Extreme Measures of Agricultural Financial Risk

By

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Abstract

Risk is an inherent feature of agricultural production and marketing and accurate measurement of it helps inform more efficient use of resources. This paper examines three tail quantile-based risk measures applied to the estimation of extreme agricultural financial risk for corn and soybean production in the US: Value at Risk (VaR), Expected Shortfall (ES) and Spectral Risk Measures (SRMs). We use Extreme Value Theory (EVT) to model the tail returns and present results for these three different risk measures using agricultural futures market data. We compare the estimated risk measures in terms of their size and precision, and find that they are all considerably higher than normal estimates; they are also quite uncertain, and become more uncertain as the risks involved become more extreme.

Keywords: Agricultural financial risk, Spectral risk measures, Expected Shortfall, Value at Risk, Extreme Value Theory.

JEL Classification: E17, G19, N52

October 6, 2008

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1. INTRODUCTION

The inherent variability in agricultural production (weather, pests, animal illness and so forth) alongside demand variations (food scares, fads, etc.) make for a marketing environment for farmers that is characterised by significant levels of risk (Moschini and Hennessy, 2001, Chern and Ricketsen (2003) and Carter and Smith (2007)). A natural question then arises - how do you measure the magnitude of risk being faced by agents? – and the last decade and a half have witnessed an explosion of research on different measures of financial risk, and especially on one particular measure, the Value-at-Risk (VaR). This 'VaR revolution' began when JP Morgan published its famous RiskMetrics model on the web in October 1994. VaR models were first used by financial institutions for their own risk management purposes, but have since been adopted by many non-financial corporates as well. Amongst their many uses, VaR models can be used to determine capital and reserving requirements, establish position limits and assess hedging strategies. They can also be used to manage cashflow, liquidity and credit risks as well as the market risks for which they were first developed. Estimation methods have improved considerably over the years, and the properties – and especially the limitations – of the VaR itself have become better understood. Various new measures of financial risk have also been proposed and these include, most notably, the coherent risk measures proposed by Artzner *et alia* (1999). These risk measures have the highly desirable property of sub-additivity, which the VaR lacks.[1] Thus, not only have VaR estimation methods improved over time, but there have also been improvements in the financial risk measures themselves, of which the VaR is but one.

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[1] Suppose we let X and Y represent any two portfolios and let $\rho(.)$ be a measure of risk over a given forecast horizon. The risk measure $\rho(.)$ is subadditive if it always satisfies the condition $\rho(X+Y) \leq \rho(X)+\rho(Y)$. Subadditivity reflects the idea that risks should not increase, and should typically decrease, when we put them together, i.e., it reflects the notion that risks should diversify. The coherent risk measures are always sub-additive by construction, because sub-additivity is one of the axioms of coherence, but the VaR is not coherent and the failure of VaR to be sub-additive leads to the VaR having some strange and undesirable properties as a risk measure. See Artzner *et al.* (1999, p. 217, Dowd (2005, pp. 31-32)

The relevance of these developments to agricultural financial risks is self-evident. Yet, ironically, to date they have had only a limited impact on the agricultural economics and finance literature. Some indication of the current state of the art in agricultural financial risk measurement can be obtained from Table 1. This lists the main points of 8 different studies on this subject. Most of these studies use multivariate parametric approaches to estimate VaR, and these are typically based on the assumption that underlying risks factors are multivariate normally distributed. Some studies also use historical simulation methods to estimate the VaR. One study (Zhang *et al.* (2007)) uses Monte Carlo methods, and two (Siaplay *et al.* (2005) and Odening and Hinrichs (2003)) include results based on Extreme-Value Theory (EVT). It is also noteworthy that all but one of these studies focuses exclusively on the VaR risk measure.[2] To our knowledge, there are no studies so far of coherent risk measures applied to agricultural risk problems.

Insert Table 1 here

This paper examines three different measures of financial risk applied to agricultural risk. The measures examined are the VaR and two members of the family of coherent risk measures. The first of the coherent risk measures is the Expected Shortfall (ES), which is loosely speaking the average of the 'tail losses' or losses exceeding the VaR. The ES takes account of the magnitude of losses exceeding the VaR. This, and the related fact that it is subadditive, makes the ES a superior risk measure to the VaR on *a priori* grounds. However, both the VaR and ES measures depend on the choice of a confidence level that delineates the cutoff to the tail region, and there is seldom an 'obvious' choice of what the confidence level should be. Moreover, the ES has the undesirable property of implying that the user is risk-

[2] The one exception (Zhang *et al.*, 2007) looks at lower partial moment measures based on the downside risk literature (e.g., Fishburn, 1977) rather than the coherent risk measures that have been much discussed in the mainstream financial risk literature. The VaR and the ES can be regarded as special cases of the lower partial moment measures if the lower partial moment parameter takes the values 0 or 1 respectively (see Dowd, 2005, p. 26).

neutral, and this sits uncomfortably with the use of such measures by risk-averse agents in the first place.[3]

The other coherent risk measure is a Spectral Risk Measure (SRM) proposed by Acerbi (2002, 2004). The distinctive feature of an SRM is that it specifically incorporates a user's degree of risk aversion. Since SRMs are a subset of the family of coherent risk measures, they have the attractions of coherent risk measures as well. A tractable type of SRM is that based on an exponential risk aversion function, and a nice feature of exponential risk aversion function is that the extent of risk aversion depends on a single parameter, the coefficient of absolute risk aversion R. Once a user chooses the value of R that reflects its attitude to risk, it can then obtain an 'optimal' risk measure that directly reflects its degree of risk aversion. So, whereas the VaR or ES are contingent on the choice of an arbitrary parameter, the confidence level, whose 'best' value cannot easily be determined, a spectral-coherent risk measure is contingent on a parameter whose 'best' value can be selected by the agent that uses it.

Our measurement of the three risk measures is for corn and soybean spot and futures contracts as these goods represent an important element of US agricultural production: corn due to its role in feed grain production and soybeans for vegetable oil production. We analyse the contracts for both long and short positions whose risk would be of interest to different possible users such as farmer producers and processors.

The focus of this study is extreme financial risk – the risk associated with the prospect of low probability, high impact losses. There has been considerable interest in extreme risks over the last decade. The literature on extremes tells us that extremes should be modelled separately from the rest of the distribution using the distributions implied by Extreme Value (EV) theory,[4] and should *not* be modelled by fitting full distributions to the data in an ad hoc way (e.g., such as assuming Gaussianity). In

[3] For its part, the VaR is even worse, as it implies that a user who chooses to use the VaR as a risk measure must be highly risk-loving (see Cotter and Dowd, 2007, p. 3472).

[4] For more on EVT, see, e.g., Embrechts *et al.*,1997, or Beirlant *et al.*, 2004. Note that tail risk measures are underestimated using Gaussianity and this estimation bias deteriorates as one moves further out into the tail (Cotter, 2007).

essence, it suggests that we can either model the extremes themselves using one of the Generalised EV distributions implied by the Extreme Value Theorem or we can model the exceedances over a high threshold using a Generalised Pareto Distribution (GPD; see, e.g., Embrechts et *alia* (1997)). This latter approach is often referred to as the Peaks-Over-Threshold approach. We choose the latter because it (typically) involves one less parameter and because it fits more easily with the likelihood that extreme losses occur in clusters. The application of the GPD can be justified by theory that tells us that the tail observations should follow a GPD in the asymptotic limit as the threshold gets bigger. Once the GDP curve is fitted to the data, it can then be extrapolated to give estimates of any extreme quantiles or tail probabilities we choose.

Accordingly, in this paper, we use the POT approach to estimate and compare the extreme VaRs, ESs and SRMs for corn and soybean contracts. Bearing in mind that the usefulness of any estimates of financial risk measures also depends crucially on their precision, we also examine alternative methods of estimating their precision.[5] Given the heavy reliance of Gaussianity in the literature, we also produce estimates of risk measures using Gaussianity.

This paper is organised as follows. Section 2 reviews the risk measures to be examined. Section 3 reviews the Peaks-Over-Threshold (POT) approach and section 4 details the POT-based risk measures. Section 5 introduces the spot and futures corn and soybean data used in our empirical work and provides some preliminary data analysis. Section 6 describes the bootstrap procedure used to derive the precision metrics used in the paper. Section 7 then estimates VaR and ES, and section 8 estimates the SRMs. Each of these sections also examines the precision of these estimated risk measures. Section 9 concludes.

[5] As noted already in the text, two of the studies listed in Table 1 present results based on EVT. Of these, Siaplay *et alia* (2005) report EV estimates of VaR in a single table obtained using the EV function in Palisade Corporation's '@Risk' package, but provide no EV analysis as such. We also note there that this function only allows the user to model a Gumbel EV distribution, and this distribution is not compatible with heavy-tailed returns. Odening and Hinrichs (2002) provide an analysis based on Generalised EV theory, but they report rather unstable estimates of the tail index parameter – a common problem in this area - and this makes their results unreliable.

2. MEASURES OF FINANCIAL RISK

Suppose X is a realised random loss variable – a variable that assigns loss outcomes a positive sign and profit outcomes a negative one - for a commodity over a given horizon. If the confidence level is α, the VaR at this confidence level is:

$$VaR_\alpha = q_\alpha \tag{1}$$

where the term q_α is the α-quantile of the loss distribution. For any given horizon, the VaR is defined in terms of its conditioning parameter, the confidence level, which is arbitrarily specified by the user. Viewed as a function of the quantiles of the loss distribution, it is useful to note here that the VaR places all its weight on a single quantile that corresponds to the chosen confidence level and places no weight on any others. This implies that the user only 'cares' about a single loss quantile, and is not concerned about higher losses, and it is this rather strange property that causes the VaR risk measure to be non-subadditive (Acerbi, 2004).

The second measure, the ES, gives equal weight to each of the worst $1-\alpha$ of losses and no weight to any other observations. The ES is superior to the VaR in a number of respects (e.g., it is subadditive and coherent and because takes account of losses beyond the VaR quantile). However, the ES is specified in terms of the same conditioning parameter as the VaR and, as with the VaR, there is generally little to tell us what value this parameter should take.

