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ANALYZING ASYMMETRIC RISKS IN CORN AND SOYBEAN MARKETS

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Abstract **Contemporaneously, Value at Risk (VaR) is one of the most important measures of risk which is percentile of the profit and loss distribution of a portfolio over a specified period. We could explore portfolio risk and loss created through quick movement of the economy by using dynamic VaR method. To analyze VaR of the Jan.2006 to Sep. 2014 corn and soybean spot prices in CBOT, we propose the application of stochastic volatility with Student-t errors (SV-*t*) model that maximizes expected returns subject to a Value-at-Risk constraint to depict the risk of heteroscedasticity and leptokurtic accuracy. We also propose the efficient and best way-- Markov Chain Monte Carlo (MCMC) simulation estimation method. Empirical results show all coefficient estimates including jump effect and leverage effect, and that the VaR value of soybean is larger than that of corn indicating more price volatility in soybean than corn with shocks in the emerging international commodity markets. Speculators as well as business operators might be able to earn risk premium or avoid risk loss by the operation of portfolio changes. However, both corn and soybean price VaR value are more than 5% indicating possible underestimates of returns from portfolio operations. It is suggested that more portfolio returns of soybean and corn futures market operation may be available.**

***Index Terms*— Value at Risk (VaR), Markov chain Monte Carlo estimation methods (MCMC), Stochastic Volatility Model with Student-t errors (SV-*t*).**

I. INTRODUCTION

Owing to soaring world oil price, increased application of biofuel energy, and raised feed demand around 2006, asymmetric volatility spillovers are much more pronounced in corn and soybean markets (Figure1&2). Corn and soybean make up the greatest composition of the feed market with direct relation to various energy, meat, human consumption, bio-fuel markets and GDP performance. Important feed prescription are 40 percent of corn and 50 percent of soybean with other nutritional supplements. Return volatility of corn and soybean should impact their utility composition in practical world. Moreover, these two markets would influence each other in response to climatic, political incentive, and other man-made changes. As a result, learning the possible portfolio behaviors from the analysis of asymmetric risks in both corn and soybean markets becomes attractive to people involved in the speculation and business operation on raw feed inputs. This paper intends to apply the stochastic volatility with student t errors (SV-t) model by using Markov Chain Monte Caro (MCMC) estimation to analyze Value at Risk (VaR) of corn and soybean returns.

There are reasons that they are not for financial establishments involved in large-scale trading operations, but for retailers, processing factories, feed companies institutional investors, non-financial enterprises and etc. In these enterprises portfolio choice, expected returns and risk class is optimization of asset allocation. It is rather difficult to compare various portfolio management strategies with the different instrument types. Therefore we might need a unique and universal risk measurement tool to solve those difficult doubts. Risk, the special topic of modern discussion in evaluation of markets, is extreme value theory and implementation of extreme value distribution in risk measurement. For these reasons, the most widely used tool to measure from 1994, gear and control market risk is Value-at-Risk (VaR). VaR has become one of the most popular and important estimation. It is the most used measures of risk to estimate even if it may be not accurate. Up to now, VaR helps to manage in the first line market risk to solve many economic doubts.

To explore portfolio risks, VaR were developed very quickly from the traditional distribution of profit and loss. The simplicity of the VaR concept has directed many organizations to recommend that VaR become a standard risk measure.

Customers would like to know about possible losses in their portfolio under the certain suggestions in markets. Investors would like to know about possible risk in their portfolio which they design in economic volatility. Today we cannot find a lot of risk estimation methods but let us measure risk in figures by VaR.

This paper proposes a dynamic portfolio selection in feed market model—stochastic volatility in Student's t-distribution that maximizes expected returns subject to a VaR constraint. The SV model is intuitively appealing since it allows the contemporaneous shock to the present transmission volatility and includes a limiting case when the standard deviation of shocks on volatility goes to zero. More importantly, the SV model is able to analyze whether the shock to the volatilities in the technological breakthrough in energy development or substitution elasticity are transmitted into the volatilities mutually or not.

