

Farm Level Risk Assessment Using Downside Risk Measures

by

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Abstract

Recent and presumable future developments tend to increase the risk associated with farming activities. This causes an increasing importance of risk management. Farmers have a wide variety of possibilities to influence the risk exposure of their operations. Among them are the choice of the production program as well as marketing activities including forward pricing and hedging with futures and options. In total all these opportunities comprise a portfolio of activities which must be selected as to match the resources of the farm as well as the farmer's attitudes towards risk. The paper addresses this issue using a whole farm stochastic optimisation approach based on a risk-value framework. The paper starts with a discussion of risk-value models and the relationship between them and the expected utility hypothesis. In the second part the approach is incorporated in a whole farm model that optimizes a portfolio of production activities and risk management instruments. A case study is used to analyse the possibilities and limitations of the approach and to illustrate the effects of yield and production risk on decision making.

Keywords: downside risk, risk management, risk measure, risk-value models, stochastic optimisation

1 Introduction

Recent and presumable future developments tend to increase the risk associated with farming activities. Globalisation and liberalisation of trade combined with declining commodity price support result in an increase of market risks. Besides this, more stringent regulations with respect to the application of agro chemicals cause an increase of yield variability. In animal production, the achieved degree in the division of labour has dramatically aggravated the consequences of contagious disease outbreaks. This list could easily be extended. In summary it illustrates the increasing importance of risk management.

Farmers have a wide variety of possibilities to influence the risk exposure of their operations. Among them are the choice of the production program as well as marketing activities including forward pricing and hedging with futures and options. In total all these opportunities comprise a portfolio of activities which must be selected as to match the resources of the farm as well as the farmer's attitudes towards risk. In our paper we address this issue using a whole farm stochastic optimisation approach based on a risk-value framework. The paper starts with a discussion of risk-value models and the relationship between them and the expected utility hypothesis. In the second part the approach is incorporated in a whole farm model that optimizes a portfolio of production activities and risk management instruments.

2 Conceptualisation and measurement of risk

In accordance with most of the relevant literature we define risk as the uncertainty of outcomes (cf Anderson et al. 1977; Hardaker 2000; Robison and Barry 1987). Adopting this definition requires that we explicitly consider the distribution of outcomes. The ordering of risky prospects X_i which are characterised by their cumulative distribution functions $F_i(x)$ then requires that an ordinal preference function $\Phi(F_i(x)) \in \mathfrak{R}$ exists, such that

$X_i \succeq X_j \Leftrightarrow \Phi(F_i(x)) \geq \Phi(F_j(x))$. The most general approach for comparing risky choices is by means of expected utility (EU). In this case the preference function is defined as

$$\begin{aligned}\Phi(F_i(x)) &= E(U(F_i(x))) \\ &= \int_{-\infty}^{\infty} U(x) f_i(x) dx\end{aligned}\tag{1}$$

where $U(x)$ marks the utility function, $f_i(x)$ represents the probability density function (PDF) and $F_i(x)$ the cumulative distribution function (CDF) under consideration, respectively. Faced with a choice amongst a set of risky prospects, the expected utility hypothesis states that the prospect with the highest expected utility is preferred.

While the EU approach is widely accepted on theoretical grounds it has some difficulties in application. First, these relate to the selection of the mathematical form of the utility function as well as to the quantification of its parameters. Furthermore neither the expected utility nor the certainty equivalent that can be derived from it is easily understood by decision makers. Therefore other concepts have widely been used, e.g. the value-at-risk or the expected value-variance approach. Both belong to a category of models which are often referred to as *risk-value models*. Following this category of models is discussed in more detail.