Our third measure is the Spectral Risk Measure (SRM). Following Acerbi (2002), consider a risk measure M_ϕ defined by:

$$M_\phi = \int_0^1 q_p \phi(p) dp \tag{3}$$

where q_p is the p loss quantile, $\phi(p)$ is a weighting function defined over p, the cumulative probabilities in the range between 0 and 1. Borrowing from Acerbi (2004, proposition 3.4), the risk measure M_ϕ is coherent if and only if $\phi(p)$ satisfies the following properties:

- *Positivity*: $\phi(p) \geq 0$, i.e., weights are always non-negative.
- *Normalisation*: $\int_0^1 \phi(p)dp = 1$, i.e., weights sum to one.
- *Increasingness*: $\phi'(p) \geq 0$, i.e., higher losses have weights that are higher than or equal to those of smaller losses.

We now need to specify a suitable weighting (or risk-aversion) function and a reasonable choice is the exponential risk-aversion function:

$$\varphi(p) = \frac{R\mathrm{e}^{-R(1-p)}}{1-e^{-R}} \tag{4}$$

where R>0 is the coefficient of absolute risk aversion. This weighting/risk-aversion attaches higher weights to larger losses, and, moreover, the weights rise more rapidly as the user becomes more risk-averse.

The value of the risk measure can then be obtained by substituting (4) into (3), viz.:

$$M_\varphi = \int_0^1 \frac{R\mathrm{e}^{-R(1-p)}}{1-e^{-R}} q_p dp = \frac{R\mathrm{e}^{-R}}{1-e^{-R}} \int_0^1 e^{Rp} q_p dp \tag{5}$$

3. THE PEAKS OVER THRESHOLD (GENERALISED PARETO) APPROACH

We model the agricultural tail risks using a Peaks over Threshold (POT) approach which focuses on the realisations of a random variable X over a high tail threshold u. More particularly, if X has the distribution function $F(x)$, we are interested in the distribution function $F_u(x)$ of exceedances of X over a high tail threshold u:

$$F_u(x) = P\{X - u \leq x \mid X > u\} = \frac{F(x+u) - F(u)}{1 - F(u)} \tag{6}$$

As u gets large, the distribution of exceedences tends to a Generalized Pareto Distribution (GPD):

$$G_{\xi,\beta}(x) = \begin{cases} 1-(1+\xi x/\beta)^{-1/\xi} & \text{if} \quad \xi \geq 0 \\ 1-\exp(-x/\beta) & \quad\quad\; \xi < 0 \end{cases} \tag{7}$$

where

$$x \in \begin{cases} [0,\infty) & \text{if} \quad \xi \geq 0 \\ [0, -\beta/\xi] & \quad\quad\; \xi < 0 \end{cases}$$

and the shape ξ and scale $\beta > 0$ parameters are estimated conditional on the threshold u (Balkema and de Haan, 1974; Embrechts *et al.*, 1997, pp. 162-164). *En passant*, note that the shape parameter ξ sometimes appears in GPD discussions couched in terms of its inverse, a tail index parameter α given by $\alpha = 1/\xi$.

The behavior of the GPD tail depends on the values of these parameters, and the shape parameter is especially important. A negative ξ is associated with very thin-tailed distributions that are rarely of relevance to financial data, and a zero ξ is associated with thin tailed distributions such as the Gaussian, but the most relevant for our purposes are heavy-tailed distributions associated with ξ>0. The tails of such distributions decay slowly and follow a heavy tailed 'power law' function. Moreover the number of finite moments is determined by the value of ξ (or α): if $\xi \leq 0.5$ (or, equivalently, $\alpha \geq 2$), we have infinite second and higher moments; if $\xi \leq 0.25$ (or α ≥ 4), we have infinite fourth and higher moments, and so forth. α therefore indicates the number of finite moments. Evidence generally suggests that the second moment is probably finite, but the fourth moment is more problematic (see, e.g., Loretan and Phillips,1994).

The values of the GPD parameters can be estimated by Maximum Likelihood (ML) methods using suitable (e.g., numerical optimization) methods. The log-likelihood function of the GPD is:

$$l(\xi,\beta) = -n(\ln(\beta) - (1+1/\xi)\sum_{i=1}^{n}\ln(1+\xi x_i/\beta) \qquad \text{for } \xi \neq 0 \qquad (8)$$

$$l(\beta) = -n(\ln(\beta) - \beta^{-1}\sum_{i=1}^{n} x_i \qquad \text{for } \xi = 0 \qquad (9)$$

where in both cases x_i satisfies the constraints specified above for x.

4. FORMULAS FOR RISK MEASURES UNDER THE POT APPROACH

Assuming that u is sufficiently high, the distribution function for exceedances is given by:

$$F_u(x) = 1 - \frac{N_u}{n}\left(1+\xi\frac{x-u}{\beta}\right)^{\frac{-1}{\xi}} \qquad (10)$$

where n is the sample size and N_u is the number of observations in excess of the threshold (Embrechts *et* al.,1997, p. 354). The p^{th} quantile of the return distribution -

which is also the VaR at the (high) confidence level p – can then be obtained by inverting the distribution function, viz.:

$$q_p = VaR_p = u + \frac{\beta}{\xi}\left\{\left(\frac{n}{N_u}p\right)^{-\xi} - 1\right\} \tag{11}$$

The ES is then given by:

$$ES_p = \frac{q_p}{1-\xi} + \frac{\beta - \xi u}{1-\xi} \tag{12}$$

To obtain our SRM, we now substitute (11) into (5) to get:

$$M_\phi = \int_0^1 \phi(p) q_p(X) dp = \int_0^1 \frac{e^{-(1-p)/R}}{R(1-e^{-1/R})}\left[u + \frac{\beta}{\xi}\left\{\left(\frac{n}{N_u}p\right)^{-\xi} - 1\right\}\right] dp \tag{13}$$

Having obtained the risk-measure formulas, estimates of the risk measures themselves are then obtained by estimating/choosing the relevant parameters and plugging these into the appropriate (i.e., (11) for the VaR, (12) for the ES, and (13) for the SRM). This is straightforward for the VaR and the ES; however, for spectral risk measures, we need to use a suitable numerical integration method (e.g., a trapezoidal rule, Simpson's rule, etc.: see Miranda and Fackler, 2002, or Cotter and Dowd, 2006, for further details).

5. DATA AND PRELIMINARY ANALYSIS

Our data set consists of weekly logarithmic price changes for Corn and Soybean contracts traded on the CBOT between January 1979 and December 2006 totalling 1461 observations. For each product there are 8 series analysed: 1 futures and 7 spot across 7 different geographical areas. We examine the tails of both long and short positions for each series, thus giving us a total of $8 \times 2 \times 2 = 32$ cases in total. We choose these particular crops for their importance in the US agricultural sector. Corn is the most widely produced feed grain in the US and accounts for 90% of the total value of feed grains produced. Approximately 80 million acres are planted to corn with most being in the heartland states. Illinois is the largest producer along with Iowa, hence the focus on the former for this analysis. Soybeans are also selected as the US is the world's largest producer and exporter of them and approximately 2.5 billion bushels were produced in 2007[6]. Illinois is again a major producer and is second only to Iowa in output terms. Soybeans are used for vegetable oil production and the meal for animal feed. Thus, we believe our choice of crop and state captures significant agricultural activity and thus could be viewed as suitably representative of arable production in the US albeit with a constrained focus.

As a preliminary, we illustrate some indicative time series properties in Figure 1 and Table 2. The mean returns are near zero for both spot and futures contacts, and the corresponding standard deviations suggest weekly volatilities in excess of 3% for both sets of contracts. The series are mostly negative skewed and always have excess kurtosis, and Jarque-Bera results indicate that normality is always rejected.

Insert Figure 1 here

Insert Table 2 here

Despite the fact that normality is rejected so strongly, it is useful to know what the risk measures would be under the counterfactual and heavily used assumption that returns are normal. These are reported in Table 3, and we will comment on these later when presenting the POT estimates of these risk measures.

Insert Table 3

[6] Data are drawn from the National Agricultural Statistics Service (NASS) of the USDA website at http://www.nass.usda.gov/

Figure 2 shows QQ plots for these series' empirical return distributions relative to a normal (or Gaussian) distribution. If the normal distribution is an adequate fit, then the QQ plot should be approximately a straight line. However, in each case, we find that the QQ plot is approximately straight only in the central region, and that the tails show steeper slopes than the central observations: this indicates that the tails exhibit heavier kurtosis than the normal distribution, and is consistent with the results of Table 2.

Insert Figure 2 here

In addition, the points where the QQ plots change shape provides us with natural estimates of tail thresholds, and these implied thresholds are also consistent with the tail index plots – plots of the estimated tail index α and its 95% confidence interval against the number of exceedances – shown in Figure 3. The number of exceedances reflects the choice of threshold, a smaller number reflecting a higher threshold. In each case the estimated tail index is stable over a wide range of exceedance numbers (or threshold size, if you prefer), and this tells us that the estimated indices are stable relative to the thresholds selected.

Insert Figure 3 here

The approach taken here focuses on both short and long positions. The rationale for this is to reflect the various agents that operate in the supply chain for agricultural commodities. At one end, the farmer faces price risk through production and thus will be interested in short positions. Equally, processors (and possibly retailers if the product can be sold without much processing such as potatoes for example) are concerned about the price of their inputs rising and will tend to take long positions in the futures market. Finally, there are also merchants who both buy and sell the commodities and potentially face input and output price risk and thus could take a mixed strategy approach to trading by going both short and long depending on their circumstances.

We now fit the distributions of exceedances and ML estimates of the GPD parameters are given in Table 4 for both long and short trading positions. The Table gives the assumed thresholds u, the associated numbers of exceedances (N_u) and the observed exceedance probabilities (*prob*). Also included and of most interest for the risk measures are the tail indices, ξ, and the scale parameter, β. The tail indices are generally positive (though not statistically significant) for the spot and futures contracts, and the scale parameters vary around 2. The numbers and probabilities of exceedances vary somewhat, but all confirm that the chosen thresholds are in the stable tail-index regions identified earlier.

Insert Table 4 here

To check that the GPD provides an adequate fit, Figure 4 shows empirical exceedances fitted to the GPDs based on the parameter estimates given in Table 1, and the results confirm that the GPD provides a good fit in all cases.