SV type models generally allow for time varying skewness and kurtosis of portfolio distributions estimating the model parameters by MCMC method (see Tsay, 2001). Kobayashi and Shi (2005) proposed a method for testing the hypothesis of the EGARCH against the SV model. Until now, Junji Shimada et al take evidence in U.S. stock market and Japanese stock market to prove that SV model is preferred to the EGARCH model in terms of the Lagrange Multiplier test of the EGARCH against the SV models.

As a promising approach, we purpose SV-t model for the flexible skewness and heavy-tailed that we consider the generalized hyperbolic (GH) distribution which is proposed by Barndorff-Nielsen (1977). It is closed under an affine transformation of in- or exogenous relationship. This method could be easily estimated by the maximum likelihood estimation for a time independent model. It exist that it is difficult to generate for the SV-t model because of many latent volatility variables. It requires a general burden to repeat the particle filtering many times to evaluate the likelihood function for each set of parameters until we find the maximum. For these reasons, we apply the MCMC algorithm for a precise and efficient estimation of the SV-t model with asymmetrically heavy-tailed error using the GH skew Student's t-distribution.

This paper purposes to investigate the value at risk whether the upturns or downturns of the corn and soybean meal exert an asymmetric influence on the conditional mean and volatility using the data issued from Jan.2006 to Sep. 2014 of the spot price in CBOT. We use the SV-t model which allows the simultaneous treatment of asymmetric global transmission in the conditional mean and volatility across the soybean meal and corn markets.

The article is organized as follows. Section 2 introduces VaR, SV-t model Section 3 we estimate results. Section 4 gives some concluding remarks.

II. Value-at-Risk(VaR), Stochastic Volatility (SV) model with Student-t errors, and Markov-Chain Monte Carlo (MCMC) estimation

A. Value-at-Risk (VaR)

In July 1993 it is widely represent to delegate VaR to describe risk, there are many users to extend the risk definition and having increased dramatically in the Group of Thirty report. Here we note that it is important to recognize that the VaR technique has gone through significant refinement. We could use the VaR to calculate vital process changes since its primary meanings. Recently there are increasing trade quantity and different price volatility, instability have prompted new domain to explain the need for market participation to develop reliable risk techniques to measure. In order to evaluate the ability of the models to forecast the future behavior of the volatility process, we study the forecasted VaR in this paper. Building an information report VaR is symmetric and asymmetric or not which help investors to measure financial and market risks.

Consequently, we find that VaR not only pass into a desirable description, but also an easily interpretable summary measure of risk. This is due to allow its users to focus attention on the so-called "normal market condition" in their routine operations. VaR models compile several constituents of volatility risk into a single quantitative measure of the potential for losses over a specified time. Due to transmit the market risk of the whole portfolio, as following models are clearly imploring in measuring estimation.

To calculate the VaR it is important to fix a confidence level and a time interval that describes the number of days. Consequently we need to hold a given portfolio and for which we are interested in evaluating the risk. In empirical evidence, VaR dates back to the computation of a quantile of interest that illustrates the probability associated to a certain exaggerated loss.

In general, we could face the market risk, credit risk and operational risk in financial or commodity environment or institutions. However, simply with derivative instruments, like structured products, it is difficult to calculate VaR at first sight for non-linearity reasons. In these reports, the risks of the investments are measured and presented in a transparent manner. The VaR presentation exhibits the potential loss for the portfolio under distinct scenarios. We clarify the VaR as the maximum possible loss that can enter within a definite period with a certain trust level. As the effective movements of a possible loss, still the VaR calculations were implemented in addition. The VaR concept scenarios are defined to calculate the changes in market risk factors and the potential losses, which would result with the occurrence of the scenarios.

In this article we recommend to follows Campbell, Huisman, and Koedijk (2001). Through maximizing the expected return subject to a risk constraint, the optimal portfolio model apportions financial assets where risk is estimated by VaR. For a selected investment horizon the maximum expected loss should not surpass the VaR in the optimal portfolio at a given confidence level α. We consider the possibility of borrowing and lending at the market interest rate, considered as given.

