

$$Cx - Iz = u(z,R) \quad (10)$$

Where A – is a vector of technical-economical coefficients per each activity;

x – is a vector of activities, $x>=0$;

b – is a vector of available resources (constraints);

C – is a vector of state of nature matrix of activity incomes;

I – is an identity matrix;

z – is a vector of farm goal variables by state of nature;

$E[U]$ – is expected utility;

R – is a coefficient of absolute or relative risk aversion;

p – is a probability of each state of nature;

$U(z,R)$ – is a vector of utilities of farm goal variable by state of nature with risk attitude level R.

Concerning risk perceptions for UEP, they can be imposed by any type of parametric and non-parametric distribution considered in a subsection of stochastic simulation. The catastrophic risks can easily be accommodated by adding states of nature (for instance, generated by simulation) with very low probabilities. In the example of arable farmers, the stochastic dependency between yield and prices on the basis of MVKDE or copula function can easily be incorporated in UEP.

Suppose the farm data are limited and contain only 10 years of observations without catastrophe events. Considering parametric or non-parametric distribution assumptions with imposed extremes (catastrophe events), the data can be extended to more observations. Taking into account that hail can have a different impact, the generated states of nature would contain different combinations of probability and impact of hail.

With a limited number of states of nature, without consideration of distribution assumptions to simulate the data, the additional risk perceptions of extreme cases could also be obtained from experts or elicited from farmers and then added to the UEP model. Then stochastic dependency can easily be incorporated into UEP model to minimise a risk from hail. Because wheat is more prone to hail than potatoes and sugar beet, the portfolio approach can be used to diversify the mix of activities by allocating more land to crops that are not prone to hail.

Quadratic risk programming and minimisation of total absolute deviation

Quadratic risk programming (QRP) combines probabilities and preferences to generate a set of farm plans lying on the efficient frontier of expected income and its variance (Hardaker et al., 2004). QRP has a goal to maximise the expected income and minimise the variance (risk) of expected income. The examples of QRP studies are Kobzar (2006) and Lien (2002). All equations of UEP, except for the goal function, are applicable for QRP.

The assumption necessary to validate the use of QRP is that utility function is quadratic or the distribution of total net revenue is normal. QRP is applicable only for CARA utility function, and will not work with power utility function that is appropriate for catastrophic risks. The distribution of revenue varies and is not always normal – in agriculture the returns from individual activities are often skewed (Hardaker et al, 2004). Due to the normality assumptions, the applicability of QRP model cannot be used for catastrophic risks (Ermoliev et al., 2000a, b), as shown below.

A normal distribution is defined by two parameters: mean and standard deviation. Suppose that a farmer has wheat with an average yield of 10,000 kg per hectare and a standard deviation of 2,000 kg per hectare. Then we simulate a normal distribution on the basis of these parameters. The probability that wheat yield will be lower than 5,000 kg is 0.05% assuming a normal distribution. Suppose wheat yield is more risky so that the standard deviation in a normal distribution changed to 2,500 kg, then the probability that yield is lower than 5,000 kg will correspond to 2.2%. In this example, it can be seen that a downside tail can have different densities, depending on the level of standard deviation.

For the assumption of a normal distribution, at least 20 observations are required, and the results will be misleading as long as data are sparse and it is hard to obtain more than 10 observations (including catastrophes) under the same economic policy, management regime, farm programme or trade policy (Richardson, 2006). Misspecification of the standard deviation as one of the main distribution parameter can seriously hamper the applicability of QRP for incorporation the downside tail.

The *minimisation of total absolute deviation (MOTAD)* method is an extension of QRP. It attempts to find linear approximations of QRP, and has been developed to handle non-linear functions. The structure of MOTAD model is the same as for QRP, except one. Instead of minimising the variance of income, it minimises the mean absolute deviation of income. We do not discuss the structure of this model, for details see Hardaker et al. (2004, pp. 197-199). For the same reasons as presented for QRP, MOTAD cannot be considered for effective modelling of catastrophic risks such as hail.

2.6 Conclusions and discussion

This paper reviewed the methods of risk perception, risk attitude and risk modelling on the basis of both indicators to generate an appropriate method to support decision making to cope with catastrophic risks faced by a farmer.

The data on catastrophes are skewed and deal with low probabilities, and therefore one of the main problems discussed concerned the risk perception elicitation of catastrophic risks. The standard strength of conviction method to elicit risk perception is not applicable to catastrophes as long as it deals with a limited number of points to estimate, so that a downside tail can be underestimated. But even if a tail was included in the questionnaires, people would have problems in interpreting low probabilities due to different psychological biases. To avoid psychological biases, the techniques of a better representation of probabilities, partly derived from a direct method of risk perception elicitation, can be applied.

SEU remains the main theory to incorporate risk attitude in the models. The main method ELCE was shown not to be applicable to elicitation of risk attitude coefficients. The limitation was that it was hard to assume 50:50 chances, and then to divide 50% into 50:50 chances and so on for approaching to very low probabilities. Besides catastrophic risks, in many studies applying ELCE, the results found were unconvincing due to interviewer's bias and bias from framing the questions. Alternatively, risk attitude was proposed to be estimated by econometric models. However, in these models the specification errors presented, that made the estimates of risk aversion doubtful.

As long as there are problems to obtain the exact value of risk attitude coefficients, their differences between portfolios values could be assumed by methods of stochastic dominance, and precisely by SERF application. In case of farmers, the relative risk aversion levels from the classification of Anderson and Dillon (1992) could be taken. Concerning the catastrophic risks, the level of risk aversion after catastrophe occurs can change, implying the changes in wealth position. Therefore, it would be easier to assume different levels of risk aversion instead of one specific value.

As methods of risk modelling, stochastic simulation and farm risk programming were reviewed. Stochastic simulation was shown to deal with parametric and non-parametric distributions assumptions that have proven to be successful to deal with the downside tail of the distribution. In complex systems, stochastic dependency can easily be incorporated, simulating historical or assumed pattern of dependencies. Concerning a method of sampling and catastrophe data for modelling, a Latin Hypercube sampling technique could be used instead of MCS. Stochastic simulation based on the Latin Hypercube sampling could be assumed with different types of skewed distributions to capture the downside tail. When the number of decisions is limited, they could be compared in terms of SERF. However, in case of more complex decisions, stochastic simulation has a limited applicability, and therefore the methods of farm risk programming seeking optimal solution given a set of constraints would be more appropriate. However, for accounting all possible realisations of the inputs, the input variables could be simulated first by Latin Hypercube simulation and used further in farm risk programming.

Three methods of farm risk programming were reviewed – QRP, MOTAD and UEP. QRP and MOTAD were shown not to be applicable to catastrophic risks, because they are based on normality assumptions and deal with only quadratic utility function. The power utility function, which incorporates changes in wealth, was shown to be more applicable to a case of catastrophes. For this purpose the UEP, which handles any function form, including power utility function, can be applied. Furthermore, all advantages of stochastic simulation to capture a downside tail of the distribution could be incorporated in UEP as states of nature.

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Chapter 3 Insurance decisions by Dutch arable and dairy farmers

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Abstract
This paper analysed the impact of farm characteristics on the adoption of an all-risk insurance package and underlying specific categories of insurance coverage for Dutch arable farmers compared to dairy farmers. Major farm characteristics considered were structural, operational and liquidity variables. The specific insurance categories reviewed were damage, disability, legal and liability insurance. The results suggest that there are common and insurance-specific factors that explain adoption of insurance coverage.

Keywords: arable farm, dairy farm, farm characteristics, insurance, risk

3.1 Introduction

In agriculture farmers often face risky situations. Risk means the possibility of a loss of income or property (Pritchet et al., 1996). Farm risks can be divided into business and financial risks. Business risk is related to production, price, institutional and personal risk. In contrast, financial risk results from the method of financing and is related to the debts and equity of the farm (Hardaker et al., 2004). To cope with risks, farmers may apply risk management strategies, such as farm financing, diversification of activities, insurance, or spot and futures marketing contracts (Hardaker et al., 2004).

Insurance is frequently used to cover the financial consequences of many risks (Pritchet et al., 1996). Many agricultural studies, for example focusing on crop insurance, have been done to derive the variables influencing a farmer's actual (objective) insurance purchase decisions on the example of crop insurance (e.g. Coble et al., 1996; Goodwin et al., 2004; Mishra et al., 2005; Mishra and Goodwin, 2003; Sherrick et al., 2004), or to predict a farmer's demand for insurance by a subjective source of data (Van Asseldonk et al., 2002). In agricultural studies, the variables were divided into farm characteristics and farmers' personal characteristics (e.g. Mishra and Goodwin, 2003; Sherrick et al., 2004). The farm characteristics analysed referred to structural, operational and liquidity variables. Farmer-specific characteristics analysed in insurance purchases were risk perception, risk attitude, age, education, tenure, previous exposure to risk and the farmer's experience level. The impact of personal characteristics on the amount of insurance purchased was extensively examined in non-agricultural studies regarding health insurance, optimal long-term care insurance and car insurance (e.g. Gupta and Li, 2004; Ma and Schmit, 2000; Polsky et al., 2005; Zweifel and Struwe, 1998). Similar to agricultural studies, the personal characteristics, such as age, marital status, risk aversion, education and income, were considered for the current analysis.

In agriculture, many of the studies were conducted as to specific risks and focused on perils such as hail, frost, drought, precipitation, storm and flood (e.g. Ganderton et al., 2000; Kunreuther and Pauly, 2004; Van Asseldonk et al., 2002).

Farmers, on the other hand, are faced with the whole set of risks, and they should opt for an integrated risk-management strategy, in which all business and financial risks are evaluated in a portfolio context. Published examples within a whole-farm perspective to analyse farmers' decisions about the purchase of all-risk insurance package and its underlying coverages are rare.

It is also important to analyse the effect of diversification in insurance decisions (Hardaker et al., 2004; Harrington and Niehaus, 1999). For instance, arable farmers usually have several crops (activities), and their selection of the optimal plan (set of crops) can be seen as an appropriate risk management strategy to cope with many risks. Alternatively, dairy farmers are more specialised compared to arable farmers, and have, next to milk production, only one additional activity: rearing calves. The potential for diversification is much lower than in arable farming.

The goal of this paper was to conduct an empirical analysis of actual (objective) insurance purchase decisions by Dutch arable and dairy farmers based on a set of specific risks. The analysis focuses on gaining a perspective as to the purchase of an all-risk insurance package within a whole-farm context and also within a partial context for the separate underlying insurance categories to cope with specific risks. All models are analysed by the generic set of variables.

The paper is organised as follows. First the conceptual model with the main definitions, estimation procedure, data and variables used for the empirical models are introduced. Then the results of the different models analysing the actual purchase of insurance by Dutch arable and dairy farmers are described. The paper finishes with conclusions and recommendations for insurance policy-makers.

3.2 Conceptual model, data and estimation

3.2.1 Conceptual model and definitions

The conceptual model is based on previous studies and available data for the current analysis. The purchases of the following insurance types are examined: all-risk insurance, damage, disability, legal and liability insurance. The *all-risk insurance package* is the summation of total premiums paid for all insurance types. *Damage insurance* protects in case of fire, storm or flooding causing property damage. *Disability insurance* covers the costs when a person is unable to perform work, due to serious injury or illness (Pritchet et al., 1996). *Legal insurance* provides coverage for losses incurred due to court actions (but excluding criminal matters). *Liability insurance* protects against loss arising if a farmer injures other persons or damages their property (a good example is mandatory insurance of driver's liabilities in car insurance).

The conceptual model is based on previous studies and available data for the current analysis. Purchase of insurance is assumed to be influenced by both farm characteristics and the farmer's personal characteristics. Farm characteristics were divided into structural variables that usually can change only in the long run, operational variables that can change in the short run and liquidity variables. The impact directions of variables influencing the amount of premiums purchased is shown in Figure 1.

Farm characteristics			***Farmer's personal characteristics***
Structural	***Operational***	***Liquidity***	
Balance sheet value (+) Rented land (+) Region	Net farm result (-) McSharry (-) Off-farm income (-) Operational expenses	Leverage (+)	Age (+)

* positive (+) or negative (-) signs imply positive or negative impact of the variable on the amount of premium paid

Figure 1. **Variables explaining the amount of insurance purchased**

As structural variables, the size of the farm, proportion of rented land and regional variable were taken. The impact of farm size had previously been tested by Goodwin et al. (2004) and Sherrick et al. (2004), where a positive relationship between farm size and insurance purchase was found. In our model the balance sheet value of the farm is used as a size indicator. The proportion of rented land was previously examined in the study by Sherrick et al. (2004). It was found that farmers having relatively more rented land purchased more insurance. Additionally, it is expected that there are regional differences between farmers concerning insurance purchase. That is why a region variable was constructed, dividing the farmers into a southern and a northern part (1= South, 0 = North).

As operational variables, the net farm result, McSharry compensations, off-farm income and operational results were taken for the models. The variables net farm result, off-farm income and McSharry compensations are variables characterising incomes. A negative impact of these variables on the amount of insurance purchased was expected, because farmers would prefer more money to less accumulating wealth than spending income sources on insurance, as was shown in the studies by Ganderton et al. (2000), Mishra and Goodwin (2003), Sherrick et al. (2004), Smith and Goodwin (1996), and Watt et al. (2001).

As operational variables, the effect of chemical use on crop insurance purchase was analysed in the study by Mishra et al. (2005), but no clear relationship was found. Smith and Goodwin (1996) found a negative relationship between purchase of crop insurance and use of chemical inputs. In our analysis, the effect of fertilisers and feed costs on the amount of premium paid is tested (Ganderton et al., 2000; Kunreuther and Pauly, 2004; Van Asseldonk et al., 2002).

The impact of liquidity variables on the amount of insurance purchased was tested by Ganderton et al. (2000), Mishra and Goodwin (2003), Mishra et al. (2005) and Sherrick et al. (2004). They found that more indebted farmers purchase more insurance. In this study the impact of debt-to-equity ratio (leverage) on insurance purchased is examined.

Of farmer-specific variables, only the variable age was available in the database analysed. In farm research the positive impact of age on insurance purchased was obtained by Mishra et al. (2005) and Sherrick et al. (2004). Non-agricultural studies, such as by Gupta and Li (2004) and Polsky et al. (2005), also reported that insurance users are relatively older.

2.2 Data

The Farm Accountancy Data Network (FADN), containing a cross-sectional dataset, was used for our analysis. The FADN dataset is an official European Union dataset. Farm-specific accounting data that are available in the FADN dataset include detailed information about all agricultural sectors. The sample of FADN data was corrected by a weighted factor to represent the whole population of Dutch arable and dairy farmers. The data corrected were compared with national statistics and were not different. In total, a sample of 117 from a total number of 9060 arable farms and 240 from 24400 dairy farms are analysed (see Table 1).

FADN data are not very detailed with respect to insurance related variables. They comprise only the premiums of underlying specific insurance categories. The descriptive statistics of farm characteristics and variables used in the models are presented in Table 1.

Table 1. **Descriptive statistics of the model variables for arable and dairy farms**

Characteristics	Units	Arable farms (n=117, N=9060)			Dairy farms (n=240, N=24400)		
		Mean	**%**	**CV**	**Mean**	**%**	**CV**
Insurance							
All-risk insurance	Euro	7667	-	96	6251	-	54
Damage insurance	Euro/participation (%)	2336	99	71	1666	94	69
Disability insurance	Euro/participation (%)	1391	68	128	1317	69	129
Legal insurance	Euro/participation (%)	195	62	147	152	55	134
Liability insurance	Euro/participation (%)	1293	97	96	886	90	87
Structural							
European size units (ESU)	units	87		36	112		28
Balance sheet value	Euro	1445175		70	2230571		39
Number of cows	units	-			60		31
Rented land	% in total area		0.49			0.34	
Region	(1=South; 0=North)		0.47			0.55	
Operational							
McSharry	Euro	2935		215	3752		99
Net farm result (excl. insurance)	Euro	1410		-806	-22648		-179
Feed costs	Euro	-			33552		56
Fertiliser costs	Euro	6917		60	-		
Financial variables							
Family-farm income	Euro	54871		114	53421		64
Liquid capital	Euro	91140		240	46210		304
Long-term loans	Euro	269964		104	371497		74
Off-farm income	Euro	5633		681	6506		181
Leverage	%		31			26	
Farmer specific							
Age	years	53		23	51		22

2.3 Descriptive statistics

As can be seen from Table 1, arable farmers pay more premiums in total than dairy farmers. With respect to underlying categories, most arable and dairy farmers have damage, disability, legal and liability insurance. On average, arable farmers participating in those insurance types pay higher premiums than dairy farmers.

From ESU and balance sheet value it can be observed that arable farms are smaller. On average, arable farmers have almost 50% of rented land, which is substantially more than dairy farmers have. The arable and dairy farmers sampled are more or less equally located.

Arable farmers had a positive net farm result in 2001, while the average dairy farm was not so profitable, despite the fact that dairy farmers received higher McSharry (price) compensations. On average, total family-farm income is a bit higher for arable farmers, whereas the off-farm income of dairy farmers is larger. From the balance sheet value and debt-to-equity ratio (leverage), it can be concluded that dairy farmers are less indebted than arable farmers, and are also wealthier. As to age the average arable farmer is a bit older than the average dairy farmer.

2.4 Data estimation

Linear regression analysis was carried out to estimate the impact of variables on the amount of premium paid, thus including only farmers who purchased insurance. In total 5 models for arable farms and 5 models for dairy farms were estimated. The models estimating the purchase of an all-risk insurance package had total premium paid as dependent variable. The other models estimated the purchases of insurance coverages related to agricultural activities and had damage, disability, legal and liability insurance as dependent variables. For those insurance categories, farmer participation was the highest, and farmers paid the highest premiums (see Table 1).

Most of the data referred to the farm data; the only variable characterising a farmer as a person was age. The variables analysed were balance sheet value, the regional variable, net farm result, McSharry compensations and off-farm incomes as additional farmer's resources, leverage (debt-to-equity ratio) and farmer's age.

To deal with multicollinearity the variance inflation factor (VIF) was calculated for each variable. The rule of thumb was that it had to be lower than 4 (Garson, 2007), while

Hair et al. (1998) and other researchers used the maximal cut-off value of 5 or even 10 (Hair et al., 1998). Beside the VIF, the multicollinearity can be inspected on the basis of the condition index with cut-off values in the range of 15-30 (for details see Garson, 2007; Hair et al., 1998). For values higher than 15, multicollinearity is a problem if the proportion of variance for two or more variables is higher than 50% (Garson, 2007). Hair et al. (1998) stated that if the proportion of variance is higher than 90%, there is a suspicion of multicollinearity.

In our models the values of VIF were lower than 4 (see Table 2 and 3), conditional indexes were much lower than 15, and proportion of variance of two or more variables was not higher than 50%. The variables net farm result, McSharry compensations operational costs (fertilisers and feeds), proportion of rented land and farmer's age were the source of the multicollinearity. Therefore, these five variables were excluded from the main set of models that consisted of the variables balance sheet value, regional differences, off-farm income and leverage. Moreover, operational costs very highly correlated with net farm result, and proportion of rented land was correlated with leverage and farmer's age. McSharry compensations were highly positively correlated with balance sheet value of the farm. For the second set of models, the variables operational expenses, McSharry compensations and proportion of rented land were excluded, and the choice was made in favour of net farm result and farmer's age.

The regressions were made by OLS estimation in SPSS 12.0. The models were estimated without a constant parameter, taking into account the limited set of variables to explain the purchases of insurance.

3.3 Results and discussion

For both arable and dairy farms, the *balance sheet value* was positively significant at the 1% level for the all-risk insurance package and also the specific underlying insurance categories (see Tables 2 and 3). This finding was according to expectations and the results of Goodwin et al. (2004) and Sherrick et al. (2004). Increased farm size is a cause of purchasing more insurance, because a farmer accepts more risk due to growth (Goodwin et al., 2004; Sherrick et al., 2004). The other reason to purchase more is related to insuring more property (Harrington and Niehaus, 1999).

Table 2. **Main variables explaining insurance purchase by arable farmers**

Variables	Damage			Disability			Legal			Liability			All-risk		
	Parameter value	St. error	VIF	Parameter value	St. error	VIF	Parameter value	St. error	VIF	Parameter value	St. error	VIF	Parameter value	St. error	VIF
1st set of models															
Balance sheet value	1.2E-03***	9.5E-05	1.7	9.0E-04***	1.6E-04	1.8	1.4E-04***	2.8E-04	1.9	7.6E-04***	7.5E-05	1.7	4.3E-03***	4.9E-04	1.7
Region (1=South; 0=North)	-155.2	229.7	1.5	578.9	382.8	1.5	77.4	71.4	1.5	163.9	183.5	1.5	-411.4	1178.7	1.5
Off-farm income	7.6E-03**	3.5E-03	1.1	7.2E-03	5.0E-03	1.1	1.3E-03	8.5E-04	1.2	2.9E-03	2.7E-03	1.1	-3.4E-03	1.8E-02	1.1
Leverage	10.6***	2.1	1.3	4.5	3.3	1.3	0.8	0.6	1.3	2.4	1.7	1.3	18.6*	10.9	1.3
Adjusted R-square		0.77			0.54			0.48			0.65			0.55	
Sample size		116			79			72			113			117	
2nd set of models															
Net farm result	3.1E-03	3.1E-03	1.0	-4.9E-03	4.1E-03	1.0	-7.7E-04	6.9E-04	1.0	4.9E-04	2.3E-03	1.0	2.7E-02**	1.3E-02	1.0
Age	42.4***	2.9	1.0	37.0***	4.0	1.0	5.7***	0.7	1.0	24.7***	2.1	1.0	142.8***	12.3	1.0
Adjusted R-square		0.77			0.54			0.49			0.54			0.54	
Sample size		116			79			72			113			117	

*, **, *** - significant at 10%, 5% or 1% level

Table 3. **Main variables explaining insurance purchase by dairy farmers**

Variables	Damage			Disability			Legal			Liability			All-risk		
	Parameter value	St. error	VIF	Parameter value	St. error	VIF	Parameter value	St. error	VIF	Parameter value	St. error	VIF	Parameter value	St. error	VIF
1st set of models															
Balance sheet value	5.6E-04***	5.6E-05	2.8	5.0E-04***	1.0E-04	3.0	9.1E-05***	1.3E-05	4.1	2.7E-04***	3.8E-05	2.80	2.3E-03***	1.7E-04	3.0
Region (1=South; 0=North)	593.7***	137.5	2.0	494.6*	262.3	2.3	97.6***	31.2	2.0	300.2***	92.7	2.00	408.8	398.4	2.0
Off-farm income	1.4E-02***	6.0E-03	1.3	-1.7E-03	1.1E-02	1.2	2.5E-03*	1.3E-03	1.3	1.8E-02***	3.9E-03	1.30	6.2E-02***	1.8E-02	1.2
Leverage	4.4	2.7	2.0	17.6***	6.4	2.6	0.6	0.7	2.4	4.0**	1.8	2.00	25.7***	8	2.0
Adjusted R-square		0.76			0.56			0.7			0.66			0.78	
Sample size		225			165			131			215			240	
2nd set of models															
Net farm result	-6.1E-03***	2.0E-03	1.4	-6.8E-03*	3.0E-03	1.2	-8.4E-04*	4.6E-04	1.3	-3.3E-03***	1.2E-03	1.4	-9.60E-03	6.0E-03	1.3
Age	29.6***	1.8	1.4	32.7***	3.1	1.2	5.0***	0.4	1.3	17.5***	1.1	1.4	111.3***	5.3	1.3
Adjusted R-square		0.73			0.55			0.65			0.65			0.72	
Sample size		225			165			131			215			240	

*, **, *** - significant at 10%, 5% or 1% level

The *regional variable* was a Dutch specific variable differentiating farmers in the South from farmers in the North. In arable farming, the regional differences were not relevant concerning insurance purchase. For dairy farms, it had a positive impact on the amount of premium paid for damage, disability, legal and liability insurance. That shows that there are differences in insurance behaviour: a dairy farmer in the South purchases more insurance coverage than a dairy farmer in the North.

In arable farming, *off-farm income* had a positive impact on purchase of damage insurance. In dairy farming, the off-farm income was positively significant at the 1% level for purchase of all-risk insurance package and damage, legal, liability insurance and all-risk insurance package. This finding was contrary to expectations as in the study by Smith and Goodwin (1996). The reason for that could be that a substantial part of off-farm income is presented by social security payments received from insurance companies.

In arable farming, the *net farm result* was irrelevant as to the purchase of specific insurance categories, but was positively significant for purchase of all-risk insurance package. The net farm result of the average dairy farmer had a negative impact on the amount of premium paid for damage, disability, legal and liability insurance. Dairy farms were wealthier than arable farms, and therefore could consider self-insurance an alternative to commercial insurance. Thus having a high initial wealth position, dairy farmers could save more money from core activities to increase financial capacities for self-insurance or would be likely to insure less (Coble et al., 1996).

For arable farms, the *leverage* was significant for the purchase of damage insurance and an all-risk insurance package. In dairy farming, also the purchase of disability, liability insurance and an all-risk insurance package was related with debt-to-equity ratio. In both sectors, leverage had a positive impact, according to the expectations and similar to the results by Coble et al. (1996), Ganderton et al. (2000), Mishra and Goodwin, (2003), Mishra et al. (2005), Sherrick et al. (2004), and Smith and Goodwin (1996), implying that more-indebted farmers need to purchase more insurance. Alternatively, less-indebted farmers with higher net worth are less likely to purchase insurance. In order to take more loans, it is often required from the bank to be insured to stabilise farm liquidity and avoid the risk of going bankrupt. Lenders will demand compensation for investing in farms with a higher probability of financial distress. In this respect, if a farmer can reduce a risk through insurance, lenders will be willing to contract the farm at better terms (Harrington and Niehaus, 1999).

The *age* was significant at 1% for purchase of an all-risk insurance package and underlying insurance categories for both arable and dairy farmers and had a positive direction of impact. This was in accordance with expectations and the results from previous studies by Gupta and Li (2004), Mishra et al. (2005), Polsky et al. (2005) and Sherrick et al. (2004). Insurance users are thought to be relatively older (Sherrick et al., 2004). Age can also be an indicator of farmer's experience, and in this respect, should have a positive impact on buying insurance (Mishra et al., 2005).

3.5 Conclusions

The goal of this paper was to investigate whether there are common or specific variables influencing the purchase of an all-risk insurance package and underlying insurance categories by arable and dairy farmers. In both types of farming, for insurance categories and all-risk insurance package considered, all variables, except the net farm result for purchase of all-risk insurance by arable farmers, had the same direction of impact.

Both arable and dairy farms showed more willingness to save money from core activities to accumulate more savings than to spend money on insurance. Both farm types were very different with respect to available finances - dairy farms are more specialised compared to arable farms having a diverse set of activities. Arable farms were expected to insure less because diversification of activities is already a form of risk management strategy. Contrary to that, the analysis showed that arable farms paid higher premiums than dairy farms. In arable farming with a diverse set of activities, the source of income is less risky than with undifferentiated commodity production as in dairy farming, but if the potential down the supply chain to cause losses is increased due to the proximity of the customer to the farmer supplier, overall risk might be increased. The other reason could be that arable farmers are less wealthy and, in general, deal with more risks than dairy farmers, and thus are more prone to paying higher premiums for insurance to avoid possible financial risks.

