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Revenue Risk Reduction of a Rainfall Index Insurance Contract Using Value-at-Risk and  
Dispersion Risk Measure

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Selected Paper prepared for presentation at the Southern Agricultural Economics  
Association Annual  
Tulsa, Oklahoma, February 18, 2004

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## REVENUE RISK REDUCTION OF A RAINFALL INDEX INSURANCE CONTRACT USING VALUE-AT-RISK AND DISPERSION RISK MEASURE

### ***Abstract:***

*Tail risk measures such as the Value-at-Risk (VaR) are being advocated as conceptually appropriate statistical and economical alternatives to dispersion measures of risk such as the standard deviation. VaR and dispersion risk measures are applied to assess the revenue risk reduction potential of an index rainfall insurance. VaR and dispersion measures indicate that a Rainfall Index Insurance Contract reduces revenue risk.*

## **Introduction**

The high dependence of agricultural production on variable weather makes it a risky enterprise. Natural disasters, such as droughts, lead to production and revenue losses for farmers which can lead to poverty. This is especially true in developing countries where both government transfers and opportunities for off-farm incomes are limited. To cope with weather-related risks, parametric weather index insurance contracts are being advocated as effective instruments to stabilize farm incomes in developing countries. Recently, Skees and researchers from the World Bank (2001) have analyzed the feasibility of rainfall index insurance contract in Morocco and, concluded that purchasing rainfall index insurance contract (RIIC) significantly reduces relative revenue risk for agricultural-dependent provinces in Morocco. The reduction in revenue risk was measured by the coefficient of variation.

The merits of index and area-based contract relative to crop insurance and other risk management mechanisms in rural areas and for developing countries are extensively discussed in Skees (1997, 2001) and Skees, Hazell and Miranda (1999). RIIC seems a low cost tool for managing agricultural production risk. Unlike traditional crop insurance tied to individual farm yields or revenue, RIIC suppliers do not have to invest in expensive information collection mechanisms. The inherent transparency of RIIC contributes to reduce significantly adverse selection risks and eliminate moral hazard. Adverse selection refers to the asymmetry of information between the parties involved in the contract. The individuals seeking to purchase an insurance contract have better information about their risk profiles than the insurance provider and will purchase the contract only if they expect a net gain. Moral hazard refers to the change in behavior of

the insurance purchaser ex post the insurance contract subscription. For an insured farmer, moral hazard involves taking action that increases the likelihood of getting paid by the insurance provider. Moral hazard and adverse selection are problems that have rendered traditional crop insurance inefficient and ineffective.

In this paper, our objective is to construct a RIIC and compare empirically the revenue risk reduction using alternatively tail risk measure, a parametric VaR and dispersion-based risk measure, the coefficient of variation. We intend to investigate whether the potential risk reduction estimate of a RIIC is sensitive to the statistic used. First a review of theoretical merits and limitations of dispersion risk measure and VaR are presented then, they are applied to measure potential revenue risk reduction of a RIIC.

### **Dispersion Measures of Risk**

The concept of risk, despite its pervasive uses in the economic literature has no consensus definition. Examples of risk definitions include: the dispersion of the risky factor around one of its distribution central tendency, the amount of potential loss, the probability of occurrence of loss and/ or the probability of realizing an outcome that is worse than some specified target. Following the works of Tobin (1958) and Markowitz (1959), the variance has become the most popular tool for measuring, ordering and assessing risk among alternatives. In the insurance literature, Houston (1964) stated that “risk is a variance concept.” Houston's quote amalgamate the concept risk and the statistic that helps for its measurement and exemplifies the preponderant use of variance as risk measure.

The use of variance as a measure of risk is not free from limitations or even refutations in the economic literature. For variance to be an appropriate measure, the risky factor has to be normally distributed or the expected utility function of the decision-maker has to be quadratic (Tobin, 1958). Variance can lead to inconsistent results if more than two moments are required to characterize the distribution of the risky factor (Hadar et al., 1969). Another problem with the variance is its sensitivity to time horizon and method of data aggregation (Joyce and Vogel, 1970). Furthermore, when attitudes toward risk and risk-return trade off are considered, higher variability of the risk factor does not necessarily correspond to higher risk. Recent research by Artzner, et al. (1999) on the properties of statistically sound risk measures refutes variance as a measure of risk. They established that variance is not a coherent risk measure. The four properties of a coherent risk measure are positive homogeneity, sub-additivity, monotonicity, and translation invariance. Variance, due to its symmetric nature, is not a coherent risk measure because the property of translation invariance is violated. The translation invariance property posits that total portfolio risk should decrease if a risk free asset is added to it.