Insert Figure 4 here

6. BOOTSTRAP ALGORITHM

The estimates of standard errors and confidence intervals reported in this paper were obtained using a semi-parametric bootstrap set out by Cotter and Dowd (2006). To implement this procedure, we begin by taking 5000 bootstrap resamples, each of which consists of n=1492 uniform random variables. Each resample is then sorted into ascending order so that its relative frequencies can be considered 'as if' they were a set of resampled cumulative probabilities. For example, for the j^{th} resample, these relative frequencies are as $p_1^j, p_2^j, ..., p_n^j$, where $p_i^j \leq p_{i+1}^j$. We then use the fitted GPD (i.e., (11)) to obtain each element of the j^{th} resample set of losses. Thus, if

p_i^j is the i^{th} cumulative probability in the j^{th} resample, then q_i^j, the i^{th} highest loss in the j^{th} resample, can be obtained from

$$q_i^j = \hat{u} + \frac{\hat{\beta}}{\hat{\xi}} \left\{ \left(\frac{n}{\hat{N}_u} p_i^j \right)^{-\hat{\xi}} - 1 \right\} \tag{14}$$

where (14) is a version of (11) in which the '^' refer to the sample-based estimates of the GPD parameters. Since the VaRs are quantiles, (14) gives us direct resample estimates of the VaRs. Resample estimates of the ES and SRM are then obtained using (12) and (13) respectively (with q_p replaced by q_i^j and parameters replaced by their '^' estimates). For each resample, the standard errors and confidence interval were obtained from the set of resample estimates of the appropriate risk measures.

7. ESTIMATES OF VALUE AT RISK AND EXPECTED SHORTFALL

GPD estimates of VaR and ES are given in Table 5 for confidence levels of 99%, 99.5% and 99.9%: Table 5a gives the results for corn contracts and Table 5b gives the results for soybean contracts. To illustrate, the VaR of 9.989 at the 99% level implies that there is a 1% chance of having losses greater than 9.989% of the value of the corn Region 1 contract for a long trading position. These show, as we might expect, that estimated risk measures rise with the confidence level, and that the estimated VaRs are notably larger than the estimated ESs. There are no great differences between the different contracts or between the corn and soybean estimates of the risk measures, but the short and long results can be somewhat different from each other. It is also noteworthy that the estimated risk measures are usually much higher than the Gaussian-based estimates in Table 3 and the divergence increases as one moves to more extreme probability levels. This suggests that extreme risks are large, and that assuming Gaussianity in these circumstances can lead to very considerable under-estimates of our risk measures.

The Table also reports the bootstrapped standard errors of the estimated risk measures, and these rise considerably with the confidence level: this indicates that estimated risk measures become considerably less precise as the confidence level rises. This is a well-known phenomenon, and reflects the fact that as the confidence level rises, we are dealing with an increasingly extreme tail measured with fewer and fewer observations.[7]

Insert Table 5 here

Table 6 shows bootstrapped estimates of the standardized 90% confidence intervals for the VaR and ES: these are estimates of the 90% confidence intervals divided by the estimated mean risk measure, and are easier to interpret than conventional confidence intervals. So, for example, the first two results in the first row of Table 6a tell us that the 90% confidence interval for the region 1 spot VaR varies from 89.3% to 111.7% of the mean VaR, and so forth. Two features of these results stand out:

- The standardized confidence intervals for the ES are generally a little narrower than those for the VaR: this confirms that in relative terms, estimates of the ES are more precise than estimates of the VaR.
- The confidence intervals are fairly symmetric for the risk measures predicated on the 99% confidence level, but become asymmetric as the confidence level rises and, in particular, we see that the right bound is further from the mean risk measure than the left bound. To give an example, at the 99.9% confidence level, the standardized confidence interval spans the range from 80% to 125.5% of the mean risk measure (i.e., down 20%, but up 25.5%). This finding is also to be expected and again reflects the fact that as we move

[7] Interestingly, we also see that the standard errors are usually only a little larger for the ESs than for the VaRs: these indicate that ES estimates are a little less precise than VaR estimates in absolute terms. However, the ratios of estimated risk measures to standard errors are often lower for the ESs than for VaRs, so in relative terms (i.e., taking account of the sizes of the two risk measures), it is often the case that the ES is more precisely estimated than the VaR.

further out into the extreme tail, we run into fewer observations and our uncertainty increases further.

Insert Table 6 here

8. ESTIMATES OF SPECTRAL RISK MEASURES

We now turn to estimates of spectral risk measures. As we have discussed already, these risk measures make use of the coefficient of absolute risk aversion R rather than the confidence level as their conditioning parameter. The value of this coefficient depends on the user's attitude to risk, and can in principle be any positive number (assuming that the user is in fact risk-averse). However, in the present EV context it only makes sense to work with fairly high values of R: the higher is R, the more we are concerned about very high (i.e., extreme) losses relative to more moderate ones. A concern with extremes therefore suggests a high value of R. Accordingly, we consider here values of R equal to 20, 100 and 200.

Once a value of R has been chosen, we can estimate the value of the integral (13) using numerical integration. The idea behind this is to discretize the continuous variable *p* into a large number *N* of discrete 'slices', where the discrete approximation gets better as *N* gets larger. We then choose a suitable numerical integration method, and the ones we considered were the trapezoidal rule, Simpson's rule, and numerical integration procedures using quasi-Monte Carlo methods based on Niederreiter and Weyl algorithms respectively.[8]

However, we first need to evaluate the accuracy of these methods. To help us do so, Table 7 gives estimates of the approximation errors generated by these alternative numerical integration methods based on alternative values of *N* and a

[8] The choice of numerical integration method was also influenced by the need to have fast integration algorithms for use in our bootstrap algorithms. We used the Miranda-Fackler (2002) CompEcon functions, which are very fast indeed.

plausible set of benchmark parameters.[9] These results indicate that all methods have a negative bias for relatively small values of *N*, but they also indicate that the bias disappears as *N* gets large. In addition, they suggest that for high *N*, the trapezoidal method is at least as accurate as any of the others.

Insert Table 7 here

For the remaining estimations, we selected a benchmark method consisting of the trapezoidal rule calibrated with *N*=1 million.[10]

Estimates of SRMs and their bootstrapped standard errors and standardised 90% confidence bounds are given in Table 8. In many respects these results are comparable to those obtained earlier for the VaR and ES, but with R playing the same role as the earlier confidence level. In particular, we see that:

- Estimated SRMs are considerably higher than the normal estimates in Table 3.
- Estimated SRMs rise notably as R increases.
- Estimated SEs and the widths of confidence intervals rise as R increases; we also see some asymmetry in the confidence intervals for very high values of R, again with the right bound being a little further away from the mean than the left bound.[11]
- Differences across contract types are fairly small, and the only noteworthy difference between the corn and soybean results is that the latter have more pronounced differences between long and short positions.

Insert Table 8 here

[9] These benchmark parameters were the mean parameters in Table 2 for the case where $R = 100$.

[10] There is of course a tradeoff between calculation time and accuracy, but the choice of *N*=1 million gives us results that are accurate to within half a percentage point in the illustrative case examined in Table 7, and this is accurate enough for our purposes.

[11] This phenomenon was also observed by Cotter and Dowd (2006), and the explanation is that as R increases, an SRM estimator places more weight on a smaller number of extreme observations, and therefore operates with a smaller effective sample size. For very high values of R, we would then get right- and left-asymmetry reflecting the greater paucity of observations on the right-hand side.

9. CONCLUSIONS

Effective and accurate measurement of risk in agricultural markets is central to informing how best to design strategies and instruments aimed at helping farmers manage the risks they face. Toward this end, this paper applies the Peaks-Over-Threshold version of Extreme Value Theory to estimate the extreme financial risk measures for a selection of agricultural contracts. The risk measures considered were the Value at Risk (VaR), the Expected Shortfall (ES), and the Spectral Risk Measure (SRM) based on an exponential risk-aversion function for a given coefficient of absolute risk aversion. We examine the properties of these risk measures and suggest that SRM is to be preferred to the ES, which in turn is to be preferred to the VaR. We also estimate both the risk measures themselves and some precision metrics obtained using a parametric bootstrap procedure. Our empirical results suggest three main conclusions, and this is the case for all three risk measures. First, we find that the estimated risk measures are all considerably higher than the estimates we would have obtained under Gaussianity. This suggests that Gaussianity can lead to major under-estimates of extreme risks. Second, we find that estimated risk measures are quite uncertain, as judged by the estimated standard errors and confidence intervals. This is to be expected, as EV problems almost by definition involve small numbers of extreme observations. Third, we find that the degree of uncertainty associated with our estimated risk measures increases as we go further out into the tail. This finding also makes intuitive sense: the further we go into the tail, the more sparse our observations become, and the more uncertain any estimates will be. In a nutshell, extreme risk measures are large, but also uncertain.