Despite the differences between degrees of specialisation/diversification, wealth, amount of premium paid by arable and dairy farmers, common variables were found – size and farmer's age - that influenced purchase of all insurance types and all-risk insurance package considered.

In most of the previous agricultural studies of crop insurance in the USA, it was found that insurance subsidies were one of the main reasons to purchase insurance coverage (e.g. Babcock and Hart, 2005; Mishra and Goodwin, 2003; Mishra et al., 2005; Sherrick et al. 2004; Smith and Goodwin, 1996). In the Netherlands, farmers do not receive insurance subsidies, and the analysis was conducted with a generic set of variables.

In this analysis, the off-farm income contained social security payments. If the data were less aggregated, only the impact of the 'real earned' off-farm income on the amount of insurance coverage purchased could be tested. Due to data limitations, farmer's personal characteristics such as risk attitude, specific risk perception, marital status, education, previous exposure to risk(s) and experience level were not used in the models. As farmer's personal characteristics, the additional information on insurance contracts such as the size of deductibles could be considered for further research.

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Chapter 4 Purchase of catastrophe insurance by Dutch arable and dairy farmers

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Abstract

This paper analysed the impact of risk perception, risk attitude and other farmer personal and farm characteristics on the actual purchase of catastrophe insurance by Dutch arable and dairy farmers. The specific catastrophe insurance types considered were hail-fire-storm insurance for buildings, disability insurance, crop insurance against hail, storm and brown rot, and insurance against epidemic animal disease outbreaks. The results suggested that risk perception was a significant variable that influence purchase of catastrophe insurance by arable and dairy farmers, whereas risk attitude was significant only in arable farming.

Keywords: risk perception, risk attitude, catastrophic risk, probit, arable farmer, dairy farmer

4.1 Introduction

Catastrophic risks can be defined as events with low probability of occurrence (rare events) leading to major and typically irreversible losses with potentially adverse impact on business results (Chichilnisky, 2000; Vose, 2001). Rarity and severity are typically associated with catastrophic risks: the more severe a risk, the rarer it usually will tend to be, and vice versa (Frohwein et al., 1999). Catastrophe events can thus inflict considerable losses on many stakeholders of private businesses (insurers, re-insurers, banks, et cetera) and society (government, tax-payers, households).

In agriculture catastrophic risks result in heavy losses for farms. For example, arable farmers are exposed to extreme meteorological events, such as heavy precipitation, excessive heat, drought, hail, storm and frost, which may result in potential damage to crops (Langeveld et al., 2003). In dairy farming, epidemic diseases, such as FMD (foot-and-mouth disease) and BSE (bovine spongiform encephalopathy), cause severe economic losses (Huirne et al., 2003). In this paper we assume that an event is catastrophic if a farmer may face cash flow problems or even go bankrupt. Somehow farmers need to manage catastrophic risks. By applying risk management strategies, such as insurance, diversification, self-insurance, forward contracting, options and futures contracts, losses associated with catastrophe events can be borne or transferred.

Insurance is a frequently used instrument to cover catastrophic risks (Pritchet et al., 1996). However, not all farmers buy insurance to protect their business against several types of catastrophic risks. Thus it is important to analyse the factors that influence purchase of catastrophe insurance to provide insight for improvement of existing and development of enhanced insurance policies. In order to understand the use of insurance decisions to cover losses due to a catastrophe, main factors that influence catastrophe insurance purchase need to be addressed. In farming, these factors refer to farm characteristics and farmers' personal characteristics (e.g. Mishra and Goodwin, 2003; Sherrick et al., 2004). Effects of farm characteristics on insurance purchase were elaborated by for example Mishra and Goodwin (2003), Ogurtsov et al. (2007) and Sherrick et al. (2004). Farm variables, including farm size, proportion of rented land, region, net farm income, governmental compensations, operating costs, off-farm income and debt use were found to have a significant impact on catastrophe insurance purchase. However, the analysis of impacts of farmer-specific factors is essential to understand real-life catastrophe insurance decisions.

The impact of farmer-specific risk on catastrophe insurance decisions can be addressed by separating the components – risk perception and risk attitude. Risk perception is a subjective statement of risk by decision-makers, it is more like the mental interpretation of risk, decomposed as the chance of a loss occurring and the magnitude of the loss (Hardaker et al., 2004; Smidts, 1990). Likewise risk perception, risk attitude plays an important role in understanding the decision-maker's behaviour. Risk attitude is a personal characteristic and deals with the decision-maker's interpretation of the risk and how much (s)he dislikes the outcomes resulting from the risk (Pennings et al., 2002). According to Dillon and Hardaker (1993), risk attitude is defined as the extent to which a decision-maker seeks to avoid risk or is willing to face risk. As most farmers are commonly assumed to be *risk-averse* (Hardaker et al., 2004), the further analysis of risk attitude is related to *risk aversion*.

Many of the previous studies were conducted on one specific type of farming – arable farming (i.e. Coble et al., 1996; Goodwin et al., 2004; Mishra et al., 2005; Mishra and Goodwin, 2003). In this paper two types of farms are analysed - the Dutch arable and dairy farmers. Most arable farms have a diversified mix of crops, whereas dairy farms are usually highly specialised. Diversification is a kind of risk management strategy and can substitute and also complement catastrophe insurance. The general purpose of diversification is to reduce the dispersion of overall return by selecting the mixture of activities that have returns with low or negative correlations. However, diversification may be costly if it means forgoing the advantages that specialisation confers through better command of superior technologies and closer attention to the special needs of one particular market (Hardaker et al., 2004, p.273). Thus it is also important to analyse the diversification effect in catastrophe insurance decisions (Hardaker et al., 2004, p.273; Harrington and Niehaus, 1999, p.154).

The goal of this paper is to provide guidance on the existing and enhanced catastrophe insurance policies for the Dutch arable and dairy farmers. For this purpose the factors that influence purchase of different catastrophe insurance types will be analysed with a major focus on the farmer-specific characteristics (risk perception, risk attitude and other farmer personal variables) that play an important role in understanding farmer's insurance behaviour. This paper analyses the actual catastrophe insurance purchase and is not focused only on specific insurance type as the majority of previous studies. The attempt is made to gain a broad perspective of insuring the risks that can be catastrophic for the two different types of farming (arable and dairy farming). As many of the crop insurance studies (i.e. Coble et al., 1996; Mishra et al., 2006; Mishra and Goodwin, 2003), this study elaborates also on the crop risks, such as hail, storm and brown rot that can be catastrophic. Beside crop risks, the study analyses insurance purchase against emerging risk of animal diseases in dairy farming. Apart from the risks that are specific per type of farming, common risks, such as damage/destruction of buildings by hail, fire and storm, and farmer's disability risks are the subjects of this study.

The paper is outlined as follows. First, other studies focusing on factors affecting catastrophe insurance purchase will be reviewed. Then the models, methods, data and variables will be introduced. Finally, the main results, discussion, conclusions and implications will be presented.

4.2 Literature review

The majority of the studies analysing the impact of variables that influence actual insurance purchase in agriculture were conducted in the USA on the crop insurance (i.e. Coble et al., 1996; Mishra et al., 2005; Mishra and Goodwin, 2003; Sherrick et al., 2004). Other studies focused on (hypothesised) demand for insurance (i.e. Ganderton et al., 2000; Van Asseldonk et al., 2002). There are hardly any studies focusing on the factors related to catastrophe insurance purchase in animal husbandry. The outbreaks in animal husbandry are systemic risks implying that outbreaks at one farm are strongly correlated with outbreaks at the other farms, and there are no many comprehensive insurance policies against epidemics.

In the bulk of the crop insurance studies, the impact of farm- and farmer-related variables on catastrophe insurance purchase were derived. In the early paper by Coble et al. (1996), the farmer's net worth (wealth) showed a significant impact on the demand to purchase crop insurance. Sherrick et al. (2004) found that the size, age, off-farm income and debt-to-asset ratio were significant on the purchase of crop insurance. In the study by Mishra et al. (2005), a purchase of crop revenue insurance coverage was caused by the value of production, soil productivity, farm diversification, hedging contracts and age. Smith and Goodwin found that a purchase of crop insurance was correlated with use of chemical inputs, relative risk aversion and debt-to-asset ratio. Mishra and Goodwin (2003) showed that a purchase of crop insurance coverage was caused by education level of the farmer, age, debt-to-asset ratio, participation in government programs, value of production, soil productivity, off-farm income, indemnity, hedging contracts and type of ownership. In the Dutch study by Van Asseldonk et al. (2002), it was concluded that age, solvency and risk perception were the factors that influence the demand for crop insurance, whereas risk attitude was not a significant variable. In the hypothetical non-agricultural study by Ganderton et al. (2000), risk perception, risk attitude, wealth, exposure and previous negative experience had an impact on the hypothetical demand of catastrophe insurance.

In general, *risk perception* and *risk attitude* are often regarded as the key farmer-specific factors to explain insurance purchase. The subjective expected utility (SEU) hypothesis states that the utility of a risky prospect is the decision-maker's expected utility for that prospect, meaning the average of the utilities of outcomes weighed by the subjective probabilities of those outcomes (Hardaker et al., 2004). In this context, risk perception is measured in terms of a subjective probability distribution, and risk attitude is measured by a shape of the Von Neumann-Morgenstern utility function (Hardaker et al., 2004; Smidts, 1990).

The SEU approach is a method of individual choice, and for reasons of practical feasibility, cannot be expected to be suitable for large-scale surveys (Smidts, 1990). Alternatively, the impact of risk perception and risk attitude can be analysed by econometric models on basis of actual purchase decisions or willingness-to-pay (WTP) studies. This approach is suitable for large-scale surveys thanks to its simplicity. In these models, risk perception and risk aversion are used as independent variables. Contrary to the prescriptive SEU approach, observed economic behaviour approach is used to describe which *decisions are indeed made,* rather than to predict what *should be taken*. A direct questionnaire procedure is usually conducted, in which psychometric ordered Likert scales are provided for elaborating variables describing or eliciting risk perception and risk attitude (Ganderton et al., 2000; Ozdemir and Kruse, 2000; Van Asseldonk et al., 2002). The questionnaires often include additional farmer related questions for inclusion into the model, such as the education, age, and experience. We present below how risk perception and risk attitude were elicited in these studies.

In the study by Ganderton et al. (2000), *risk attitude* was included in the models as a linear variable measured on a scale from 1 to 6. In a similar way Coble et al. (1996) measured risk attitude on a scale from 0 to 10. Ozdemir and Kruse (2000) assessed a degree of *risk aversion* compared to other persons by asking binary questions about the use of smoke, burglar and car alarms, emergency items/food and participation in natural disaster and health insurance. According to their 'relative risk aversion' measurement, individuals were labelled 'relatively risk-averse' or as 'risk lovers'. In a similar way, a measure of relative risk aversion was derived in studies by Meuwissen et al. (2001), Van Asseldonk et al. (2002). They used subjective risk attitude Likert scales as developed by Pennings (1998). Meuwissen et al. (2001) used five 5-point Likert statements to elicit risk aversion. Likewise Van Asseldonk et al. (2002) used five 7-point Likert statements for calculating the average score, labelling farmers as less- and more risk-averse.

As relative risk attitude, relative *risk perception* was used in many studies as a scale variable. In the study by Ozdemir and Kruse (2000) risk perception was elicited on a 5-point scale, based on whether a house will be damaged by a tornado. Similarly, using linear scales, Van Asseldonk et al. (2002) elicited risk perception by decomposing farmer total cultivated area into a high risk, average risk, moderate risk, and low risk of loss. The linear risk perception variables ranged from 1 (proportion of area with a relatively low risk) to 4 (proportion of the area with a relatively high risk).

4.3 Materials and methods

3.1 Binary probit model

Probit or logit models are often used for the evaluation of actual or hypothetical decisions about insurance purchase (i.e. Ganderton et al., 2000; Mishra and Goodwin, 2003; Sherrick et al., 2004; Van Asseldonk et al., 2002). In this paper a probit specification of binary and ordered models was used.

Binary probit models determine which variables influence the choice to purchase or not to purchase catastrophe insurance. The following specification of a binary probit model was used (for details see Verbeek, 2002, p.179-180):

$$y_{ni}^{*} = \beta_i' x_{ni} + \varepsilon_{ni} \tag{1}$$

Where y_{ni}^{*} - is the amount of premium paid by the farmer *n* for catastrophe insurance type *i*;

x_{ni} - is a vector of explanatory variables describing the purchase of *i* catastrophe insurance by farmer *n*;

β_i' - is a vector of parameters to be estimated per catastrophe insurance type *i*;

ε_{ni} - is a random error term assumed to follow a standard normal distribution.

The dependent variable y_{ni} has two outcomes:

$$y_{ni} = \begin{cases} 1 \ \ if \ \ y_{ni}^{*} > 0 \\ 0 \ \ if \ \ y_{ni}^{*} = 0 \end{cases} \tag{2}$$

Formulation (2) is used to describe two decision options: if farmer *n* purchases catastrophe insurance type *i* (value 1) or not (value 0).

3.2 Ordered probit model

In addition to analysing the purchase (or not) of catastrophe insurance, it is important to analyse the amount of premium paid by a farmer for a certain type of catastrophe insurance. The amount of premium paid is a continuous (dependent) variable that is analysed by standard ordered probit models. For ease of interpretation, the insurance premium payments were divided into *j* groups (see also Verbeek, 2002, p.190-191):

$$y_{ni} = \begin{cases} 0 & \text{if } y^*_{ni} = 0 \quad \text{Euro (group 1)} \\ 1 & \text{if } 1 < y^*_{ni} \le \mu_1 \quad \text{Euro (group 2)} \\ 2 & \text{if } \mu_1 < y^*_{ni} \le \mu_2 \quad \text{Euro (group 3)} \\ \dots & \dots \\ j-1 & \text{if } y^*_{ni} > \mu_{j-1} \quad \text{Euro (group } j\text{)} \end{cases} \tag{3}$$

Where μ - is cut-off point, dividing farmers into different insurance premium groups;

j - is a finite number of groups to categorise a catastrophe insurance type i.

The cumulative probabilities *Pr* of the discrete continuous variables are formulated as follows:

$$Pr(y^*_{ni} \le \mu_j) = F(\mu_j - \beta'_i x_{ni}) \tag{4}$$

where F – is a standard normal cumulative distribution function.

Subsequently, the marginal probability effects of significant variables can be calculated to test significant differences between premium groups. The marginal probability effects (*MPE*) were calculated for each group j as:

$$MPE_{nij} = \frac{\partial Pr(y^*_{ni} = \mu_j)}{\partial x_l} = [f(\mu_{j-1} - \beta'_i x_{ni}) - f(\mu_j - \beta'_i x_{ni})] \times \beta_l \tag{5}$$

where Δx_l - denotes to the change of outcome from μ_{j-1} to μ_j, and

$$f(z)=dF(z)/dz \tag{6}$$

The marginal probability coefficients are interpreted as a quantitative impact of some significant variable on the amount of premium paid for catastrophe insurance type *i* purchased by farmers from different insurance premium groups.

4.3.3 Data from FADN and questionnaire

Two types of data were used for the analysis: (1) farm- and farmer-specific data from the Farm Accountancy Data Network (FADN) cross-sectional dataset of the year 2003, including detailed data on costs, returns, cropping and livestock plan of the farm, and (2) farm- and farmer-specific data collected by a questionnaire survey. The FADN data is an official European Union dataset comprising all agricultural sectors.

The questionnaires were sent to 393 farmers, i.e. 135 arable and 258 dairy farmers, who were all members of a group that was sampled by the Landbouw Economisch Instituut (LEI) from the Netherlands. After 2 weeks a reminder was sent to the farmers. This resulted into a response rate of 54.8% for arable farmers (74 farms) and 48.5% for dairy (125 farms). In total, after combining FADN data and data from the questionnaire, 65 arable farms and 113 dairy farms were used for the analysis.

In this study, the main variables that influence the decisions how to cope with catastrophic risks are the risk variables risk perception and risk attitude. The impact of other variables that were found significant in the previous studies - off-farm income, debt use, farm size, wealth, age and previous negative experience - is also tested in this study. We expect that the additional variables willingness to accept risk, maximal risk-bearing capacity, availability of a successor and net farm result will be relevant for the catastrophe insurance purchase. The detailed description of all variables is presented below.

Dependent variables

In arable farming, purchases of five types of insurance purchase were analysed, i.e. (1) damage of building by hail, fire or storm, and crop perils related to (2) hail, (3) storm and (4) brown rot, and also (5) farmer disability. For dairy farmers, purchases of four insurance types were analysed: (1) damage of building by hail, fire or storm, (2) FMD, (3) BSE and (4) disability risk.

Table 1. **Groups of farmers on the basis of the amount of premium paid**

Arable farmers (n = 65)					
Insurance premium groups	Hail-fire-storm buildings	Hail crop	Storm crop	Brown rot	Disability
	Proportion of farmers in the group				
Not insured	0.25	0.38	0.80	0.52	0.51
0-100	0.00	0.03	0.05	0.08	0.02
101-500	0.05	0.12	0.08	0.18	0.02
501-1000	0.14	0.22	0.02	0.14	0.08
1000-2000	0.29	0.20	0.03	0.08	0.17
2001-4000	0.20	0.05	0.03	-	0.17
4001-6000	0.08	-	-	-	0.02
6001-8000	-	-	-	-	0.02
8001-10000	-	-	-	-	0.02
Insured	0.75	0.62	0.20	0.48	0.49

Dairy farmers (n = 113)				
Insurance premium groups	Hail-fire-storm buildings	FMD	BSE	Disability
	Proportion of farmers in the group			
Not insured	0.16	0.90	0.92	0.35
0-100	0.03	0.02	0.02	0.01
101-500	0.04	0.07	0.07	0.02
501-1000	0.15	0.01	0.01	0.05
1001-2000	0.35	-	-	0.12
2001-4000	0.22	-	-	0.26
4001-6000	0.04	-	-	0.16
6001-8000	0.01	-	-	0.02
8001-10000	-	-	-	0.01
Insured	0.84	0.10	0.10	0.65

Table 2. **Descriptive statistics of model variables**

Variables	Units, type of variable	Arable (n=65, N=9060)			Dairy (n=113, N=24400)		
		Mean	%	SD	Mean	%	SD
Premium hail/fire/storm building	Euro (classes)	2657	-	-	2493	-	-
Premium FMD	Euro (classes)	-	-	-	473	-	-
Premium BSE	Euro (classes)	-	-	-	473	-	-
Premium disability	Euro (classes)	2988	-	-	3851	-	-
Premium hail crop	Euro (classes)	1380	-	-	-	-	-
Premium storm crop	Euro (classes)	1215	-	-	-	-	-
Premium brown rot crop	Euro (classes)	823	-	-	-	-	-
Insurance hail/fire/storm building	Dummy	-	75	-	-	84	-
Insurance FMD	Dummy	-	-	-	-	10	-
Insurance BSE	Dummy	-	-	-	-	10	-
Insurance disability	Dummy	-	49	-	-	65	-
Insurance hail crop	Dummy	-	62	-	-	-	-
Insurance storm crop	Dummy	-	74	-	-	-	-
Insurance brown rot crop	Dummy	-	48	-	-	-	-
Risk perception hail building	Linear	2.8	-	0.6	2.8	-	0.6
Risk perception storm building	Linear	3	-	0.6	2.9	-	0.5
Risk perception fire building	Linear	3	-	0.5	2.9	-	0.5
Risk perception FMD	Linear	-	-	-	2.8	-	0.6
Risk perception BSE	Linear	-	-	-	2.7	-	0.7
Risk perception disability	Linear	3	-	0.3	3	-	0.5
Risk perception brown rot	Linear	2.6	-	0.7	-	-	-
Risk perception hail crop	Linear	2.7	-	0.6	-	-	-
Risk perception storm crop	Linear	2.9	-	0.5	-	-	-
Relative risk aversion	Dummy	-	48	-	-	50	-
Previous negative experience	Dummy	-	55	-	-	20	-
Financial capacity to bear risk	Classes	3.4	-	1.9	3	-	1.8
Willingness to accept risk	Classes	2.2	-	1.3	2	-	1.5
Successor	Dummy	-	14	-	-	29	-
Age	Years	52	-	10	51	-	11
Region	Dummy	-	35	-	-	37	-
Rented land in total land	Ratio	-	44	-	-	58	-
Net farm income	Euro	-10717	-	55808	-59825	-	52573
Off-farm income	Euro	11156	-	18298	8903	-	11660
McSharry compensations	Euro	2013	-	5363	4541	-	6536
Balance sheet value	Euro	1973597	-	1284427	2666302	-	1501761
ESU	Units	114	-	82	130	-	68
Solvency	Ratio	-	78	-	-	67	-

With respect to arable farmers, the crops were mostly insured against hail, followed by storm and brown rot of potatoes (see Table 1). Arable farmers paid higher premiums for insurance to protect buildings, whereas dairy farmers paid substantially more for disability. Concerning crop insurance, the highest premiums were paid for insurance against hail, then storm and brown rot for potatoes (see Table 2). Dairy farmers had a higher participation in insurance for their buildings and also in insurance against disability. There was only a 10% participation of respondents in insurance against the epidemic disease outbreaks FMD and BSE. In dairy farming, the highest premiums were paid for disability and insurance for buildings (see Table 2). Dairy farmers paid about € 473 per year per farm for insurance against the animal diseases FMD and BSE.

Catastrophe insurance purchase decisions were correlated for both arable and dairy farmers. In arable farming, all pair wise correlations between purchasing types of catastrophe insurance were significant and highly positively correlated: if an arable farmer was insured for one catastrophic peril, he was also likely to be insured against other catastrophic perils.

In dairy farming, there were two significant pair wise correlations: correlation of 0.90 between purchasing insurance against FMD and BSE, and a correlation of 0.19 between purchasing disability insurance and insurance for buildings against hail, fire or storm. A positive high correlation between purchase of catastrophe insurance against FMD and BSE was observed, because both perils were insured under one insurance policy. The other correlations were not significant, implying that purchase of one type of insurance was not related to purchasing another.

Independent variables from FADN

In the Ogurtsov et al. (2007) the following independent variables available in the FADN dataset were included in the models: successor, age, region, rented land, net farm income, off-farm income, McSharry[2] compensations, balance sheet value, European size units (ESU[3]) and solvency rate (see Table 2).

As to the availability of a *successor,* only 14% of the arable farms had already a person to replace the main farm operator, whereas in dairy farming 29% of farmers had a successor. The average *age* of both types of farmers was almost identical. The share of *rented land* in total farm land was substantially larger in dairy farming. Arable farmers had higher *net farm* and *off-farm incomes* and received twice lower amount of *McSharry* price compensations from the government. However, dairy farmers were larger, as could be seen by the size variables amount of *ESU* and *balance sheet value* of the farm. Dairy farmers were also wealthier, that was comprised by the *solvency rate* (share of own capital) and the balance sheet value.

Independent variables from questionnaire

The *relative risk perception* was elicited by comparing the subjective risk perception of the farmer to the 'average' arable/dairy farmer in the Netherlands. Farmers were asked to indicate their risk perception on a 5-point scale, where a score of 1 means that the probability of a certain risk is four times smaller than for the average farmer; a score of 2 means two times smaller; a score of 3 implies an equal probability as of an average farmer; a score of 4 means that the probability is two times larger than for the average farmer; and a score of 5 means that the probability is four times larger than for the average farmer. As indicated in Table 2, for arable and dairy farmers, the relative risk perception score was slightly below 3, implying that the farmers perceived their probability of catastrophic risk to be slightly lower than the average farmer. Risk perceptions of different risks were highly correlated. In arable farming, a pattern of highly positive significant correlations was observed. In dairy farming, there was a significant high positive pair wise correlation between risk perception of FMD and BSE occurrence. Moderate correlations were observed for risk perceptions

[2] A form of price compensation to agricultural producers in the European Union (for details see ''McSharry'' reform of the Common Agricultural Policy (CAP) at http://ec.europa.eu/agriculture/index_en.htm).

[3] A European Size Unit (ESU) is a measure of the economic size of a farm business based on the gross margin calculated from standard coefficients for each commodity on the farm. 1 ESU roughly corresponds to 1 dairy cow or 1.3 hectares of cereals (see http://statistics.defra.gov.uk/esg/asd/fbs/sub/europe_size.htm).

between hail, fire and storm for buildings and also between FMD, BSE, disability and risk perceptions as to perils related do damage of buildings.

Risk aversion was also measured relative to other farmers (for details see Meuwissen et al., 2001; Pennings, 1998; Van Asseldonk et al., 2002). The questionnaire combined statements of Meuwissen et al. (2001) and Van Asseldonk et al. (2002). The construct describing the *relative risk aversion* (dummy variables) was obtained via an aggregation procedure on the basis of 11 statements (see Figure 1) with 7-point Likert scale (1 – do not agree; 7 – fully agree) for questions 1-7 and (1 – fewer risks than others; 7 – more risks than others) for questions 8-11 (see Figure 1). The responses to statements 5, 6 and 7 were rated in reverse order for an aggregation procedure. The average score of statement values was calculated per farm. Farmers with an average score less than 4 (the median value) were counted as *less-risk-averse* (0), and with a score higher than 4 as *more-risk-averse* (1). In arable farming, 48% of the farmers considered themselves more risk-averse than others, whereas in dairy farming this proportion was a bit higher and constituted 50% (see Table 2).

The correlation tables showed that risk aversion of both arable and dairy farmers was correlated with the same set of variables. In arable farming, an important factor differentiating less- and more-risk-averse farmers was also farm size. For more-risk-averse arable farmers, negative correlations were observed for ESU, value of turnover, amount of rented and used land. More-risk-averse dairy farmers had smaller farms compared to less-risk-averse farmers, as explained by variables ESU, long-term debt, used and rented land, balance sheet value and turnover.

Concerning a *previous negative experience* with respect to catastrophic risks, the farmers were asked whether they had experienced financial losses higher than € 10,000 from some catastrophe event during the past 10 years. In arable farming, 55% of the farmers had experienced such losses, whereas in dairy farming this proportion constituted 20% (Table 2).

In order to estimate the amount of money per year farmers can, in principle, use for self-insurance, they were asked to state their *maximal annual risk-bearing capacity*. Farmers were asked to mark the appropriate range of financial capacity: a score of 1 means a maximal annual risk-bearing capacity of € 0 to 20,000, other scores were 2 (€ 20,001 - 50,000), 3 (€ 50,001 - 80,000), 4 (€ 80,001 - 120,000), 5 (€ 120,001 - 160,000), 6 (€ 160,001 - 200,000), 7 (€ 200,001 - 250,000) and 8 (> € 250,001). The average risk-bearing capacity of arable farmers was 3.4, while dairy farmers had a score 3.0 (see Table 2).

With the same financial ranges as used in measuring the maximal annual risk-bearing capacity, the *willingness to accept risk (WTA)* variable was used to estimate farmer's willingness to self-insure. The average WTA of the arable and dairy farmers turned out to have a score of 2.0.