Define m_t as the investor's wealth at time t, b_t the amount of money that can be borrowed (b_t > 0) or lent (b_t < 0) at the risk free rate r_f. Consider n financial assets with prices at time t given by $p_{i,t}$, with $i=1,2,....,n$. Define $y_t \equiv \left[y_t \in R^n : \sum_{i=1}^{n} y_{i,t} = 1 \right]$ as the set of portfolios weights at time t, with well-defined expected rates of return, such that $m_{i,t} = y_{i,t}(M_t + b_t) \ / p_{i,t}$ is the number of shares of asset i at time t. The budget constraint of the investor is given by:

$$M_t + b_t = \sum_{i=1}^{n} m_{i,t} p_{i,t} = m_t^{'} p_t$$

…………………..1

The value of the portfolio at $t+1$ is:

$$(M_{t+1|m_t}) = (M_t + b_t)(1 + R_{t+1|m_t}) - b_t(1 + r_f)$$

…………………..2

where $R_{t+1|m_t}$ is the portfolio return at maturity. The VaR of the portfolio is defined as the maximum expected loss over a given investment horizon and for a given confidence level α:

$$P_t \left[M_{t+1|m_t} \le M_t - VaR^{\bullet} \right] \le 1 - \alpha$$

……………………3

Where the probability P_t is conditioned on the available information at time t and $VaR^{\bullet}$ is the cutoff return or the investor's desired VaR level. Note that (1−α) is the probability of occurrence. Equation (3) represents the second constraint that the investor has to take into account. The portfolio optimization problem can be expressed in terms of the maximization of the expected returns $E(M_{t+1|m_t})$, subject to the budget restriction and the VaR-constraint:

$$M_t^{\bullet} \equiv \arg \max_{m_t} (M_t + b_t)(1 + E(M_{t=1|m_t})) - b_t(1 + r_f)$$

……………….4

s.t. (1) and (3). $E(M_{t+1|m_t})$ represents the expected return of the portfolio given the information at time t. The optimization problem may be rewritten in an unconstrained way. To do so, replacing (1) in (2) and taking expectations yields:

$$E(M_{t+1|m_t}) = m_t^{'} p_t (E(R_{t+1|m_t}) - r_f) + M_t(1 + r_f)$$

…………………5

Equation (5) shows that a risk-averse investor wants to invest a fraction of his wealth in risky assets if the expected return of the portfolio is bigger than the risk free rate. Substituting (5) in (3) gives:

$$p_t \left[m_t^{'} p_t (R_{t+1|m_t}) - r_f + M_t(1 + r_f) \le M_t - VaR^{\bullet} \right] \le 1 - \alpha$$

…………………6

so that,

$$p_t \left[R_{t+1|m_t} \le r_f - \frac{VaR^{\bullet} + M_t r_f}{m_t^{'} p_t} \right] \le 1 - \alpha$$

……….………….7

Here we define the quantile $q(m_{t,}\alpha)$ of the distribution of the return of the portfolio at a given confidence level α or probability of occurrence of ($1-\alpha$). The value of α is the distance of the means measures in number of standard deviations. In standard distribution we know that 1.65 corresponds to 95% confidence level.

B. Stochastic Volatility (SV-t) model

Unlike these chosen classes that prevent a simple comparison of competing SV models, our advocated class is based on a single parameter which allows effortless testing on the functional form specifications for the SV. We clarify the stochastic volatility model as a logarithmic first-order autoregressive process. Simultaneously the SV which is ever used in the option-pricing literature is a discrete-time approximation of the continuous-time Ornstein-Uhlenbeck diffusion process (see Hull & White, 1987). It is a choice to the GARCH models, which have counted on concomitant modeling of the first and second moment. For certain financial time series such as stock index return, which have been demonstrated to illustrate high positive first-order autocorrelations, this composes amelioration in terms of efficiency; (see Campbell et al. 1997, Chapter 2). The volatility of daily stock index returns has been calculated with SV models but usually results have depended on extensive pre-modeling of these series, thus evading the problem of concomitant estimation of the mean and variance. In SV model, we should look that this single parameter also provides a measure of degree of departure from the classical SV models in asymmetric effect. Furthermore, with this general approach to modeling SV, one obtains the functional form of transformation, which induces marginal normality of volatility.