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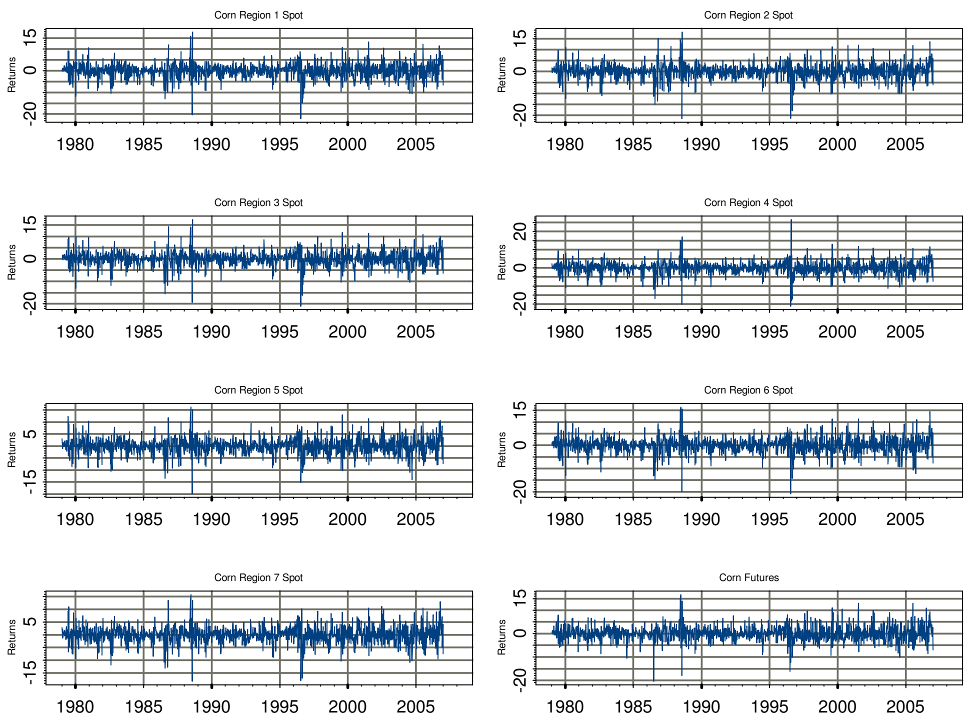
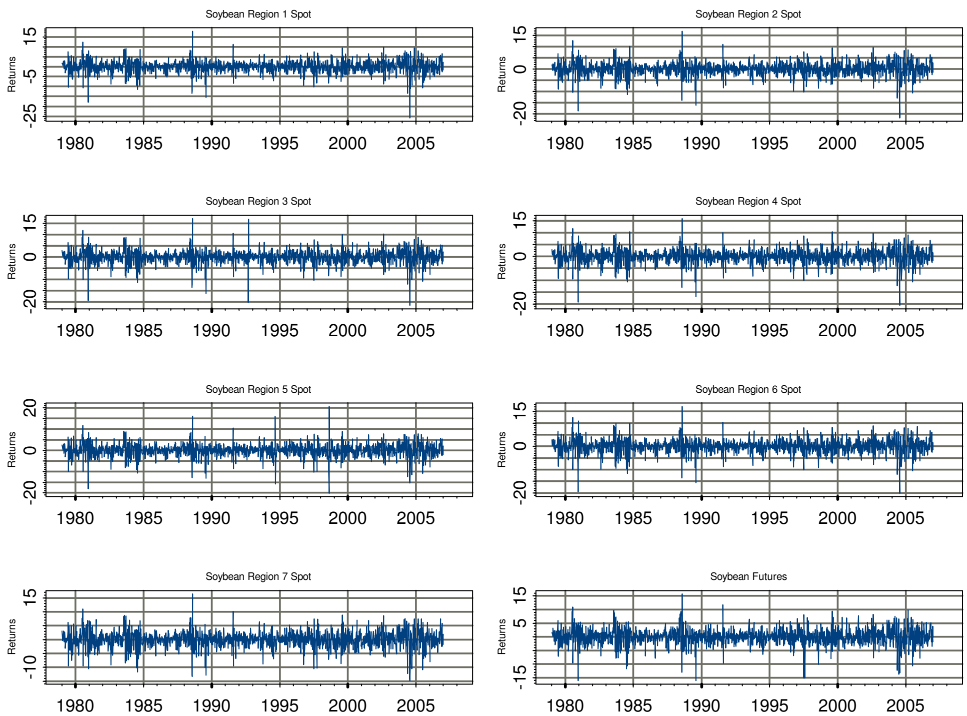
FIGURES

Figure 1a: Time Series Plots of Weekly Series: Corn



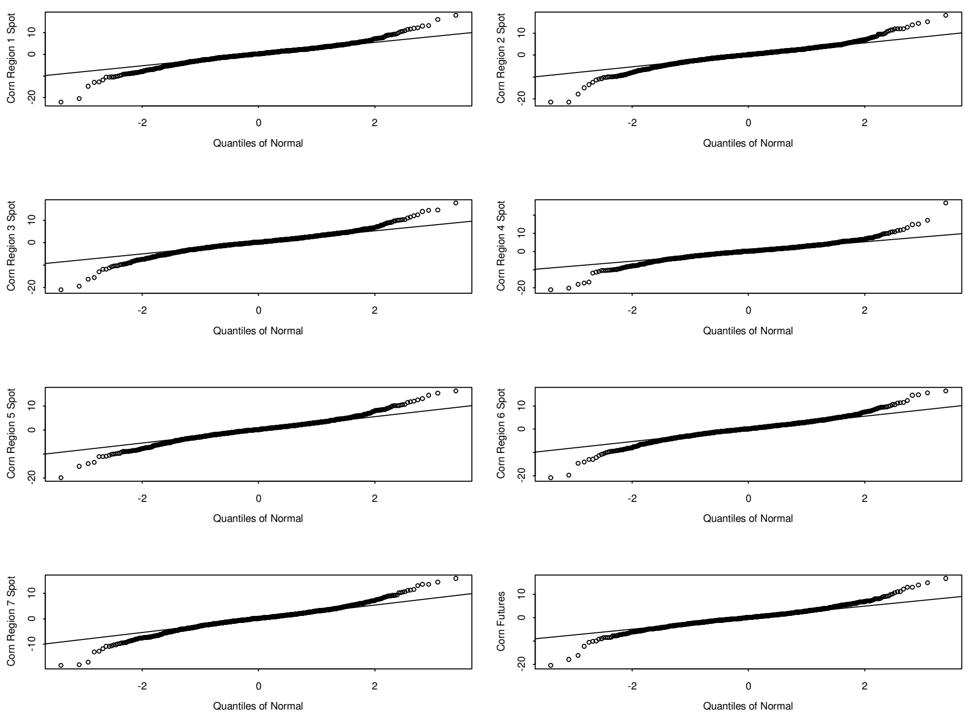
Notes: Plots show weekly % returns for each contract over the period January 1979 to December 2006. The sample size is 1461.

Figure 1b: Time Series Plots of Weekly Series: Soybeans



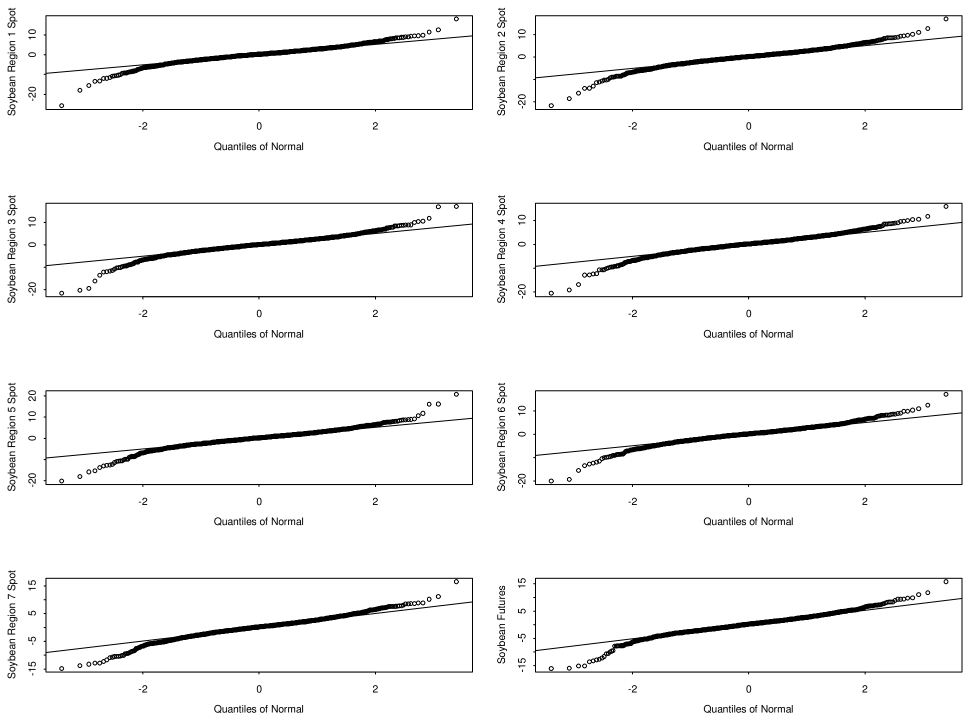
Notes: Plots show weekly % returns for each contract over the period January 1979 to December 2006. The sample size is 1461.

Figure 2a: QQ Plots for Corn Spot and Futures Returns



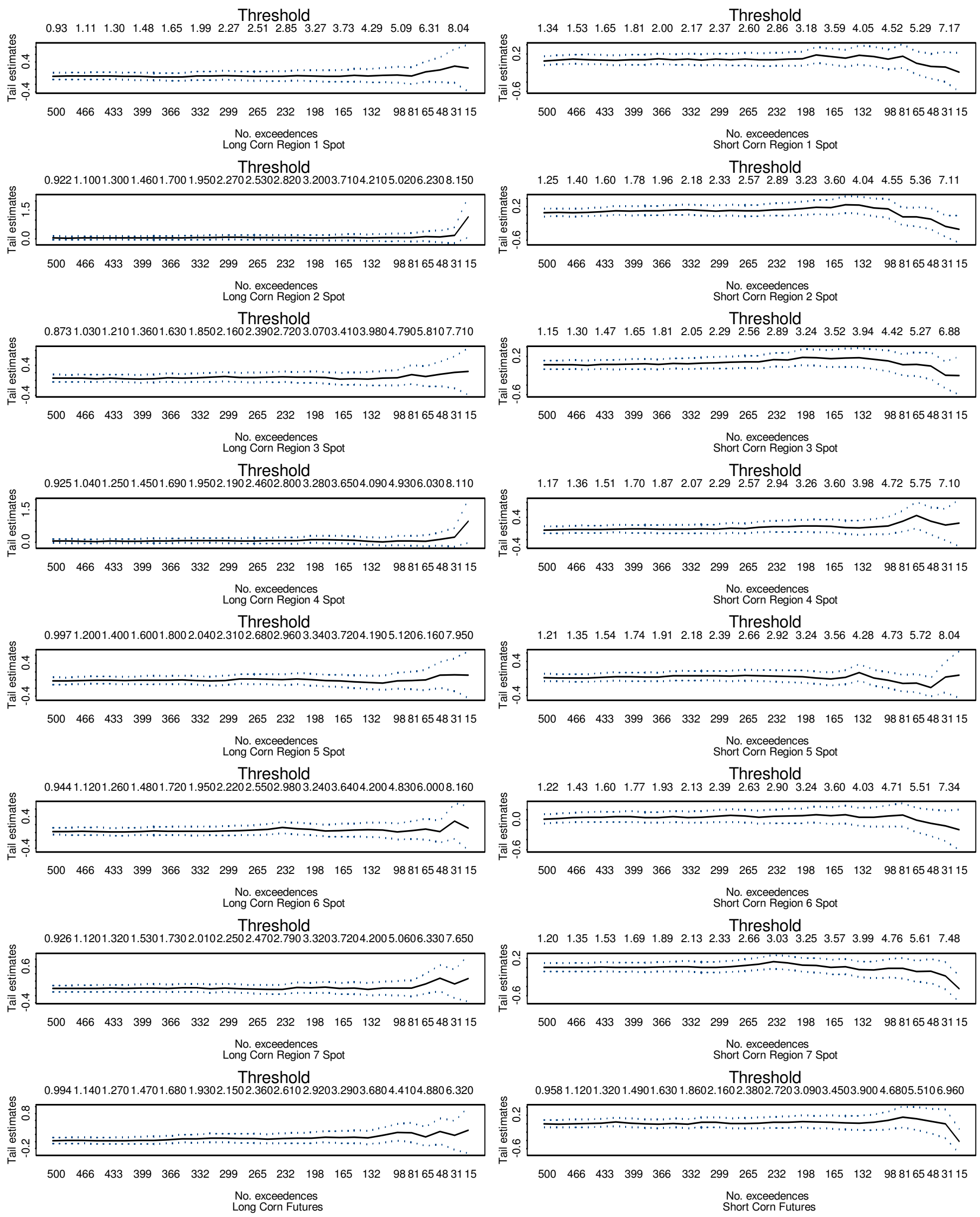
Notes: Plots show empirical quantiles of return series against those of a normal distribution. Based on 1461 weekly observations over the period January 1979 to December 2006.

