Speculation and Volatility Spillover in the Crude Oil and Agricultural Commodity Markets: A Bayesian Analysis

Xiaodong Du
Center for Agricultural and Rural Development
Department of Economics
Iowa State University
565 Heady Hall
Ames, IA 50011 (USA)
xdu@iastate.edu

Cindy L. Yu
Assistant Professor
Department of Statistics
Iowa State University
2625 N. Loop
Ames, IA 50011 (USA)
cindyyu@iastate.edu

Dermot J. Hayes
Professor
Department of Economics and
Department of Finance
Iowa State University
578C Heady Hall
Ames, IA 50011 (USA)
dhayes@iastate.edu

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association 2009 AAEA & ACCI Joint Annual Meeting, Milwaukee, WI, July 26-28, 2009.

Abstract: This paper assesses the roles of various factors influencing the volatility of crude oil prices and the possible linkage between this volatility and agricultural commodity markets. Stochastic volatility models are applied to weekly crude oil, corn and wheat futures prices from November 1998 to January 2009. Model parameters are estimated using Bayesian Markov chain Monte Carlo methods. The main results are as follows. Speculation, scalping, and petroleum inventories are found to be important in explaining oil price variation. Several properties of crude oil price dynamics are established including mean-reversion, a negative correlation between price and volatility, volatility clustering, and infrequent compound Poisson jumps. We find evidence of volatility spillover among crude oil, corn and wheat markets after the fall of 2006. This could be largely explained by tightened interdependence between these markets induced by ethanol production.

JEL Classification: G13; Q4.
Keywords: Gibbs sampling, Merton jump, leverage effect, stochastic volatility.

1. Introduction

Crude oil prices exhibited exceptional volatility through much of 2008. After setting a record high of over $147 per barrel in July, the benchmark price of the West Texas Intermediate (WTI) crude oil fell to just over $40 per barrel in early December. Oil price shocks and their transmission through various channels impact the U.S. and global economy significantly (Kilian 2008). In various studies seeking to explain this sharp price increase, speculation was found to play an important role. Hamilton (2008) concludes that a low demand price elasticity, strong demand growth, and stagnant global production induced upward pressure on crude oil prices and triggered commodity speculation from 2006 to 2008. Caballero, Farhi, and Gourinchas (2008) also link the oil price surge to large speculative capital flows that moved into the U.S. oil market.

Agricultural commodity prices have displayed similar behavior. Chicago cash corn prices rose over $3/bushel to reach $7.2/bushel in July 2008. They then fell to

$3.6/bushel in December 2008. Volatile agricultural commodity prices have been, and continue to be a cause for concern among governments, traders, producers and consumers. When an increasing portion of corn used as feedstock in the production of alternative energy sources (e.g. ethanol), crude oil prices may have contributed to the increase in prices of agricultural crop by not only rising input costs but also boosting demand. Given the relatively fixed number of acres that can be allocated for crop production it is likely that shocks to the corn market may spillover into other crops and ultimately into food prices. Thus the interdependency between energy and agricultural commodity markets warrants further investigation.

In this study, we attempt to investigate the role of speculation in driving crude oil price variation after controlling other influencing factors. We also attempt to quantify the extent to which volatility in the crude oil market transmits into agricultural commodity markets, especially the corn and wheat markets. We hypothesize that the linkage between these markets has tightened and that volatility has spilled over from crude oil to corn and wheat as large scale of corn ethanol production has impacted agricultural commodity price formation.

A considerable body of researches has been devoted to investigate the price volatility in the crude oil market. For example, Sadorsky (2006) evaluates various statistical models in forecasting volatility of crude oil futures prices. Cheong (2009) investigates and compares time-varying volatility of the Europe Brent and the WTI markets, and finds volatility persistence in both markets and a significant leverage effect in the European Brent market. Kaufmann and Ullman (2009) explore role of speculation in the crude oil futures market. While there are a number of papers on volatility transmission in financial and/or energy markets (e.g., Hamao, Masulis, and Ng 1990; Ewing, Malik, and Ozfidan 2002; Baele 2005), specific studies on volatility transmission between crude oil and agricultural markets is sparse. Babula and Somwaru (1992) investigate the dynamic impacts of oil price shocks on prices of petroleum-based inputs such as agricultural chemical and fertilizer. The effect of oil price shock on the U.S. agricultural employment is investigated in Uri (1996).

For the purpose of modeling conditional heteroskedasticity, ARCH/GARCH models, originally introduced by Engle (1982), and stochastic volatility (SV) models proposed by

Taylor (1994) are the two main approaches that are used in the literature. While ARCH/GARCH models define volatility as a deterministic function of past return innovations, volatility is assumed to vary through its own stochastic process in SV models. ARCH-type models are relatively easy to estimate and remain popular (see Engle 2002 for a recent survey). SV models are directly connected to diffusion processes and thus allow for a volatility process that does not depend on observable variables. SV models provide greater flexibility in describing stylized facts about returns and volatilities, but are relatively difficult to estimate (Shephard 2005). Much progress has been achieved on the estimation of SV models using Bayesian MCMC techniques, and this appears to yield relatively good results (e.g., Chib, Nardari and Shephard, 2002; Jacquier, Polson, and Rossi, 2004; Li, Wells, and Yu 2008).