2.1 Risk-value models

During the recent years risk-value models have regained considerable attention, often referring to the ground-breaking article of Sarin and Weber (1993). The risk-value approach distinguishes explicitly between a risk measure $R[F(x)]$ and a measure of the value or worth $W[F(x)]$, respectively (cf Albrecht & Maurer 2002, p. 171). Considering these two measures leads to a preference statement of the form (Sarin & Weber 1993, p. 131):

$$\begin{aligned}\Phi(F_i(x)) \geq \Phi(F_j(x)) \quad &\text{if and only if} \\ H(W[F_i(x)], R[F_i(x)]) \succeq &H(W[F_j(x)], R[F_j(x)])\end{aligned}\tag{2}$$

The function $H(\cdot)$ determines the trade-off between risk and worth according to the decision maker's preferences. The usual assumption is that $H(\cdot)$ grows with increasing worth and falls

with increasing risk. Neither the value measure nor the risk measure depends on wealth. Only the trade-off function is wealth dependent. If the decision maker is able to specify the trade-off function, comparing pairs of distributions leads to an optimal choice. If $H(\cdot)$ remains unspecified, it is still possible to determine the efficient set consisting of the distributions which are not dominated. A distribution $F_i(x)$ dominates the distribution $F_j(x)$ if the condition

$$W[F_i(x)] \geq W[F_j(x)] \text{ and } R[F_i(x)] \leq R[F_j(x)] \quad (3)$$

holds with at least one strict inequality (Fishburn 1977, p. 118). All non dominated alternatives lie on the efficient frontier which can be determined by solving the optimisation problem

$$\begin{aligned} &W[F_j(x)] \rightarrow \text{Max!} \\ &\text{subject to} \\ &R[F(x)] \leq c \end{aligned} \quad (4)$$

where c must be varied across all possible numerals of $R[F(x)]$.

Implementing risk-value models requires the definition of measures for risk and worth to be used in the approach. Following we discuss some of these measures.¹

2.2 Risk measures

Since risk has primarily been associated with the dispersion of the corresponding random variable it is common to measure the riskiness of an alternative using its variance or standard deviation. If the outcome is normally distributed the distribution is fully defined by mean and variance. Otherwise higher order moments, particularly skewness and kurtosis can be employed to obtain more information about the shape of the distribution.

The moments of the distribution are based on the variations around the mean, i.e. $M_k(x) = E[(x-\mu)^k]$, where k and μ denote the order of the moment and the mean, respectively and $E[\cdot]$ represents the expectation operator. When using these measures, the mean or expected value is therefore (implicitly) considered as the relevant target and risk is quantified using the magnitude of deviations from this target. Furthermore the above measures are two-

¹ For a more comprehensive discussion of risk measures see e.g. Albrecht (2003).

sided in that they consider the magnitude of the distance from the realisations of x to $E(x)$ in both directions.

Conventional wisdom, however, states that risk is perceived by the majority of humans as the chance of something bad happening. In this regard, risk is associated with an outcome that is worse than some specific target. This brings about a further class of risk measurers, often referred to as shortfall measures. This class of measures dates back to the work of Fishburn (1977). Considering only the lower part of the distribution, these measures account for the downside-risk and are called lower partial moments (LPM). They are defined as

$$LPM_n(z) = \int_{-\infty}^z (z-x)^n f(x) dx \quad (n \geq 0) \quad (5)$$

Setting the target z and the order k of the LPM yields a specific measure. Basic cases that play an important role in applications, are obtained for $k = 0, 1$ and 2 . Setting $k=0$ yields the *shortfall probability* $LPM_0(z)$ that is closely related with the *value-at-risk*.²

$$LPM_0(z) = \int_{-\infty}^z (z-x)^0 f(x) dx = F(z) \quad (6)$$

For $k=1$ the resulting measure is the *shortfall expectation*:

$$LPM_1(z) = \int_{-\infty}^z (z-x)^1 f(x) dx = E[z-x | x < z] F(z) \quad (7)$$

$LPM_1(z)$ denotes the (conditional) expected value of shortfalls multiplied by the probability of the occurrence of below target returns. Thus, it accounts for the probability as well as for the magnitude of shortfalls. Finally $k=2$ leads to the *shortfall variance*

$$LPM_2(z) = \int_{-\infty}^z (z-x)^2 f(x) dx = E[(z-x)^2 | x < z] F(z) \quad (8)$$

the square root of which denotes the *shortfall standard deviation*. Here the squared downside deviations from target are considered in the risk measure.