Multicollinearity of selected independent variables

Analysis of correlation tables showed that there were considerable correlations between the independent variables. The size variables ESU and maximal annual risk-bearing capacity, proportion of rented land, solvency, McSharry compensations that were the sources of multicollinearity, were excluded from the analysis. The remaining non-correlated variables were used for further analysis. Two sets of models were constructed for all considered catastrophic risks in arable and dairy farming. The first set of models contained variables risk perception, risk attitude, WTA, successor and region. For second set of models the variables previous negative experience, age, net farm income and off-farm income were taken.

4.4 Results

4.4.1 Binary probit models

The results of the binary probit models used to determine which variables influence the purchase of different types of catastrophe insurance are presented in Tables 3 and 4. All models showed quite reasonable values of R-square values (Verbeek, 2002).

Table 3. **Results of binary probit models in arable farming**

Variables	Hail-fire-storm buildings	Hail-crop	Storm-crop	Brown rot	Disability
First set of models					
Risk perception hail-buildings	-0.89**	-	-	-	-
Risk perception fire-buildings	-2.26***	-	-	-	-
Risk perception	-	-5.6E-02	1.55*	0.28	-0.45
Relative risk aversion	1.65**	0.85***	0.76**	0.62*	0.71*
WTA	-0.24	-0.16	-0.37**	-9.3E-02	-0.29*
Successor	1.51**	-0.12	-6.8E-02	4.6E-03	0.43
Region	0.63	-0.61*	7.7E-02	-0.37	0.3
Constant	7.0**	-5.4E-02	-4.95*	-1.54	0.45
Pseudo R-square	0.39	0.13	0.15	0.08	0.1
Second set of models					
Previous negative experience	0.71*	-0.26	-0.21	0.19	0.69**
Age	-8.9E-03	-2.2E-0.2*	-2.8E-02*	-1.5E-02	-1.5E-02
Net farm income	-3.8E-06	-2.2E-0.7	-2.7E-06	-5.0E-06*	-5.4E-06*
Off-farm income	8.0E-06	2.2E-05***	5.5E-06	8.9E-06	7.3E-06
Constant	-1.24	0.74	0.86	-0.17	-0.74
Pseudo R-square	0.08	0.08	0.04	0.05	0.09

***, **, * - significant at 5%, 10% or 20% level

Table 4. **Results of binary probit models in a dairy farming**

Variables	Hail-fire-storm buildings	FMD	BSE	Disability
	First set of models			
Risk perception storm-buildings	-0.67	-	-	-
Risk perception	-	0.14	0.13	0.46*
Relative risk aversion	-0.1	-0.11	-0.35	-0.33
WTA	2.0E-02	-0.20*	-0.26*	-0.13*
Successor	-0.16	-0.60*	-0.94**	-6.7E-02
Region	-0.11	0.16	-4.0E-02	-4.7E-02
Constant	3.61***	-0.85	-0.55	-0.41
Pseudo R-square	0.04	0.06	0.1	0.06
	Second set of models			
Previous negative experience	-0.47*	6.7E-03	0.19	-0.38*
Age	-1.0E-02	-2.4E-02*	-3.0E-02**	-1.5E-02
Net farm income	-1.3E-06	8.3E-06**	6.6E-06*	1.8E-06
Off-farm income	-7.5E-06	1.7E-05*	8.4E-06	8.6E-07
Previous negative experience	-0.47*	6.7E-03	0.19	-0.38*
Constant	1.96***	0.47	0.61	1.32***
Pseudo R-square	0.04	0.1	0.09	0.03

***, **, * - significant at 5%, 10% or 20% level

Farmer-specific variables

Six farmer-specific variables were estimated in binary probit models. In dairy farming, *risk perception* showed a positive impact only on the purchase of the disability insurance. In arable farming, concerning the risk perception about storm that can destroy crops, a positive impact was observed. It implies that arable farmers who perceive it as more risky were more likely to insure their crops against storm. This finding was consistent with previous studies by Ganderton et al. (2000), Kunreuther (2002), Kunreuther and Pauly (2004), Sherrick et al. (2004), Van Asseldonk et al. (2002), and theoretical insights of Harrington and Niehaus (1999, p.150). Due to the worry of the negative outcomes, the probabilities of catastrophic risks can be perceived higher than true objective probabilities. Thus arable farmers were more likely to insure for avoiding of downside catastrophic risks. Contrary to the expected positive impact, the negative impact of risk perceptions concerning damage to buildings by hail and fire was observed with a probability of purchasing building insurance against hail, fire or storm in arable farming. This can be explained by 1) the fact that participation in this insurance was mandatory by some banks and 2) a very low risk perception that hail, fire or storm can damage their buildings (Kunreuther, 2002; Kunreuther and Pauly, 2004).

In arable farming, the *relative risk aversion* had a positive impact on the probability to purchase all insurance types considered – building insurance, crop insurance against hail, storm and brown rot, and also disability insurance. This was consistent with a study by Van Asseldonk et al. (2002). As according to the expected utility theory, for increased levels of risk aversion decision-makers pay higher risk premiums (Hardaker et al., 2004; Harrington and Niehaus, 1999). Therefore more-risk-averse arable farmers had a higher probability of purchasing catastrophe insurance than less-risk-averse farmers. Contrary to our expectations and the results from previous studies, the relative risk aversion of dairy farmers did not have any clear impact on the purchase of considered insurance types.

In arable farming, a *previous negative experience* had a positive impact on the probability of purchasing of insurance coverage of building's and disability insurance. Arable farmers usually have diversified set of activities and often experience losses from the weather risks, and thus they were more prone to purchase insurance coverage from weather related risks. A previous negative experience by dairy farmers, however, had a negative impact on the purchase of the identical insurance types. This can be explained by the fact that every farmer in the Netherlands has to insure the buildings, and the same concerns to the purchase of disability insurance. But on the other hand, they rarely experience catastrophic risks. Therefore, historical payment for 'almost nothing' might have a negative impact on the future payments for these insurance types.

In arable farming, *WTA* had a negative impact on the purchase of catastrophe insurance against storm that can damage crops and disability. The similar pattern was observed by dairy farmers concerning purchasing of insurance coverage against FMD, BSE and disability. WTA is considered as a substitute to catastrophe insurance, and thus farmers relying on their wealth, were less probable to purchase catastrophe insurance.

The *age* of a farmer was expected to have a positive impact on the purchase of catastrophe insurance because older farmers were assumed to be more experienced with catastrophic risks (Mishra and Goodwin, 2003). Contrary to the expectations, the age of arable farmers had a negative impact on the probability to purchase crop insurance against hail and storm. The absence of negative disability experience could be the reason of being less likely to purchase disability insurance. Older dairy farmers were less likely to purchase FMD and BSE insurance. Only a few outbreaks occurred in the Netherlands, and many farmers responded the questionnaire did not experience these catastrophic risks. On the other hand, insurance against FMD and BSE is quite an expensive new product, and farmers who believe that outbreaks will never happen to them were less likely to pay high premiums for FMD and BSE insurance.

The age of a dairy farmer had a high positive correlation with the *availability of a successor*. Likewise the farmer's age, availability of a successor in dairy farming also had a negative impact on the purchase of insurance against FMD and BSE. Most of the dairy farmers who were less likely to purchase FMD and BSE insurance have not experienced FMD and BSE outbreaks, and the same attitude could be communicated to their successors (sons). In arable farming, the availability of a successor showed a positive significant impact on purchasing of insurance coverage against building's damage/destruction by hail, fire or storm. Oppose to dairy farmers, arable farmers were more experienced with weather risks. Thus the negative experience of father or both a farmer and a successor, if they work together, could force to purchase a catastrophe insurance against weather-related risks.

Farm variables

Three farm variables were estimated in binary probit models. For arable farmers, the *regional variable* was significant and had a negative impact: farmers in the South were less likely to purchase crop insurance against hail than farmers in the North. The regional variable did not have any impact on the purchase of insurance against FMD and disability.

In arable farming, as expected, the *net farm income* had a negative impact on the probability that a farmer would purchase insurance against brown rot and disability, implying that they would prefer to accumulate their core profits instead of spending them on insurance. In dairy farming, net farm income had a positive impact on the purchase of insurance against FMD. This finding was contrary to the expectation that dairy farmers that are wealthier (because of accumulating incomes) than arable farmers could consider self-insurance as an alternative to commercial insurance. Thus having a high initial wealth position, dairy farmers could save more income from core activities to increase financial capacities for self-insurance or would be likely to insure less (Coble et al., 1996).

As net farm income, the *off-farm income* was expected to have a negative impact on purchase of catastrophe insurance because it could be viewed as a source of accumulating wealth that is a substitute to catastrophe insurance. Oppose to that, a positive impact was observed for the purchase of crop insurance against hail in arable farming. Off-farm income showed a positive impact on FMD and BSE insurance purchase by dairy farmers. This finding was consistent with Ogurtsov et al. (2007), but not with empirical studies by Ganderton et al. (2000), Mishra and Goodwin (2003), and Sherrick et al. (2004). The reason for that could be that the substantial part of the off-farm income in the Netherlands is presented by social security payments received from insurance companies.

4.4.2 Ordered probit models

In both sectors, farmers were divided into groups for each type of insurance considered, based on the annual premium paid. For both types of farmers the following groups were taken: 1) non-insured farmers, 2) farmers in the group of € 1-1000, 3) farmers in the group of € 1001-4000, 4) and farmers paying above € 4001 per year per insurance type. The results of the ordered probit models were similar to the results of the binary probit models (see Table 5) and will be briefly presented without repeating of argumentation provided before.

Table 5. **Results of ordered probit models**

Variables	Model coefficient	Marginal effects			
		Not insured	1-1000 Euro	1001-4000 Euro	> 4001 Euro
			Arable farming		
			Buildings		
Number of farms	65	16	12	32	5
Risk perception hail-buildings	-0.38*	8.0E-02*	5.8E-02	-8.8E-02	-5.0E-02*
Net farm income	7.0E-06***	-2.1E-06***	-6.3E-07	1.9E-06***	8.5E-07***
			Hail-crop		
Number of farms	65	25	24	16	-
Risk perception	0.36*	-0.13*	2.1E-02	0.11*	-
WTA	-0.23**	8.6E-02**	-1.3E-02	-7.30E-02	-
Net farm income	6.7E-06***	-2.5E-06***	5.2E-07	2.0E-06***	-
			Storm-crop		
Number of farms	65	17	10	33	5
Risk perception	-0.51*	0.13*	5.9E-02	-0.11*	-7.5E-02*
WTA	-0.28***	7.2E-02***	1.9E-02**	-6.3E-02**	-4.1E-02**
Successor	0.67*	-0.13**	-8.5E-02	8.5E-02**	0.13
Net farm income	6.2E-06***	-1.9E-06***	-4.6E-07*	1.7E-06***	7.5E-07**
			Brown rot		
Number of farms	65	34	26	5	-
Risk perception	0.88***	-0.35***	0.25**	9.9E-02**	-
WTA	-0.26*	0.10*	-7.4E-02*	-2.9E-02*	-
Successor	1.64***	-0.49***	9.70E-02	0.39**	-
Region	-0.80**	-0.31***	-0.24**	-7.2E-02*	-
Off-farm income	-2.9E-05***	1.1E-05***	-8.6E-06**	-2.7E-06**	-
Net farm income	7.5E-06***	-3.0E-06***	2.3E-03***	7.1E-07**	-
			Disability		
Number of farms	65	33	7	22	3
Successor	0.83**	-031***	-1.3E-02	0.20***	0.12
Region	-0.72**	0.28***	-1.2E-02	-0.21**	-5.6E-02*
Off-farm income	-2.0E-05**	8.1E-06**	-4.3E-07	-6.1E-06**	-1.6E-06*
			Dairy farming		
			Buildings		
Number of farms	113	18	26	63	6
Risk perception storm-buildings	0.29*	-5.7E-02	-4.9E-02	4.7E-02	2.9E-02
Net farm income	-3.3E-06*	7.7E-07*	4.7E-07*	-9.3E-07*	-3.1E-07*
Off-farm income	1.6E-05**	-3.8E-06*	-2.3E-06*	4.5E-06*	1.5E-06*
			Disability		
Number of farms	113	40	9	42	22
WTA	-0.11*	3.8E-02*	3.1E-03	-9.6E-03	-3.2E-02*
Net farm income	3.7E-06*	-1.4E-06*	-8.5E-08	-4.6E-07*	9.9E-07*

***, **, * - significant at 5%, 10% or 20% level

In arable farming, the set of insurance types analysed in binary probit models was also used for ordered probit models. As stated above, for dairy farmers, premiums of four types of insurance were analysed: FMD, BSE, buildings and disability. However, in models of purchasing insurance against FMD and BSE, it was not possible to make a distinction between groups, because 90% of the farmers were in the uninsured group, and the remaining 10% were in the low-premium group (see Table 1). We present the variables that had a significant impact on the amount of the insurance coverage purchased.

Positive impacts of *risk perception* were obtained in arable farming concerning purchase of crop insurance against hail, brown rot of potatoes, and disability insurance mainly because of the farmers from the highest premium groups. Note that risk perception in non-insured group had a negative impact on the amount of premium paid. The explanation used in binary models is also applicable for ordered models. As in binary model of building's insurance, in ordered model the negative impact of risk perception on purchase of building's insurance was observed in arable farming. Contrary to binary model, the risk perception concerning storm affecting crops was negatively correlated with the amount of premium paid for corresponding insurance, and that was represented by arable farmers from the highest premium groups. In dairy farming, only the risk perception concerning storm that can damage/destroy buildings was significant and had a positive impact on the amount of premium paid for building's insurance. Note that in binary models risk perceptions were not significant for dairy farmers.

In both types of farming, *WTA* had a negative relationship with catastrophe insurance coverage purchase, as in binary models. This concerned purchase of crop insurance against hail, storm and brown rot by arable farmers, and also to disability insurance by both arable and dairy farmers.

Likewise in binary model of building's insurance purchase, arable farmers with a *successor* paid higher insurance premiums for crop insurance against storm and disability insurance than arable farmers without a successor. The availability of a successor was not correlated with purchases of catastrophe insurance in dairy farming.

As in hail-crop binary model in arable farming, the *regional variable* was significant for purchase of brown rot and disability insurance by arable farmers and had the same direction of impact: farmers in the North purchased more insurance coverage than farmers in the South of the Netherlands. This finding was observed for all premium groups, except the non-insured group of farmers for disability insurance.

Likewise in binary models in dairy farming, in ordered probit models the *net farm income* had a positive impact on purchase of disability insurance by arable farmers and dairy farmers, and also on purchase of crop insurance against hail, storm and brown rot by arable farmers. Oppose to this finding, in general, dairy farmers with higher net farm incomes paid more premium for building's insurance, however different impacts were observed between premium groups.

Arable farmers with higher *off-farm incomes* purchased less disability insurance against insurance against brown rot affecting potatoes. This result was opposite to the positive relationship observed in binary model for purchase of crop insurance against hail. As in binary model on FMD insurance, dairy farmers with higher off-farm incomes purchased more insurance coverage to protect their buildings.

4.5 Discussion

Arable and dairy farmers showed to some extent different behaviours with respect to purchase of catastrophe insurance, originating from different conditions of doing business. In *arable farming,* the situation was more in line with expectations from previous studies. Purchase of insurance against one peril was strongly correlated with purchase of insurance against another one. The main catastrophe insurance types were insurance of crops against hail, storm and brown rot. Purchase of various forms of crop insurance, a well-known type of insurance, was influenced by both farmer and farm variables, with the same direction of impact observed as in previous studies. Risk perception and risk attitude were found as important variables that explain purchase of catastrophe insurance coverage.

Arable farmers faced catastrophic risks more often, and so they tended to buy more insurance and insure more risks. Greater negative experience of such risks may also lead to higher risk perceptions, compared with dairy farmers. Catastrophe events in arable farming are mostly of a natural character and usually considered an 'act of God', and happen more often than in dairy farming. In this sense, it was easier for arable farmers to form a judgment about the probability of occurrence of various perils, and to assess how big the losses could be, in order to be able to compare the perceived risk with the cost of insuring.

On the other hand, arable farmers, in general, are also likely to take into account the effect of global warming that may potentially increase the probability of hail, storm and brown rot. Arable farmers also tended to insure their buildings against hail and storm, and in this respect the decisions concerning crop insurance and/or previous crop damage may influence purchase of insurance against damage of buildings. Compared to dairy farming, insurance of buildings in arable farming could be better explained by farm and farmer characteristics in line with previous studies.

FMD and BSE epidemics were the most severe risks for *dairy farmers*. Insurance policies against FMD and BSE are quite new in the Netherlands, and only few farmers were insured. Little previous negative experience of catastrophe events seemed to play a crucial role in catastrophe insurance decision making by the Dutch dairy farmers. Dairy farmers may also underestimate these catastrophic risks, speculating that they will never happen to them (Kunreuther, 2002; Kunreuther and Pauly, 2004). Only a few outbreaks of livestock epidemics have occurred in the Netherlands, and these affected only a limited number of farmers.

Therefore, due to the lack of historical data, it was also hard for farmers to estimate the probability of occurrence of such catastrophe events. The lack of historical data and experience probably explain the failure of models to estimate the impact of risk attitude in all models in dairy farming. The same reasoning could be concerned to the impact of risk perception on insurance purchase in the models of FMD and BSE insurance.

Other farmer-specific and farm variables were also found important determinants in the purchase of insurance in dairy farming. Farm/farmer wealth seemed to play an important role in the insurance purchase of dairy farmers: wealthy dairy farmers tend to prefer to self-insure rather than to purchase what they perceived as expensive commercial insurance.

Risks related to damage to buildings by hail, fire or storm and disability insurance, were perceived by dairy farmers as secondary. The other reason for the failure to estimate the impact of risk perception could be that almost every dairy farmer insures buildings in the Netherlands, since such insurance is required by banks providing long-term credit.

A potential limitation of this study could be a presence of self-selection bias resulting after conducting a questionnaire survey. One might expect that one type of farmers was more likely to respond or responded accurately so that, for instance, risk attitude was significant only in arable farming. Unfortunately, due to unavailability of data on the non-respondents from both arable and dairy farming, we could not test differences on gathered data between respondents and non-respondents. Biased answers could occur due to the difficulties to provide insurance information because farmers often purchased combined insurance policies. Some bias could be also present in elicitation of scores for risk perception and risk attitude.

However, we could argue that the potential bias was reduced to some extent by high response rates in both types of farming (about 50%) obtained by random selection of farmers by LEI, which was high enough for these types of surveys. This means that farmers did not have much difficulty in providing answers. The bias that one type of farmers is more likely to respond could be mitigated by the fact that both arable and dairy farmers participating in the questionnaire were identically represented by regional variable.

4.6 Conclusions and implications

This paper presents the results on models that explain purchase of catastrophe insurance. A major contribution of the paper is the investigation of farmer-specific (risk perception, risk attitude and other variables) and farm variables that influence purchase of different types of catastrophe insurance by two different types of farming. The results of the study could be used as guidance for improvement of existing and development of the new agricultural insurance policies. The major implications of the study are presented below.

This study showed that for both types of farming the risk perception, highly correlated with previous negative experience and insurance practice, was the most important farmer-specific variable explaining purchase catastrophe insurance. Concerning risk attitude, it was significant mainly in arable farming.

Insurance companies need to realise that risk perceptions can change in course of time. That was observed by their impacts on purchases of different types of catastrophe insurance. For existing insurance products, such as building's and disability insurance, farmers rarely experience losses, and that might result to low perception of those risks, and thus to unwillingness to purchase these types of insurance. However, high perception of crop risks that farmers experience quite often, may result in purchases of higher insurance coverage. That was observed on the risk perceptions concerning the crop risks by arable farmers.

Risk aversion was found as an important variable explaining purchase of catastrophe insurance by arable farmers. In reality, risk aversion can hardly be observed, however a complex of variables associated with a farm size, used and rented land, value of debt and turnover, could be an indication to the risk aversion and be used by insurance policymakers.

Insurance companies need to realise that farmers, even highly perceiving catastrophic risks, are much concerned about their wealth. And thus, farmers with higher net farm incomes used for wealth accumulation, can be viewed by insurance companies willing to self-insure and purchase less catastrophe insurance.

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Chapter 5 Modelling of catastrophic farm risks using sparse data

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Abstract

This paper compares alternative ways of conducting a farm risk analysis using sparse data with a special reference to catastrophe events. For this purpose kernel and multivariate normal smoothing procedures are proposed and applied to generate (simulate) the joint distributions of crop yields and prices. The analysis showed that the functional forms chosen to generate the joint distribution substantially impacted the density in the tail of the distribution, although they were parameterised with the same data. The differences in the optimal farm plan (i.e. activity levels) resulting from the optimisation of net farm income, obtained from a utility-efficient programming model, were less profound.

Keywords: catastrophic risk, kernel, normality, utility-efficient programming, SERF, arable farmer

5.1 Introduction

Farmers often face risky events in agriculture. Risk means the possibility of a loss of income or property resulting from some event (Pritchet et al., 1996). Catastrophic risks are infrequent events, but can cause large losses to farmers. For a proper risk assessment of catastrophe event, its probability and magnitude needs to be taken into account. The assessment should ideally be based on a long-term and reliable farm-level history. But, in practice, farm-level data is often very sparse to provide a good and reliable basis for such a risk assessment (Hardaker et al., 2004), and this is certainly the case when focusing on catastrophe events. The reliability can be enhanced by eliciting subjective probability judgments, in addition to the available data (Hardaker and Lien, 2005). Furthermore, it is advised to smooth the sparse data (i.e. interpolating between observations and extrapolating outside observations) by fitting a parametric or empirical distribution (Shlaifer, 1959; Anderson et al., 1977, pp.42-44). However, by smoothing the data in such a way, the risk analyst might face the problem of over representing the middle part of the distribution and underestimating one or both tails. Catastrophes cause a serious downside risk, and therefore it is important to analyse the tail of the distribution very carefully by investigating alternative tail estimations. Before the smoothing procedure, a realistic assumption should be made about the upper and lower bounds, ensuring that the distribution will be a reasonable approach to include the downside and upside tails.

One of the ways to smooth data and to include the downside and upside tails is to fit the sparse data to a (parametric) normal distribution. There is a continuous discussion about the applicability of normal distribution assumptions of yields in agriculture (i.e. Antwood et al., 2003; Galagher, 1987; Just and Weninger, 1999; Ramirez et al., 2003; Swinton and King, 1991). The problem arises because it is difficult to reject normality assumptions, especially when data is sparse. For catastrophe events, it is generally hard to obtain 10 relevant observations under the same economic policy, management regime, farm program or trade policy (Just and Weninger, 1999; Richardson, 2006). At least twenty or more observations are usually required to test with any accuracy whether a distribution is normally distributed or not Richardson (2006). Non-normality might therefore be masqueraded as normality, simply because of the misspecification of the test (Just and Weninger, 1999).

Normality is not likely because upward potential of yields is biologically bounded and there is a risk of (complete) crop failure because of, for example, adverse meteorological circumstances (Galagher, 1987). Many studies stated that crop yields are skewed and do not follow normality (Just and Weninger, 1999; Galagher, 1987; Antwood et al., 2003;

Swinton and King, 1991; Ramirez et al., 2001). However, Just and Weninger (1999) argued that many studies that rejected normality are typically cited as the basis for making non-normality assumptions but are no better individually justified than normality.

Alternatively to a parametric normal distribution, the technique of kernel density estimation (KDE) can be used to generate unobserved data to supplement sparse data. The KDE procedure is a non-parametric approach of smoothing data by hand. Instead of minimising the sum of squared residuals, the KDE method weights observations on relative proximity to estimate the probability. The estimation of the probability at a given point depends on a pre-selected probability density. In that way the kernel is analogous to the principle of local averaging, by smoothing, using evaluations of the function at neighbouring observations (Yatchew, 1998). Therefore, the probabilities in the tails depend largely on the choice of kernel. Kernel density smoothing procedure is popular in many fields, but it is not widely used in agriculture (Richardson et al., 2006), and only a limited number of agricultural studies were conducted (i.e. Hardaker et al., 2006; Richardson et al., 2000; Richardson et al., 2006). In the early work of Richardson et al. (2000), analysis of simulated statistics showed that the KDE gives acceptable results for simulating sparse data. Hardaker et al. (2006) suggested that in case of sparse historical data, additional information and judgments need to be incorporated about the tails of the distribution when applying the KDE approach to improve the confidence of the results. Richardson et al. (2006) found that KDE provided better results than parametric distributions and a linear interpolation of the empirical distribution.

In complex systems with more than one activity, like farming, the stochastic dependency needs to be accounted for (Hardaker et al., 2004). Ignoring stochastic dependency between risky prospects in farm planning can be seriously misleading (Richardson et al., 2000). For example, crop yields tend to be positively correlated in that a good year for one crop also often suits other crops, and vice versa. Similarly, prices for several kinds of farm products tend to move together, depending on general economic conditions (Hardaker and Lien, 2005). Therefore the univariate normality versus the univariate KDE debate needs to be up scaled to multivariate normality (MVN) versus multivariate kernel density estimation (MVKDE).

This paper compares alternative ways of conducting a farm risk analysis using sparse data with special reference to catastrophe events. For this purpose MVKDE and MVN procedures are applied to simulate the joint distributions of crop yields and prices. Six case farms were chosen to reflect the conditions of typical Dutch arable farms. The risk analysis focuses on the impact of the functional form, chosen to generate the joint distribution, on the density in the downside tail. Subsequently, the result of incorporating the downside tail alternatively into optimised net farm income and obtain farm plan is addressed by applying utility-efficient programming (UEP).

5.2 Methods to characterise catastrophe events in farm planning models

In this section the methods of MVN and MVKDE procedures are described, which can be used to generate the required probability distributions that then can be incorporated into UEP models for obtaining the optimal farm plans.

5.2.1 Simulation procedure for the multivariate normal distribution

An MVN distribution for some random variables (crop yields and prices) is specified by three components: a (deterministic) component capturing the mean (i.e. the expected value of the observations), a (stochastic) component based on the variance, and a multivariate component based on covariances of the observations. The steps for constructing an MVN distribution are the following (Richardson, 2006):

1. Calculate the best possible model to predict each variable, whether this is simply the arithmetic mean, or based on a trend regression, a multiple regression, or a time-series model;

2. Calculate the residuals based on the prediction for each random variable;

3. Calculate variances for each variable using their residuals;

4. Calculate covariances using their residuals.

5.2.2 Simulation procedure for the MVKDE

Besides the MVN procedure also the MVKDE simulation procedure will be applied to simulate the joint distribution of random variables (crop yields and prices) alternatively. The procedure in specifying MVKDE distribution consists of the following steps (Richardson et al., 2006):

- From the matrix of observations (yields and prices, usually historical de-trended) the covariance matrix R_{kxk} is estimated and then factored by Cholesky decomposition so that $P=RR^T$, where P is identity matrix, where k is a set of variables (yields and prices) and T is used to transpose matrix R into R^T.
- The minimum, $X_{Min,j}$ and maximum $X_{Max,j}$ bounds for each variable k are then determined. The cumulative probabilities for these values are assumed $F(X_{Min,j})=0$ and $F(X_{Max,j})=1$, where $j=1,\ldots k$ is one of the k variables.
- For each variable k, a new vector of X_{sj}^A, of dimension S $(s=2,\ldots,S)$ is created with a given minimum $X_{1j}^A = X_{Min,j}$ (i.e. s=1 for the minimum observation) and maximum $X_{Sj}^A = X_{Max,j}$ by the formula:

$$X_{sj}^A = \left(\frac{1}{S-1}\right)\left(X_{Max,j} - X_{Min,j}\right) + X_{(S-1)j}^A \tag{1}$$

- The smoothed percentiles for each X_{sj}^A between the extreme points $F(X_{Min,j})=0$ and $F(X_{Max,j})=1$ are calculated based on KDE (Silverman, 1986; Scott, 1992). For each variable j the smoothed percentile is evaluated at a given point X_{sj}^A as:

$$\hat{F}(X_{sj}^A) = \frac{1}{nh_j}\sum_{i=1}^{n} K\left[\frac{(X_{sj}^A - X_{ij})}{h_j}\right] \tag{2}$$

Where $K(\cdot)$ is cumulative kernel function associated with a symmetric continuous kernel density $k(\cdot)$ such that $K(x) = \int_{-\infty}^{x} k(t)dt,$ and h_j is the bandwidth of the variable j.