Tail risk measures such as VaR can be a coherent risk measure and can be consistency with economic decision-making under uncertainty. Levy (1998) proved that VaR is consistent with first-degree stochastic dominance and can be consistent with second-degree stochastic dominance under the assumption of normality.

### **The Value-at-Risk**

VaR is a measure of downside risk that quantifies in monetary term or rate of return, the expected loss of at the user defined level of confidence and time period, under

normal market condition. For example, a value at risk estimate of one millions dollars at 95% level of confidence implies that portfolio losses should not exceed 1 millions dollars more than 5% of the time over the given holding period (Jorion 1997).

Formally VaR at  $\alpha$  probability level is defined as:

$$\text{VaR}_\alpha = F^{-1}(\alpha)$$

$F^{-1}(\cdot)$  represents a quantile of the cumulative distribution of revenue.

Besides its conceptual simplicity, VaR has been shown by Levy (1998) to be consistent with the decision making criterion of stochastic dominance. More specifically VaR is consistent with first degree stochastic dominance and is consistent with second degree stochastic dominance if the assumption of normal distribution holds.

Applying the coherent risk measure metric to VaR, Artzner et al. established that VaR in its general form is not convex and thus does not pass the test of sub-additivity for coherent measure of risk. The non-convexity of VaR renders its application in optimization problem difficult. However, according to Embrechts et al. (1999), VaR can be a coherent risk measure if the distribution of the random variable is elliptic. Elliptical distributions are a general class of distributions that extend the multivariate symmetric distributions such as the normal distribution and the Student's t-distribution. Elliptic distributions are fully characterized by their scale parameters matrix and their location parameter vector.

VaR can also produces contradictory ranking of risk alternative for different confidence levels. Just like variance, VaR embodies major theoretical drawbacks when examined in terms of utility maximization. Kaplanski and Kroll (2002) proved that the use of VaR implies irrational utility function where the assumption of non-satiation is contradicted.

Another major drawback of VaR is its inability to measure the size of the potential losses. VaR essentially express risk in probabilistic terms.

### **Derivation of VaR**

In spite of the theoretical and empirical limitations mentioned in previous paragraphs, VaR has become the standard technique for measuring and controlling risk in the finance and insurance industries (Jorion 1997) and its application in agricultural economics analysis has been increasing (Manfredo and Leuthold 2001). Despite the widespread utilization of VaR there is no standard method for its calculation. The challenge in estimating VaR resides in the appropriate characterization of the expected probability distribution for the risk factor. There exist several procedures to estimate VaR which, are often categorized into parametric and Monte Carlo simulation-based procedures. The Monte Carlo methods require simulating the entire distribution of changes in revenue and finding the appropriate quantile of the distribution at the desired likelihood level.

Parametric procedures which will be used to compute VaR in this paper, rest on the assumption that risky factors come from a known distribution. The normal distribution being characterized by its first two moments, if assumed, essentially involves forecasting the mean and the variance of the risky factor's distribution.

Let denote  $r_i = R_t - R_{t-i}$ , the change in revenue over the period  $i$ , and assume that revenue changes have a known parametric distribution with location parameter  $\mu$  and a scale parameter  $\sigma^2$ . The Value at Risk is a number that satisfies:

$$\text{Prob}(r_i < -\text{VaR}_{\alpha,i}) = \alpha$$



where  $\alpha$  is the probability of decrease in revenue over period  $i$  will be less than VaR.

Assuming that the random revenue changes distribution can be characterized by a location-scale family of distribution, in which, the location parameter is expected return and the scale parameter is the standard deviation, the following standard transformation holds for a parametric probability density function  $D(.)$ :

$$\text{Prob} \{(r_t - \mu)/\sigma_t\} < (-\text{VaR}_{\alpha,h} - \mu)/\sigma_t\} = D(-\text{VaR}_{\alpha,h} - \mu)/\sigma_t = \alpha$$

For a standard normal variate  $Z_t$ ,  $\text{Prob}(Z_t < Z_\alpha) = \alpha$ , where  $Z_\alpha$  represents the quantile  $\alpha$  of the distribution.