² For details on the value-at-risk concept see e.g. Jorion (1997), Manfredo and Leuthold (1999)

Further variations are obtained if the expected value serves as target, i.e. $z=E[x]$. The corresponding measures are the probability of falling short of the expected value ($k=0$), its expected underrun ($k=1$) and the semi-variance ($k=2$). These measures do not change if a certain amount c is added to an uncertain outcome X , i.e. $R[X]=R[X+c]$. Contrary, if z is determined exogenously, adding a certain quantity to an uncertain prospect reduces the risk associated with it, i.e. $R[X]>R[X+c]$. Generally, one would consider a situation to be less risky if a certain income is earned in addition to the uncertain prospect. Furthermore Schneeweiß (1967, p. 111) has shown that risk-value models which use risk measures with an endogenous target (e.g. $E[x]$), are not consistent with the utility model, except for certain classes of distributions. The further discussion therefore is limited to those risk measures where the target is determined exogenously.

2.3 Value measures

While the appropriateness of risk measures is still controversially discussed in the relevant literature it is widely agreed that the expected value is the best measure of worth in risk-value models, i.e. $W[F(x)]=E[x]$. Only in the recent literature the appropriateness of the expected value is sometimes questioned (Maurer 2000; Frowein 2002). It is criticised that the computations of the expected value takes data into account that have already been considered in the risk measure.

Alternatively, upper partial moments (UPM) can be used which are complementary to the LPMs in that they consider the upper part of the distribution by measuring the excess of a target z :

$$UPM_k(z) = \int_z^{\infty} (x-z)^k f(x) dx \quad (k \geq 0) \quad (9)$$

For $k=0$ the above formula yields the probability that x exceeds z , i.e. $UPM_0(z) = 1-F(z)$. This measure is called *excess probability* (Albrecht et al. 1999, p. 263). If k equals 1 the *excess expectation* is returned and $k=2$ leads to the *excess variance*. The UPMs are partly less

informative than the expected value (e.g. $UPM_0(z)$) and in any case less understandable for a decision maker. In accordance with most of the literature we therefore use the expected value $E[x]$ as measure of worth.

2.4 Risk value models in relation to utility functions

The preference function of the risk-value model using the expected value $E[x]$ as value measure and a lower partial moment $LPM_k(z)$ as risk measure can be stated as

$$\Phi(F(x)) = E[x] - c LPM_k(z) \quad (10)$$

where $c > 0$ denotes the weighting factor and k is the order of the LPM. Increasing c therefore means increasing risk aversion. Schneeweiß (1967, p. 89ff) has shown that the corresponding utility function has the following form:

$$u(x) = \begin{cases} x & \text{if } x > z \\ x - c(z - x)^k & \text{if } x \leq z \end{cases} \quad (11)$$

Figure 1 contains the graph of the utility functions according to (11) using the *shortfall probability* ($k=0$), the *shortfall expectation* ($k=1$) and the *shortfall variance* ($k=2$) as risk measures. The target was set to $z=0$ assuming that losses are considered as downside risk. Above the target level all three cases result in the same utility function which is given by $u(x) = x$. The differences between them occur in the range where x falls below the target.

For $k=0$ the utility function is linearly increasing at constant slope but has a discontinuity at the target z . It does not allow a general statement about the decision maker's attitude towards risk which depends on the target level relative to the distribution of outcomes. The utility function implies risk neutral behaviour if all realisations of the random variable lie either below or above the target level. In this case the shortfall probability of all alternatives is the same and equals either 1 or 0. Thus, the choice is only based on the expected value and the alternatives can be ordered using first degree stochastic dominance (FSD). In most cases however, the stochastic outcomes will scatter around the target. In this case the implied risk attitude depends on the target level. If this is low, the choice may be in accordance with sec-

second degree stochastic dominance (SSD) indicating risk aversion. At higher target levels however, alternatives may be chosen that require risk loving behaviour to become optimal in the sense of expected utility. Thus using the shortfall probability as risk measure in an optimisation approach is likely to yield ambiguous results.