With a specific kernel function, the value of bandwidth, called a smoothing parameter, determines the degree of averaging in the estimate of the density function. Bandwidth is also called standard deviation of the kernel density function. It is important to choose the most appropriate bandwidth because a value that is too small leads to under-smoothed data, or if too large to over-smoothed data. When a bandwidth decreases towards zero, the number of modes increases and the KDE is very noisy. As bandwidth increases to infinity, the number of modes drops to one, so that the KDE displays a unimodal pattern.

The best criterion to select a kernel is the smallest root mean square (RMSE) of residuals between the historical kernel cumulative probabilities and probabilities for the kernel function.

Formula (2) can be used for a univariate KDE. If the interest is in a multivariate distribution, covariances of underlying random variables have to be taken into account. In this way the MVKDE procedure can be used to incorporate the stochastic dependency (Richardson et al., 2006). Then the simulation of MVKDE would take the following steps:

1. Generate correlated uniform standard deviates (CUSDs) from the observed random variables; the result will be a value between 0 and 1.
2. Given the $CUSD_j$, along with respective vectors X_{sj}^{A} and smoothed percentiles $\hat{F}(X_{sj}^{A})$ with a scale (including $F(X_{Min,j})=0$ and $F(X_{Max,j})=1$) between the nearest lower $\hat{F}_L(X_{Lj}^{A})$ and nearest upper $\hat{F}_L(X_{Uj}^{A})$ percentiles interpolate among the X_{sj}^{A} random vector of $\widetilde{X}_j$ is generated.

The final formula of the generated MVKDE vector is the following:

$$\widetilde{X}_j = X_{Lj}^{A} + \left(X_{Uj}^{A} - X_{Lj}^{A}\right) * \frac{\left(CUSD_j - \hat{F}_L\left(X_{Lj}^{A}\right)\right)}{\left(\hat{F}_U\left(X_{Uj}^{A}\right) - \hat{F}_L\left(X_{Lj}^{A}\right)\right)} \quad (3)$$

Goodness-of-fit tests can be conducted whether the simulated joint MVN and MVKDE distributions of yields and prices are appropriate.

5.2.3 Utility efficient programming (UEP)

UEP is a mathematical programming method and can be used for optimising farm plans. In UEP the expected utility of the farm plan is maximised. UEP is a non-parametric method, which implies that it is free of distribution assumptions and includes the joint distribution by means of so-called ‘states of nature’ (i.e., specific combinations and probabilities of possible outcomes). UEP takes the following form (Hardaker et al., 2004):

Maximise $E[U]=p\ U(z, r)$, r is varied (4)

Subject to

$A\,x <= b$ (5)

$Cx - Iz = U(z, r)$ (6)

And $x>=0$, (7)

Where $E[U]$ – is expected utility;

z – is a vector of farm incomes by state of nature;

r – is a coefficient of risk aversion;

p – is a probability of each state of nature;

$U(z,r)$ – is a vector of utilities of farm incomes by state of nature with risk aversion level r;

A – is a vector of technical-economic coefficients per each activity;

x – is a vector of activities;

b – is a vector of available resources (constraints) ;

C – is a vector of state of nature matrix of activity incomes;

I – is an identity matrix.

In most cases r represents a coefficient of absolute risk aversion. As long as the risk aversion coefficient of a farmer is not known, a range of risk aversion coefficients can be considered for modelling. Hardaker et al. (2004) developed a method of SERF, where alternative farm plans can be provided in terms of certainty equivalents as a measure of risk aversion over a definite range, developed by Anderson and Dillon (1992). For a risk-averse farmer, the coefficient of relative risk aversion of wealth $r_r(W)$[4] varies from 0.5 to 4, typically about 1, with the following interpretation: 0.5 – hardly risk-averse at all, 1.0 – somewhat risk-averse (normal), 2.0 – rather risk-averse, 3.0 - very risk-averse, 4.0 – almost paranoid about risk.

5.2.4 Available sparse data and optimisation constraints

For the current analysis, six Dutch arable farms were selected from the Farm Accountancy Data Network (FADN) database. The FADN data is an official European Union dataset, which includes detailed farm-specific data of, among other things, yields per unit per crop. Prerequisite for the selection of the arable farms was that at least ten consecutive years with observations were available for a farm to be selected. The corresponding number of states

[4] Absolute risk aversion coefficient is usually calculated as a proportion of the relative risk aversion coefficient to wealth.

of nature ranged from 11 up to 13 for the farms under study (Table 1). The main crops in the production plan constituted consumption potato, wheat, rye and sugar beet.

Table 1. **Summary of characteristics of the farms selected**

Farm number	Period with observations	Cultivated area (ha)	Main activities in production plan
I	1992-2004	17	potato, wheat, rye, sugar beet
II	1994-2004	80	potato, wheat, sugar beet
III	1994-2004	101	wheat, rye, sugar beet
IV	1994-2004	37	potato, wheat, sugar beet
V	1994-2004	205	wheat, rye, sugar beet
VI	1994-2004	155	potato, wheat, sugar beet

The farm-specific yields observed in the states of nature were de-trended by a linear function (formula 8):

$$y_{qit} = \alpha_{qi} + \beta_{qi1} + \varepsilon, \quad \varepsilon \sim N(0,\sigma^2) \tag{8}$$

where y_{qit} - is yield unit of activity q on farm i in year t (t=1,…,T);

α_{qi} - is the regression constant for activity q on farm i;

β_{qi} - is the systematic change per activity q on farm i (it is assumed that the trend caused by technological change among other things will continue in the future);

ε is a normal distributed random error term (Murdoch, 1966, p.34).

Farm gate prices and costs of production were assumed to be identical for all farms considered. The average annual crop prices were de-trended by Paasche equation with the consumer price index (CPI) as deflator (Mas-Colell, 1995, p.37).

$$I(p)_{qt} = \frac{p_{qt}}{p_{qy}} \tag{9}$$

where $I(p)_{qt}$ is a deflator price of activity q in year t (t=1…T);

p_{qt} is volume of price of activity q in year t, and p_{qy} is the fixed volume of price of activity q in basic year y.

Crop specific production costs were obtained from norms (see Dekkers, 2002) and were equivalent to prices de-flated. Following usual crop-rotation rules, cereal crops (e.g., wheat and rye) were restricted to a maximum of two-thirds of the cultivated area. Tuberous crops (consumption potato and sugar beet) were restricted to a maximum of one-third of the cultivated area. Each crop was also restricted to the maximum observed area in its past (i.e., 11-13 years). Moreover, for sugar beet, the maximum quota limitations were accounted for.

5.2.5 Expanding the states of nature matrix for MVN and MVKDE to account for catastrophe events

MVN and MVKDE approaches can be applied to generate a more enhanced sample than the observed sparse data as explained before. By doing so, it will make them more relevant and reliable to the uncertainty to be faced in the future farm planning period to date having been accounted for, among other things, catastrophe events. The densities in the downside tails are predefined when applying the MVN approach and root from the specified means, variances and covariances. The MVN distribution can be truncated to prevent anomalies occurring (e.g., negative yields and prices). Given the MVKDE procedure, subjective maximums and minimums need be added prior to the sampling.

Catastrophe events in arable farming, resulting into high losses, stem from numerous risks (perils), for example, weather-related perils as hail, storm and drought. However, the different catastrophic risks are generated simultaneously, since the applied MVN and MVKDE approaches do not discriminate if a downside outcome originates from one peril or another (no separate distributions are generated for different perils). Note that catastrophe events correspond to extreme unfavourable outcomes, not necessarily the minimum value that is specified for each KDE. For instance, a 50% reduction of the expected level is often regarded as a catastrophe event.

5.2.6 Computations

We used Simetar software to compare the MVN procedure with the MVKDE procedures (Richardson, 2006). The following kernel density functions were applied: Cauchy, cosinus, double exponential, Epanechnikov, Gaussian, Parzen, quartic, triangle, triweight and uniform (see Richardson, 2006). On the basis of the available historical yields, prices and corresponding covariance matrix, the MVN distribution and each MVKDE alternative were parameterised, and subsequently 500 states of nature (of yields and prices) were derived by the Latin Hypercube (LH) sampling procedure. In this way, the impact of the functional form on the joint distribution and the density in the downside tail could be studied. The LH procedure was taken in favour of Monte Carlo simulation (MCS), because it divides the distribution in an equal number of intervals so that tails with a downside risk and upside potential are taken into account (Richardson, 2006). Contrary, MCS randomly selects points, so that the tails can be underestimated even with a higher number of replications. The minimum values, for both MVN distribution and MVKDE, equalled zero. The change of the maximum affects the shape of the distribution, and the maximum values imposed arbitrarily were calculated as the observed (from the limited sparse data) maximum value plus one standard deviation[5].

Subsequently, the impact of incorporating the downside tail alternatively when optimising net farm income was addressed by applying UEP. Hereto, the 500 generated samples per alternative were incorporated as states of nature in UEP. Detailed results are presented for farm II, whereas only the aggregated results for the other five farms.

5.3 Results

5.3.1. Probability distributions of random variables

Graphical representation

The kernel functions under study were parameterised with the available states of nature, as discussed before. The appropriate approach is to select subsequently the kernel function with the smallest RMSE between the kernel itself and the historical (derived from the available states of nature complemented with the specified bandwidth). It was observed, however, that the density in the downside tail was underestimated for the majority of the kernels. The only kernel function that encompassed a denser downside tail, inherent to catastrophic risks and imposed by an extremely lower bound, was the Cauchy kernel. The remainder kernels definitely overestimated the middle section of the distribution and were

[5] Different assumptions in defining the maximum value were considered: 'maximum plus one standard deviation', 'maximum plus two standard deviation' and 'maximum plus three standard deviations'. The choice was made in favour of the 'maximum plus one standard deviation' because it accommodates a more dense tail.

equivalent to each other with respect to the downside tail. The double exponential and the Parzen kernel functions are typical representatives of kernels that overestimate the middle part and underestimate the downside tail. The remainder of this paper focuses therefore on the normal distribution as well as the Cauchy, the double exponential and the Parzen kernel functions.

For only farm II we elaborate on the generated cumulative distribution functions (CDF's) and the corresponding test characteristics. Then, the general results for all farms will be presented. In Figure 1 the CDF's of yields and prices for consumption potato, wheat and sugar beet are shown. For both yields and prices it can be seen that the Cauchy kernel matched the downside tail better (e.g., entire crop failure). Exceptions were consumption potato prices, where negative values of the downside tail were generated.

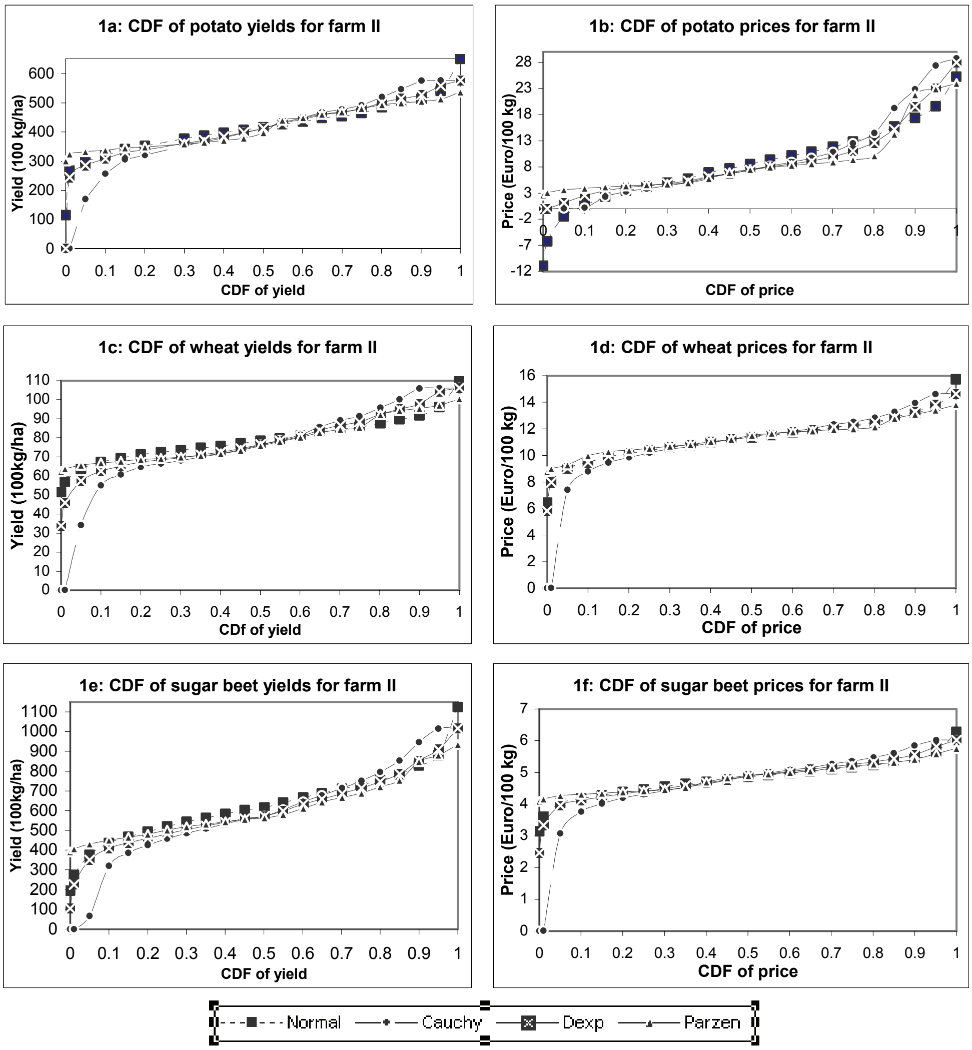

Figure 1. **Cumulative distributions of yields and prices for farm II**

Since the Cauchy kernel captured the downside tail best, the crop yield distributions simulated by the Cauchy kernel for all six farms were compared in Figure 2. As presented before, identical prices were assumed for all the farms and are therefore not presented.

As can be seen, the Cauchy kernels of the several farms had a similar pattern, but there were significant differences between the yield levels of the farms. The probability of an entire potato failure was almost 5% for farms I, IV and VI, while for farm II the most extreme event was a potato yield of 5 tons per hectare with a probability of 2%. Note that the observed crop plans of farms III and V did not comprise potatoes (Table 2).

In general, more extreme unfavourable wheat and sugar beet yields were generated for farm II than for the other five farms. For example, given farm II the probability of an entire wheat or sugar beet failure was approximately 3% and 5% respectively.

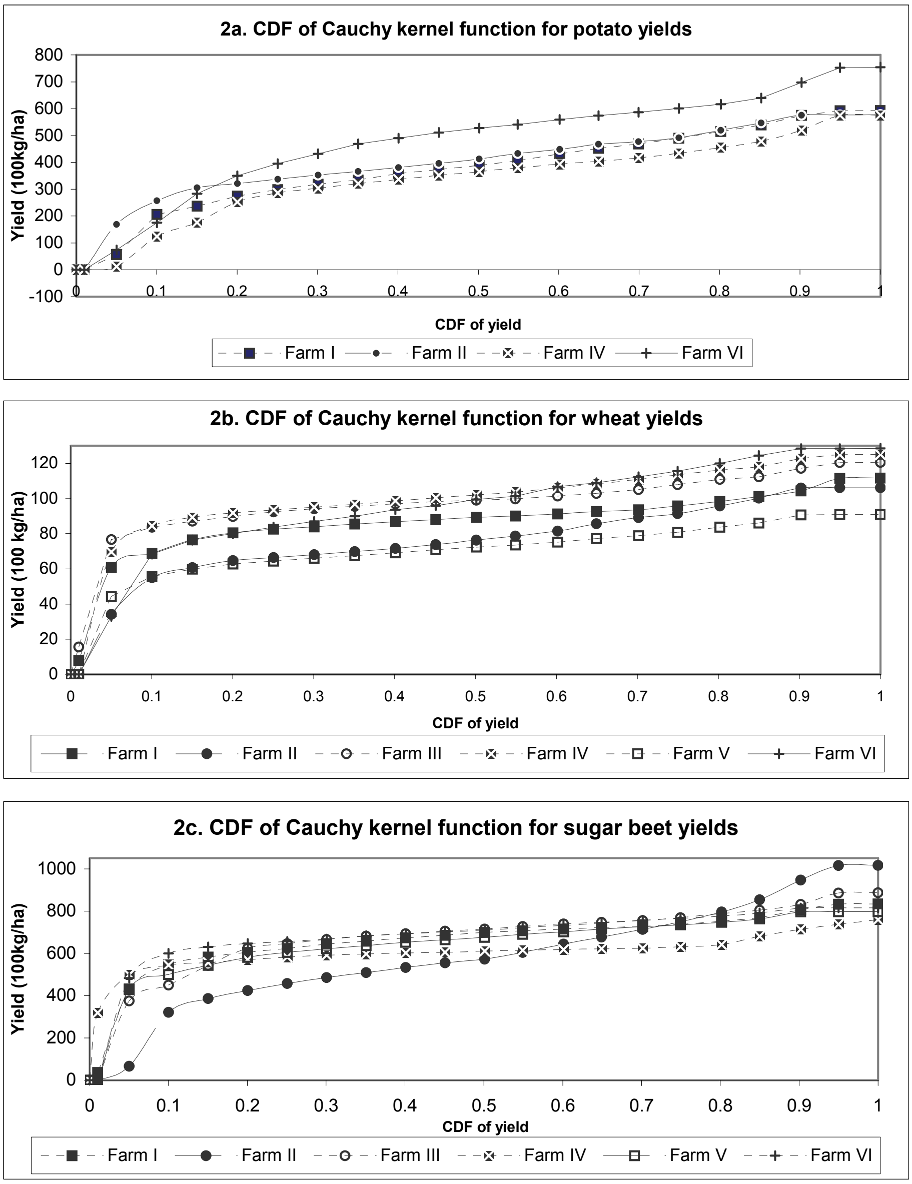

Figure 2. **CDFs of Cauchy kernel function yield distributions**

Test statistics

Several statistical tests were performed to validate whether the structure of the simulated data adequately captured the structure present in the available sparse dataset. In Table 2 test values and critical values for normality tests, Two Sample Hotelling T^2 Box's M test and Complete Homogeneity test were summarised at the 95% confidence level. If the test value does not exceed its critical value, then the null hypothesis is not rejected for the test under consideration. The critical values for farms II-VI were identical and are shown in the last column (equal number of degrees of freedom given three activities). The preceding column depicts the critical values for farm I (number of degrees of freedom given four activities).

The skewness and kurtosis criterion of the MVN distribution showed that the hypothesis that the data are multivariate normally distributed was not rejected (Table 2). However, this finding can illustrate that the model with a limited number of states of nature can be misspecified as in the study by Just and Weninger (1999).

Table 2. **Tests statistics of different distribution assumptions**

Distributions	Farm I	Farm II	Farm III	Farm IV	Farm V	Farm VI	Crit. values for farms:	
	Test value						I	II,III,IV,V and VI
				Skewness criterion				
Normal	93.75	48.4	81.2	57.49	63.73	49.11	146.57	74.47
				Kurtosis criterion				
	1.02	0.06	0.96	0.06	-0.98	-1.02	1.96	1.96
				2 Sample Hotelling T2 Test				
Normal	2.4E-05	0.277	2.5E-05	3.2E-05	1.7E-05	1.4E-05	15.87	12.83
Cauchy	1.623	0.534	0.588	0.545	0.829	0.658	15.87	12.83
Double exp.	0.022	0.01	0.005	0.005	0.023	0.02	15.87	12.83
Parzen	0.043	0.003	0.006	0.018	0.03	0.03	15.87	12.83
				Box's M Test				
Normal	31.65	25.24	21.3	22.9	32.96	23.23	51	32.67
Cauchy	61.9	47.36	41.07	48.23	60.5	43.8	51	32.67
Double exp.	16.61	27.79	23.43	24.92	35.85	26.23	51	32.67
Parzen	11.91	24.74	22.07	22.7	33.59	33.59	51	32.67
				Complete Homogeneity Test				
Normal	45.14	37.7	33	33.51	48.25	33.96	60.48	40.11
Cauchy	96.6	73.15	67.13	74.38	92.48	67.01	60.48	40.11
Double exp.	27.01	42.51	37.43	37.9	53.94	40.06	60.48	40.11
Parzen	17.88	35.75	33.42	32.84	48.7	48.7	60.48	40.11

The Two Sample Hotelling T^2 test was applied to test whether the mean vectors of the simulated data and available sparse data were different. The hypothesis that the mean vectors are equal was not rejected for all four distributions for each farm (at 95% confidence level).

The Box's M test was used to test whether the covariance matrices were equivalent. The simulated and the historical covariance matrices were not statistically different at the 95% confidence level for the multivariate normal distribution for almost all farms (except in case of farm V, where the test value of 32.96 was slightly higher than the critical value of 32.67). The hypothesis that the covariance matrices obtained from the Cauchy kernels are equal to the historical covariance matrices was persistently rejected. For the double exponential kernel, the hypothesis of maintaining the covariance structure was accepted for five farms out of six (except farm V), while the Parzen kernel was appropriate four times (farms I up to IV).

To test simultaneously whether both simulated mean vectors and covariance matrices were equal to the historical ones, the Complete Homogeneity test was used. The test failed to reject (at 95% confidence level) that both simulated mean vectors and covariance matrices are statistically equivalent to the historical ones for the normal distribution (except farm V). Maintaining of the mean and covariance structure simulated by means of Cauchy kernels was always rejected. The results from the double exponential and Parzen kernels were rather mixed.

The test results differ from the study by Richardson et al. (2006), where the hypothesis of the appropriate covariate structure between sparse and simulated data was preserved. This might be explained by the fact that in their state of nature matrix very low yields were observed, close to our extreme subjective minimums, whereas in this study the observed states of nature did not represent observations in the downside tail.

5.3.2. Impact of input distributions on optimal farm plan

The optimal farm plans resulting in the maximal expected utility were obtained in GAMS on the basis of a negative exponential utility function. The absolute risk aversion coefficients (*Ra*) were calculated as the proportion of the relative risk aversion (*Rr*) coefficients (on a scale from 0.5 to 4) to the permanent income (for details see Hardaker et al, 2004). The permanent income was obtained for each farm with a separate linear programming model. Then for each level of risk aversion the optimal farm plan with corresponding certainty equivalents (*CEs*), expected money values (*EMV*) of net farm income and risk premiums (*RP*) were calculated[6].

Table 3 presents the results obtained from UEP for farm II on the basis of MVN distribution and MVKDE (Cauchy, double exponential and Parzen kernels) of inputs. In general, it can be seen, that if a farmer was more risk-averse, he was more prone to choose a production plan comprising more less-profitable lower-variance crops (wheat instead of potato) compared to the optimal plan achieved with *Ra1* (implying that the decision-maker is almost risk-neutral). The changes in the production plan correspondingly resulted into changes in the net farm income. With increase of risk aversion the farmer was willing to pay a higher risk premium.

[6] The risk premium is defined as the difference between EMV and CE and is expressed as a percentage, it is calculated as RP%=Risk premium/EMV).

Table 3. **UEP results for farm II**

	Ra		Rr	EMV, Euro	CE, Euro	Risk premium (RP), Euro	RP, %	Activities		
								Potato	Wheat	Sugar beet
						Normality				
Ra1=Ra min	5E-06	≈	0.5	94941	81122	13819	14.6	26.4	37.6	16.0
Ra2	1E-05	≈	1	83656	70826	12830	15.3	17.8	46.2	16.0
Ra3	2E-05	≈	2	81356	61047	20309	25	16.0	48.0	16.0
Ra4	3E-05	≈	3	81356	52406	28950	35.6	16.0	48.0	16.0
Ra5 =Ra max	4E-05	≈	4	81356	44753	36604	45	16.0	48.0	16.0
						Cauchy				
Ra1=Ra min	5.0E-06	≈	0.5	94422	74662	19760	20.9	26.4	37.6	16.0
Ra2	1.0E-05	≈	1	82443	62262	20181	24.5	18.7	45.3	16.0
Ra3	2.0E-05	≈	2	78243	50519	27724	35.4	16.0	48.0	16.0
Ra4	3.0E-05	≈	3	78243	41702	36541	46.7	16.0	48.0	16.0
Ra5 =Ra max	4.0E-05	≈	4	78243	34617	43625	55.8	16.0	48.0	16.0
						Double exponential				
Ra1=Ra min	5E-06	≈	0.5	93886	81586	12300	13.1	26.4	37.6	16.0
Ra2	1E-05	≈	1	93458	72202	21257	22.7	26.1	37.9	16.0
Ra3	2E-05	≈	2	79884	63047	16838	21.1	16.0	48.0	16.0
Ra4	3E-05	≈	3	79884	57352	22532	28.2	16.0	48.0	16.0
Ra5 =Ra max	4E-05	≈	4	79884	52669	27216	34.1	16.0	48.0	16.0
						Parzen				
Ra1=Ra min	5E-06	≈	0.5	93656	84150	9505	10.1	26.4	37.6	16.0
Ra2	1E-05	≈	1	93656	77292	16364	17.5	26.4	37.6	16.0
Ra3	2E-05	≈	2	89239	68300	20939	23.5	23.1	40.9	16.0
Ra4	3E-05	≈	3	79897	63781	16116	20.2	16.0	48.0	16.0
Ra5 =Ra max	4E-05	≈	4	79897	60779	19118	23.9	16.0	48.0	16.0

The impacts of alternatively specified input distributions on the optimal farm plan (i.e., level of activities) were mixed. The allotted acreage in the farm plan of sugar beet, which was the most profitable cropping activity, always corresponded to the maximum quota allowed. The changes in production plans between potato and sugar beet between the distribution alternatives were considerable for a 'somewhat risk-averse' (*Ra2*) and 'rather risk-averse' (*Ra3*) farmer. For a 'very risk-averse' (*Ra4*) and 'almost paranoid about risk' (*Ra5*) farmer the production plan did not alter despite the differences in input distributions. The net farm incomes (*EMV*) were not much different between the models based on a normal distribution, Cauchy, double exponential and Parzen kernels. For farm II, with Cauchy kernel distribution, which better incorporates the lower tail, the net farm income was lower than for other distribution assumptions.