For period  $h=1$ ,  $\text{VaR}_{\alpha,h} = Z_\alpha \sigma_t - \mu$ ,

In a large sample,  $Z_{0.05} = -1.645$ , for  $\sigma_t$  equal to one and  $\mu$  equal to zero, we have  $\text{VaR}_{\alpha,1}$  of  $-\$1.645$

To estimate VaR, a specific type of distribution  $D(r)$  is assumed and then the scale and location parameters are estimated from the assumed distribution. More precisely, VaR being a prediction of loss of an asset over a time horizon and at a given probability, the mean and standard deviation should be forecasted assuming a specific parametric distribution.

## **Data and Methodology**

### **Design of the Rainfall Index Contract**

The data used to in this study is similar to those utilized by Skees et al (2001) in their study in the feasibility of index rainfall insurance in Morocco. The data set spans from 1979 to 1999 and include annual production and plantings observations for corn, soft wheat, hard wheat and barley for thirteen Moroccan's provinces. All four crops are

planted in the same season in Morocco and are therefore subject to the same level of rainfall. Rainfall observations consist of monthly data for each province.

The revenue for each year is calculated price using fixed national price of 190 MAD<sup>1</sup>/quintal for corn, 190 MAD/quintal for barley, 250 Mad/quintal for soft wheat and 280 MAD/quintal for hard wheat. The revenue is a product of yields, planted acreage and price. The formula for calculating revenue is:

$$\text{Revenue}_{tpc} = \text{Yield}_{tpc} * \text{Hectares}_{tpc} * \text{Price}_{c, 1999}$$

where t= year, 79-99, p= province, 1-17 and c= crop, 1-4.

The RIIC designed for this paper is similar in structure to one implemented by Skees et al. With the premises that variability in precipitation can induce variability in net revenues for agricultural-dependent provinces, some of the variability in revenues and costs due rainfall can be cross-hedged by purchasing a rainfall index contract. The RIIC is constructed in a manner that linked the indemnity payment to the level of rainfall in observed in each province.

The RIIC is priced using as base, the percentage of rainfall from the period of November to March below the strike level of rainfall. For this study, the strike at 250 millimeters<sup>2</sup> and cumulative rainfall from November to March is used because it is found to be critical for crops yields.

$$\text{Payment rate} = \begin{cases} = 0 & \text{if rainfall from Nov to Mars} > 250 \\ \text{else} \\ = (250 - \text{rainfall from Nov to Mars})/250 \end{cases}$$

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<sup>1</sup> MAD for Moroccan Dirham, local currency

It is assumed that protection is bought each year for the historic average revenue level. The proportion of revenue covered per province is the product of average revenue and correlation coefficient. The Pearson correlation coefficient between rainfall and revenues will be considered as a proxy for revenue variance minimizing coverage level.

The estimated correlation coefficients between rainfall and revenue range from 37.5 % for the province of Rabat to 84.7 % for the province of Agadir (Table 1). The validity of the Pearson correlation coefficient rests on the assumption of joint normal distribution of the correlated variables. Tests for normality of rainfall and revenue for each province is conducted using the Shapiro-Wilk test (Table 2). Normality assumption of revenue for each of the province seems acceptable as we fail to reject the null hypothesis. Regarding cumulative rainfall, the assumption of normal distribution is rejected for four geographical locations namely Agadir, El-Kelaa, Essaouira, and Settat. In this paper, we will implicitly assume that cumulative rainfall and revenue per province are jointly normally distributed.

The RIIC being not tied to individual farmer or province losses, it embeds the possibility of high basis risk. The basis risk is the risk of suffering revenue losses and not getting indemnified by the insurance company. The magnitude of the basis risk is lower for the insured agent located in the proximity of the rainfall collection stations and for area where the correlation between the RIIC and the revenue is high.