Figure 2b: QQ Plots for Soybean Spot and Futures Returns



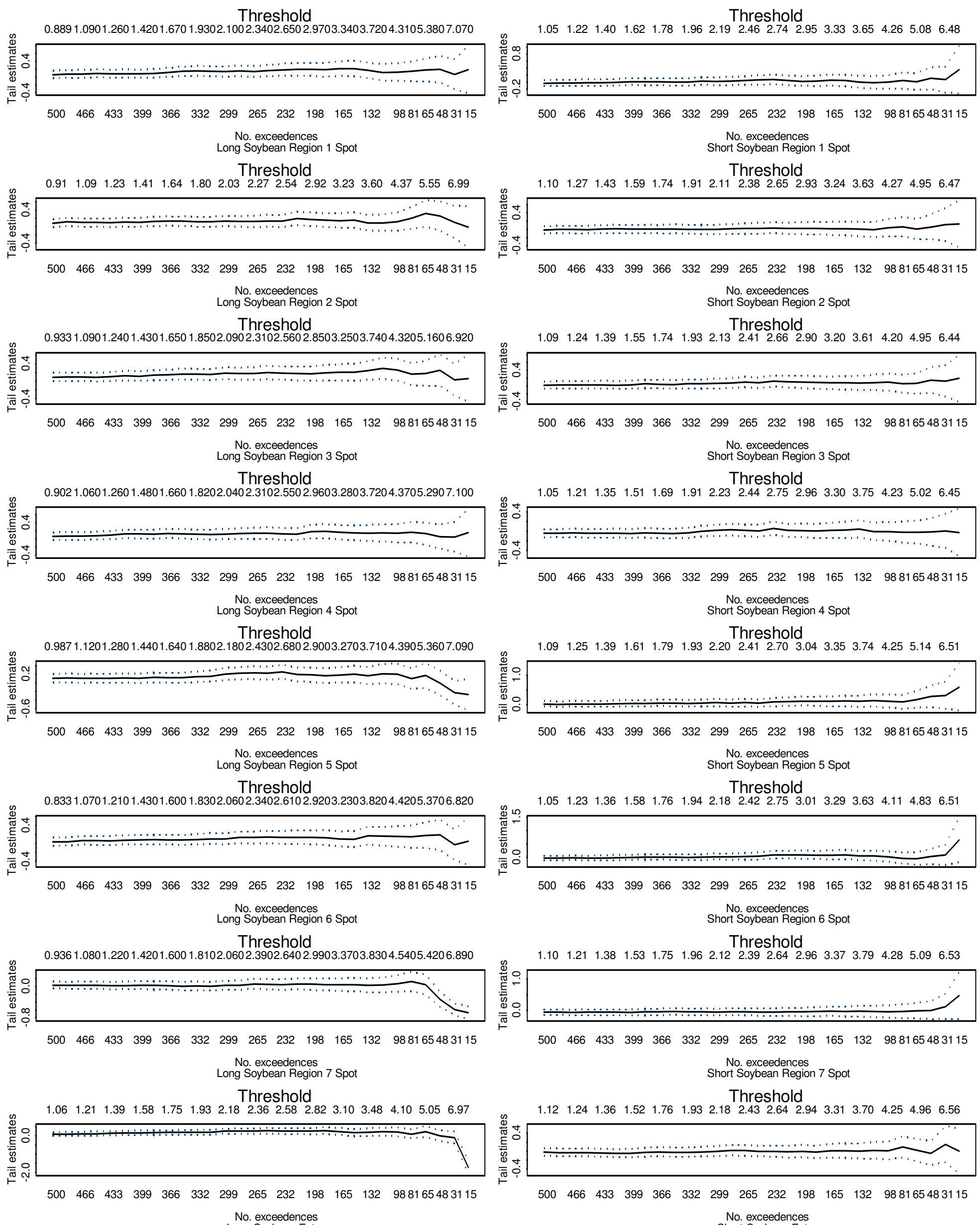
Notes: Plots show empirical quantiles of return series against those of a normal distribution. Based on 1461 weekly observations over the period January 1979 to December 2006.

Figure 3a: Tail Index Plots as Functions of Numbers of Exceedances: Corn Spot and Futures



Notes: Plots show tail index (ξ) estimates and 95% confidence bands are presented as a function of threshold size and number of exceedences. Based on 1461 weekly observations over the period January 1979 to December 2006.

Figure 3b: Tail Index Plots as Functions of Numbers of Exceedances: Soybean Spot and Futures



Notes: Plots show tail index (ξ) estimates and 95% confidence bands are presented as a function of threshold size and number of exceedences. Based on 1461 weekly observations over the period January 1979 to December 2006.

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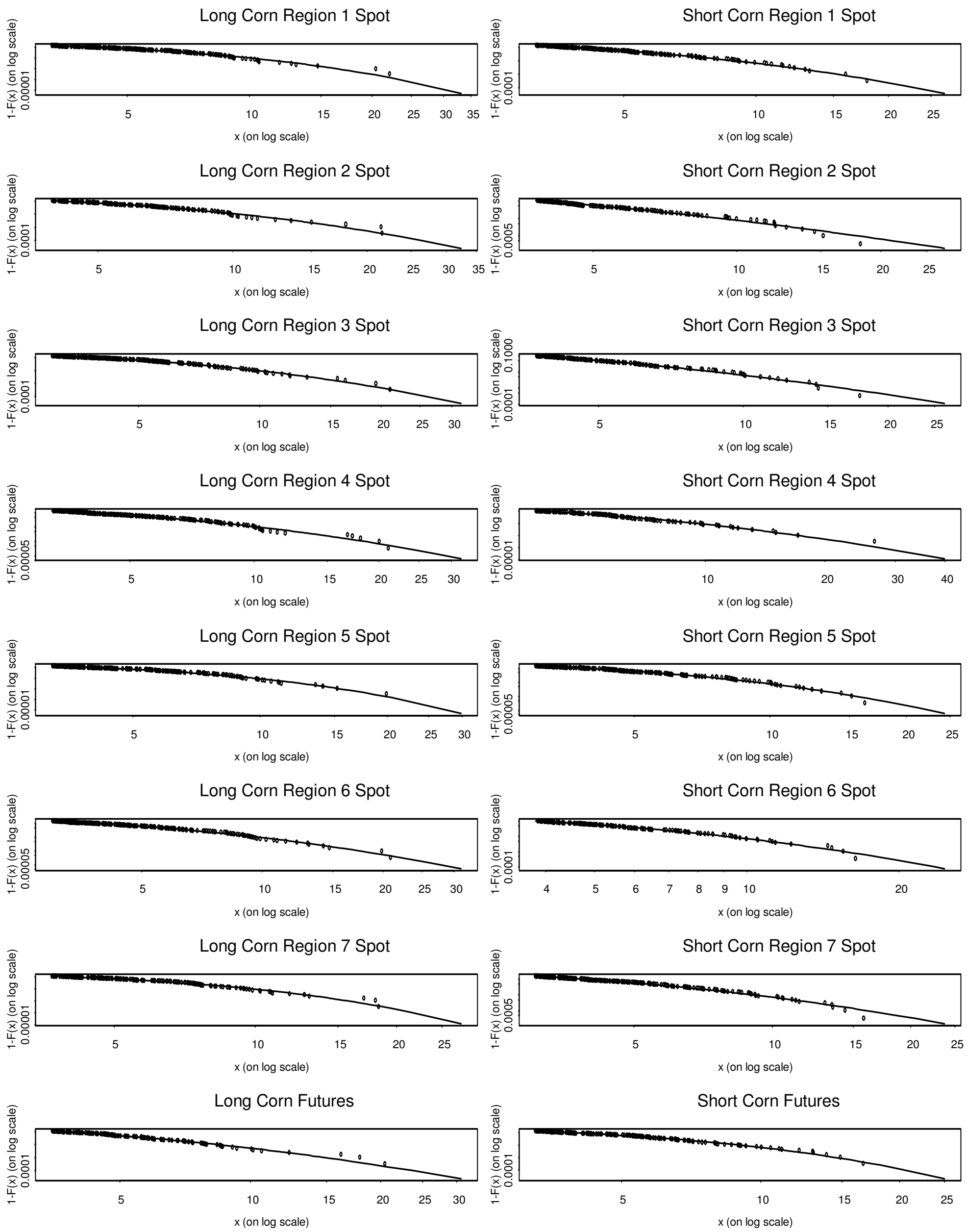
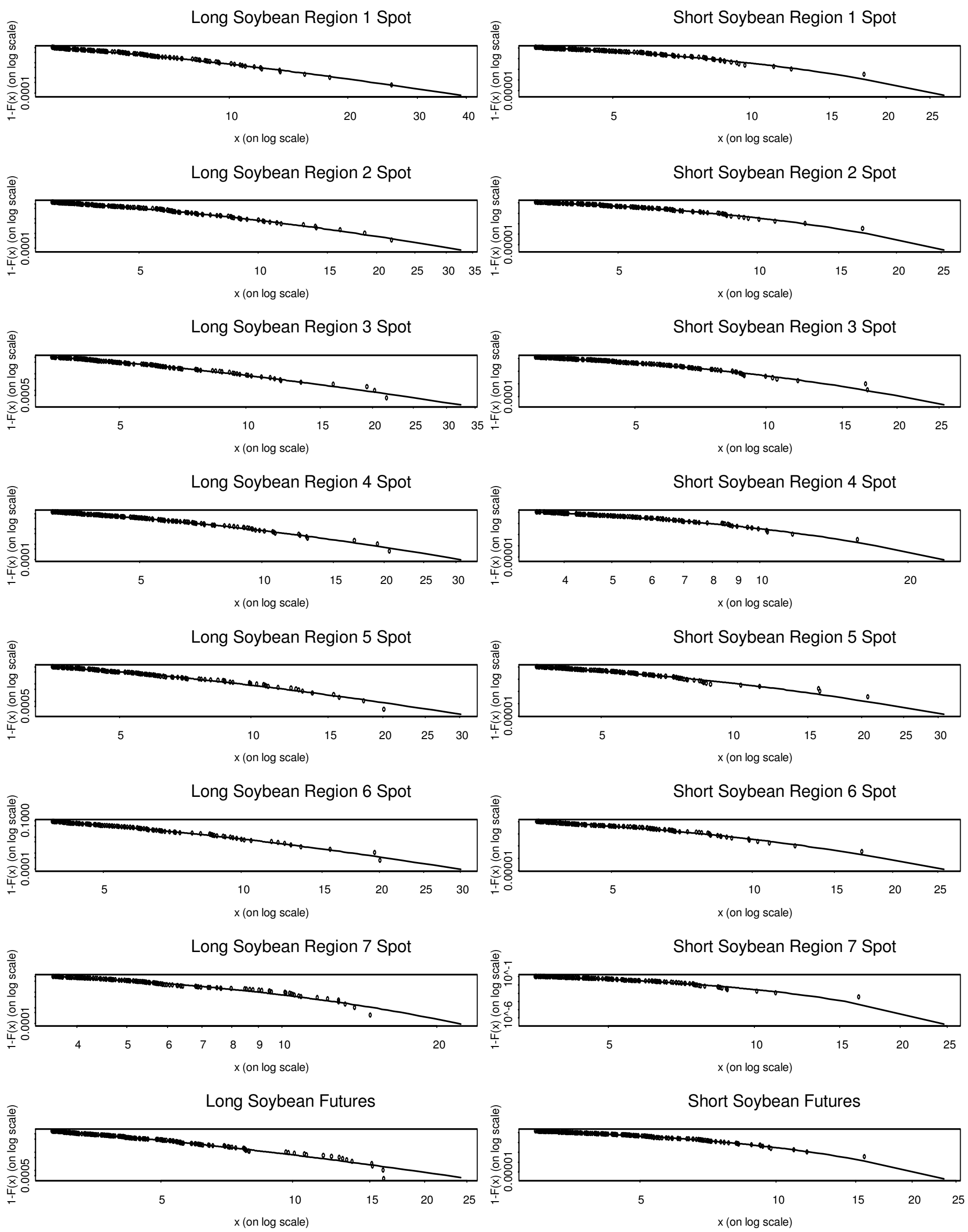
Figure 4a: Exceedances Fitted to GPD: Corn Spot and Futures