Substantial changes in the size of *CEs* were observed (Figure 3). As in theory, the CEs are decreasing as a cost of paying for increasing risk aversion (Hardaker et al, 2004). The decrease of *CEs* was steeper for Cauchy kernel, which better incorporates the downside tail.

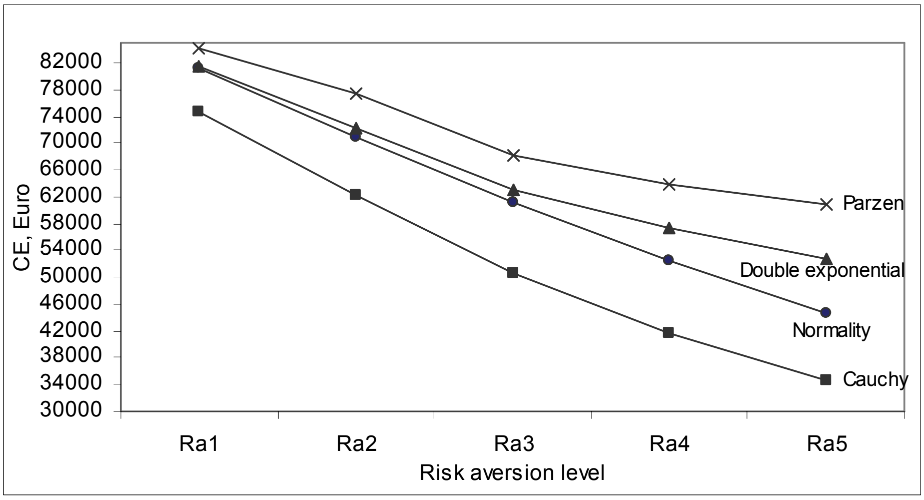

Figure 3. **CEs for farm II**

The conclusions drawn from farm II were also valid for the other farms under study. The risk premiums increased if the level of risk aversion increased. It corresponded to the decrease in *CEs,* due to worse optimal plans and increased levels of risk aversion.

5.4 Conclusions and discussion

Initially, the sample of historical data comprising 11 up to 13 observations of annual returns for an individual farm situation, which is already difficult to obtain, was not appropriate to analyse the impact of catastrophe events. However, the available sparse data was then used to generate data by applying MVN and MVKDE procedures to incorporate the downside tail. The analysis showed that the functional form chosen to generate the joint distribution substantially impacted the density in tail, although they were parameterised with the same observations. The differences in the optimal farm plan obtained (i.e. activity levels) generated by UEP were less profound.

To specify kernel density functions, usually expert opinions are elicited to define subjectively the minimum and the maximum values. If, on the basis of these subjective judgments, it is believed that catastrophe losses do occur (such as an entire crop failure), one might be inclined to specify the lower bound accordingly (equal or close to zero). It was observed that the normal distribution and all kernels, except the Cauchy kernel function, underestimated the impact of these beliefs, thereby neglecting the downside tail of the distribution. Note that the upper bound was arbitrary augmented to the value of the mean plus one standard deviation. Limiting the upside potential will definitely have its impact of the density over the whole distribution, thus also the downside tail.

The statistical tests showed that the simulated mean vectors from the Cauchy kernel were not statistically different from the mean vectors of the sparse data. Furthermore, the covariance structure was statistically different. However, it was not logical to expect that on the basis of the available sparse data, in which catastrophe states of nature were absent, the covariance structure of the Cauchy kernel distribution would not change. Sensitivity analysis, by altering minimum and maximum values, consequently rejected the hypothesis that the covariance structures of sparse and simulated data were approximately identical. The limited available observations were only positioned in the mode part of the kernel density, and therefore it was not possible to simulate the appropriate tail data on the basis of the observed data (under the assumption that catastrophe events did not occur).

In the statistical field, there is extensive discussion about the choice of bandwidth. For this paper we used the standard bandwidth settings in Simetar. However, changing of bandwidth parameters could result in different estimates of the low tail. Thus, there is a need to explore the effect of bandwidth choice in farm-level catastrophe simulation models.

Contrary to the asset integration assumptions, in which the decision-maker views gains and losses as a change in wealth position, this paper applied the measure of permanent income for UEP on the basis of constant absolute risk aversion properties of the expected utility function. According to these assumptions, farmers make their decisions on the basis of the annual incomes that are permanent in the long term. By doing so, relatively high risk premiums to avoid downside risks are expected. Alternatively, if wealth measures were taken as the basis of rational decision making, differences in the optimal farm plans would be limited between alternatively generated joint distributions. However, when a more simplistic utility function containing target minimum level of net farm income is the basis for decision making, then the approach how the tail is included does certainly affect the optimal farm plan.

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Chapter 6 Modelling of catastrophe insurance decisions in arable farming

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Abstract

This paper analyses the decision making problem describing how farmers can cope with catastrophic yield risks, and more specific to the option to insure and not to insure. For this purpose a single-crop two-state approach was compared to a multi-crop multi-state portfolio approach, which were both parameterised with farm-specific production data as well as farmer-specific perceptions. We compare the preferred options whether the decisions is based on a farm income or terminal wealth. The analysis showed that if a farmer makes decisions only in terms of an income-based utility function he is more prone to purchase catastrophe insurance. The models showed that those decision-makers who perceived that a risk would relatively seldom occur were less inclined to insure and self-insurance would be preferable. However, if insurance decisions are made only on the basis of the single-crop two-state approach, they may differ from portfolio results because of alternative risk reducing options such as a diversification are not taken into account.

Keywords: catastrophic risk, insurance, normality, Cauchy kernel, utility-efficient programming

6.1 Introduction

Arable farming is a risky business. Risk means the possibility of a loss of income or property resulting from some event (Pritchet et al., 1996). Catastrophic risks are infrequent events, but can cause large losses to farmers. To cope with catastrophic yield risks, arable farmers can transfer the risk by purchasing insurance (being either single-peril or multi-peril crop insurance). In multi-peril crop yield insurance, indemnities are paid to a farmer if the actual yield falls below its guaranteed yield (Helms et al., 1990), while in case of a single peril insurance farmers are indemnified if that specific peril caused losses exceeding the deductible level.

It is difficult for crop producers to fully understand the complex steps in evaluating the crop insurance decision (Helms et al., 1990; Zering et al., 1987). The decision entails often which perils should be insured and at what levels of deductibles in case of single-peril crop insurance (e.g. hail or storm if such coverages are available). For multi-peril crop insurance the decision entails the level of guarantee preferred. Given a typical diversified arable farm the decision problem becomes even more complex since these options should be explored for all crops. However, the merits of each particular insurance option cannot be assessed stand-alone since such partial analyses may be flawed, perhaps misleading, especially (but not solely) where the activities analysed are strongly negatively correlated with other parts of the farm firm (Hardaker and Lien, 2005; Hardaker et al., 2006; Richardson et al., 2006), and need therefore to be accounted for (Hardaker et al., 2004).

Without proper individual farm production data, it is impossible to examine the effectiveness of crop insurance at an individual farm level (Wang and Zang, 2003). However, it is generally hard to obtain 10 relevant historical farm observations under the same economic policy, management regime, farm program or trade policy (Just and Weninger, 1999; Richardson, 2006). One of the ways to smooth data and to include downside and upside tails properly is to fit the sparse data to a (parametric) normal distribution. However, normality is not likely because upward potential of yields is biologically bounded and there is a risk of (complete) crop failure because of, for example, adverse meteorological circumstances (Galagher, 1987). Many studies concluded that crop yields are skewed and do not follow normality (Antwood et al., 2003; Galagher, 1987; Just and Weninger, 1999; Ramirez et al., 2001; Swinton and King, 1991). Some studies stated that the beta distribution is advantageous to a normal distribution (e.g. Hart et al., 2006). However, Just and Weninger (1999) argued that many studies that rejected (multivariate) normality are typically cited as the basis for making non-normality assumptions but are no better individually justified than normality. An alternative way to generate unobserved data to supplement sparse data is to apply the multivariate kernel density estimation (MVKDE) that also accounts for stochastic dependency (Hardaker et al., 2006; Richardson et al., 2006). This is a non-parametric approach with similarities to the approach of smoothing data by hand. The estimation of the probability at a given point depends on pre-selected probability density characteristics. In general, the normative methods applied and assumption made to supplement sparse data will definitely affect the estimated effectiveness and thus the adoption of crop insurance.

In literature, it is hardly recognised that such normative models with personal characteristics of the farm manager himself (i.e., risk attitude and risk perception) influences decisions to insure catastrophic risks or not. According to Dillon and Hardaker (1993), risk attitude is the extent to which a decision-maker seeks to avoid risk or is willing to face risk. Risk perception is the subjective statement by decision-makers of the risky event under consideration; it is more like the mental interpretation, decomposed as the probability of the event occurring and the magnitude of the loss (Hardaker et al., 2004; Smidts, 1990).

The expected utility approach is often applied to encompass these farmer's personal characteristics. The incorporated utility functions are based on either constant absolute risk aversion (CARA) properties for income or constant relative risk aversion (CRRA) properties for wealth. The shape of utility function refers to degree of farmer's risk aversion. Most farmers are commonly assumed to be risk-averse (Hardaker et al., 2004).

The insurance decisions in terms of CARA and CRRA can be modelled either by a simple single-crop two-state risk models discriminating between the option to insure a single risk or not, and including only the states of nature describing the catastrophe event occurring or not with its probabilities (i.e. Kunreuther and Pauly, 2004). Alternatively, catastrophe insurance decisions can be compared in a portfolio optimisation context taking into account stochastic dependency between cropping activities capturing many more states of nature. In general, analyses in the literature to support crop insurance decision making are often very general in nature and not tailored to individual (farm) production circumstances, nor do they encompass the farmer personal characteristics (i.e., risk attitude and risk perception).

The goal of this paper is to define under which conditions it is likely that farmers decide to purchase insurance that protect them against crop failures. For this purpose the decisions-making problem is analysed within a partial single-crop context as well as within a portfolio context. For portfolio context the multivariate normal distribution (MVN) and multivariate kernel density estimation (MVKDE) procedures will be applied. Furthermore, alternative assumptions with respect to risk attitude as well as risk perceptions (individual and group average) are considered.

6.2 Methods

6.2.1 Single-crop two-state risk modelling

Kunreuther and Pauly (2004) applied a two-state risk model to analyse whether it is beneficial to purchase a catastrophe insurance against a specific single risk. This approach compares the expected utilities of two decisions (insure or not to insure), for example in terms of final wealth. For each of the decisions two possible outcomes were considered: there is no catastrophe and there is a catastrophe from a specific risk. If a farmer does not purchase a catastrophe insurance cover against a single-peril catastrophic risk, the expected utility is derived as follows:

$$EU_{NO} = pU(W - L) + (1 - p)U(W) \tag{1}$$

Where:

EU_{NO} – is the expected utility without having insurance;

p – is the perceived probability of a catastrophic risk occurring;

$U(.)$ – is the expected utility of final wealth,

W – is the volume of wealth;

L – is the loss a farmer experiences after catastrophic risk.

If a farmer purchases catastrophe insurance, then the expected utility is derived as follows:

$$EU_{YES} = pU(W - L + C - Pr) + (1 - p)U(W - Pr) \tag{2}$$

Where:

EU_{YES} – is the expected utility with insurance coverage;

C – indemnity received after experiencing catastrophic risk;

Pr – annual premium paid for insuring catastrophic risk.

If EU_{YES} exceeds EU_{NO} the optimal decision for a decision-maker is to purchase catastrophe insurance, otherwise the option to disregard insurance will dominate.

Kunreuther and Pauly (2004) used simple utility functions, such as the square root, i.e., $U(.)=\sqrt{(.)}$, in terms of final wealth. In their approach, the choice of the functional form of the utility function defined the risk aversion level of a farmer. Alternatively, more general functional forms on the basis of CARA and CRRA can be used to model insurance decisions based on income and wealth measures. These functional forms can a priory incorporate any value of risk aversion coefficients. The decisions then can be compared at different given levels of risk aversion by the stochastic efficiency with respect to a function (SERF) method (Hardaker et al., 2004). Then the alternatives whether to insure or not to insure a single catastrophic risk can be compared by certainty equivalents (CEs), where the alternative with a highest CE is dominating. CE, indirectly derived from the utility, is the maximum sure payment the farmer would be willing to accept (pay) rather than face the risk (Hardaker et al., 2004).

The disadvantage of a single-crop two-state model is that stochastic dependencies (e.g., covariances) between yields and prices within a crop as well as between crops (or in more general terms defined as activities) cannot by accounted for. Alternatively, those stochastic dependencies, and more general the full joint distribution, can be incorporated by portfolio models

6.2.2 Multi-crop multi-state risk modelling

As single-crop two-state risk models, utility efficient programming (UEP) is also based on the principle to maximise expected utility. In SERF the UEP takes the following form (Hardaker et al., 2004):

Maximise $E[U]=p\ U(z, r)$, r is varied (3)

Subject to

$A\ x <= b$ (4)

$Cx - Iz = uf$ (5)

And $x>=0$ (6)

Where:

$E[U]$ – is expected utility;

p – is the probability of each state of nature;

$U(z,r)$ – is a vector of utilities of farm goal variable by state of nature with risk attitude level r;

z – is a vector of farm goal variables by state of nature;

r – is a coefficient of absolute or relative risk aversion;

A – is a vector of technical-economical coefficients for each activity;

x – is a vector of activities;

b – is a vector of available resources (constraints);

C – is a vector of state of nature matrix of activity incomes;

I – is an identity matrix.

The risk aversion parameter r represents the coefficient of relative risk aversion (Rr) or the coefficient of absolute risk aversion (Ra). Logarithmic and power utility functions are the basis to incorporate Rr. The power function, which is commonly used, takes the following form:

$$U = \left[\frac{1}{\left(1 - Rr\right)}\right] W^{(1-Rr)} \qquad (7)$$

As long as risk aversion coefficient of a farmer is not known, the range of risk aversion coefficients can be considered for modelling. For a risk-averse farmer Rr for wealth varies from 0.5 to 4, and amounts typically about 1, with the following meanings: 0.5 – hardly risk-averse at all; 1.0 – somewhat risk-averse (normal); 2.0 – rather risk-averse; 3.0 - very risk-averse; and 4.0 – almost paranoid about risk (Anderson and Dillon 1992, Hardaker et al., 2004).

In case if the relative risk aversion coefficient equals one, the power utility function is undefined, and therefore the logarithmic function can be used. It takes the following form:

$$U = ln(W) \qquad (8)$$

In decision analysis, the negative exponential function incorporating Ra is extensively used. The negative exponential function takes the following form:

$$U = 1 - exp(-Ra \cdot W) \qquad (9)$$

Where Ra is calculated as $Ra = \frac{Rr}{W}$ (10)

Note that *Rr* are taken from the classification by Anderson and Dillon (1992). According to reasonable asset integration assumptions, a farmer would view losses or gains from specific risks as being equivalent to changes in wealth. If asset integration assumption does not hold and farmers fail to see losses and gains as equivalent changes in wealth, the *W* argument is replaced by the permanent income (*Y*) (for details see Hardaker et al., 2004):

$$U = 1 - exp(-Ra \cdot Y) \tag{11}$$

Where *Ra* is calculated as $Ra = \dfrac{Rr}{Y}$ (12)

For both CARA and CRRA utility function forms, the annual income needs to be calculated. For the CARA function it serves as the farmer's objective function. For CRRA, the annual income is added to the initial wealth. For the calculation of income, the joint probability distribution is incorporated via states of nature matrix, whereby crop income distributions are often decomposed into its yields and prices. In order to supplement sparse data it is possible to generate unobserved data on basis of MVN assumptions (Richardson, 2006) or MVKDE assumptions (Richardson et al., 2006). The states of nature generated by MVN and MVKDE procedures have equal objective probabilities. In order to supplement these data with subjective catastrophic risk perception, a number of additional states of nature accounting for subjective probability and outcome of a catastrophic risk, can be incorporated into the UEP model. Then for these states of nature, the indemnities that a farmer receives in case of a catastrophe need to be incorporated, while premium paid need to be added to all states.

6.3 Data and assumptions

6.3.1 Available objective data

For the current analysis, four arable farms were selected from the Farm Accountancy Data Network (FADN) database. The FADN data is an official European Union dataset, which includes detailed objective farm-specific data of, among other things, yields per unit per crop. The prerequisite for the selection was that at least ten consecutive years with observations were available. For the selected arable farms, the main crops in the production plan constituted consumption potato, wheat, rye and sugar beet (Table 1). All four crops are present in the production plan on farm I. On farm II, III and IV, three crops are cultivated.

Farm II, with 80 ha which is a bit larger than the average Dutch crop farm (50-60 hectares), will be presented more in detail to illustrate the approaches and their implications.

Table 1. **Objective and subjective input data**

Farm #	Period with observations	Cultivated area (ha)	WTA (Euro, range)	RBC (Euro, range)	Main activities in production plan				
					Potato		Wheat	Rye	Sugar beat
I	1992-2004	17	50001 - 80000	50001 - 80000	x		x	x	x
II	1994-2004	80	1 - 20000	2001 - 50000	x		x	-	x
III	1994-2004	101	20001 - 50000	50001 - 80000	-		x	x	x
IV	1994-2004	205	na	80001 - 120000	-		x	x	x
					Perils associated with crops				
					Brown rot	Hail	Hail	Hail	Hail
I	Elicited annual risk perception per peril for farm I				3.3%	10.0%	10.0%	10.0%	10.0%
II	Elicited annual risk perception per peril for farm II				0.5%	3.3%	3.3%	-	3.3%
III	Elicited annual risk perception per peril for farm III				-	-	10.0%	10.0%	10.0%
IV	Elicited annual risk perception per peril for farm IV				-	-	0.7%	0.7%	0.7%
	Average risk perception per peril in the sample (n=74)				4.0%	9.0%	9.0%	9.0%	9.0%
	Standard deviation of risk perception (absolute value)				3.5%	6.6%	6.6%	6.6%	6.6%
I	Actual premium paid per peril by farm I, Euro (range)				na	na	na	na	na
II	Actual premium paid per peril by farm II, Euro (range)				na		1001 - 2000		
III	Actual premium paid per peril by farm III, Euro (range)				1001 - 2000		501-1000		
IV	Actual premium paid per peril by farm IV, Euro (range)				501 - 1000		1001-2000		
	Average premium paid in the sample, Euro (n=74)				823		1380		
	Proportion of farmers insured in the sample, %				48		62		
					Normative data				
I	Premium paid per peril per ha by farmer I, Euro				37.52	28.51	6.93	41.57	6.18
II	Premium paid per peril per ha by farmer II, Euro				18.76	14.25	3.46	-	3.09
III	Premium paid per peril per ha by farmer III, Euro				-	-	3.96	23.76	3.53
IV	Premium paid per peril per ha by farmer IV, Euro				-	-	4.95	29.69	4.41

´x´ - refers to the availability of crop in production plan; ´-´ refers to absense of crop in production plan
´na´ - not available; WTA - willingness-to-accept risk; RBC - risk-bearing capacity

Annual linear de-trended crop yields, farm size and initial wealth were obtained from FADN for the current analysis. Prices and costs were assumed to be the same for all farms considered. Individual crop prices were used to calculate the average prices that were de-trended by Paasche equations with the consumer price index (CPI) as deflator (Mas-Colell, 1995). Costs were calculated on the basis of normatives (Dekkers, 2002). As prices, costs were de-trended by Paasche equations.

6.3.2. Available subjective data

The FADN database does not contain specific insurance coverages purchased, nor does it contain risk perceptions per peril and the risk attitude of a farmer. Specific insurance and subjective risk information was collected by a questionnaire. The questionnaire was sent to 135 arable farmers who were already being surveyed for the Dutch FADN. After 2 weeks a reminder was sent to the farmers. This resulted into a response rate of 54.8% (74 farms).

Concerning risk perception, the perceived probability of a specific peril occurring at the farm was elicited but no losses were assigned to each catastrophic peril. The perils under study were brown rot (a potato disease) and hail which could damage one or more crops. In the study by Van Asseldonk et al. (2002) the attempt was made to elicit probability directly, however farmers could hardly provide these probabilities. To avoid to a certain extent the problem of over- and under-estimation of probabilities, some illustrative risks which any person faces often in life, were presented as a reference. Of these illustrative risks the objective probabilities were depicted as well, which were derived from long-term historical databases. The examples were, among others, the probability of a car theft, the probability of a certain minimal or maximal temperature in a certain period, the probability of a breakdown of a fresh-water or salt-water dikes in the Netherlands, and the probability of a certain insured accident occurring. Multiple boxes with different probabilities could be ticked if a farmer was inconclusive about the most likely probability. Then the average perceived probability was calculated and used for our analysis. For farmers II and IV, the perceived probabilities were much lower than the average probabilities in the sample as a whole (Table 1). The perceived probabilities of hail by farmer I and III were a somewhat higher than the average level.

Premiums paid for a brown rot or hail cover are not recorded detailed enough in the FADN database. For easiness of farmers' interpretation, since farmers do not know exactly the amount of premium paid for each peril and crop, the farmer was asked to tick one of the presented insurance premium boxes. The following intervals were possible: € 1-100; €

101-500, € 501-1,000; € 1,001-2000; € 2,001-4000; € 4,001-6000; € 6,001-8,000 and € 8,001-10,000 per year. The four farms under study paid either € 501-1,000 per year or € 1,001-2,000 per year. About half of the farmers in the questionnaire were insured against brown rot of potatoes with an average annual premium paid of € 823. The proportion of farmers purchasing insurance against hail was 62%, and on average farmers paid € 1,380 per year. The value of hail insurance is aggregated into farm level because it was difficult to obtain premiums per specific crop (it is difficult to retrieve this specific information from the documents that insurance companies provided to farmers).

In Table 1 we also present two subjective measures that provide some information concerning their risk attitude, and capture their willingness-to accept (WTA) a single risk as well as their perceived risk bearing capacity (RBC) to cover the maximum annual risk at farm level. For WTA and RBC elicitation, farmers were asked to mark the appropriate range of financial capacity: a score of 1 means a maximal willingness-to accept or a maximal annual risk-bearing capacity of € 1 to 20,000. Other scores were: 2 (€ 20,001 - 50,000); 3 (€ 50,001 - 80,000); 4 (€ 80,001 - 120,000); 5 (€ 120,001 - 160,000); 6 (€ 160,001 - 200,000); 7 (€ 200,001 - 250,000); and 8 (> € 250,001).

6.3.3 Outline modelling approach

By means of the single-crop two-state modelling approach, crop-related brown rot of potatoes and hail risks of potatoes, wheat, rye and sugar beet, were analysed each in a separate model. The analysis requires the risk perception of brown rot and hail occurring. To characterise the probability of a catastrophe event two alternative probability levels will be considered: 1) the individual perceived probability; and 2) the average perceived probability (Table 1). To characterise the magnitude of a catastrophe event, two situations will be considered: 1) complete crop failure, and 2) 25% yield loss (that is more in line with the loss according to the Dutch claim statistics). In summary, we distinguish 2*2*2*(4+1+1)=48 models per farm (two levels of perceived probabilities; two levels of crop failures; two types of utility functions; two perils nested within four crops of which one peril is only relevant for one crop, plus a worst case scenario). In the worst case scenario we assume that hail affects all crops simultaneously. The individual premium rates per hectare per crop (Table 1) and indemnities were included in Equation 2 to evaluate the insurance option. If a farmer does not experience a catastrophic risk, the individual premiums are deducted from his wealth. After a catastrophic risk occurs, the indemnities are added to his wealth accounted for the deduction of insurance premiums. To avoid some moral hazard, the insurance contracts included a 10% deductible (note that alternative deductible options are available to farmers but are not considered in the current analysis). For the state describing the absence of a catastrophe event occurring, the average permanent net farm income was taken.

By means of UEP the production plan will be optimised on basis of a multi-crop and multi-states approach. For the generation of states of nature on the basis of sparse data, the MVN and MVKDE procedures will be applied. First, the available de-trended sparse data was enriched by the Latin Hypercube (LH) simulation procedure with 500 iterations. LH is advantageous over Monte Carlo simulation as it divides a whole distribution into equal number of intervals that is equal a number of iterations, so that all areas of the distribution (including tails) are accounted for. For the MVKDE procedure the minimum and maximum values were added prior to the simulation. The minimum yield was set at zero. In order to represent an upper tail, the maximum value of yield was calculated as the maximum observed value plus one standard deviation as by Ogurtsov et al. (2007). Ogurtsov et al. (2007) made analysis on applicability of different kernel functions for a proper representation the tails of the distribution. A tail was better represented by the Cauchy kernel than other kernels that represented much similarity with a normal distribution.

For UEP, we explore the idea of Kunreuther and Pauly (2004) to incorporate two situations: there is and there is no catastrophic risk. For the situation if there is a catastrophic risk, we assumed a complete crop failure by hail for wheat, rye and sugar beet (note that partial crop failures are analysed but not reported). The probabilities and losses at farm level of catastrophic risks were identical to the ones from single-crop two-state risk models. Therefore a number of additional states assuming zero yields were added to the previously generated 500 states of nature. The number of states added was based on the perception of a catastrophe occurring. For instance, if a hail risk perception is 10%, then a number of additional states of nature is 56 (i.e. 10/(100-10)*500). For these additional states, the indemnities that can be received from insurance companies were added, while premiums paid were added to all states. As in two-state single-crop models, the insurance contracts included 10% deductible.

For UEP, constraints need to be specified. Cereal crops (wheat and rye) were restricted to a maximum of two third of the cultivated area. Tuberous crops (consumption potato and sugar beat) were restricted to maximum one third of the cultivated area. Each crop was also restricted to its maximal observed amount in the past 11-13 years (this accounted for, among others, quota limitations in sugar beet production).

In summary, we distinguish 2*2*2=8 models per farm (two levels of perceived probabilities, two types of distribution assumptions, and two types of utility functions). For each model, five optimisations representing the five levels of risk aversion were run. The results within and between the models applied (single-peril two-state versus multi-peril multi-state) will be compared on basis of their CEs.

6.4 Results

6.4.1 Results single-crop two-state risk modelling

The results of the single-crop two-state risk models of each alternative explored focus on the absolute CE levels and the differences in CEs between the insured and not insured option (ΔCE =CEyes-CEno). As an example, the impacts of purchasing catastrophe insurance against brown rot, indemnifying complete failures of potato yields, are presented in Table 2 for farm II. Given that the brown rot insurance decision is based on CARA utility income-based function and that the model is parameterised with individual risk perception levels, CE values for the insurance strategy are lower than for the no-insurance strategy (negative ΔCE) at absolute risk aversion levels Ra1 and Ra2. At higher risk absolute risk aversion levels the insurance strategy becomes dominant. An increment of the absolute risk aversion level from Ra3 to Ra5 is associated with an increased ΔCE of 313 Euro and 5,560 Euro respectively. If farmer II makes decisions concerning insurance against brown rot based on CRRA utility function, still under the assumption that the model is parameterised with individual risk perception levels, the optimal solution is not to purchase insurance at all levels of relative risk aversion. Note that, in comparison to the CARA income-based utility function, the results for CRRA function are rather stable, and the benefits of no-insurance strategy do not differ much between relative risk aversion levels. If farmer II perceives that only 25% of yields can be destroyed by brown rot, for both CARA and CRRA utility functions at the individual risk perception level, it is not optimal to purchase catastrophe insurance against brown at given insurance premium rates.