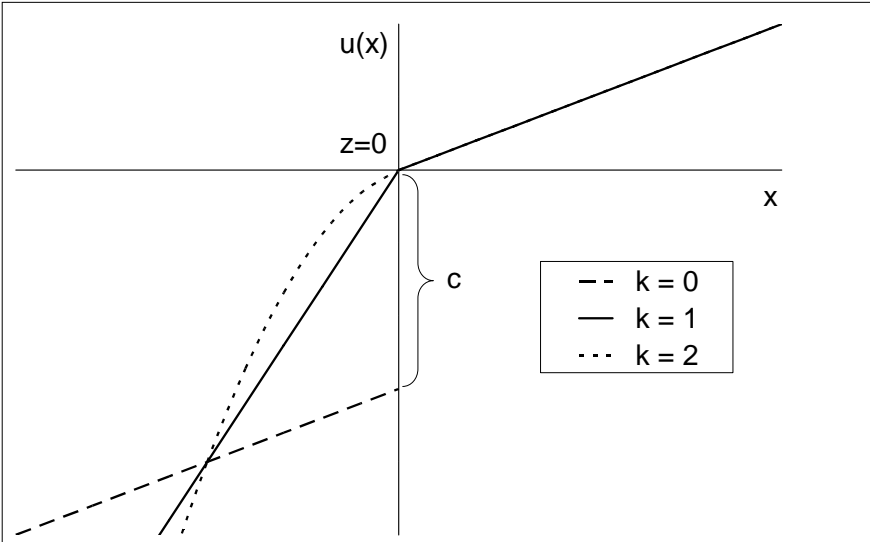


Figure 1: Corresponding utility functions of risk-value models

The *shortfall expectation*, i.e. $k=1$, considers not only the shortfall probability but also its extent. The corresponding utility function is represented by the solid line in Figure 1. It is piecewise linear with the steeper slope in the lower part. Only if all possible outcomes fall either below or above the target level, respectively, the utility function implies risk neutral behaviour. Otherwise the shape of the utility function is approximately concave and therefore implies risk aversion.

The use of higher order LPMs, i.e. higher values of k , implies stronger local risk aversion in the lower part of the domain while above the target local risk neutrality remains (cf Nawrocki 1991, p. 466). Using $LPM_2(z)$, i.e. the *shortfall variance*, the shortfalls are squared, thus giving particular weight to the higher losses. The corresponding utility function is quadratic in the range below the target level and therefore also implies risk aversion. Different from the former case, the utility function is strictly concave in the lower part.

From the above framework and given the assumption that most decision makers are risk averse to some extent the shortfall expectation and the shortfall variance appear as suitable risk measures. Since a desirable feature of any measure is that it has an obvious meaning for the decision maker we have chosen LPM_l . The risk value model to be implemented in the following section therefore is based on the expected profit and the shortfall expectation as value and risk measures, respectively.

3 The whole farm model

Farms in Europe are typically multi-product operations. The decision problem for a farmer therefore is to choose a portfolio of risk management instruments and production activities that meets his objectives in terms of profit and the risk associated with it. The model developed for this purpose is a two step approach. In the first step the joint distributions of prices and yields are estimated. In the second step these estimates are incorporated in the optimisation model.

3.1 Optimisation approach

The model is set up as to compute a risk efficient frontier in the way that the expected profit enters the objective function while the risk measure is considered as a constraint. The objective function therefore is to select the portfolio of activities \mathbf{x} that maximizes the expected profit π

$$\max_{\mathbf{x}} \int_0^{\infty} \int_0^{\infty} \pi(\mathbf{p}, \mathbf{y}, \mathbf{x}) g(\mathbf{p}, \mathbf{y} | \mathbf{\Omega}) d\mathbf{p} d\mathbf{y} \quad (12)$$

subject to the resource constraints $\mathbf{A} \mathbf{x} \leq \mathbf{b}$ and the constraint on the risk measure $LPM_1(z) \leq c$, where c is parameterised in order to compute the efficient frontier.