In this paper we find that customary wisdom would dictate that when there are insufficient numbers of observations in data, we would obtain an imprecise and biased estimate of parameters we would wish to deduce. Although SV models are known to be more suitable to delineate the tail thickness of financial returns than ARCH-type models, extreme movements in returns occur more frequently in the observed data than the models implies. We purpose this theorem to describe the heavy tails of returns and face the problem of the comparison taking into account both goodness-of-fit statistics which obey Student's t-distribution and forecasting performance which relies on the ability to forecast conditional variances in this paper.

Due to insufficient to express the tail fatness of returns and the jump components, which may be correlated, SV with Student-t errors have innovated to explain the tail behavior. The jump component is considered to be discretion of a L'evy process which is used in the continuous time modeling of financial asset pricing widely.

The corn and soybean market prices are assumed to have a first-order autoregressive (AR) relationship, possibly with asymmetric effects of the lagged variable. Due to increases in the market price, these data represent the residuals calculated from the following equation:

$$y_t \left| \theta_t, \rho = d\exp(\theta_t) + \sqrt{z_t}\varepsilon_t \exp(\theta_t / 2) \right.$$

$$\sqrt{z_t}\varepsilon_t \sim i.i.d.t_k(0,1,v), \quad t = 1,2,......n \qquad 8$$

$$\theta_{t+1} | \;\; \theta_t, u, \phi, \sigma^2, \rho = u + \phi(\theta_t - u) + \sigma\eta_t$$

$$\eta_t \sim i.i.dN(0,\sigma^2) \quad t = 1,2,......n-1 \qquad 9$$

$$z_t^{-1} \sim Gamma(v/2, v/2) \qquad \varepsilon_t \sim i.i.d.N(0,1),$$

$$\frac{\phi+1}{2} \sim Beta(20,1.5),$$

$$\delta^{-2} \sim Gamma(2.5, 0.025), \qquad u \sim N -(\quad 1$$

$$v \sim Gamma(16, 0.8)I(v > 4),$$

Where y_t is the response variable, and θ_t is the unobserved log-volatility, μ_t and η_t are Gaussian white noise sequences. $|\phi| < 1,$

$$\begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix} \sim i.i.dN\left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho\delta \\ \rho\delta & \delta^2 \end{pmatrix} \right\}$$

$$\theta_t \sim N(0, \delta^2 / 1 - \phi^2),$$

In this paper we set a heavy-tailed Student (t) distribution for the return shock, and extra excess kurtosis is allowed. In order to mitigate the computational problems, we estimate the number of parameters in the SV model. On the one hand, we also capture the common features of the feed returns and volatilities. The GH skew Student's t-error distribution in the SV type models is successful in clearly showing the distribution of the commercial returns data. In contrast, lower-dimensional factor SV models have been proposed in the literature and have recently attracted some attention in the field. Apparently, the SV model allows for excess kurtosis and volatility clustering and for cross dependence in both the returns and the volatilities.

C. Estimation and inference using MCMC

In this paper we refer the reader to Koopman and Hol Uspensky (2002) for more explanations. We estimate with the parameters of the SV model by exact maximum likelihood methods which we make use of Monte Carlo importance sampling techniques. The likelihood function for the SV model can be constructed using simulation methods proposed by Shephard and Pitt (1997) and Durbin and Koopman (1997). In this section, we recommend a likelihood-based technique for model estimation and inference using MCMC. We advocate the Bayesian Markov Chain Monte Carlo (MCMC) method (Jacquier, Polson and Rossi, 1994 and Kim et al., 1998) for estimating the SV models throughout this paper.

We know that the likelihood function is difficult to estimate the discrete-time SV type model. It would be possible to calculate the likelihood. This method uses a simulation-based method for a given set of parameter which is a particle filter. Since then it recounts the particle strain many times we evaluate the likelihood function for each set of parameters. It necessitates a computational task until we reach the maximum. To vanquish these difficulties, we take Bayesian estimation approach and proffer the Markov Chain Monte Carlo (MCMC) method to solve these issues.