Table 2. **Results of two-state risk models for farm II**

	Potato - brown rot				Potato - hail				Wheat - hail				Sugar beet - hail				Potato/wheat/sugar beet - hail			
	100% loss		25% loss		100% loss		25% loss		100% loss		25% loss		100% loss		25% loss		100% loss		25% loss	
	No ins.	ΔCE[1)]	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE
Individual risk perceptions																				
CARA utility function properties																				
Ra1	93241	-725	93768	-1213	89540	2684	93009	-526	92749	-289	93631	-1090	92254	165	93524	-993	84500	7457	92267	153
Ra2	93012	-498	93758	-1204	88125	4090	92949	-466	92648	-188	93625	-1084	92045	372	93513	-983	78193	13735	92061	357
Ra3	92198	313	93737	-1182	83555	8641	92811	-330	92411	47	93613	-1073	91526	887	93490	-960	53556	38310	91551	863
Ra4	90462	2046	93711	-1156	75921	16254	92649	-169	92119	337	93601	-1061	90833	1577	93465	-935	21635	70160	90872	1540
Ra5	86945	5560	93679	-1125	65796	26358	92458	21	91761	693	93588	-1048	89922	2485	93438	-908	-2433	94149	89979	2429
CRRA utility function properties																				
Rr1	976986	-998	977375	-1349	974068	1635	976660	-705	976431	-123	977236	-1223	976017	251	977134	-1132	971388	4065	976027	-134
Rr2	976972	-984	977375	-1348	973976	1727	976654	-699	976423	-114	977235	-1223	976000	268	977133	-1130	971083	4367	976010	-118
Rr3	976943	-955	977373	-1347	973787	1914	976644	-689	976405	-97	977234	-1222	975966	302	977130	-1128	970434	5012	975977	-85
Rr4	976911	-923	977371	-1345	973583	2116	976633	-678	976387	-79	977233	-1221	975930	337	977128	-1126	969691	5749	975942	-50
Rr5	976877	-889	977369	-1343	973365	2333	976622	-667	976369	-61	977232	-1220	975894	373	977126	-1124	968851	6584	975906	-15
Average risk perceptions																				
CARA utility function properties																				
Ra1	88680	3476	92831	-365	82349	9293	91502	838	90805	1473	93171	-676	89440	2722	92873	-406	69286	21622	89475	2690
Ra2	87011	5134	92759	-293	79047	12571	91350	989	90553	1723	93157	-662	88922	3236	92845	-379	56008	34827	88965	3196
Ra3	81731	10391	92596	-132	69919	21653	91013	1322	89980	2292	93128	-632	87684	4465	92786	-320	20952	69726	87748	4405
Ra4	73292	18806	92405	58	58466	33055	90628	1705	89302	2965	93097	-602	86148	5992	92724	-258	-7953	98457	86238	5905
Ra5	62715	29358	92180	282	47326	44142	90190	2140	88514	3748	93065	-570	84313	7818	92657	-192	-25938	116252	84436	7698
CRRA utility function properties																				
Rr1	973382	2254	976492	-553	968245	6889	975230	583	974613	1515	976784	-817	973454	2560	976498	-559	960874	13567	973483	2157
Rr2	973272	2363	976485	-547	968011	7120	975216	597	974591	1537	976782	-815	973411	2603	976495	-557	960097	14337	973440	2200
Rr3	973047	2586	976472	-534	967536	7591	975189	623	974547	1580	976780	-813	973324	2689	976490	-551	958463	15959	973355	2285
Rr4	972805	2826	976459	-521	967028	8095	975161	651	974502	1625	976777	-810	973234	2778	976485	-546	956630	17778	973266	2373
Rr5	972546	3083	976446	-508	966490	8628	975133	678	974456	1670	976774	-807	973142	2869	976479	-541	954600	19794	973175	2463

[1)] $\Delta CE = CE_{insurance} - CE_{no\ insurance}$

Farmer II perceives that the chance of brown rot is less likely than an average arable farmer in our sample (0.5% versus 4%). Supposing that farmer II bases his decision on the average risk perception level would imply for both CARA and CRRA utility functions, that the optimal solution is to insure against brown rot (at all levels of risk aversion). More profound differences for ΔCE between CARA and CRRA utility functions indicate that if the farmer makes decisions in terms of income, insurance offers more benefits than that he would have based his decisions on terminal wealth. Note that if risk perception of a catastrophe increases, the absolute CE levels for CARA and CRRA utility functions decrease since the probability of the no-catastrophe state decreases. Under the assumption of only 25% yield loss, brown rot insurance is seldom a dominant strategy for farmer II.

Hail damaging potato has a more severe economical impact than hail affecting other crops because of a higher revenues received (revenues for wheat are lowest followed by those of sugar beet). This can be seen, for example, by a sharp decrease in values of CEs for no-insurance strategy for CARA utility function from 89,540 Euro at Ra1 to 65,796 Euro at Ra5 (given individual risk perceptions). This slope is less profound for sugar beet and hardly present for wheat. To cope with the possibility of a completely deprived potato yield incurred by hail, the insurance strategy was found to be always the best solution. If farmer II assumes a potential loss of only 25%, no-insurance strategy dominates insurance strategy given his relative low individual risk perceptions levels (except for CARA at Ra4). As perception of hail probabilities increases up to average levels, insurance purchase increases farmer's CEs.

The pattern of the wheat models assuming a complete crop failure is similar to the pattern of the brown rot model, however purchase of hail insurance for wheat provides less perceived benefits than purchase of brown rot insurance for potatoes. Purchase of hail insurance for sugar beet, in case of complete crop failure, was found to be the optimal solution in all models. The opposite conclusions were drawn if assuming only 25% sugar beet yield loss.

The worst case scenario of hail that could occur is a simultaneous failure of potato, wheat and sugar beet. Table 2 indicates that this worst case scenario will result into large perceived losses as can be seen by negative CE-values for the no-insurance strategy at higher absolute risk aversion levels. The results of the models imply that in order to avoid the worst case scenario, if decisions are made in terms of annual income, the best strategy is to insure simultaneously potato, wheat and sugar beet against hail. For wealth measures, the benefits of no-insurance strategy are limited. If a farmer perceives that only 25% of all three yields might be destroyed simultaneously by hail, the purchase of catastrophe insurance increases his utility given the decisions are taken in terms of income and wealth.

In a similar way presented for farm II, the more aggregated results can be interpreted for farm I, III and IV (Table 3 and 4). Note that for farmer I and III the individual risk perception of hail is a somewhat higher than the average risk perception (Table 1). This resulted into slightly lower values of CEs for the models of individual risk perceptions. For example, in the model of 100% potato loss resulting after hail occurring, if farmer makes decisions in terms of income, the CE of the no-insurance strategy of individual risk perception alternative is 19,396 Euro (Table 3). It is lower than the CE of 19,658 Euro (Table 4) for the average risk perception alternative. As could be seen in Table I, farmers pay different insurance premiums per peril per crop that also affect their decisions.

Table 3. **Results of two-state risk models for individual risk perceptions**

		Potato - brown rot				Potato - hail				Wheat - hail				Rye - hail				Sugar beet - hail				Potato/wheat/sugar beet - hail			
		100% loss		25% loss		100% loss		25% loss		100% loss		25% loss		100% loss		25% loss		100% loss		25% loss		100% loss		25% loss	
		No ins.	ΔCE[1]	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE
		CARA utility function properties																							
I	Ra1	21949	-437	22059	-538	21172	277	21896	-392	21940	-431	22052	-532	21997	-483	22065	-544	21690	-203	21996	-482	20071	1317	21728	-237
	Ra5	20929	581	22042	-522	16881	4555	21793	-289	21882	-374	22049	-529	21976	-462	22064	-543	21114	371	21975	-461	1930	19409	21275	213
II	Ra1	93241	-725	93768	-1213	89540	2684	93009	-526	92749	-289	93631	-1090	-	-	-	-	92254	165	93524	-993	84500	7457	92267	153
	Ra5	86945	5560	93679	-1125	65796	26358	92458	21	91761	693	93588	-1048	-	-	-	-	89922	2485	93438	-908	-2433	94149	89979	2429
III	Ra1	-	-	-	-	-	-	-	-	95816	3435	99467	112	97524	1874	99845	-231	90631	8216	98415	1065	78603	19489	96370	2928
	Ra5	-	-	-	-	-	-	-	-	91071	8149	99258	319	95727	3658	99758	-144	68499	30230	97561	1912	3499	94143	92748	6525
IV	Ra1	-	-	-	-	-	-	-	-	171014	-1923	171275	-2160	170839	-1764	171236	-2125	170039	-1024	171076	-1980	168631	300	170848	-1771
	Ra5	-	-	-	-	-	-	-	-	170802	-1713	171265	-2150	170284	-1211	171214	-2103	163316	5681	170942	-1847	114345	54526	170315	-1241
		CRRA utility function properties																							
I	Rr1	332775	-465	332858	-540	332153	95	332704	-402	332744	-437	332850	-533	332797	-485	332863	-545	332529	-243	332797	-485	331554	638	332560	-271
	Rr5	332762	-452	332857	-539	332065	183	332699	-397	332741	-434	332850	-532	332796	-484	332863	-544	332508	-223	332795	-483	331233	956	332543	-254
II	Rr1	976986	-998	977375	-1349	974068	1635	976660	-705	976431	-123	977236	-1223	-	-	-	-	976017	251	977134	-1132	971388	4065	976027	-134
	Rr5	976877	-889	977369	-1343	973365	2333	976622	-667	976369	-61	977232	-1220	-	-	-	-	975894	373	977126	-1124	968851	6584	975906	-15
III	Rr1	-	-	-	-	-	-	-	-	3738330	3005	3741573	86	3739791	1690	3741937	-242	3734379	6564	3740591	970	3727110	13116	3738793	2588
	Rr5	-	-	-	-	-	-	-	-	3738250	3084	3741568	91	3739756	1724	3741935	-240	3734084	6856	3740573	988	3726044	14171	3738730	2651
IV	Rr1	-	-	-	-	-	-	-	-	4894305	-1943	4894547	-2161	4894155	-1808	4894509	-2127	4893556	-1268	4894361	-1994	4892746	-537	4894162	-1814
	Rr5	-	-	-	-	-	-	-	-	4894299	-1938	4894547	-2160	4894143	-1796	4894509	-2126	4893493	-1205	4894357	-1990	4892543	-336	4894150	-1803

[1] $\Delta CE = CE_{insurance} - CE_{no\ insurance}$

Table 4. **Results of two-state risk models for average risk perceptions**

		Potato - brown rot				Potato - hail				Wheat - hail				Rye - hail				Sugar beet - hail				Potato/wheat/sugar beet - hail			
		100% loss		25% loss		100% loss		25% loss		100% loss		25% loss		100% loss		25% loss		100% loss		25% loss		100% loss		25% loss	
		No ins.	ΔCE1)	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE	No ins.	ΔCE
CARA utility function properties																									
I	Ra1	20991	443	21858	-357	19658	1666	21574	-100	21691	-207	21991	-478	21843	-344	22027	-511	21011	414	21839	-341	21011	414	21113	321
	Ra5	16240	5178	21735	-235	12912	8379	21325	147	21549	-65	21984	-471	21792	-294	22025	-508	19749	1668	21787	-288	-3606	24641	20100	1327
II	Ra1	88680	3476	92831	-365	82349	9293	91502	838	90805	1473	93171	-676	-	-	-	-	89440	2722	92873	-406	69286	21622	89475	2690
	Ra5	62715	29358	92180	282	47326	44142	90190	2140	88514	3748	93065	-570	-	-	-	-	84313	7818	92657	-192	-25938	116252	84436	7698
III	Ra1	-	-	-	-	-	-		-	96287	3008	99577	12	97827	1601	99918	-296	91603	7328	98629	871	80694	17557	96786	2551
	Ra5	-	-	-	-	-	-		-	91874	7393	99386	201	96171	3244	99838	-217	70371	28452	97846	1648	6067	91772	93429	5886
IV	Ra1	-	-	-	-	-	-		-	166780	1908	170261	-1246	164467	4018	169741	-776	154027	13642	167613	1152	136290	30257	164582	3913
	Ra5	-	-	-	-	-	-		-	164407	4264	170143	-1129	158655	9791	169478	-516	112276	55181	166074	2678	6933	158918	158981	9476
CRRA utility function properties																									
I	Rr1	332007	227	332668	-369	330911	1215	332397	-125	332505	-222	332790	-479	332647	-350	332826	-511	331914	311	332644	-347	329260	2708	331998	235
	Rr5	331901	332	332662	-363	330688	1436	332384	-112	332497	-214	332790	-478	332644	-347	332826	-511	331862	362	332641	-344	328454	3506	331955	278
II	Rr1	973382	2254	976492	-553	968245	6889	975230	583	974613	1515	976784	-817	-	-	-	-	973454	2560	976498	-559	960874	13567	973483	2157
	Rr5	972546	3083	976446	-508	966490	8628	975133	678	974456	1670	976774	-807	-	-	-	-	973142	2869	976479	-541	954600	19794	973175	2463
III	Rr1	-	-	-	-	-	-	-	-	3738762	2617	3741680	-11	3740077	1432	3742008	-306	3735206	5819	3740797	784	3728662	11717	3739179	2241
	Rr5	-	-	-	-	-	-	-	-	3738689	2688	3741676	-7	3740045	1464	3742006	-304	3734937	6086	3740780	801	3727692	12678	3739121	2298
IV	Rr1	-	-	-	-	-	-	-	-	4890300	1662	4893547	-1261	4888280	3481	4893044	-809	4880248	10718	4891053	985	4869381	20518	4888378	3393
	Rr5	-	-	-	-	-	-	-	-	4890231	1730	4893543	-1257	4888132	3627	4893035	-800	4879472	11486	4891006	1031	4866919	22958	4888235	3535

[1] $\Delta CE = CE_{insurance} - CE_{no\ insurance}$

Farmer I, which operates the smallest farm of the four case farms, has the highest risk perceptions for all perils considered. He also pays the highest premiums per hectare, indicating that this farm, among other premium differentiating variables, is located at a more risk prone area. Given his individual risk perception levels, in all models the pattern of results is similar to the pattern of results obtained from farm II (Table 3). The average risk perceptions for farmer I are a bit lower than his individual risk perceptions. Therefore the insurance strategy provides slightly smaller benefits than in individual risk perceptions alternative, but the general pattern stays the same.

As farmer I, farmer III has the same high individual perception of hail that is a 10% probability that this event would occur. Given this high level of risk perception, insurance provides him substantial perceived benefits against complete crop failure. The results are almost identical for the average risk perceptions which are a bit lower than the individual ones. In case of perceiving only 25% yield loss by the farmer III, the pattern of models is rather mixed. Farmer IV has relative low risk perception levels. This resulted into the dominance of no-insurance above insurance strategy in all models (except for sugar beet model for income measure). Imposing average risk perception levels insurance would be more advantageous.

6.4.2 Results multi-crop multi-state risk modelling

The disadvantage of the previous described risk models is that only two states are considered, namely an average yield in years without a catastrophe and crop failure(s) in adverse years. No intermediate or even more favourable outcomes are considered, nor does it take into account that entire crop failures could occur as a result of other perils (e.g., drought and precipitation). The omission of these states of nature will be adjusted for by portfolio models, thereby also recognising the stabilising impact that multiple crops in the production plan will have on the whole-farm level. The distribution of farm yields is based on Cauchy kernel functions and normal distributions which are both updated with elicited risk perceptions. For farm II we present the detailed results including production plans (Table 5).

Table 5. **Results of multi-peril multi-state risk models for farm II** [2)]

Risk aversion level		Not insured				Insurance with 10% deductible				
		CE	Optimal plan			CE	ΔCE[1)]	Optimal plan		
			Potato	Wheat	Sugar beet			Potato	Wheat	Sugar beet
Individual risk perception										
Cauchy kernel / CARA utility function properties										
Ra1	5.3E-06	68089	26.4	37.6	16.0	74132	6043	26.4	37.6	16.0
Ra2	1.1E-05	54727	16.1	47.9	16.0	61873	7145	19.3	44.7	16.0
Ra3	2.1E-05	37903	16.0	48.0	16.0	50338	12435	16.0	48.0	16.0
Ra4	3.2E-05	22256	16.0	48.0	16.0	41634	19378	16.0	48.0	16.0
Ra5	4.2E-05	8240	16.0	48.0	16.0	34550	26310	16.0	48.0	16.0
Cauchy kernel / CRRA utility function properties										
Rr1	0.5	970832	26.4	37.6	16.0	974708	3876	26.4	37.6	16.0
Rr2	1	968670	26.4	37.6	16.0	972792	4122	26.4	37.6	16.0
Rr3	2	964097	26.4	37.6	16.0	968718	4622	26.4	37.6	16.0
Rr4	3	959884	26.4	37.6	16.0	965021	5137	26.4	37.6	16.0
Rr5	4	955880	26.4	37.6	16.0	961549	5668	26.4	37.6	16.0
Normal distribution / CARA utility function properties										
Ra1	5.3E-06	74152	26.4	37.6	16.0	80128	5976	26.4	37.6	16.0
Ra2	1.1E-05	62499	16.0	48.0	16.0	69964	7465	18.0	46.0	16.0
Ra3	2.1E-05	45521	16.0	48.0	16.0	60411	14891	16.0	48.0	16.0
Ra4	3.2E-05	27429	16.0	48.0	16.0	51908	24479	16.0	48.0	16.0
Ra5	4.2E-05	11032	16.0	48.0	16.0	44285	33253	16.0	48.0	16.0
Normal distribution / CRRA utility function properties										
Rr1	0.5	972129	26.4	37.6	16.0	975790	3661	26.4	37.6	16.0
Rr2	1	970696	26.4	37.6	16.0	974602	3906	26.4	37.6	16.0
Rr3	2	967388	26.4	37.6	16.0	971803	4415	26.4	37.6	16.0
Rr4	3	961491	22.3	41.7	16.0	966159	4668	22.4	41.6	16.0
Rr5	4	942780	26.4	48.0	5.6	947468	4687	26.4	48.0	5.6
Average risk perception										
Cauchy kernel / CARA utility function properties										
Ra1	5.3E-06	55398	26.4	37.6	16.0	77000	21602	26.4	37.6	16.0
Ra2	1.1E-05	41407	16.0	48.0	16.0	64757	23349	23.0	41.0	16.0
Ra3	2.1E-05	19494	16.0	48.0	16.0	53155	33662	16.0	48.0	16.0
Ra4	3.2E-05	1426	16.0	48.0	16.0	44898	43472	16.0	48.0	16.0
Ra5	4.2E-05	-12142	16.0	48.0	16.0	37967	50109	16.0	48.0	16.0
Cauchy kernel / CRRA utility function properties										
Rr1	0.5	960719	26.4	37.6	16.0	976170	15451	26.4	37.6	16.0
Rr2	1	958303	26.4	37.6	16.0	974488	16184	26.4	37.6	16.0
Rr3	2	953040	26.4	37.6	16.0	970691	17651	26.4	37.6	16.0
Rr4	3	948174	26.4	37.6	16.0	967310	19136	26.4	37.6	16.0
Rr5	4	943504	26.4	37.6	16.0	964133	20629	26.4	37.6	16.0
Normal distribution / CARA utility function properties										
Ra1	5.3E-06	60736	26.4	37.6	16.0	80796	20060	26.4	37.6	16.0
Ra2	1.1E-05	47727	16.0	48.0	16.0	70491	22764	19.6	44.4	16.0
Ra3	2.1E-05	24221	16.0	48.0	16.0	61223	37002	16.0	48.0	16.0
Ra4	3.2E-05	3843	16.0	48.0	16.0	53102	49258	16.0	48.0	16.0
Ra5	4.2E-05	-11068	16.0	48.0	16.0	45648	56716	16.0	48.0	16.0
Normal distribution / CRRA utility function properties										
Rr1	0.5	961936	26.4	37.6	16.0	975682	13746	26.4	37.6	16.0
Rr2	1	960193	26.4	37.6	16.0	974638	14445	26.4	37.6	16.0
Rr3	2	956072	26.4	37.6	16.0	971953	15881	26.4	37.6	16.0
Rr4	3	950052	22.0	42.0	16.0	969483	19432	26.4	37.6	16.0
Rr5	4	932031	26.4	48.0	5.6	948206	16175	26.4	37.6	16.0

[1)] $\Delta CE = CE_{insurance} - CE_{no\ insurance}$

Compared to the worst case scenario of the two-state risk models with 100% crop losses, UEP of no-insurance strategy for CARA utility function produces lower CEs for the lowest levels of absolute risk aversion. For example, for farmer II the CE of no insurance strategy at Ra1 in portfolio optimisation approach under individual risk perception assumption is equal 68,089 Euro (see Table 5) versus 84,500 Euro in two-state risk model (see Table 2). However, for highest risk aversion levels, results of UEP models provide higher utilities (i.e. CEs) in comparison to the two-state risk models: for farmer II the CE of no insurance strategy at Ra5 is equal 8,240 Euro (see Table 5) versus minus 2,433 Euro in two-state risk model (see Table 2). For CARA utility function properties, the results of multi-state multi-risk models provide lower CEs than the two-state single-risk models per specific crop. Such a result was expected because these models account the damage of one crop by hail, however in reality all crops can be damaged by hail.

For CRRA utility function at 100% crop losses, the results of UEP portfolio dominate the results of the two-state risk models (single crop and worst case scenario) at all levels of relation risk aversion, except Rr1.

Suppose that the decisions made are based on the CARA utility function for the alternative of individual risk perceptions, and yields following a Cauchy distribution. The results indicate that the level of absolute risk aversion does affect the optimal production plan. Assuming that farmer II is hardly risk-averse (i.e. Ra1) and is not insured, the optimal solution is to cultivate 26.4 hectares of land with potatoes, 37.6 hectares wheat, and 16 hectares sugar beet (Table 5). If farmer II purchases catastrophe insurance, the production plan at Ra1 does not alter. With Ra2 the production plan of no-insurance strategy changes in favour of wheat as in the insurance strategy. At the absolute risk aversion levels Ra3, Ra4 and Ra5 the production plans for both insurance and no-insurance strategies are identical. However, farmer II perceives the followings benefits (ΔCEs) of insurance purchase: 12,435 Euro at Ra3; 19,378 Euro at Ra4; and 26,310 Euro at Ra5. Note that sugar beet is the most stable crop that is planned to be grown at the maximum allowed level II. If farmer II makes his decisions on the basis of CRRA utility function and given the model assumptions described previously, the production plan remains stable, even at higher relative risk aversion levels.

If decisions by farmer II are made on the basis of CARA utility function, and yields follow a normal distribution, the pattern of results is not much different from Cauchy kernel assumptions. However, the down-side risk is less accounted for by a normal distribution compared to Cauchy kernel that could be seen by higher CEs of incomes for no-insurance strategy. That was also confirmed by lower perceived benefits of insurance provided. As for CARA function, the models based on CRRA utility function and a normal distribution, produce higher CEs compared to Cauchy kernel. This resulted into stable production plans at the range between Rr1 and Rr3 for both insurance and no-insurance strategies. However, at higher levels of relative risk aversion, if farmer is not insured, the optimal plan changes drastically so that for the 'almost paranoid about risk' farmer (Rr5) the tilled land for the most stable crop sugar beet decreases from 16 to 5.6 hectares. Given the highest level of risk aversion, the purchase of catastrophe insurance does not affect production plan.

If it is assumed that farmer II perceives the perils under study as risky as the average Dutch arable farmer, it will result into lower utilities (CEs) of income and wealth in all models compared to the models of individual risk perceptions. However, the pattern remains the same as for individual risk perception levels, and also as in two-state risk models. Note that at CARA properties of utility function for both Cauchy kernel and a normal distribution, at the highest level of risk aversion (Ra4) the CE is negative. However, purchasing insurance, farmer II would receive a stable annual income.

The aggregated results for all four farms are presented in Table 6. The pattern is similar as for the farm II and also corresponds to the pattern of aggregated results on two-state risk models.

Table 6. **Aggregated results of multi-peril multi-state risk models** [2)]

Farm #	Risk aversion level		Not insured CE	Insured CE	Insured ΔCE[1)]	Not insured CE	Insured CE	Insured ΔCE
Individual risk perceptions								
			Cauchy / CARA			Normal / CARA		
I	Ra1	2.2E-05	13467	18221	4754	14910	19362	4452
	Ra5	1.8E-04	141	9998	9857	632	13256	12625
II	Ra1	5.3E-06	68089	74132	6043	74152	80128	5976
	Ra5	4.2E-05	8240	34550	26310	11032	44285	33253
III	Ra1	5.0E-06	78676	96156	17480	85685	103855	18170
	Ra5	4.0E-05	6732	76726	69994	7610	99086	91476
IV	Ra1	2.6E-06	165065	165065	0	182323	182427	104
	Ra5	2.1E-05	98080	123336	25256	120481	176528	56047
			Cauchy / CRRA			Normal / CRRA		
I	Rr1	0.5	330649	333977	3328	330037	332993	2957
	Rr5	4	326179	330804	4625	326731	330116	3385
II	Rr1	0.5	970832	974708	3876	972129	975790	3661
	Rr5	4	955880	961549	5668	942780	947468	4687
III	Rr1	0.5	3728574	3740347	11773	3734877	3746661	11784
	Rr5	4	3726990	3739680	12690	3733389	3746173	12784
IV	Rr1	0.5	4893010	4892287	-724	4907254	4906532	-721
	Rr5	4	4889852	4889299	-553	4905213	4904682	-531
Average risk perceptions								
			Cauchy / CARA			Normal / CARA		
I	Ra1	2.2E-05	13846	18400	4554	15323	19407	4083
	Ra5	1.8E-04	576	10131	9554	1113	13227	12114
II	Ra1	5.3E-06	55398	77000	21602	60736	80796	20060
	Ra5	4.2E-05	-12142	37967	50109	-11068	45648	56716
III	Ra1	5.0E-06	80402	96276	15874	87539	104052	16512
	Ra5	4.0E-05	8953	76672	67719	9924	99285	89361
IV	Ra1	2.6E-06	135767	163190	27423	150457	179105	28648
	Ra5	2.1E-05	11733	124509	112776	14896	172678	157782
			Cauchy / CRRA			Normal / CRRA		
I	Rr1	0.5	330381	333552	3171	329764	332458	2694
	Rr5	4	326630	331103	4473	327190	330285	3095
II	Rr1	0.5	960719	976170	15451	961936	975682	13746
	Rr5	4	943504	964133	20629	932031	948206	16175
III	Rr1	0.5	3729867	3740480	10613	3736229	3746852	10623
	Rr5	4	3728356	3739811	11455	3734824	3746365	11541
IV	Rr1	0.5	4871513	4890155	18642	4884629	4903299	18670
	Rr5	4	4866336	4887237	20901	4880235	4901404	21169

[1)] $\Delta CE = CE_{insurance} - CE_{no\ insurance}$

6.5 Conclusions and discussion

This paper analysed the decision making problem describing how farmers can cope with catastrophic yield risks, and more specific to the option to insure and not to insure. For this purpose a single-crop two-state approach was compared to a multi-crop multi-state approach. We compare the preferred options whether the decision is based on a farm income or terminal wealth. In general, the results of all models showed that risk perception and the level of risk aversion do affect the decision to insure. If the perception of risk is low, the decisions in favour of no-insurance strategy dominate the decisions to insure. However, at higher levels of risk perceptions the decision to purchase catastrophe insurance will dominate.