In (12) the term $\pi(\cdot)$ denotes the profit function and $g(\cdot | \mathbf{\Omega})$ is the joint density function of prices and yields conditional on $\mathbf{\Omega}$, the set of information available when the portfolio is selected. The random price vector \mathbf{p} consists of cash prices for all products and in addition

futures prices for pigs and forward contract prices for potatoes. The random yield vector \mathbf{y} contains the individual crop yields. The resource constraints reflect the physical capacities of the farm as well as institutional constraints, e.g. rotational restrictions and agricultural policy regulations. The profit function consists of the following components:

$$\begin{aligned}\pi(\mathbf{p}, \mathbf{y}, \mathbf{x}) &= PA + PS + FO + FU - CF \\ \text{where } PA &= \sum_j (p_j y_j - c_j(y_j)) x_j \\ PS &= (p_s y_s - p_F - c_s(y_s)) x_s \\ FO &= (p_{FK} - p_{MK}) x_{FO} \\ FU &= \sum_i (pf_{t,t+i} - pf_{t+i,t+i}) x_{F,i}\end{aligned}\tag{13}$$

The PA component is the profit from producing crops and selling them in the cash market without using other risk management instruments than a diversified crop mix itself. Thus p_j denotes the cash price, y_j the yield and $c_j(y_j)$ the variable cost function of commodity j . The chosen acreage is given by x_j . The term PS represents the profit from pig production, where p_s is the price of finished pigs, y_s the carcass weight, p_F the price of piglets and $c_s(y_s)$ denotes the variable cost. The profit per head is multiplied by the number of finished pigs, x_s . FO is the net return from forward contracting that applies for potatoes. Here, p_{FK} is the contract price while p_{MK} represents the cash price at harvest and x_{FO} denotes the contracted amount. The FU component reflects the net return from hedging with futures which is possible only for pigs. In this context, $x_{F,i}$ is the amount of futures contracts with maturity date i that are sold, $pf_{t,t+i}$ is the futures price at the time when $x_{F,i}$ is selected and $pf_{t+i,t+i}$ is the futures price at maturity. Finally, CF accounts for cost and returns which are independent from the selected portfolio. These include all fixed costs minus the direct payments according to the present European agricultural policy.

3.2 Determination of price and yield distributions

The generation of price distributions is based on an ARCH model that has been derived from time series data of the years 1992 to 2004 for cereals and 1985 to 2004 for potatoes. The ARCH model has the following structure:

$$p_t = T_t + \sum_{i=1} \phi_i (p_{t-i} - T_{t-1}) - \sum_{z=1} \theta_z \sigma_{t-z} \varepsilon_{t-z} + \sigma_t \varepsilon_t \quad (14)$$

where

$$\sigma_t^2 = \overline{\sigma_t^2} + \sum_j \alpha_j (e_{t-j}^2 - \overline{\sigma_{t-j}^2})$$

and the variables and coefficients have the following meaning:

p_t = price at time t

T_t = trend variable (function of time and season)

ϕ_i = auto regression coefficient for lag i

θ_z = moving average coefficient for lag z

e_t = residuals

ε_t = e_t / σ_t standardized residuals with mean 0 and standard deviation 1

σ_t^2 = conditional variance

$\overline{\sigma_t^2}$ = unconditional variance (function of time and season)

α_j = auto regression coefficient for lag j

After estimating the parameters, the process of price generation is stochastically simulated³ (1 000 random runs), using the price information available at the starting point $t=0$. For $t>0$ only the innovations ε_t are stochastic and represent realizations of independent and identically distributed random variables. Thus, conditional on the current market conditions, the probability density functions of the prices and their autocorrelations are determined for all relevant dates within the planning horizon (see Figure 2). The correlations between the residuals of the different price processes are taken into account during the generation of the ε_t . This assures that existing correlations between the residuals are reflected in the generated forecasts.