This method of MCMC we select in this paper, there are some advantage and disadvantage points. For example, it could augment the parameter space by including latent variables and be applicable for many types of SV models. Beside these virtues, MCMC could have many parameters and be numerical optimization. MCMC is not needed which is importance in pragmatic evidence. That is the reason why MCMC could show settings to have superior sampling properties comparing to other competing methods. It could calculate efficiently which enables us to check the accuracy of the method by using simulations. On the contrary, the disadvantage is that it is more difficult to compute the estimators in variable designing.

There are two important reasons which we executed MCMC to check the reliability of our estimated approach. First, we check the model which we need not introduce any biases in parameter estimates in discrete the continuous-time model. Second, these models except MCMC could be not well if we develop multivariate jump diffusion models in general. Due to these models verify to reliably estimate the parameters for the given sample size.

III. Empirical Result

In this paper, the use of the VaR concept in portfolio management with examples from the ten-day trading price volatility issued from the spot price volatility in the CBOT is undertaken from Jan. 2006 to Sep. 2014. We would recommend to purchase or sale in terms of percentage whether on the spot and future market in the risky portfolio of corn and soybean or not. VaR is a percentile of the profit and loss distribution of a portfolio over a specified time. The distribution results are then used in the MCMC process by the application of randomly generated rate path to those that are statistically relevant given the portfolio anticipated risk profiles.

In this paper we calculate the return: $\overleftrightarrow{y_t} = \ln P_{t+1} - \ln P_t$

In order to eliminate instability average, we modify the observed value: $y_t = (\overline{y_t} - \frac{1}{n}\sum_{i=1}^{n}\overleftrightarrow{y_t})$

In these Tables, we outline the results for the corn and soybean form the asymmetric SV model. It contains the posterior means, standard deviations, 95% Bayes credible intervals, simulation inefficiency factors for all the parameters, and the MCMC for both models.

MCMC estimation calculates 100,000 times and give up the first 30,000 times to pursue final convergence result of SV-t model coefficients in Table 1. The estimated coefficients are then applied into equation 9 to obtain equations 10 and 12. As a result, VaR values can be obtained and expressed in equations 11 and 13.

$$\theta_{t,corn} = 0.001872 + 0.8581(\theta_{t-1,corn} - 0.02923) + 0.1188\eta_t$$ ……………..10

$$t = 1, 2, ..., n-1 \quad \eta_t \sim iidN(0, 0.0141)$$

$$VaR_{corn} = 0.0202 + 1.65\sigma_{t,corn}$$ ………………11

$$\theta_{t,soybean} = 0.007732 + 0.8594(\theta_{t-1,soybean} + 0.01032) + 0.$$ …………12

$$t = 1, 2, ..., n-1 \quad \eta_t \sim iidN(0, 0.0142)$$

$$VaR_{soybean} = 0.038 + 1.65\sigma_{t,soybean}$$ …………13

About VaR, we calculate the average value by using the SV model. The estimates are $VaR_{corn} = 0.054$ & $VaR_{soybean} = 0.059$. These VaR values are about 5% but are higher than 5%. This suggests that we underestimate the market risk. We know that VaR is the linear function of σ. There are the characteristics of long memory and persistence to the σ.

According to the data of VaR in this paper, it suggests we underestimate the markets risk which we find some possibilities to suggestion in the corn and soybean. The $VaR_{soybean}$ is larger than VaR_{corn} which indicate the degree of reduce or increase price in soybean is bigger than in corn market when shock coming. In surplus of consumer or producer, the risk in soybean market is larger than in corn market. It is opportunity that speculators might create mass surplus of these markets and wide application in energy and bio-tech markets. Mainland China grows more soybeans to balance the whole soybean market and dominate the market in future. Stringing along these following, speculators would manipulate the feed future market and get more surplus. It would make VaR higher and social welfare lower in future.