The indemnity paid to each province is calculated by multiplying the payment rate by the proportion of historic average revenue insured. Thus, the selected liability is the average if the insured revenue. The pure premium rate is set to equal the average

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<sup>2</sup> Skees et al also set the strike at 250 mm and indicate that the cumulative rainfall of November to Mars has

indemnity paid which in each region with no consideration of transaction costs, administrative costs and risk characteristic. With the RIIC, the revenue is now:

$$\text{RIIC Revenue}_{\text{tpc}} = \text{Revenue}_{\text{tpc}} + \text{Indemnity} - \text{Premium}_{\text{tpc}}$$

The estimate revenues per province with RIIC and without RIIC are assembled and the series of changes in revenue are used as input for VaR calculation.

### **Empirical Results and Discussion**

The dispersion risk measures indicate that purchasing RIIC reduce the revenue risk for all regions. The mean revenue with RIIC and without RIIC being similar, the risk reduction potential of RIIC is presented in term of reduction of the coefficient of variation. The reduction in coefficient of variation ranges from 3.04 % in Rabat to 12.81 % in Essaouira (Table 3).

### **Parametric Value at risk Estimation**

The Autogressive Conditional Heteroskedastic (ARCH) process introduced by Engle (1982) and extended by Bollerslev (1986) with the Generalized Autoregressive Conditional Heteroskedastic (GARCH) model will be used to forecast the variance. The ARCH model and its extensions essentially define current variance as a function of past information. The following equations characterize the mean and the variance equation in ARCH-type models:

$$r_t = \phi_0 + \sum_{i=1}^p \phi_i r_{t-i} + \varepsilon_t \quad (*)$$

$$\varepsilon_t = z_t \sqrt{h_t} \quad \text{where } z_t \sim iid N(0,1)$$

$$h_t = \delta + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \quad \text{where } \delta > 0, \alpha > 0, \beta > 0 \text{ and } \alpha + \beta < 1 \quad (***)$$

The parameters of the conditional mean and the conditional variance equations are estimated using maximum likelihood approach. After the parameters estimation, their one-period ahead forecast is used for VaR calculation. The quantile revenue VaR were calculated by multiplying the forecasted conditional standard deviation by the associated normal deviate.

Before estimating the forecasted conditional standard deviation the revenue changes series were transformed to achieve covariance stationarity and convergence of the likelihood function. Absolute revenue changes series were found stationary but the likelihood function did not converged. So the GARCH processes were estimated using changes in the logarithm of revenue. With logarithmic transformation and first differencing, revenues change series were found stationary. For most series only lag one and/or two autocorrelation and one partial autocorrelation coefficients are statistically significant.

Following the recommendation of Figlewski (1997), the mean revenue equations were set to zero to provide reliable conditional standard deviation forecast. The limited number of significant autocorrelation coefficients provides evidence in support of Figlewski recommendation. The existence of ARCH effects were tested using the Lagrange Multiplier (LM) and Q-statistics tests and proof of time varying conditional standard

deviations were found for most of the provinces. But, for most series significant ARCH in the residuals were found for only to the first two orders<sup>3</sup>.

It is important to note that both the LM and Q-statistic tests were developed to test ARCH effect in large sample size and their desirable asymptotic property might not hold for small sample (20 observations in this example). It can be postulated that the limited number of observations explains the absence of stronger evidence of conditional heteroskedasticity. To minimize the bias associate with the small sample size, the simplest type of ARCH process, the ARCH (1) is imposed. An ARCH (1) models current variance to be as linear function of previous period squared residuals<sup>4</sup>.

An ARCH (1) equation was estimated for each province using the logarithm of revenue changes series with and without RIIC. In all but two provinces (Rabat and Essaouira), the conditional variance stationarity condition is met, VaR is calculated only in case of non-explosive conditional variance.

After estimating the ARCH one process for each province, the standardized conditional residuals were tested for normality using Jarque-Bera test. Evidence of normality was found as we fail to reject the null hypothesis of normally distributed residuals of revenue changes with RIIC and without RIIC.