Notes: Plots show empirical exceedances against GPD-fitted exceedance curves. Based on 1461 weekly observations over the period January 1979 to December 2006.

Figure 4b: Exceedances Fitted to GPD: Soybean Spot and Futures



Notes: Plots show empirical exceedances against GPD-fitted exceedance curves. Based on 1461 weekly observations over the period January 1979 to December 2006.

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TABLES

Table 1: Existing Studies of Measures of Agricultural Financial Risk

Study	Application	Data	Estimation method
Manfredo and Leuthold (2001)	US cattle market	Weekly cash prices	Parametric methods, including RiskMetrics, and Garch and implied volatility estimates of volatility. Historical simulation
Odening and Mußhoff (2002)	German hog market	Weekly prices	Multivariate parametric methods including EWM A and GARCH volatility models. Historical simulation
Odening and Hinrichs (2003)	German hogs and farrows. Focus on cashflow-at-risk rather than VaR per se	Weekly prices.	Parametric methods with GARCH, square-root rule and Drost-Nijman formula for volatilities. Historical simulation and Generalized Extreme Value approaches
Pritchett et alia (2004)	Impact of alternative risk management strategies in US agriculture	Annual	Unspecified
Dawson and White (2005)	A typical UK arable farm	Weekly cash prices	Multivariate parametric methods, including RiskMetrics and GARCH volatility models
Katchova and Barry (2005)	Portfolio of Illinois farms	Annual 1995-2002	CreditMetrics and KMV models of credit quality used to estimate default VaRs
Siaplay et alia (2005)	US turkey market, with the emphasis on food safety	Monthly prices and costs	Various parametric methods (including Extreme Value distribution) estimated using @Risk software
Wilson et alia (2005)	US bakeries	Monthly	Monte Carlo
Zhang et alia (2007)	Applies downside risk management techniques to investigate how US Govt. policies affect a typical farm's financial risk management	Cotton in Colquitt County GA Daily futures prices	Monte Carlo simulation, conditional kernel approach, copula methods

Table 2: Summary Statistics for Weekly Series

	Mean	Std Dev	Skewness	Kurtosis	JB P-value
			Corn		
Reg 1 Spot	0.033	3.495	-0.331	6.557	0
Reg 2 Spot	0.033	3.554	-0.342	7.022	0
Reg 3 Spot	0.034	3.402	-0.347	6.942	0
Reg 4 Spot	0.033	3.585	-0.153	8.540	0
Reg 5 Spot	0.029	3.512	-0.109	5.491	0
Reg 6 Spot	0.030	3.497	-0.279	6.362	0
Reg 7 Spot	0.029	3.485	-0.219	5.698	0
Futures	0.032	3.205	0.005	6.857	0
			Soybean		
Reg 1 Spot	-0.001	3.224	-0.640	8.379	0
Reg 2 Spot	0.000	3.166	-0.577	7.435	0
Reg 3 Spot	-0.001	3.210	-0.597	8.488	0
Reg 4 Spot	-0.001	3.169	-0.571	7.058	0
Reg 5 Spot	-0.001	3.272	-0.393	7.849	0
Reg 6 Spot	0.000	3.161	-0.516	7.092	0
Reg 7 Spot	-0.001	3.127	-0.383	5.404	0
Futures	-0.001	3.100	-0.444	6.359	0

Notes: Based on 1462 weekly % return observations for each of the stated series indexes over the period January 1979 through December 2006. Mean and standard deviation are in percentage form. 'JB P-value' is the P-value of the Jarque-Bera normality test.

Table 3: Estimated Risk Measures Under the Assumption that Returns are Normal

	VaR at $\alpha =$			ES at $\alpha =$			SRM at γ ARA=		
	0.99	0.995	0.999	0.99	0.995	0.999	20	100	200
					Corn				
Reg 1 Spot	8.098	8.970	10.767	9.282	10.074	11.735	6.512	8.788	9.624
Reg 2 Spot	8.235	9.122	10.950	9.439	10.245	11.934	6.621	8.936	9.786
Reg 3 Spot	7.880	8.729	10.479	9.033	9.804	11.421	6.340	8.556	9.370
Reg 4 Spot	8.307	9.201	11.046	9.522	10.335	12.038	6.678	9.014	9.871
Reg 5 Spot	8.141	9.017	10.824	9.331	10.128	11.796	6.539	8.827	9.666
Reg 6 Spot	8.105	8.978	10.777	9.290	10.083	11.745	6.512	8.790	9.626
Reg 7 Spot	8.078	8.948	10.741	9.259	10.049	11.705	6.489	8.759	9.592
Futures	7.424	8.224	9.872	8.510	9.237	10.760	5.973	8.061	8.827
					Soybeans				
Reg 1 Spot	7.501	8.306	9.964	8.594	9.325	10.857	5.975	8.075	8.846
Reg 2 Spot	7.365	8.155	9.784	8.438	9.156	10.660	5.869	7.931	8.688
Reg 3 Spot	7.469	8.269	9.921	8.556	9.284	10.809	5.949	8.040	8.808
Reg 4 Spot	7.373	8.164	9.794	8.447	9.166	10.671	5.873	7.938	8.695
Reg 5 Spot	7.613	8.429	10.112	8.722	9.464	11.018	6.064	8.196	8.978
Reg 6 Spot	7.354	8.142	9.768	8.425	9.141	10.643	5.859	7.919	8.674
Reg 7 Spot	7.275	8.055	9.663	8.334	9.043	10.529	5.796	7.833	8.581
Futures	7.213	7.986	9.581	8.263	8.966	10.439	5.745	7.765	8.506

Notes: Based on 1462 weekly % return observations for each of the stated series indexes over the period January 1979 through December 2006. Estimates of SRMs obtained using the CompEcon software of Miranda and Fackler (2002) written in MATLAB using the trapezoidal rule and N=1m 'slices'.