The results of the models imply that the individual amounts of premium that a farmer needs to pay for insurance, do affect the catastrophe insurance decisions. If premiums are high compared to the perceived risk, farmers would prefer to neglect catastrophe insurance purchase (Zering et al., 1987). And vice versa, if premiums are low, high risk perception would stimulate farmers to purchase catastrophe insurance.

If insurance decisions are made only on the basis of two states of nature concerning single crop, they may differ from portfolio results because of alternative risk reducing options such as a diversification are not taken into account. In our analysis, the results of the majority of models showed that insuring single risks is not beneficial and self-insurance is preferable. However, in arable farming more variability can be observed. We tried to formalise the variability of crop yields and prices in UEP by MVN and MVKDE procedures. The results of UEP models accounting the worst case scenario showed that relying only on two simple states of nature, the impact of low yields resulting into decrease of income and wealth may be underestimated. MVKDE, compared to the MVN procedure, better incorporated tail events to estimate the impact of catastrophic risks. This resulted into lower income and wealth.

In our analysis, the probabilities of catastrophes in the single-crop two-state approach were identical to the probabilities of catastrophes in the multi-crop multi-state approach, and the negative impact of catastrophes was higher in the multi-crop multi-state approach, especially after applying the MVKDE procedure. Alternatively, for both approaches the alternative of equal probabilities and equal magnitude of catastrophes can be considered. Then higher income and wealth will be expected for multi-crop multi-state approach because a significant part of catastrophic risk can be transferred due to diversification of activities resulting into an optimal production plan. However, if the probabilities and magnitude of catastrophes will be deliberately set higher in single-crop two-state models, the results would dominate the results of multi-crop multi-state models despite the benefits of diversification.

The analysis showed that if a farmer makes decisions only in terms of income he is more prone to purchase catastrophe insurance. Then catastrophe insurance purchase strategy dominates no-insurance strategy at higher levels of risk aversion if a farmer makes decisions in terms of income. However, the decisions made and taken by income measures to some extent can be treated as non-rational. This could be explained by failure to asset integration assumptions stating that a farmer would view losses or gains from specific risks as being equivalent to changes in wealth (Hardaker at al., 2004). In our models, because of highest risk aversion if farmers make decisions in terms of income, they are willing to purchase catastrophe insurance to cover losses that are low in comparison to their wealth. Contrary to the behaviour if farmer decisions are taken in terms of income, if a farmer makes decisions in terms of wealth, the increase of risk aversion has a limited impact on the wealth. This effect is higher for the farms with highest initial wealth. To support asset integration assumption, the results of the UEP models showed that production plan in wealth framework hardly change.

The results on portfolio models showed that increased level of risk aversion changes the production plan if decisions are made in terms of income as in the research by Kaylen et al. (1989). For increasing cost of risk aversion, farmers decrease the tilled land of more risky crops in favour of less risky crops. In this way, diversification of farm activities accounting for stochastic dependency between crop yields and prices mitigates the catastrophic yield risk.

However, highest risk is much related to the highest return. Higher level of absolute risk aversion thus results into worse production plans. Selecting more tilled land for less-risky crops automatically results into decrease of incomes.

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Chapter 7 General Discussion and Conclusions

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7.1 Introduction

Farmers often face risky situations. Risk means the possibility of a loss of income or property (Pritchet et al., 1996). For example, arable farmers are exposed to meteorological events, such as hail, storm, drought, frost, heavy precipitation, excessive heat, and crop diseases such as brown rot, which may result in potential damage to crops (Langeveld et al., 2003). In dairy farming, epidemic diseases, such as FMD (foot-and-mouth disease) and BSE (bovine spongiform encephalopathy), can cause severe economic losses (Huirne et al., 2003).

Catastrophic risks can be defined as events with low probability of occurrence (rare events) leading to major and typically irreversible losses with potentially adverse impact on business results (Chichilnisky, 2000; Vose, 2001). Rarity and severity are typically associated with catastrophic risks: the more severe a risk, the rarer it usually will tend to be, and vice versa (Frohwein et al., 1999). Farmers can be faced with serious losses if catastrophic risks are ignored. Therefore catastrophic risks need to be managed. Insurance is a frequently used instrument to cover catastrophic risks (Pritchet et al., 1996). However, not all farmers buy insurance to protect their business against several types of catastrophic risks.

Concerning insurance decisions to cope with catastrophic risks, the impact of possible factors influencing insurance purchase need to be analysed. These factors are farmer personal and farm characteristics (Mishra and Goodwin, 2003; Sherrick et al., 2004). In general, the main farmer personal characteristics risk perception and risk attitude are often regarded as the key farmer-specific factors to explain and model catastrophe insurance purchase.

The subjective expected utility (SEU) hypothesis states that the utility of a risky prospect (being insured or not) is the decision-maker's expected utility for that prospect, meaning the average of the utilities of outcomes weighed by the subjective probabilities of those outcomes (Hardaker et al., 2004). In this context, risk perception is measured in terms of a subjective probability distribution, and risk attitude is measured by a shape of the Von Neumann-Morgenstern utility function (Hardaker et al., 2004; Smidts, 1990). The SEU approach is a prescriptive approach applicable for small scale surveys (Smidts, 1990). Often, for large scale surveys, the impacts of risk perception and risk attitude are analysed by econometric models on basis of actual purchase decisions studies. Contrary to the prescriptive SEU approach, observed economic behaviour approach is used to describe why decisions are indeed made, rather than to predict what should be taken.

The main goal of the research was to analyse the actual farmer's behaviour concerning catastrophes and to model the impact of catastrophe insurance purchase. The objectives are the following:

- To describe the methods that analyse risk perception and risk attitude to model decisions to cope with catastrophes;
- To analyse actual purchase of all-risk insurance and specific types of insurance;
- To analyse the relationship between purchase of catastrophe insurance and risk perception and risk attitude;
- To model the economic impact of catastrophes;
- To model the purchases of catastrophe insurance in a partial and whole-farm context.

The implications of the applied (econometric and normative) methods and issues concerning results obtained have been discussed in detail in the previous chapters. However, there are some important general issues that deserve attention in this chapter. These general issues are data availability, severity of catastrophic risks, capturing the potential tails of the distribution, and alternative insurance schemes. These issues will be addressed subsequently.

7.2 Available data

In this research two types of data were used: objective FADN data and subjective data from the questionnaire survey. In practice, the objective farm-level data such as FADN is often very sparse to provide a good and reliable basis for risk modelling, and this is certainly the case when focusing on catastrophic risks. The modelling of catastrophic risks should ideally be based on a long-term and reliable farm-level history. However, it is generally hard to obtain 10 relevant historical farm observations under the same economic policy, management regime, farm program or trade policy (Just and Weninger, 1999; Richardson, 2006).

Concerning insurance application, FADN data is heavily aggregated. It consists of the premiums paid for specific insurance categories (damage, accident, disability, liability, legal and health insurance). Farmers in the Netherlands are insured by different insurance companies so that insurance policies per insurer are different. For instance, very often insurance policy that provides financial aid in case of damage at one insurer serves as an accident insurance at another insurer. Taking into account this type of bias, we summed up all insurance premiums recorded by the FADN to construct a so-called all-risk insurance product. With regard to catastrophes in arable farming, one could assume that they are covered by damage insurance recorded in the FADN. However, such aggregated data does not provide an answer on which amount of premium is paid per specific catastrophic risk. Therefore we conducted a questionnaire where we asked farmers whether they insure specific catastrophic risks and the amount of premium they paid per risk.

The additional farmer's subjective data, such as farmer's risk perception of catastrophes, risk attitude and other personal characteristics can complement the objective data in modelling and describing of catastrophe insurance decisions. The major difficulties occur in elicitation of catastrophic risk perceptions (Ekenberg et al., 2001). When a farmer moves from events with considerable historical and scientific data to those where there is greater uncertainty and ambiguity such as catastrophic risks, there is a much greater degree of discomfort in eliciting of risk perceptions (Kunreuther, 2002). In this research, risk perception was elicited in two ways: relative risk perception and absolute risk perception. The relative risk perception was elicited by comparing a particular subjective risk perception of the farmer to the 'average' arable/dairy farmer in the Netherlands. Farmers were asked to indicate their risk perception on a 5-point scale. Risk perception, elicited in this way, was used as a scale variable in regression models explaining actual participation in insurance of specific catastrophic risks and the amount of premium paid per specific catastrophic risk. The absolute risk perception, elicited as a probability of occurrence of a particular catastrophic risk, was used in the further modelling of catastrophe insurance decisions. However, elicitation of subjective risk perceptions has its difficulties. Perceptions of catastrophic risks can be over- or underestimated due to judgmental biases such as availability heuristic, vividness, denial and evaluability. To avoid to a certain extent the problem of over- and underestimation of probabilities, some illustrative risks which any person faces often in life, were presented as a reference.

Risk attitude coefficients can be either elicited by a direct or indirect method. In this research we applied a direct method. Risk attitude was elicited in relative terms compared to the average arable/dairy farmer in the Netherlands. The construct describing the relative risk aversion was obtained via an aggregation procedure on the basis of 11 statements. Then farmers were labelled as less-risk-averse and more-risk-averse. Several attempts have been made in literature to elicit utility functions to put SEU hypothesis to work in the analysis of risky alternatives in agriculture. The results were, however, often unconvincing (Anderson and Hardaker, 2002; Hardaker et al., 2004; King and Robison, 1984; Smidts, 1990). One disadvantage of the expected utility approach is its complexity. The elicitation of certainty equivalents (CEs) is judged as fairly difficult and quite time-consuming, requiring an active role of an interviewer. However, taking into account the limitations, the results found may be even more surprising and unconvincing (Hardaker et al., 2004; Smidts, 1990). There is evidence that the functions obtained are vulnerable to interviewer's bias and to bias from the way the questions are framed to elicit CEs (Hardaker et al., 2004). Instead, to avoid the problems of SEU theory with respect to risk attitude elicitation, the assumptions about the nature of the utility function were based on literature.

7.3 Severity of catastrophic risks

A question that still remains open is the size of a catastrophic risk. We restrict this discussion to arable farming. On average, 62% of farmers from our sample were insured against hail and 48% against brown rot. With such a high participation in catastrophe insurance, arable farmers perceive hail and brown rot as a severe events affecting continuity of their farms.

In reality a certain amount of farmers does not maximise utility on their wealth basis. Instead, they make their decisions on the basis of annual income. This could be explained by failure of their asset integration assumption stating that a farmer would view losses or gains from specific risks as being equivalent to changes in wealth (Hardaker at al., 2004). Losses are relatively larger in terms of annual income and are relatively lower in terms of wealth. On average, farm income did not exceed 5% of the initial wealth implying that a substantial part of self-insurance reserves may be underestimated by arable farmers. In addition, farmers were asked to express the maximum amount of risk-bearing capacity to cover the maximum annual catastrophic risk. The proportion of risk-bearing capacity was relatively low and comparable to their annual income rather than wealth. This could explain that the reported risk bearing-capacity has been already encountered in the current risk management strategy(s) including catastrophe insurance.

Making decisions on basis of annual income, arable farmers can overestimate the impact of hail and brown rot. The results of the models accounting for 100% loss of yields showed that if a farmer makes decisions only in terms of annual income, he is more prone to purchase catastrophe insurance. However, according to the Dutch claim statistics, the average loss of farmer after experiencing catastrophic risks does not exceed 25% of the average yield. In our analysis, in majority of the models accounting for 25% of yield loss the results implied that purchase of catastrophe insurance did not dominate the no-insurance strategy.

However, focusing on the average loss occurring, farmers may substantially underestimate extreme impact of a certain risk. Catastrophic risks in arable farming stem mostly from a natural character and usually considered an ‘act of God’, so that the probabilities of occurrence and losses are unpredictable. To address a high severity, we also run the worst case scenarios. The results of the majority of the models based on both income and wealth assumptions, showed that if one believes that hail would affect all activities insurance provides substantial benefits against this worst-case scenario.

7.4 Capturing the potential tails of the distribution

In order to support farmer’s decisions with regard to catastrophe insurance purchase, the probability and magnitude of a catastrophic risk needs to be taken into account. The assessment should ideally be based on a long-term and reliable farm-level history. But, in practice, farm-level data is often very sparse to provide a good and reliable basis for such a risk assessment (Hardaker et al., 2004). In our research, the maximum number of available years per farm was 13, however it was not sufficient. Moreover, the available data did not contain information about the downside tail of the distribution sufficiently. Without proper individual farm production data, it was impossible to examine the effectiveness of crop insurance at an individual farm level. Therefore, in analysing catastrophe insurances some assumptions about the tail characteristics of the underlying probability distribution of crop yields had to be made. In our research, we smoothed the sparse data (i.e. interpolating between observations and extrapolating outside observations) by fitting a parametric normal distribution or empirical MVKDE distribution (Anderson et al., 1977; Shlaifer, 1959). The analysis of UEP models showed that relying on normal distribution assumptions, farmers can underestimate the impact of catastrophes on their income and wealth. Alternatively, modelling of catastrophe insurance decisions on the basis of non-parametric MVKDE estimation by Cauchy kernel showed that larger risks can be accounted for.

However, before the smoothing MVKDE procedure by Cauchy kernel, a realistic assumption should be made about the upper and lower bounds of yield distributions, ensuring that the distribution will be a reasonable approach to include the downside and upside tails. In our research, the upper bound was arbitrary augmented to the value of the mean plus one standard deviation, and the lower bound was set to zero. Limiting the upside potential will definitely have its impact of the density over the whole distribution, thus also the downside tail. Consequently, this will impact catastrophe insurance purchase decisions. Therefore the extreme levels of yields need to be extensively tested by experts.

But even augmenting yield distribution with realistic bounds, we can doubt robustness of the results. The results of tests showed that covariance structure of sparse and simulated data was statistically different, but mean vectors were identical. Even after many manipulations with the lower and upper bounds, the correlation structure was not maintained. This could be explained by a fact that available sparse data did not contain catastrophe events. The limited available observations were only positioned in the mode part of the kernel density, and therefore it was not possible to simulate the appropriate tail data on the basis of the observed data (under the assumption that catastrophe events did not occur in the observation period). However, it is not logical to expect that on the basis of the available sparse data, in which catastrophe states of nature were most likely absent, the covariance structure of the Cauchy kernel distribution would remain the same compared to the situation without those additional assumptions.

7.5 Alternative insurance schemes

In this research, we modelled an application of farm-level yield indemnity-based catastrophe insurance. Farm-level yield insurance usually protects farmers against both systemic and non-systemic risks. Many studies noted that the application of farm-level yield insurance was not effective because of asymmetry information between insurance companies and farmers caused by moral hazard and adverse selection problems (i.e. Chambers and Quiggin, 2002; Ramaswami and Roe, 2004; Skees, 2000).

Moral hazard refers to the hidden action by farmers resulting after purchasing insurance. Adverse selection means that farmers who are more likely to suffer from the insured event will be more willing to insure at a given insurance premium (Quiggin et al., 1993). The basic implication for purchase of yield insurance is the same for moral hazard as for adverse selection: farmers who are insured will produce low yields more frequently than uninsured farmers with similar observed characteristics. According to those studies, many farmers exercised the benefits from low yields caused by a bad management instead of natural yield risks so that small deviations from the expected yield were insured. In our research, we did not model purchase of the typical yield insurance indemnity-based contracts insuring any negative deviation from the expected yield. Contrary, only the yield insurance protecting farmers against catastrophic risks was modelled. To avoid moral hazard, we included a 10% deductible into (hypothetical) insurance contracts.

Alternatively to our approach focussing on named-peril indemnity-based insurance, there are insurance and income stabilisation schemes to cope with catastrophic risks (currently not available in the Netherlands). The problems of moral hazard and adverse selection are to a certain extent also relevant for these schemes. One of these schemes is multi-peril crop insurance (MPCI). This is an individual indemnity-based yield insurance providing indemnities to a farmer if the actual yield falls below its guaranteed yield (Helms et al., 1990). As for farm-level yield indemnity-based catastrophe insurance, a farmer will account for his individual risk perceptions before purchasing MPCI. This scheme is prone to the moral hazard and adverse selection presented above, and was not successful in the USA. The problem raised by adverse selection was based on the perception that a farmer had of his farm yields. Therefore farmers will low perception of yield (due to a bad management) were inclined to purchase MPCI insurance.

Alternatively to individual-based insurance, catastrophic risks could be insured by area-yield indemnity-based insurance called a Group Risk Plan (GRP). GRP operates as a put option at the area level: the holder of GRP receives an indemnity whenever the realised area yield falls below some specified critical yield (i.e. strike), regardless of the realised yield on his farm (Barnett et al., 2005). If a complete area was affected by catastrophic risk uniformly then all farmers participating in GRP would receive indemnities. Contrary to farm-level insurance insuring both systemic and non-systemic risks, GRP insures only against systemic risk (Ramaswami and Roe, 2004). With GRP, the basis risk is an important factor affecting the efficacy of the GRP. The basis risk exists if only a portion of an area or a single farmer is affected by a non-systemic risk such as a hail. The higher the positive correlation between the farm and area yield, the lower the basis risk (Barnett et al., 2005). Therefore, for making a decision to purchase a GRP plan, a farmer needs to account for the average area probabilities of catastrophic systemic risks instead of his individual risk perceptions. If a basis risk does exist, the decision induced by his individual risk perceptions to purchase individual-yield catastrophe insurance will be important to consider.

Another form of area-yield insurance is the weather crop index-based insurance. In this insurance scheme, the premiums and indemnities are based on the weather records of the locality in which the insurance is sold (Halcrow, 1949). Therefore, for making a purchase decision on index-based insurance, a farmer needs to account for objective weather parameters instead of his individual risk perceptions. The trigger yield in weather crop-based insurance is determined by known weather phenomena such as a rainfall and temperature selected on the basis of prior knowledge. The indemnities are paid to a farmer if weather, in terms of some measurable criterion, is below the certain limits of tolerance. Weather crop index based insurance would be adapted more easily to an area yield in which one or two weather factors such as precipitation and temperature are generally limiting and are highly significant in determination of crop yields (Halcrow, 1949). However, it will be of little value for crops affected by diseases such as brown rot.

In addition to the addressed yield insurance schemes, catastrophic risks can be covered by income stabilisation schemes such as Group Risk Income Protection Plan (GRIP) and Net Income Stabilisation Accounts (NISA). Similarly to the GRP, GRIP operates as a put option, but on the expected area revenue. As for GRP, farmers purchasing the GRIP can be faced with basis risk when a farmer is suffering a crop loss after a catastrophic risk occurred and receiving no payment because the area yield did not decline sufficiently to trigger indemnity payments (Barnaby, 2005). The greatest basis risk is also created by a non-systemic catastrophic hail risk. In addition to the GRIP or GRP plans, the hail cover can be purchased. As for the GRP plan purchase, a farmer needs to account for the average area probabilities of systemic risks for GRIP plan purchase.

NISA indemnity-based program is partly supported by the Canadian government. To cope with catastrophic risks, a farmer may set up a NISA account at financial institution to handle deposits and withdrawals (Springs and Nelson, 1997). This account consists of two funds: 1) producer deposits as a percentage of the net sales, and 2) government deposits. In the Fund 1, farmer's deposits receive a competitive interest plus an interest bonus of 3%. All money accruing to Fund 2 earn an interest rate equal to 90% of the 90-day Treasury bill rates. All interest earned in Fund 1 and Fund 2 is accrued in Fund 2. For a participation in NISA program, a farmer needs priory account for his individual risk perceptions of catastrophic risks. After a catastrophic risk occurs, a farmer can withdraw money when his gross margin falls below the preceding five year average. The maximal amount of withdrawal is limited to the difference between the preceding five year average and the farmer's gross margin. The disadvantage of this program is that it can be costly for the government. Then the perception of risks is probably less driving the farmer's decision to insure or not. Other issues, such as getting governmental subsidy and opportunities to reduce tax payments will be relevant as well. In all alternative insurance and income stabilisation schemes, risk perception and risk attitude are important characteristics for the adoption of catastrophe insurance, and thus the issues addressed in this thesis are also relevant for these schemes.

7.6 Main conclusions

The main conclusions of the thesis can be summarised as follows:

- In modelling catastrophic risks, tail characteristics of probability distribution functions need to be accounted for explicitly. Otherwise losses associated with downside catastrophic risks can be seriously underestimated and ultimately will affect catastrophe insurance decisions (Chapters 2, 5 and 6).
- Wealthier farmers are less inclined to insure and rely more on self-insurance (Chapters 2, 3 and 6).
- Substantial differences in risk perception levels between farmers were observed affecting catastrophe insurance purchase. If a farmer perceives that a catastrophic peril is more risky, he is more prone to insure catastrophic risks (Chapters 4 and 6).
- Farmers with higher level of risk aversion are more prone to purchase catastrophe insurance. The results of the prescriptive models showed that higher level of risk aversion induces a farmer to select less optimal production plans resulting into loss of some part of income. With purchasing catastrophe insurance, a highly risk-averse farmer can also stabilise his results (Chapters 4 and 6).
- If decisions are taken on the basis of wealth, in comparison when taken in terms of income, the perceived insurance benefits are more limited. The impact of catastrophe insurance purchase is lower if the farmers are utility maximisers on the basis of asset integration assumption (Chapter 6).

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Summary

Farming is a risky business. Facing a risk implies a possibility of losing property or income. Experiencing catastrophic risks by arable farmers can cause severe cash flow problems or even result in bankruptcy. To cope with catastrophic risks farmers need to apply risk management strategies. Insurance is a frequently used instrument to cover catastrophic risk. However, not all farmers buy insurance to protect their business against several types of catastrophic risks. Therefore the impact of factors that influence purchase of catastrophe insurance needs to be evaluated. These factors are farmer personal and farm characteristics. The main farmer personal characteristics affecting catastrophe insurance decisions that need to be evaluated are the farmer's personal risk perception and his risk attitude.

The objective of the research was to analyse the actual farmer's behaviour concerning catastrophes (descriptive approach) and to model the impact of catastrophe insurance purchase on the farmer's goals (prescriptive approach). The following objectives were identified:

- To describe the methods that analyse risk perception and risk attitude to model decisions to cope with catastrophes;
- To analyse actual purchase of all-risk insurance and specific types of insurance;
- To analyse the relationship between purchase of catastrophe insurance and risk perception and risk attitude;
- To model the economic impact of catastrophes;
- To model the purchases of catastrophe insurance in a partial and whole-farm context.

In Chapter *1* the general introduction was provided. It comprises problem statement, research objectives, research structure and methodologies employed.

Chapter 2 reviewed the techniques to elicit risk perception and risk attitude, and describes how the simultaneous impact of risk perception and risk-attitude could be accounted for in risk programming models. The standard strength of conviction method to elicit risk perception and standard Equally Likely Certainty Equivalent (ELCE) method to elicit risk attitude coefficients are not applicable to catastrophes as long as they deal with a limited number of points to estimate, so that a downside tail can be underestimated. To avoid psychological biases, the techniques of a better representation of probabilities can be applied in elicitation of risk perceptions. Risk attitude was proposed to be estimated by econometric

models or assumed by methods of stochastic dominance, and precisely by Stochastic Efficiency with Respect to a Function (SERF) application. Concerning a method of sampling and catastrophe data for modelling, a Latin Hypercube sampling technique could be used accounting for stochastic dependency between activities in arable farming. Concerning a method of farm risk programming, utility-efficient programming (UEP), which handles any functional form of utility function (including power utility function), can be applied for modelling of catastrophic risks. The power utility function, which incorporates changes in wealth, was shown to be more applicable to a case of catastrophes. However when farmers do not behave as utility maximisers of wealth, the additional restriction on their risk-bearing capacity is needed to be included.

Chapter 3 analyses the impact of farm characteristics and some farmer personal characteristics on the adoption of an all-risk insurance package and underlying specific categories of insurance coverage for Dutch arable farmers compared to dairy farmers. Major farm characteristics considered were structural, operational and liquidity variables. The specific insurance categories reviewed were damage, disability, legal and liability insurance. The results suggest that there are common and insurance-specific factors that explain adoption of insurance coverage. In both types of farming, for insurance categories and all-risk insurance package considered, all variables, except the net farm result for purchase of all-risk insurance by arable farmers, had the same direction of impact. Both arable and dairy farms showed more willingness to save money from core activities to accumulate more savings than to spend money on insurance. Arable farms were expected to insure less because diversification of activities is already a form of risk management. Contrary to that, the analysis showed that arable farms paid higher premiums than dairy farms. Despite the differences between degrees of specialisation/diversification, wealth, amount of premium paid by arable and dairy farmers, common variables were found – size and farmer's age - that influenced purchase of all insurance types and all-risk insurance package considered.

Chapter 4 analyses the impact of risk perception, risk attitude and other farmer personal and farm characteristics on the actual purchase of catastrophe insurance by Dutch arable and dairy farmers. The specific catastrophe insurance types considered were hail-fire-storm insurance for buildings, disability insurance, crop insurance against hail, storm and brown rot, and insurance against epidemic animal disease outbreaks. Arable and dairy farmers showed to some extent different behaviours with respect to purchase of catastrophe insurance, originating from different conditions of doing business. Purchase of insurance against one peril was strongly correlated with purchase of insurance against another one. Purchase of various forms of crop insurance was influenced by both farmer and farm variables, with the same direction of impact observed as in previous studies. Risk perception and risk attitude were found as important variables that explain purchase of catastrophe insurance coverage. Arable farmers also tended to insure their buildings against hail and storm, and in this respect the decisions concerning crop insurance and/or previous crop damage may influence purchase of insurance against damage of buildings. FMD and BSE epidemics were the most severe risks for dairy farmers. Insurance policies against FMD and BSE are quite new in the Netherlands, and only few farmers were insured. Little previous negative experience of catastrophe events seemed to play a crucial role in catastrophe insurance decision making by the Dutch dairy farmers. The lack of historical data and experience probably explain the failure of models to estimate the impact of risk attitude in all models in dairy farming. The same reasoning could be concerned to the impact of risk perception on insurance purchase in the models of FMD and BSE insurance. Other farmer-specific and farm variables were also found important determinants in the purchase of insurance in dairy farming. Farm/farmer wealth seemed to play an important role in the insurance purchase of dairy farmers: wealthy dairy farmers tend to prefer to self-insure rather than to purchase what they perceived as expensive commercial insurance.

Chapter 5 compares alternative ways of conducting a farm risk analysis using sparse data with a special reference to catastrophe events. For this purpose kernel and multivariate normal smoothing procedures were proposed and applied to generate (simulate) the joint distributions of crop yields and prices. The analysis showed that the functional forms chosen to generate the joint distribution substantially impacted the density in the tail of the distribution, although they were parameterised with the same data. It was observed that the normal distribution and all kernels, except the Cauchy kernel function, underestimated the impact of these beliefs, thereby neglecting the downside tail of the distribution. The statistical tests showed that the simulated mean vectors from the Cauchy kernel were not statistically different from the mean vectors of the sparse data. Furthermore, the covariance structure was statistically different. However, it is not logical to expect that on the basis of the available sparse data, in which catastrophe states of nature were absent, the covariance structure of the Cauchy kernel distribution would not change.