In-sample forecasted VaR indicate that RIIC reduce revenue risk and thus the potential to stabilize income. For most years, the revenue VaR with RIIC is smaller than the revenue VaR without RIIC. Illustration the year-to-year variations of VaR for five provinces are presented in graph 1, 2, 3, 4, 5 and 6. Each VaR is computed using the 90 % confidence

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<sup>3</sup> Details on specification and diagnostic tests are available upon request

<sup>4</sup> GARCH (1,1) was estimated but the coefficients of past conditional variance had statistical significance

level and one-month forecast horizon. Both the dispersion measure of risk and the tail measure indicate that the RIIC reduce revenue risk.

## **Conclusion and Discussion**

Empirical evidence of the revenue risk reduction potential of a parametric index insurance contract is found using measures of risk that focus on different areas of the revenue change distribution. VaR focuses on negative deviation but due to the small number of data available for this study, the robustness of VaR estimated parameters can be questioned. Furthermore, while there is debate regarding the appropriate method for VaR calculation, dispersion risk measure such as standard deviation and coefficient of variation are well established statistics. Kaplanski et al. argue that when distribution has to be estimated from actual data, standard deviation is more robust than the VaR because its calculation is based on the entire distribution. Finally, a useful measure of risk should indicate not just the likelihood of potential losses but the magnitude extreme losses in the tail of the distribution. The Conditional Value at Risk defined as the expected value of the losses exceeding the VaR, is advocated as a superior alternative to VaR (Artzner et al,1999 ). The Conditional VaR satisfies the properties for coherent measure of risk and is compatible with second degree stochastic dominance. Just like VaR, large data set or simulation procedures are required to estimate of Conditional VaR which, limits the scope of application of those modern measures of risk.

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Table I Correlation

Revenues and Rainfall

Provinces	Pearson Correlation
Bensilman	63.31%
Fes	48.85%
Kenitra	50.80%
Khemisset	62.82%
Meknes	46.90%
Rabat	37.46%
Taza	50.75%
Agadir	84.73%
El-Kelaa	75.82%
Essaouira	73.60%
Safi	66.16%
El-Jadida	76.78%
Setta	68.00%

Table 2 Normality test

NAME	RIIC Shapiro-Wilk	p-Value	No RIIC Shapiro-Wilk	p-Value
BEN_SLIMANE	0.97	0.9	0.96	0.67
FES	0.97	0.86	0.93	0.14
KENITRA	0.96	0.54	0.93	0.17
KHEMISSET	0.97	0.9	0.97	0.82
MEKNES	0.99	0.99	0.92	0.12
RABAT	0.93	0.16	0.98	0.17
TAZA	0.97	0.86	0.95	0.41
AGADIR	0.9	0.04	0.91	0.08
EL_KELAA	0.87	0.01	0.92	0.14
ESSAOUIRA	0.87	0.01	0.94	0.27
SAFI	0.88	0.015	0.97	0.92
EL_JADIDA	0.93	0.2	0.96	0.62
SETTAT	0.91	0.04	0.93	0.14

Table 3 Coefficient of Variation

Region	CV no RIIC	CV RIIC	Reduction in CV
BEN_SLIMANE	58.89%	53.93%	4.96%
FES	55.53%	48.51%	7.02%
KENITRA	49.60%	45.19%	4.41%
KHEMISSET	49.30%	44.36%	4.94%
MEKNES	48.66%	45.48%	3.18%

RABAT	52.00%	48.95%	3.04%
TAZA	53.98%	49.72%	4.26%
AGADIR	67.15%	54.41%	12.74%
EL_KELAA	72.37%	61.26%	11.11%
ESSAOUIRA	60.28%	47.47%	12.81%
SAFI	54.72%	42.76%	11.96%
EL_JADIDA	46.03%	36.90%	9.14%
SETTAT	74.60%	66.85%	7.74%

Table 4: Estimated ARCH parameters of Revenue Changes without Rainfall Index Insurance Contract