Table 4: GPD Parameters for Weekly Series

	Long Position					Short Position				
	u	*prob*	N_u	$\hat{\xi}$ (tail)	$\hat{\beta}$ (scale)	u	*prob*	N_u	$\hat{\xi}$ (tail)	$\hat{\beta}$ (scale)
					Corn					
Reg 1 Spot	3.269	0.862	201	0.036	2.445	3.153	0.863	200	0.089	1.978
				(0.068)	(0.239)				(0.078)	(0.208)
Reg 2 Spot	3.957	0.897	150	0.073	2.478	3.793	0.897	150	0.207	1.813
				(0.085)	(0.292)				(0.113)	(0.250)
Reg 3 Spot	3.052	0.863	200	0.084	2.320	3.697	(0.897	150	0.167	1.786
				(0.078)	(0.243)				(0.106)	(0.238)
Reg 4 Spot	3.238	0.863	200	0.118	2.293	3.748	0.897	150	0.135	2.080
				(0.068)	(0.239)				(0.078)	(0.208)
Reg 5 Spot	3.223	0.856	210	0.016	2.357	3.031	0.849	220	0.056	2.165
				(0.073)	(0.237)				(0.080)	(0.226)
Reg 6 Spot	2.993	0.843	230	0.120	2.104	3.822	0.897	150	0.091	2.037
				(0.080)	(0.217)				(0.098)	(0.260)
Reg 7 Spot	3.685	0.884	170	0.012	2.454	3.048	0.843	230	0.130	1.828
				(0.076)	(0.264)				(0.087)	(0.200)
Futures	3.484	0.897	150	0.132	1.781	3.256	0.877	180	0.033	2.162
				(0.084)	(0.208)				(0.078)	(0.234)
					Soybean					
Reg 1 Spot	3.550	0.897	150	0.229	1.875	3.377	0.890	160	0.040	1.843
				(0.109)	(0.254)				(0.082)	(0.210)
Reg 2 Spot	3.008	0.870	190	0.177	1.921	3.308	0.890	160	0.022	1.863
				(0.090)	(0.221)				(0.078)	(0.207)
Reg 3 Spot	3.462	0.897	150	0.223	1.921	2.951	0.870	190	0.083	1.795
				(0.102)	(0.248)				(0.078)	(0.191)
Reg 4 Spot	3.043	0.870	190	0.178	1.903	3.494	0.897	150	0.028	1.801
				(0.109)	(0.254)				(0.082)	(0.210)
Reg 5 Spot	3.506	0.897	150	0.205	2.021	3.525	0.897	150	0.116	1.752
				(0.107)	(0.270)				(0.083)	(0.203)
Reg 6 Spot	3.870	0.911	130	0.179	1.958	3.433	0.897	150	0.075	1.732
				(0.109)	(0.272)				(0.095)	(0.216)
Reg 7 Spot	3.580	0.897	150	0.052	2.200	3.533	0.897	150	-0.023	1.856
				(0.100)	(0.283)				(0.068)	(0.197)
Futures	2.821	0.863	200	0.252	1.627	2.934	0.863	200	0.000	1.842
				(0.095)	(0.191)				(0.007)	(0.131)

Notes: The Table presents estimates of the GPD parameters for long and short positions in spot and futures corn and soybean contracts. The sample size n is 1462, the threshold is u, the probability of an observation in excess of u is *prob*, the number of exceedences in excess of u is N_u, the estimated tail parameter is $\hat{\xi}$ and the estimated scale parameter is $\hat{\beta}$. The numbers in brackets are the estimated standard errors of the parameters concerned. The thresholds u are chosen as the approximate points where the QQ plots for each series change slope.

Table 5a: GPD Values-at-Risk and Expected Shortfalls: Corn Spot and Futures Contracts

	Long positions			Short positions		
	α =0.99	α =0.995	α =0.999	α =0.99	α =0.995	α =0.999
			Values-at-Risk			
Region 1 spot	9.989	11.875	16.440	8.979	10.764	15.359
SE	0.678	1.008	2.304	0.629	0.975	2.458
Region 2 spot	10.246	12.334	17.610	7.327	8.752	12.969
SE	0.741	1.133	2.772	0.482	0.819	2.595
Region 3 spot	9.839	11.902	17.181	8.779	10.716	16.178
SE	0.729	1.124	2.808	0.664	1.093	3.199
Region 4 spot	10.265	12.520	18.526	9.438	11.508	17.130
SE	0.787	1.247	3.320	0.718	1.153	3.170
Region 5 spot	9.640	11.354	15.409	9.370	11.151	15.563
SE	0.621	0.909	2.004	0.636	0.960	2.276
Region 6 spot	9.865	11.981	17.632	9.105	10.906	15.554
SE	0.738	1.171	3.131	0.635	0.985	2.492
Region 7 spot	9.795	11.554	15.696	9.106	11.003	16.127
SE	0.638	0.931	2.038	0.659	1.054	2.872
Futures	8.338	10.096	14.855	8.915	10.562	14.534
SE	0.610	0.978	2.674	0.593	0.879	1.998
			Expected Shortfalls			
Region 1 spot	12.777	14.733	19.468	11.720	13.679	18.723
SE	0.703	1.045	2.390	0.691	1.070	2.698
Region 2 spot	13.414	15.667	21.359	9.739	11.537	16.855
SE	0.799	1.222	2.991	0.607	1.033	3.272
Region 3 spot	12.995	15.247	21.010	11.942	14.267	20.824
SE	0.796	1.227	3.066	0.797	1.313	3.841
Region 4 spot	13.805	16.362	23.171	12.731	15.124	21.623
SE	0.892	1.414	3.764	0.830	1.333	3.665
Region 5 spot	12.139	13.882	18.002	12.039	13.926	18.600
SE	0.631	0.923	2.036	0.673	1.017	2.410
Region 6 spot	13.193	15.598	22.019	11.874	13.856	18.969
SE	0.839	1.331	3.558	0.698	1.083	2.741
Region 7 spot	12.353	14.134	18.325	12.112	14.293	20.182
SE	0.646	0.942	2.063	0.758	1.212	3.301
Futures	11.129	13.154	18.636	11.344	13.047	17.155
SE	0.703	1.126	3.081	0.613	0.909	2.067

Notes: Based on 1462 weekly % return observations for each of the stated series indexes over the period January 1979 through December 2006. α indicates the confidence level and SE indicates the standard error of the risk measure in the box above. Standard errors are based on 5000 semi-parametric bootstrap resamples.

Table 5b: GPD Values-at-Risk and Expected Shortfalls: Soybean Spot and Futures Contracts

	Long positions			Short positions		
	α =0.99	α =0.995	α =0.999	α =0.99	α =0.995	α =0.999
			Values-at-Risk			
Region 1 spot	9.317	11.717	19.006	8.005	9.430	12.897
SE	0.805	1.393	4.611	0.512	0.763	1.757
Region 2 spot	9.243	11.474	17.841	7.885	9.257	12.523
SE	0.762	1.265	3.775	0.496	0.729	1.624
Region 3 spot	9.326	11.746	19.042	8.081	9.666	13.716
SE	0.813	1.401	4.580	0.560	0.863	2.152
Region 4 spot	9.228	11.444	17.778	7.827	9.172	12.399
SE	0.757	1.257	3.759	0.485	0.717	1.615
Region 5 spot	9.537	11.963	19.122	8.208	9.865	14.266
SE	0.820	1.393	4.394	0.578	0.915	2.428
Region 6 spot	9.106	11.243	17.356	7.839	9.306	13.023
SE	0.729	1.213	3.633	0.520	0.797	1.957
Region 7 spot	9.025	10.778	15.099	7.741	8.950	11.686
SE	0.626	0.943	2.219	0.445	0.631	1.298
Futures	8.847	11.229	18.663	7.753	9.029	11.994
SE	0.792	1.397	4.846	0.465	0.672	1.441
			Expected Shortfalls			
Region 1 spot	13.462	16.575	26.029	10.118	11.602	15.213
SE	1.044	1.807	5.981	0.533	0.795	1.830
Region 2 spot	12.918	15.629	23.365	9.893	11.296	14.635
SE	0.926	1.537	4.587	0.507	0.745	1.661
Region 3 spot	13.481	16.596	25.985	10.503	12.231	16.648
SE	-1.046	1.803	5.895	0.611	0.941	2.347
Region 4 spot	12.883	15.579	23.284	9.805	11.189	14.508
SE	0.920	1.530	4.574	0.499	0.737	1.661
Region 5 spot	13.634	16.685	25.690	10.805	12.679	17.658
SE	1.032	1.752	5.526	0.654	1.035	2.746
Region 6 spot	12.632	15.235	22.681	10.069	11.655	15.673
SE	0.888	1.477	4.426	0.562	0.861	2.116
Region 7 spot	11.645	13.493	18.052	9.460	10.643	13.317
SE	0.661	0.994	2.341	0.435	0.617	1.269
Futures	13.052	16.237	26.176	9.595	10.872	13.836
SE	1.059	1.867	6.478	0.465	0.672	1.441

Notes: Based on 1462 weekly % return observations for each of the stated series indexes over the period January 1979 through December 2006. α indicates the confidence level and SE indicates the standard error of the risk measure in the box above. Standard errors are based on 5000 semi-parametric bootstrap resamples.

Table 6a: Standardised 90% Confidence Intervals for Values-at-Risk and Expected Shortfalls: Corn Spot and Futures Contracts

	Long positions						Short positions					
	α =0.99		α =0.995		α =0.999		α =0.99		α =0.995		α =0.999	
contract	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB
Values-at-Risk												
region 1 spot	0.893	1.117	0.871	1.148	0.800	1.255	0.890	1.121	0.864	1.159	0.780	1.293
region 2 spot	0.886	1.125	0.861	1.161	0.781	1.288	0.899	1.115	0.864	1.166	0.748	1.366
region 3 spot	0.884	1.128	0.858	1.165	0.774	1.299	0.883	1.132	0.850	1.180	0.743	1.363
region 4 spot	0.880	1.133	0.851	1.175	0.758	1.329	0.882	1.132	0.851	1.176	0.754	1.340
region 5 spot	0.898	1.110	0.877	1.139	0.812	1.236	0.893	1.117	0.870	1.150	0.794	1.267
region 6 spot	0.883	1.130	0.854	1.172	0.761	1.326	0.891	1.121	0.864	1.158	0.780	1.293
region 7 spot	0.897	1.112	0.877	1.140	0.812	1.236	0.887	1.126	0.858	1.168	0.762	1.327
futures	0.886	1.127	0.856	1.170	0.760	1.330	0.895	1.114	0.873	1.145	0.804	1.250
Expected Shortfalls												
region 1 spot	0.913	1.094	0.892	1.123	0.825	1.223	0.908	1.102	0.882	1.137	0.802	1.264
region 2 spot	0.907	1.103	0.882	1.136	0.805	1.256	0.904	1.109	0.870	1.159	0.756	1.355
region 3 spot	0.904	1.106	0.879	1.141	0.799	1.267	0.897	1.116	0.865	1.162	0.760	1.338
region 4 spot	0.899	1.112	0.871	1.152	0.781	1.298	0.899	1.113	0.869	1.155	0.774	1.311
region 5 spot	0.918	1.089	0.898	1.115	0.837	1.205	0.912	1.096	0.889	1.127	0.818	1.236
region 6 spot	0.901	1.110	0.873	1.150	0.783	1.296	0.908	1.101	0.883	1.137	0.802	1.265
region 7 spot	0.917	1.089	0.898	1.116	0.837	1.204	0.903	1.108	0.874	1.149	0.782	1.300
futures	0.902	1.110	0.873	1.151	0.780	1.303	0.915	1.093	0.894	1.121	0.828	1.219

Notes: Based on 1462 weekly % return observations for each of the stated series indexes over the period January 1979 through December 2006, and based on 5000 semi-parametric bootstrap resamples. α indicates the confidence level, and LB and UB refer to the lower and upper bounds of the 90% confidence interval divided by the estimated mean of the risk measure concerned.