³ The EXCEL add in @Risk from Palisade was used to carry out the stochastic simulation

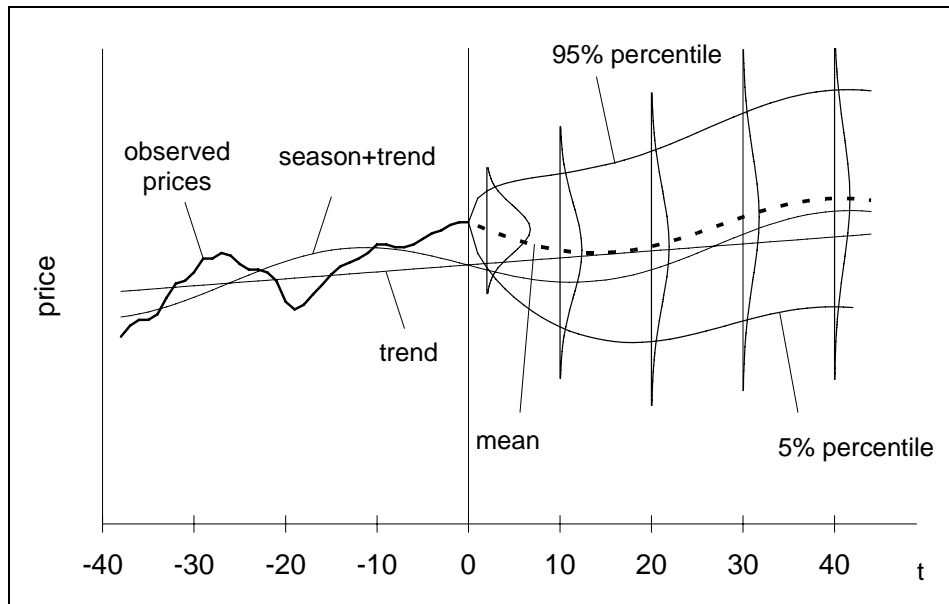


Figure 2: Conditional probability density functions generated from a price process

Crop yields are assumed to be normally distributed with the means and standard deviations given in Table 1. Yield correlations were set to 0.3 between all crops. A negative price yield correlation of -0.5 was assumed for potatoes. In all other cases yield and price fluctuations are assumed to be independent.

On combining the generated prices and yields and considering the variable cost gross margins for all crops at harvest can be generated. The means and standard deviations of these distributions are also depicted in Table 1. The differences between the two years are due to the respective differences in price forecasts.

Table 1: Means and standard deviation of crop yields and gross margins

	Yields [dt/ha]		GM*) 2005 [€/ha]		GM*) 2006	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Winter wheat	92	7,7	240	105	285	125
Winter barley	83	7,8	157	91	174	98
Spring Barley	60	6,6	172	94	256	117
Potatoes	442	57	378	995	378	1043
Land Set-aside	0	0	-86	0	-86	0

*) GM = Gross Margin

3.3 Model results

The following model calculations refer to a German farm. The farm size is 75 ha of arable land and a hog barn holding a total of 1 000 finishing pigs which are subdivided into 4 compartments. Each compartment contains 250 pigs that are sold at the same time. According to the actual policy regulations, 8.05 % of the land must be set aside in order to obtain the direct payments. The latter amount to roughly 21 000 € per year. The share of potatoes is limited to 30 % of the total acreage on agronomic grounds. The fixed cost amount to 105 000 € per year.

The planning process is assumed to take place at the beginning of the year 2005. Thus, winter grain is already planted so only the acreage of the spring crops (spring barley and potatoes) has to be allocated for the harvest 2005. Further activities include marketing of stored grain, forward contracting of potatoes and hedging with futures in the case of pigs. With respect to pig production it is assumed that the capacity of the barn is always fully utilised. Since the model is run over two cropping years the crop mix for the 2006 harvest is also determined by the model.

Optimisation is carried out using Microsoft EXCEL along with Solver and Visual Basic for Applications. To compute the objective function according to (12) and (13), the model uses the random yield and price realisations generated during the prior step. The target z of the $LPM_I(z)$ that serves as risk measure is set to zero yielding the loss expectation. Six optimisations for different values of c are performed to obtain the efficient frontier. These include the minimisation of risk (no. 1) and the maximisation of expected profit (no. 6) as endpoints. The model results are depicted in Table 2 while Figure 3 illustrates the resulting efficient frontier.