Bensilman:	$0.34 + 0.74 \sigma_{t-1}^2$ (0.28) (0.49)	Log-Likelihood = -24.94	Unconditional Variance = 1.34
Fes:	$0.54 + 0.79 \sigma_{t-1}^2$ (0.29) (0.69)	Log-Likelihood = -29.56	Unconditional Variance = 2.59
Kenitra:	$0.33 + 0.38 \sigma_{t-1}^2$ (0.15) (0.50)	Log-Likelihood = -21.36	Unconditional Variance = 0.54
Khemisset:	$0.39 + 0.73 \sigma_{t-1}^2$ (0.29) (0.69)	Log-Likelihood = -26.79	Unconditional Variance = 1.47
Meknes:	$0.44 + 0.32 \sigma_{t-1}^2$ (0.29) (0.63)	Log-Likelihood = -23.76	Unconditional Variance = 0.66
Rabat:	$0.08 + 0.104 \sigma_{t-1}^2$ (0.11) (0.73)	Log-Likelihood = -20.84	Unconditional Variance =
Taza:	$0.45 + 0.48 \sigma_{t-1}^2$ (0.20) (0.53)	Log-Likelihood = -25.56	Unconditional Variance = 0.88
Agadir:	$0.46 + 0.65 \sigma_{t-1}^2$ (1.23) (1.03)	Log-Likelihood = -28.76	Unconditional Variance = 1.33
El Kelaa:	$0.58 + 1.25 \sigma_{t-1}^2$ (0.28) (0.49)	Log-Likelihood = -34.51	Unconditional Variance = .
Essaouira:	$1.03 + 0.28 \sigma_{t-1}^2$ (0.48) (0.39)	Log-Likelihood = -31.65	Unconditional Variance = 1.42
Safi:	$0.62 + 0.61 \sigma_{t-1}^2$ (0.39) (0.52)	Log-Likelihood = -29.86	Unconditional Variance = 1.60

El-Jadida:	$0.49 + 0.16\sigma_{t-1}^2$ (0.18) (0.38)	Log-Likelihood = -23.06	Unconditional Variance = 0.59
Settat:	$0.80 + 0.71\sigma_{t-1}^2$ (0.77) (0.73)	Log-Likelihood = -35.41	Unconditional Variance = 2.74

Table 5: Estimated ARCH parameters of Revenue Changes with Rainfall Index Insurance Contract

Bensilman:	$0.23 + 0.16\sigma_{t-1}^2$ (0.17) (0.54)	Log-Likelihood = -16.54	Unconditional Variance = 0.28
Fes:	$0.39 + 0.49\sigma_{t-1}^2$ (0.22) (0.77)	Log-Likelihood = -23.84	Unconditional Variance = 0.77
Kenitra:	$0.18 + 0.51\sigma_{t-1}^2$ (0.13) (0.69)	Log-Likelihood = -16.64	Unconditional Variance = 0.37
Khemisset:	$0.39 + 0.73\sigma_{t-1}^2$ (0.19) (0.55)	Log-Likelihood = -26.79	Unconditional Variance = 1.47
Meknes:	$0.48 + 0.03\sigma_{t-1}^2$ (0.40) (0.77)	Log-Likelihood = -21.47	Unconditional Variance = 0.50
Rabat:	$0.06 + 1.07\sigma_{t-1}^2$ (0.01) (0.71)	Log-Likelihood = -18.15	Unconditional Variance =
Taza:	$0.39 + 0.31\sigma_{t-1}^2$ (0.18) (0.63)	Log-Likelihood = -22.24	Unconditional Variance = 0.57
Agadir:	$0.33 + 0.44\sigma_{t-1}^2$ (0.51) (0.21)	Log-Likelihood = -22.54	Unconditional Variance = 0.55
El Kelaa:	$0.66 + 0.08\sigma_{t-1}^2$ (0.34) (0.56)	Log-Likelihood = -25.09	Unconditional Variance = 0.72
Essaouira:	$0.40 + 0.27\sigma_{t-1}^2$ (0.24) (0.58)	Log-Likelihood = -22.26	Unconditional Variance = 1.42
Safi:	$0.22 + 0.26\sigma_{t-1}^2$ (0.26) (0.64)	Log-Likelihood = -19.62	Unconditional Variance = 0.45

El-Jadida:	$0.23 + 0.008\sigma_{t-1}^2$ (0.13) (0.42)	Log-Likelihood = -13.84	Unconditional Variance = 0.23
Settat:	$0.98 + 0.26\sigma_{t-1}^2$ (0.48) (0.68)	Log-Likelihood = -31.06	Unconditional Variance = 1.34

## Graphical Representation of VaR