Chapter 6 analyses the decision making problem describing how farmers can cope with catastrophic yield risks, and more specific to the option to insure and not to insure. For this purpose a single-crop two-state approach was compared to a multi-crop multi-state approach. We compared the preferred options whether the decisions accounts for farm income or terminal wealth. The analysis showed that if a farmer makes decisions only in terms of an income-based utility function he is more prone to purchase catastrophe insurance. The models showed that those decision-makers who perceived that a risk would relatively seldom occur were less inclined to insure and self-insurance would be preferable. However, if insurance decisions are made only on the basis of the single-crop two-state approach, they may differ from portfolio results because of alternative risk reducing options such as a diversification are not taken into account.

Chapter 7 discusses some general problems of the research and thesis applicability in reality. The following issues are discussed: data availability, severity of catastrophic risks, capturing the potential tails of the distribution, and alternative insurance schemes.

Following main conclusions were derived:

- In modelling catastrophic risks, tail characteristics of probability distribution functions need to be accounted for explicitly. Otherwise losses associated with downside catastrophic risks can be seriously underestimated and ultimately will affect catastrophe insurance decisions (Chapters 2, 5 and 6).
- Wealthier farmers are less inclined to insure and rely more on self-insurance (Chapters 2, 3 and 6).
- Substantial differences in risk perception levels between farmers were observed affecting catastrophe insurance purchase. If a farmer perceives that a catastrophic peril is more risky, he is more prone to insure catastrophic risks (Chapters 4 and 6).
- Farmers with higher level of risk aversion are more prone to purchase catastrophe insurance. The results of the prescriptive models showed that higher level of risk aversion induces a farmer to select less optimal production plans resulting into loss of some part of income. With purchasing catastrophe insurance, a highly risk-averse farmer can also stabilise his results (Chapters 4 and 6).
- If decisions are taken on the basis of wealth, in comparison when taken in terms of income, the perceived insurance benefits are more limited. The impact of catastrophe insurance purchase is lower if the farmers are utility maximisers on the basis of asset integration assumption (Chapter 6).

Samenvatting

De agrarische sector is een risicovolle sector waarbij ondernemers geconfronteerd kunnen worden met een mogelijk verlies van hun eigendom of inkomen. Het begrip risico wordt bepaald door de twee elementen, namelijk 'kans' en 'ernst' van een potentieel gevaar. De kans is de waarschijnlijkheid dat het gevaar optreedt. Ernst is het gevolg indien blootgesteld aan het gevaar. Met name catastrofale risico's, zoals zeer lage oogstopbrengsten veroorzaakt door extreme weersomstandigheden, kunnen het inkomen danig reduceren of zelfs een faillissement veroorzaken. Het risico kan beperkt worden door risicomanagement waarbij een strategie gekozen wordt op basis van een systematische analyse. Het afsluiten van een verzekering is een veelvuldig gebruikte strategie om catastrofale risico's te verminderen. Echter, niet alle boeren kopen een verzekering. Verschillen in het risicogedrag van ondernemers zijn deels te verklaren door hun risicohouding (ook wel risicoattitude of risicoaversie genoemd) en risicoperceptie. De meeste agrarische ondernemers tonen bij hun besluitvorming een risicomijdend gedrag. Zij zijn dus bereid om een deel van hun rendement op te geven om (extreem) negatieve uitkomsten te vermijden. Risicohouding zegt iets over de preferenties van ondernemers ten opzichte van mogelijke uitkomsten van risicovolle besluiten en verklaart de mate waarin zij bereid zijn om extra risico's te lopen omwille van een hoger rendement, en omgekeerd. Risicoperceptie heeft betrekking op de subjectieve beleving van risico's (inschatting over de kansverdeling van de mogelijke schadelast).

Het doel *van* dit onderzoek omvat zowel een analyse van het waargenomen gedrag betreffende catastrofeverzekeringen (descriptieve aanpak) als het modeleren van de besluitvorming (prescriptieve aanpak). Hiertoe zijn de volgende subdoelstellingen geformuleerd:

- Het beschrijven van de methoden om risicohouding en risicoperceptie te kwantificeren;
- Het analyseren van de aankoop van een 'all-risk' verzekering en verschillende verzekeringstypen;
- Het analyseren van de relatie tussen enerzijds verzekeringsbeslissingen en anderzijds risicohouding en risicoperceptie;
- Het modeleren van de economische effecten van catastrofen;
- Het modeleren van verzekeringsbeslissingen in individueel en in portfolio context.

In *Hoofdstuk 1 wordt* de algemene introductie met de bijbehorende probleemstellingen, onderzoeksdoelen en onderzoeksstructuur beschreven.

Hoofdstuk 2 beschrijft de technieken om risicohouding en risicoperceptie te kwantificeren, en beschrijft hoe ze tezamen in risicomodellen opgenomen kunnen worden. Zowel de standaard methode als de "Equally Likely Certainty Equivalent" (ELCE) methode zijn slechts beperkt bruikbaar ter bepaling van de risicohouding indien men catastrofes wil modelleren. Gezien het geringe aantal waarnemingen bestaat het gevaar dat de voorkeuren bij extreem negatieve uitkomsten niet zuiver geschat worden. Tevens blijkt uit tal van onderzoeken dat de subjectieve risicobeoordeling niet noodzakelijkerwijs overeenkomt met de uitkomst die volgt uit de objectief waarneembare risicobeoordeling (gesteld dat de objectieve risicobeoordeling van soms moeilijk te kwantificeren risico's aan zou sluiten bij het werkelijke risico). Er is veeleer sprake van een 'psychologische paradigma' waarbij de perceptie vertroebeld kan zijn door verschillende factoren. Zo hebben mensen in het algemeen moeite met het inschatten van risico's met een lage kans. Ondanks de complexiteit en het subjectieve karakter om risicohouding en risicoperceptie te meten is het zinvol om ze op te nemen in risicomodellen. Het gebruik van een stochastische dominantie methode biedt enige uitkomst, bijvoorbeeld op basis van "Stochastic Efficiency with Respect to a Function" (SERF). Per risicohouding wordt het optimale bedrijfsplan bepaald middels een portfoliomodel en kan nagegaan worden of een catastrofeverzekering hiervan deel uitmaakt. Inkomen of vermogen wordt daarbij in nut (utility) omgezet volgens een relatie die afhankelijk is van de risicohouding terwijl de kansverdelingen gebaseerd zijn op percepties.

In *Hoofdstukken 3 en 4* wordt de relatie tussen enerzijds bedrijfskenmerken en persoonlijke kenmerken en *anderzijds* de eventuele aankoop van een verzekering beschreven. In de toegepaste regressieanalyse zijn zowel akkerbouwbedrijven als melkveebedrijven verwerkt. Om inzicht te krijgen is een beroep gedaan op het Bedrijven-Informatienet van het LEI (het Informatienet). In dit databestand met een representatieve steekproef van de Nederlandse akkerbouw en melkveehouderij zijn kengetallen beschikbaar die de bedrijfsstructuur beschrijven als ook de operationele en financiële situatie. Daarnaast hebben de geselecteerde ondernemers een schriftelijke vragenlijst ingevuld om zodoende aanvullende informatie te verkrijgen over hun risicohouding, risicoperceptie en afgesloten schadeverzekeringen. Er is onderscheid gemaakt tussen diverse typen verzekeringen, te weten schadeverzekeringen, arbeidsongeschiktheidverzekeringen, rechtsbijstandverzekeringen en aansprakelijkheidsverzekeringen. De schadeverzekeringen zijn verder onderverdeeld in polissen die een dekking bieden tegen schade aan gebouwen door storm, brand en hagel, gewasschade als gevolg van hagel, storm of bruinrot/ringrot, en schade als gevolg van besmettelijke dierziekten. Met betrekking tot de financiële variabelen kan gesteld worden dat een risicovollere financiële positie (lagere solvabiliteit en eigen vermogen) gepaard gaat met een grotere vraag naar een verzekering. Ondanks de complexiteit en het subjectieve karakter om risicohouding en risicoperceptie te meten is er een significante relatie aangetoond met de aankoopbeslissing van een verzekering. De (substantiële) verschillen in risicopercepties en risicohouding tussen agrarische ondernemers verklaren deels waarom verzekeringen worden afgesloten.

In *Hoofdstuk 5* worden extreem negatieve uitkomsten, die in een kansverdeling zijn opgenomen, gekwantificeerd met behulp van een aantal verschillende technieken en met elkaar vergeleken. *Hiertoe* worden zowel kernels als multivariate normale kansverdelingen geschat op basis van waargenomen fysieke gewasopbrengsten en gewasprijzen. De toegepaste technieken genereren afwijkende kansverdelingen waarbij extreem negatieve uitkomsten ondervertegenwoordigd zijn. Een uitzondering hierop is de Cauchy kernel waarbij de gesimuleerde covarianties statistisch afwijken van de waargenomen covarianties. Echter, dit is ook niet te verwachten omdat de waargenomen covarianties enkel en alleen berekend zijn op basis van een beperkt aantal observaties in welke extremiteiten afwezig zijn.

Hoofdstuk 6 analyseert het effect van risicohouding en risicoperceptie op de optimale mix van bedrijfsactiviteiten en richt zich specifiek op de vraag in hoeverre verzekeringen worden opgenomen in het optimale bedrijfsplan. Hiertoe zijn een tweetal modellen ontwikkeld en vergeleken, namelijk een partieel model (één gewas en twee mogelijke uikomsten) en een *portfoliomodel* (meerdere gewassen en meerdere mogelijke uitkomsten). In de ontwikkelde modellen wordt het inkomen of vermogen omgezet in nut (utility) volgens een relatie die afhankelijk is van de risicohouding. De modelresultaten laten zien dat diegene die een potentieel gevaar risicovoller beleven eerder genegen zijn een verzekering af te sluiten. Hetzelfde geldt voor agrarische ondernemers met een hogere mate van risicoaversie. Deze groep van ondernemers is bereid om een deel van hun verwachte inkomen op te geven om extreem negatieve uitkomsten te vermijden. Echter, de verkregen optimale (efficiënte) strategieën zoals die voortkomen uit het partiële model wijken deels af van de resultaten die verkregen zijn middels het portfoliomodel omdat geen rekening wordt gehouden met de mogelijkheid van diversificatie. Het ervaren voordeel van een verzekering is geringer indien de besluitvorming geschiedt op basis van het totale eigen vermogen dan wanneer enkel en alleen rekening wordt gehouden met het verwachte inkomen.

Hoofdstuk 7 gaat in op een aantal overkoepelende, algemene problemen die naar voren kwamen tijdens de ontwikkelingen van de diverse modellen voor dit onderzoek. Met name wordt aandacht besteed aan de problemen van de beschikbaarheid van relevante data, extremiteiten van risico's, en alternatieve verzekeringsproducten.

Belangrijkste conclusies

- Voor het modeleren van catastrofe risico's dienen de extreem negatieve uitkomsten die deel uitmaken van een kansverdeling expliciet gemaakt te worden omdat ze verzekeringsbeslissingen beïnvloeden (Hoofdstukken 2, 5 en 6).
- Een minder risicovolle financiële positie van een bedrijf (hogere solvabiliteit en eigen vermogen) gaat gepaard met een geringere vraag naar een verzekering (Hoofdstukken 4 en 6).
- Substantiële verschillen in risicopercepties tussen agrarische ondernemers zijn waargenomen. Diegene die een potentieel gevaar risicovoller beleven zijn eerder genegen een verzekering af te sluiten (Hoofdstukken 4 en 6).
- Agrarische ondernemers met een hogere mate van risicoaversie zijn eerder genegen een verzekering af te sluiten. Deze groep van ondernemers is bereid om een deel van hun verwachte inkomen op te geven om extreem negatieve uitkomsten te vermijden (Hoofdstukken 4 en 6).
- Het ervaren voordeel van een verzekering is geringer indien de besluitvorming geschiedt op basis van het totale eigen vermogen dan wanneer enkel en alleen rekening wordt gehouden met het verwachte inkomen (Hoofdstuk 6).

Краткий Автореферат

Фермерство – это бизнес, связанный с риском. Столкновение с риском подразумевает потерю дохода или собственности. Растениеводческие хозяйства, имеющие опыт с катастрофическими рисками, могут столкнуться с серьёзными проблемами денежных потоков или даже банкротством. Для того чтобы нивелировать последствия катастрофических рисков, фермерам необходимо применять стратегии управления рисками. Страхование – это наиболее часто используемый инструмент для покрытия катастрофических рисков. Поэтому необходимо оценить степень воздействия факторов влияющих на покупку страховки от катастроф. Этими факторами являются личные характеристики фермера и характеристики фермы. Главными личными характеристиками фермера, влияющими на покупку страховки от катастроф, являются его личное восприятие риска(ов) и его отношение к риску.

Восприятие риска определяется как мысленная интерпретация риска в виде вероятности и величины потерь от катастрофы. Отношение к риску – это мера, с которой фермер стремится избежать или столкнуться с риском. Большинство фермеров предпочитают избегать риски.

Целью данной диссертации был анализ фактического поведения фермера в отношении катастроф (описательный подход) и моделирование воздействия покупки страховки от катастроф на конечные цели фермера (предписывающий подход). В диссертации были поставлены следующие задачи:

- Описание методов анализа восприятия риска и отношения к риску в целях моделирования решений для управления катастрофических рисков;
- Анализ фактической покупки ‘полного пакета страхования’ и отдельных типов страхования;
- Анализ зависимости покупки страховки от катастроф с восприятием рисков и отношением к риску;
- Моделирование экономических результатов катастрофических рисков;
- Моделирование покупок страховки от катастроф в контексте всей фермы и отдельного риска.

Первая глава включает общее введение в диссертацию. Оно состоит из изложения проблемы, целей исследования, структуры исследования и применяемых методов.

Во **второй главе** рассмотрены методики извлечения восприятий риска и отношения к риску, которые могут использоваться в моделях программирования рисков. Стандартный метод ‘силы убеждения’ для извлечения восприятий риска и стандартный метод ‘‘Одинаково Равного Эквивалента Определённости’’ для извлечения отношения к риску не подходят для случая катастроф, поскольку оперируют с ограниченным количеством точек для оценки, и поэтому нижняя часть хвоста кривой распределения может быть недооценена. Во избежание психологических предубеждений, методики улучшенного представления вероятностей могут быть применены для извлечения восприятий риска. Отношение к риску было предложено оценить с помощью эконометрических моделей или предположить с помощью методов стохастического доминирования, а именно - метода ‘‘Стохастической Эффективности по Отношению к Функции Полезности’’. Относительно метода выборки и данных для моделирования катастроф, метод Латинской Гиперкубической (Latin Hypercube) выборки может быть использован для принятия во внимание стохастической зависимости между видами деятельности в растениеводстве. Относительно метода программирования фермерских рисков, метод ‘‘Программирования Эффективной Полезности’’, оперирующий с любой формой функции ожидаемой полезности (включая степенную функцию полезности) может быть применён для программирования катастрофических рисков. Степенная функция полезности, оперирующая с изменениями любой величины благосостояния фермера, оказалась наиболее подходящей для ситуации с катастрофами. Однако когда фермеры не ведут себя как искатели ожидаемой полезности, дополнительные ограничения по величине рисковых резервов должны быть включены в модели.

В **третье главе** проанализировано воздействие характеристик фермы и некоторых личных характеристик фермера в отношении покупки ‘полного пакета страхования’ и его отдельных типов страхования на примере голландских растениеводческих ферм по сравнению с молочно-мясными хозяйствами. Следующие отдельные типы страхования были рассмотрены: страхование повреждений, нетрудоспособности, правое/судебное страхование и страхование ответственности. Результаты моделей показывают, что покупка страховок связана с общими факторами и факторами, свойственные отдельному типу страхования. В обоих растениеводческих и молочно-мясных хозяйствах, для отдельных страховых типов и ‘полного пакета страхования’ все переменные, за исключением чистого дохода фермы для покупки ‘полного пакета страхования’ в растениеводстве, имели одинаковое направление. В обоих типах хозяйств фермеры были более склонны сохранять деньги от основных видов деятельности для аккумулирования сбережений, нежели тратить их на страхование. Изначально ожидалось, что растениеводческие фермеры меньше страхуются, потому что диверсификация видов деятельности уже является формой управления рисков. Однако анализ показал, что растениеводческие фермеры тратили больше денег на покупку страховок, чем фермеры молочно-мясных хозяйств. Несмотря на различия между диверсификацией/специализацией, благосостоянием фермера, величиной премии, уплаченной в растениеводстве и молочном скотоводстве, были найдены общие переменные, объясняющие покупку всех рассмотренных страховых типов и ‘полного пакета страхования’: размер фермы и возраст фермера.

Четвертая глава анализирует воздействие восприятия риска, отношения к риску и других личных характеристик фермера и характеристик фермы на фактическую покупку страховки от катастроф растениеводческими фермерами и фермерами молочно-мясных хозяйств. Были рассмотрены следующие специфические типы катастрофического страхования: страхование зданий и сооружений от града-пожара-шторма, страхование нетрудоспособности, страхование сельскохозяйственных культур от града, шторма и коричневой гнили (для картофеля), а также страхование от эпидемий в молочно-мясном скотоводстве. Фермерам растениеводства и молочно-мясным скотоводства были свойственные различные типы поведения в отношении покупок страховки от катастроф, что было вызвано различными условиями ведения бизнеса. Покупка страховки от одного типа катастрофического риска была сильно связана с покупкой против другого катастрофического риска. Покупки различных форм страховок сельскохозяйственных культур были вызваны переменными, связанными с фермером и его фермой в одинаковом направлении, что и в предыдущих исследованиях в данной области. Восприятие риска и отношение к риску оказались важными переменными, объясняющими покупку страховки от катастроф. Растениеводческие фермеры были также более склонны страховать здания и сооружения от града и шторма, и в этом отношении решения, связанные с покупкой страховки для культур и/или предыдущим повреждением культур, могли повлиять на покупку страховок от повреждения зданий и сооружений. Ящур и коровья губчатая энцефалопатия оказались наиболее серьёзными катастрофическими рисками в молочно-мясном скотоводстве. Ящур и коровья губчатая энцефалопатия являются довольно новыми рисками в Нидерландах, и только несколько фермеров было застраховано. Незначительный предыдущий опыт катастрофических событий представляется определяющим фактором в принятии решений относительно катастроф в молочно-мясном скотоводстве. Недостаток исторических данных и опыта фермеров управлять катастрофами, возможно, объясняют неспособность моделей оценить воздействие отношения к риску во всех моделях, применимых для молочно-мясного скотоводства. По той же причине было невозможно оценить степень воздействия отношения к риску на покупку страховок от ящура и коровьей губчатой энцефалопатии. Другие переменные, характеризующие фермера и ферму, были определяющими факторами покупок страховки от катастроф в молочно-мясном скотоводстве. Благосостояние фермера играет важную роль в покупке страховок в молочно-мясном скотоводстве: состоятельные молочно-мясные фермеры имеют тенденцию предпочитать самострахование вместо воспринимаемого дорогим коммерческого страхования.

В **пятой главе** сравниваются различные пути проведения анализа рисков со ссылкой на катастрофические события фермы на примере редких разбросанных данных. Для этой цели мультивариационная ‘кернэл’- и основанная на нормальном распределении мультивариационая процедура сглаживания были предложены и применены для генерирования (симуляции) комбинированных распределений урожайности и цен сельскохозяйственных культур. Анализ показал, что функциональные формы, выбранные для генерирования комбинированного распределения, существенно влияют на плотность в хвосте кривой распределения, несмотря на то, что были параметризованы для одинаковых данных. Было обнаружено, что нормальное распределение и все кернэл-функции, за исключением Коши-кернэл, пренебрегают нижней частью хвоста кривой распределения. Результаты статистических тестов показали, что симулированные средние вектора Коши-кернэл функции статистически отличны от средних векторов имеющихся редких разбросанных данных. Более того, ковариационная структура оказалась статистически отличимой. Однако не представляется логичным ожидать, что на основании имеющихся редких разбросанных данных (в которых данные по катастрофам отсутствуют) ковариационная структура кернэл-функции не изменится.

В **шестой главе** моделируется, как фермеры могут принимать решения по управлению катастрофических рисков урожайности, а именно опции страховаться или не страховаться. Для этой цели подход одной культуры с двумя вариантами событий сравнивается с подходом, анализирующим несколько культур с большим множеством вариантов событий. Мы сравнили опции, в которых растениеводческие фермеры принимают решения в условиях годового дохода и конечного уровня благосостояния. Анализ показал, что если фермер принимает решения только в условиях функции полезности от годового объёма дохода, он более предрасположен к покупке страховки от катастроф. Модели показали что фермеры, которые воспринимали, что риск происходит относительно редко, были менее склонны страховаться, и самострахование было более предпочтительным. Однако если страховые решения были приняты на основании подхода одной культуры с двумя вариантами событий, они могут отличаться от результатов портфельного подхода, потому что альтернативные опции снижения риска, такие как диверсификация, не были учтены.

В **седьмой главе** обсуждаются некоторые общие проблемы исследования и их применение на практике. Следующие проблемы были затронуты: наличие данных, суровость катастрофических рисков, предположения по хвостам кривой распределения и альтернативные схемы страхования.

Основные выводы данной диссертации следующие:

- В моделировании катастрофических рисков, характеристики хвостов кривой распределения должны быть учтены. Иначе убытки, связанные с хвостом левой стороны кривой распределения, могут быть серьёзно недооценены, и окончательно будут отрицательно влиять на принятие решений в отношении катастроф (Главы 2,5 и 6);
- Более состоятельные фермеры менее склонны к покупке страховок и больше полагаются на самострахование (Главы 2,3 и 6);
- Были обнаружены существенные различия в уровнях восприятия риска между фермерами, что повлияло на покупку страховки от катастроф. Если фермер воспринимает, что катастрофическое событие более рискованным, чем другие фермеры, он более склонен также к страхованию и других катастрофических рисков (Главы 4 и 6);
- Фермеры с более высоким уровнем отношения к риску более предрасположены к покупке страховки от катастроф. Результаты предписывающего подхода показали, что более высокий уровень отношения к риску побуждает фермера выбирать неоптимальный производственный

план, в результате чего фермер теряет некоторую часть дохода. С покупкой катастрофической страховки, фермер с высоким уровнем отношения к риску может также стабилизировать свои результаты (Главы 4 и 6);

- Если решения принимаются фермерами в условиях конечного уровня благосостояния по сравнению, если бы они принимались в условиях годового дохода, то воспринимаемые выгоды катастрофического страхования более ограниченны. Фермеры менее склонны к покупке страховки от катастроф, если являются искателями ожидаемой полезности на основании предположения об интеграции активов (Глава 6).

Publications

Peer-reviewed scientific publications

Ogurtsov, V.A., van Asseldonk, M.A.P.M., and Huirne, R.B.M. Assessment and modelling of catastrophic risk perceptions and attitudes in Dutch farming: a review. *Submitted to Wageningen Journal of Agricultural Sciences, NJAS.*

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Ogurtsov, V.A., van Asseldonk, M.A.P.M., and Huirne, R.B.M. Factors explaining farmer's insurance purchase in the Dutch dairy sector. Trust and Risk in Business Networks. 99th seminar of the EAAE, February 2006, Bonn, Germany. Proceedings, pp. 297-305.

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Curriculum Vitae

Victor Andreevich Ogurtsov was born in September 3rd 1980 in Moscow, Russia. In 1997 he entered Moscow Timiryzev Agricultural Academy (MTAA), to follow the specialisation 'Agrarian Economy'. He graduated from MTAA in 2001 with distinction. In 2001-2003 under the EU Tempus project Victor was an MSc student at Wageningen University, following specialisation 'Agricultural Economics and Management'. From March 2003 until April 2007 he worked at the Institute for Risk Management in Agriculture (IRMA), Business Economics Group of Wageningen University, the Netherlands. He enrolled in a PhD program in 2003 entitled as 'Catastrophic risks and insurance in farm-level decision making'. He followed his PhD education program in the Mansholt Graduate School of Wageningen University.

From June 2007 Victor works at ING Bank, as a market risk manager in Amsterdam, the Netherlands.

Автобиография

Виктор Андреевич Огурцов родился 3-го сентября 1980 г. в г. Москва. В 1997 г. поступил в Московскую Сельскохозяйственную Академию (МСХА) имени К.А. Тимирязева на специальность ‘Аграрная Экономика’. В 2001 г. закончил МСХА им. К.А. Тимирязева с отличием. В 2001-2003 гг. в рамках проекта ‘Темпус-Тасис’ Европейского Союза обучался в магистратуре Университета г. Вагенинген, Нидерланды, по специальности ‘Экономика и Управление Сельским Хозяйством’. С марта 2003 г. по апрель 2007 г. работал и обучался по PhD-программе на кафедре ‘Экономика Бизнеса’ университета г. Вагенинген и института Управления Рисками в Сельском Хозяйстве. Тема его диссертации ‘Катастрофические риски и страхование в принятии решений на уровне сельскохозяйственного предприятия’. В период работы над диссертацией Виктор посещал PhD-курсы школы им. Мансхолта университета г. Вагенинген.

С июня 2007 г. Виктор работает в ИНГ-банке в должности менеджера по рыночным рискам в Амстердаме, Нидерланды.

Completed Training and Supervision Plan

Name of the course	Department/Institute	Year	Credits*
General part			
Research Methodology	Mansholt Graduate School	2003	2
Techniques for Writing and Presenting a Scientific Paper	Mansholt Graduate School	2003	0.8
Time planning and Project Management	Mansholt Graduate School	2003	0.6
Scientific Writing	CENTA, Mansholt Graduate School	2005	1.5
Written English	CENTA, Mansholt Graduate School	2004	1
Mansholt-Specific Part			
Mansholt Introduction course	Mansholt Graduate School	2003	1
Mansholt Multidisciplinary Seminar	Mansholt Graduate School	2004	1
Business Economics Phd – meetings	Business Economics, Mansholt Graduate School	2003-2007	4
Presentations at the international conferences	99th EAAE Seminar on Trust and Risk in Business Networks, Bonn, Germany	2005	2
	NJF Seminar 375 Farm Risk Management, Oslo, Norway	2006	
	SRA-E Conference on Innovation and Technical Progress: Benefit Without Risk? Ljubljana, Slovenia	2006	
Discipline-specific Part			
Information and Decision Making in Agriculture	WUR	2002	3
Food-Safety Risk Analysis	Mansholt Graduate School	2003	3
Capita Selecta Commodity Futures and Options	Marketing and Consumer Behaviour Group, Mansholt Graduate School	2004	2
Econometrics of Panel Data	NAKE	2004	2
Behavioural Economics	NAKE	2005	3
Multivariate Analysis Techniques	WUR	2003	3
TOTAL (min. 20 credits)			29.9

*1 credit is equivalent to 40 hours of course work (1 credit = 1.4ECTS)

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