The principal changes of the portfolio of activities across the model runs can be summarized as follows (see Table 2): With growing risk aversion potatoes are gradually replaced by wheat (harvest 2006) and spring barley (harvest 2005). At the same time forward contracting is suggested for 2005 potatoes. Hedging with hog futures also turns out to be a valid instru-

ment to reduce risk. Increasing risk aversion furthermore results in an increase of the number and duration of hog futures contracts.

Table 2: Model Results

Result	1	2	3	4	5	6
$E(X) \rightarrow \text{Max}$	32 617	37 299	38 482	39 293	39 357	39 804
$\sigma(X)$	19 568	23 943	25 426	28 211	29 391	30 672
$\gamma(X)$	0.07	0.14	0.19	0.29	0.31	0.40
$LPM_0(0)$	4.6 %	5.6 %	6.1 %	7.3 %	8.2 %	8.6 %
$LPM_1(0) = c$	304	443	581	720	859	998
$LPM_1(0)/LPM_0(0)$	6 638	7 977	9 578	9 824	10 486	11 572
$\sqrt{LPM_2(0)}$	2 124	2 695	3 186	3 650	4 081	4 471
Crop mix as share of the total acreage (harvest 2005)						
Winter wheat	30 %	30 %	30 %	30 %	30 %	30 %
Winter barley	10 %	10 %	10 %	10 %	10 %	10 %
Spring barley	42 %	32 %	22 %	22 %	22 %	22 %
Potatoes	10 %	20 %	30 %	30 %	30 %	30 %
Land set-aside	8 %	8 %	8 %	8 %	8 %	8 %
Forward contract ratio of potatoes (harvest 2005)	64 %	48 %	42 %	23 %	10 %	0 %
Crop mix as share of the total acreage (harvest 2006)						
Winter wheat	87 %	83 %	79 %	72 %	66 %	62 %
Potatoes	5 %	9 %	13 %	20 %	25 %	30 %
Land set-aside	8 %	8 %	8 %	8 %	8 %	8 %
Forward contract ratio of potatoes (harvest 2006)	0 %	0 %	0 %	0 %	0 %	0 %
Number of futures contracts (date of maturity)						
Jan 05	0	0	2	0	1	0
Feb 05	5	5	3	1	0	0
Mar 05	3	0	0	0	0	0
Apr 05	0	0	0	0	0	0
May 05	0	0	0	0	0	0
Jun 05	0	0	0	0	0	0
Jul 05	0	0	0	0	0	0
Aug 05	2	0	0	0	0	0

Figure 3 depicts the efficient frontier. It can be seen that the use of risk management instruments can reduce the loss expectation by 70 %. However, this is achieved only at the expense of a declining expected profit, where the trade-off becomes less favourable as risk decreases. After all it is up to the decision maker to determine which trade-off between expected profit and the associated risk is still acceptable.