IV. CONCLUSION

This paper believes that learning the possible portfolio behaviors from the analysis of asymmetric risks in both corn and soybean markets are attractive to speculators and business operators. Using the Jan.2006 to Sep. 2014 corn and soybean spot prices in CBOT, we apply SV-t model and MCMC estimation to calculate the Value-at-Risk (VaR) value of both markets. Empirical results show all coefficient estimates including jump effect and leverage effect are reasonably obtained. After the application of estimated coefficients into estimated MCMC simulations, we receive the VaR value of corn and soybean. The VaR value of soybean is larger than that of corn indicating more price volatility in soybean than corn with shocks in the emerging international commodity markets. Speculators as well as business operators might be able to earn risk premium or avoid risk loss by the operation of portfolio changes. However, VaR value of both corn and soybean price returns are more than 5% indicating possible underestimates of returns from portfolio operations. It is suggested that more portfolio returns of soybean and corn futures market operation may be available.

Table 1: MCMC estimation results of the SV-t model for simulated data in the corn and soybean markets

market\node	d	u	v	ϕ	ρ	σ
corn	0.001872	0.02923	8.305	0.8581	-0.00288	0.1188
soybean	0.007732	-0.01032	7.842	0.8594	-0.00167	0.1192

Figure 1: Corn and soybean price history (Jan.2006-Sep.2014)

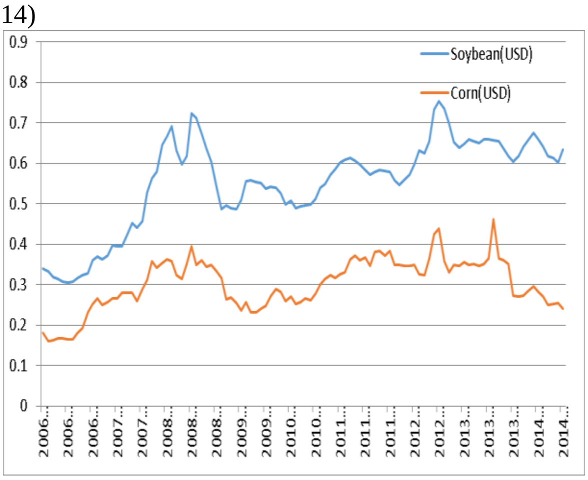
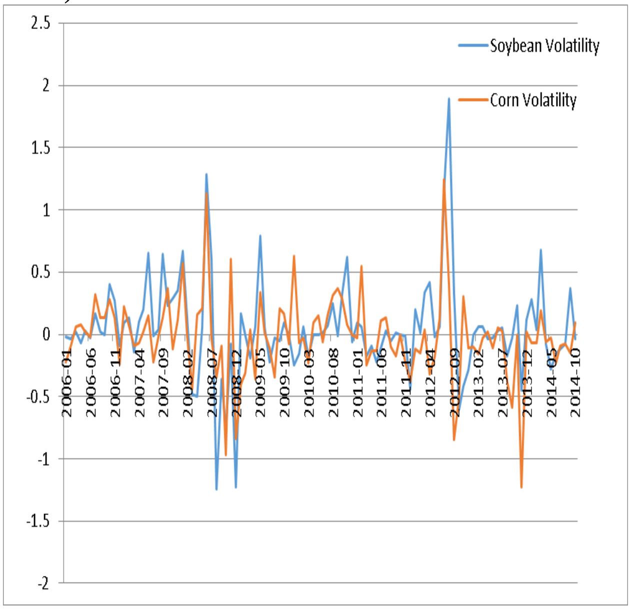


Figure 2: Corn and soybean volatility history (Jan.2006-Sep.2014)



REFERENCES

Andersen, T.,1994. Stochastic autoregressive volatility: a framework for volatility modeling. Math. Finance 4,75-102

Andersen, T., Chung, H., & Sorensen, B. E. (1999). Efficient method of moments estimation of a stochastic volatility model: A Monte Carlo study. Journal of Econometrics, 91, 61–87.

Anderson, H. M., & Vahid, F. (2001). Market architecture and nonlinear dynamics of Australian stock and futures indices. Australian Economic Papers, 40, 541–566.

Campbell, R., R. Huisman, and K. Koedijk (2001): "Optimal Portfolio Selection in a Valueat-Risk Framework," Journal of Banking and Finance, 25, 1789–1804.

Consigli, G. (2002): "Tail Estimation and mean-VaR Portfolio Selection in Markets Subject to Financial Inestability," Journal of Banking and Finance, 26, 1355–1382