Table 6b: Standardised 90% Confidence Intervals for Values-at-Risk and Expected Shortfalls: Soybean Spot and Futures Contracts

	Long positions						Short positions					
	α =0.99		α =0.995		α =0.999		α =0.99		α =0.995		α =0.999	
contract	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB
Values-at-Risk												
region 1 spot	0.867	1.152	0.828	1.211	0.701	1.443	0.899	1.110	0.877	1.141	0.806	1.248
region 2 spot	0.872	1.144	0.838	1.195	0.727	1.388	0.901	1.108	0.880	1.137	0.814	1.236
region 3 spot	0.866	1.153	0.827	1.211	0.702	1.439	0.891	1.120	0.866	1.156	0.783	1.287
region 4 spot	0.873	1.143	0.839	1.194	0.728	1.388	0.902	1.106	0.881	1.136	0.814	1.237
region 5 spot	0.867	1.151	0.830	1.206	0.711	1.421	0.890	1.122	0.862	1.163	0.770	1.312
region 6 spot	0.876	1.140	0.842	1.191	0.731	1.384	0.896	1.114	0.871	1.150	0.791	1.275
region 7 spot	0.891	1.120	0.867	1.152	0.793	1.268	0.909	1.098	0.891	1.122	0.836	1.200
futures	0.863	1.158	0.821	1.221	0.686	1.472	0.905	1.103	0.886	1.129	0.825	1.217
Expected Shortfalls												
region 1 spot	0.881	1.136	0.842	1.193	0.716	1.420	0.917	1.090	0.896	1.119	0.829	1.219
region 2 spot	0.889	1.125	0.856	1.174	0.747	1.360	0.919	1.088	0.899	1.114	0.837	1.206
region 3 spot	0.881	1.136	0.843	1.193	0.719	1.415	0.909	1.100	0.884	1.135	0.805	1.258
region 4 spot	0.890	1.125	0.856	1.173	0.747	1.360	0.920	1.087	0.899	1.114	0.836	1.208
region 5 spot	0.884	1.132	0.847	1.186	0.729	1.394	0.906	1.105	0.878	1.143	0.790	1.285
region 6 spot	0.891	1.123	0.858	1.171	0.749	1.358	0.913	1.096	0.889	1.129	0.813	1.247
region 7 spot	0.911	1.097	0.888	1.128	0.817	1.236	0.927	1.078	0.910	1.100	0.859	1.172
futures	0.876	1.143	0.835	1.204	0.701	1.450	0.923	1.083	0.905	1.107	0.848	1.188

Notes: Based on 1462 weekly % return observations for each of the stated series indexes over the period January 1979 through December 2006, and based on 5000 semi-parametric bootstrap resamples. α indicates the confidence level, and LB and UB refer to the lower and upper bounds of the 90% confidence interval divided by the estimated mean of the risk measure concerned.

Table 7: Spectral Risk Measure Estimates and % Errors

Numerical Integration Method	N =1000	N =10,000	N =100,000	N =1m	N =10m	N =20m
			Spectral Risk Measure (SRM) Estimates			
Trapezoidal rule	8.926	10.451	10.693	10.728	10.733	10.733
Simpson's rule	8.894	10.448	10.693	10.728	10.733	10.733
Niederreiter QMC	9.154	10.340	10.668	10.725	10.733	10.733
Weyl QMC	9.154	10.340	10.668	10.725	10.733	10.733
			% errors in SRM estimates			
Trapezoidal rule	N =1000	N =10,000	N =100,000	N =1m	N =10m	
Simpson's rule	-16.835	-2.628	-0.372	-0.048	-0.003	NA
Niederreiter QMC	-17.131	-2.658	-0.376	-0.048	-0.003	NA
Weyl QMC	-14.712	-3.666	-0.610	-0.075	-0.005	NA
Trapezoidal rule	-14.712	-3.666	-0.610	-0.075	-0.005	NA

Notes: Based on the mean parameters from Table 1 (i.e., β=1.98, ξ=0.1042, threshold = 3.3701 and N_u=173.7813) and R (coefficient of absolute risk aversion) =100, where N is the number of slices in the numerical integration. Errors are assessed against a 'true' value obtained using N=20m. Calculations carried out using the CompEcon software of Miranda and Fackler (2002) written in MATLAB using the trapezoidal rule.

Table 8a: Spectral Risk Measures and Associated Precision Statistics for Corn Spot and Futures

	Long Position						Short position					
	R =20		*R* =100		*R* =200		*R* =20		*R* =100		*R* =200	
	UB	LB	UB	LB	UB	UB	LB	UB	LB	UB	LB	UB
Region 1	7.344		11.635		13.558		6.691		10.655		12.542	
SE	0.435		1.423		2.289		0.398		1.330		2.166	
CI	0.903	1.097	0.808	1.205	0.737	1.288	0.903	1.097	0.806	1.210	0.733	1.297
Region 2	7.494		12.163		14.346		5.847		8.910		10.574	
SE	0.454		1.520		2.474		0.338		1.151		1.918	
CI	0.901	1.099	0.805	1.209	0.733	1.296	0.906	1.095	0.800	1.218	0.724	1.317
Region 3	7.172		11.762		13.935		6.617		10.809		12.987	
SE	0.438		1.482		2.422		0.406		1.412		2.356	
CI	0.900	1.101	0.804	1.212	0.732	1.299	0.901	1.102	0.797	1.221	0.722	1.314
Region 4	7.516		12.470		14.906		6.990		11.510		13.777	
SE	0.465		1.600		2.642		0.430		1.484		2.459	
CI	0.900	1.102	0.800	1.216	0.729	1.306	0.900	1.102	0.799	1.217	0.727	1.308
Region 5	7.153		11.095		12.822		6.954		10.967		12.807	
SE	0.416		1.339		2.138		0.410		1.348		2.176	
CI	0.904	1.094	0.811	1.201	0.739	1.285	0.903	1.096	0.808	1.206	0.736	1.290
Region 6	7.293		11.940		14.230		6.803		10.800		12.707	
SE	0.446		1.526		2.515		0.404		1.347		2.195	
CI	0.901	1.101	0.801	1.216	0.729	1.305	0.903	1.097	0.806	1.210	0.733	1.297
Region 7	7.227		11.281		13.049		6.842		10.992		13.061	
SE	0.422		1.363		2.176		0.412		1.400		2.307	
CI	0.904	1.095	0.811	1.201	0.739	1.285	0.902	1.099	0.802	1.215	0.730	1.305
Futures	6.248		10.091		12.011		6.593		10.346		12.022	
SE	0.378		1.289		2.128		0.387		1.260		2.023	
CI	0.901	1.100	0.801	1.216	0.729	1.306	0.903	1.096	0.809	1.203	0.737	1.287

Notes: Based on 1462 weekly % return observations for each of the stated series indexes over the period January 1979 through December 2006, and based on 5000 semi-parametric bootstrap resamples. *R* is the coefficient of absolute risk aversion, SE indicates the standard error, CI indicates the standardised 90% confidence interval, and LB and UB refer to its bounds. Calculations carried out using the CompEcon software of Miranda and Fackler (2002) written in MATLAB using the trapezoidal rule and *N*=1m 'slices'.

Table 8b: Spectral Risk Measures and Associated Precision Statistics for Soybean Spot and Futures

	Long Position						Short position					
	R =20		*R* =100		*R* =200		*R* =20		*R* =100		*R* =200	
	UB	LB	UB	LB	UB	UB	LB	UB	LB	UB	LB	UB
Region 1	6.928		12.072		14.935		6.019		9.256		10.713	
SE	0.458		1.691		2.904		0.347		1.122		1.797	
CI	0.896	1.109	0.785	1.238	0.706	1.339	0.905	1.094	0.810	1.202	0.738	1.287
Region 2	6.796		11.615		14.147		5.916		9.059		10.446	
SE	0.436		1.556		2.622		0.340		1.090		1.740	
CI	0.898	1.106	0.792	1.227	0.717	1.324	0.905	1.093	0.811	1.200	0.740	1.284
Region 3	6.889		12.079		14.947		6.029		9.556		11.224	
SE	0.458		1.689		2.897		0.358		1.188		1.931	
CI	0.895	1.109	0.785	1.238	0.706	1.337	0.903	1.097	0.806	1.208	0.734	1.295
Region 4	6.802		11.588		14.106		5.914		8.988		10.353	
SE	0.435		1.551		2.614		0.338		1.081		1.724	
CI	0.898	1.106	0.792	1.227	0.717	1.324	0.906	1.093	0.811	1.200	0.740	1.284
Region 5	7.010		12.224		15.049		6.182		9.823		11.610	
SE	0.461		1.682		2.868		0.368		1.238		2.029	
CI	0.896	1.109	0.787	1.233	0.711	1.334	0.903	1.098	0.803	1.213	0.732	1.301
Region 6	6.771		11.384		13.814		5.912		9.190		10.726	
SE	0.428		1.516		2.550		0.345		1.131		1.829	
CI	0.899	1.105	0.793	1.226	0.718	1.322	0.904	1.095	0.808	1.207	0.735	1.291
Region 7	6.632		10.588		12.394		5.869		8.715		9.906	
SE	0.395		1.305		2.110		0.329		1.026		1.615	
CI	0.902	1.098	0.807	1.207	0.735	1.290	0.907	1.090	0.815	1.196	0.745	1.278
Futures	6.579		11.677		14.586		5.851		8.813		10.087	
SE	0.447		1.682		2.919		0.332		1.048		1.661	
CI	0.893	1.113	0.781	1.245	0.700	1.346	0.907	1.091	0.813	1.198	0.742	1.281

Notes: Based on 1462 weekly % return observations for each of the stated series indexes over the period January 1979 through December 2006, and based on 5000 semi-parametric bootstrap resamples. *R* is the coefficient of absolute risk aversion, SE indicates the standard error, CI indicates the standardised 90% confidence interval, and LB and UB refer to its bounds. Calculations carried out using the CompEcon software of Miranda and Fackler (2002) written in MATLAB written in MATLAB using the trapezoidal and *N*=1m 'slices'.