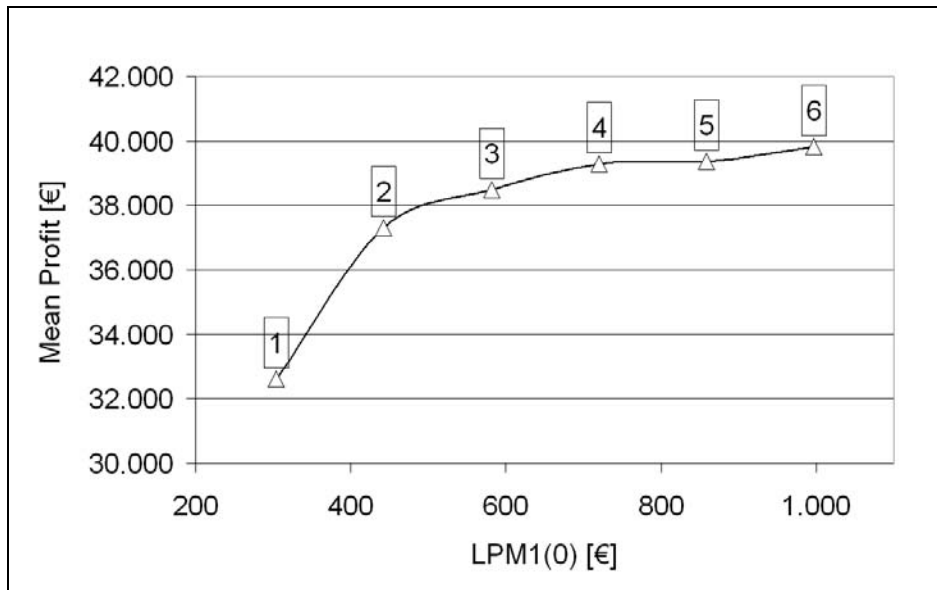


Figure 3: E(x)-LPM₁(0) efficient frontier

For comparison with the risk-value approach the model is also used to maximise expected utility (EU) using the negative exponential utility function $u(x) = 1 - e^{-\lambda x}$, where x denotes profit and λ is the absolute risk aversion parameter. λ was set to values ranging from 0.000015 to 0.001 to account for increasing risk aversion. The computed expected profits and $LPM_1(0)$ values for these solutions are plotted in Figure 5 along with the efficient frontier of the risk-value model.

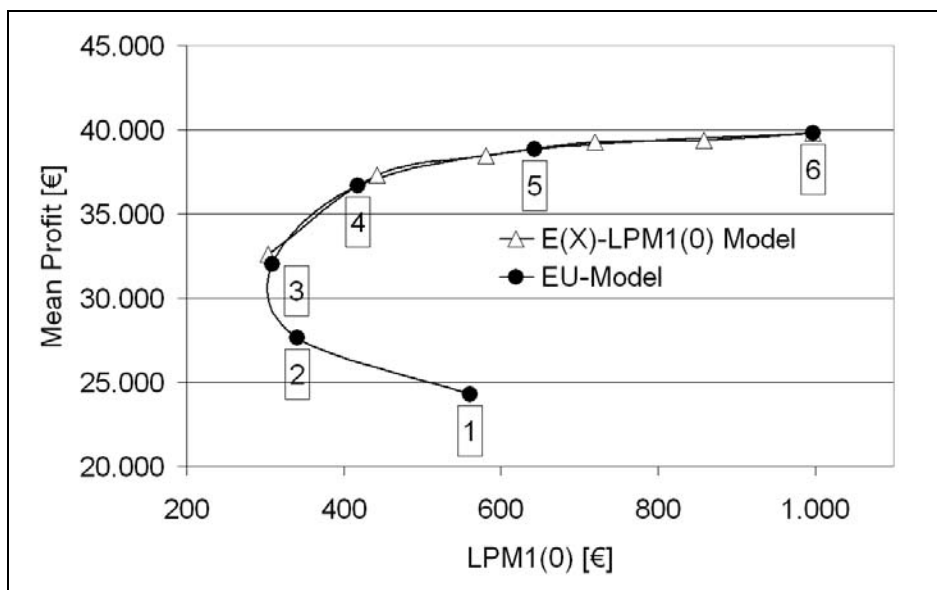


Figure 5: Comparison of the E(x)-LPM₁(0) efficient frontier with the results of the EU model

The graph indicates that at moderate risk aversion the results of the EU model match the efficient frontier of the risk-value model. However, at higher degrees of risk aversion according to the EU model, the respective solutions become inefficient in terms of $LPM_I(0)$. The reason for this is that the utility function associated with LPM_I (see Figure 1) can hardly approximate the exponential function at high degrees of risk aversion.

4 Conclusions

If we accept the hypothesis that risk aversion rather than risk indifference is the standard attitude of farmers, then we can conclude from the model results that uncertainty of yields and prices significantly influences decision making. Applying risk management instruments appropriately can reduce the income risk considerably. However, finding the right mix of instruments is a complex task that requires the support by computerised tools. Risk-value models, as the one presented in this paper, are intuitively appealing in this context, as the employed measures (expected value and shortfall expectation) are easily understood by decision makers. At moderate degrees of risk aversion the results of the presented risk-value model are very similar to those of the more general expected utility approach. At higher degrees of risk aversion, however, the approaches yield different results because the LPM_I model cannot approximate the utility function close enough. Using higher order LPMs might lead to improvements, but only at the expense of losing much of the understandability of the risk measure.

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