Oil price dynamics are characterized by random variation, high volatility, and jumps (Askari and Krichene 2008), which may possibly be induced by demand uncertainty and a sluggish energy production system (Wirl 2008). Incorporating the leverage effect; a negative correlation between price and volatility, is found to provide superior forecasting results for crude oil price changes (Morana 2001). To fully capture the stylized facts of oil price dynamics, we adopt a stochastic volatility with Merton jump in return (SVMJ) model. In the model, the instantaneous volatility is described by a mean-reverting square-root process, while the jump component is assumed to follow a compound Poisson process with constant jump intensity, and the jump size that follow a normal distribution.

The applied SVMJ model belongs to the class of affine jump-diffusions models (Duffie, Pan, and Singleton 2000), which is tractable and capable to capture salient features of price and volatility in an economical fashion. It has the advantage of ensuring that the volatility process can never be negative or reach zero in finite time and providing close-form solutions for pricing a wide range of equity and derivatives. The Bayesian MCMC method that we employ in this study is particularly suitable for dealing with this type of model. Based on a conditional simulation strategy, MCMC method avoids marginalizing high dimensional latent variables including instantaneous volatility and jumps to obtain parameter estimates. MCMC also affords special techniques to overcome the difficulty of drawing from complex posterior distributions with unknown functional forms which can significantly complicate likelihood-based inferences.

To the best of our knowledge our study is the first to apply an SVMJ model to crude oil prices and to empirically examine crude oil price and volatility dynamics in a model that allows for mean-reversion, the leverage effect, and infrequent jumps.

Our results suggest that volatility peaks are found to be associated with significant political and economic events. The explanatory variables we use have the hypothesized signs and can explain a large portion of the price variation. Scalping and speculation are shown to have had a significantly positive impact on price volatility. Petroleum inventories are found to reduce oil price variation. We find evidence of volatility spillover among crude oil, corn and wheat markets after the fall of 2006, which is consistent with the large scale production of ethanol.

A methodological innovation of our approach is that we introduce a Bayesian estimation method capable of accommodating parameters of the underlying dynamic process and additional explanatory variables in the volatility formulation. The coefficients of the endogenized variables are estimated using a weighted least square (WLS) method given MCMC draws of other model parameters and latent realizations. The WLS method performs well in our generated data experiment and provides an adequate fit to the real data.

The outline of this paper is as follows. In the following section we describe the model and the associated Bayesian posterior simulators for the stochastic volatility models. Section 3 describes our data, while Section 4 presents the empirical results. Concluding remarks are presented in Section 5.

2. The Model

2.1 The Univariate SVMJ model

Let P_t be the crude oil futures prices and y_t denote the logarithm of prices, i.e., $y_t = \log P_t$. The dynamics of y_t are characterized by the SVMJ model as the following:

$$
\begin{aligned}
y_{t+1} &= y_t + \mu + \sqrt{v_t}\varepsilon^y_{t+1} + J^y_t,\ J^y_t = \xi^y_t N^y_t \\
v_{t+1} &= v_t + \kappa(\theta - v_t) + Z_{t+1}\beta + \sigma_v\sqrt{v_t}\varepsilon^v_{t+1}.
\end{aligned}
\tag{1}
$$

where both ε_{t+1}^{y} and ε_{t+1}^{v} are assumed to follow $N(0,1)$ with correlation $\mathrm{corr}(\varepsilon_{t+1}^{y},\varepsilon_{t+1}^{v})=\rho$, which measures the correlation between returns and instantaneous volatility, this is the leverage effect. The instantaneous volatility of returns, v_t, is stochastic and assumed to follow the mean-reverting square-root process developed by Heston (1993). While J_t^y represents a jump in returns, the jump time N_t^y is assumed to follow a $Poisson(\lambda t)$ with the probability $P(N_t^y=1)=\lambda_y$ and the jump size ξ_t^y follows the distribution of $N(\mu_y,\sigma_y^2)$, both of which are independent of ε_{t+1}^{y} and ε_{t+1}^{v}.

The symbol μ measures the mean return, θ is the long-run mean of the stochastic volatility, κ is the speed of mean reversion of volatility, while σ_v represents the volatility of volatility variable. $Z_t=(Z_{1t},Z_{2t},...,Z_{nt})'$ is a $n\times 1$ vector of n explanatory variables at time t, whose effects on volatility are represented by β. For this process, we have observations $(y_t)_{t=1}^{T+1}$ and $(Z_t)_{t=1}^{T+1}$, latent volatility variables $(v_t)_{t=1}^{T+1}$, a jump time $(N_t^y)_{t=1}^{T}$ and size $(\xi_t^y)_{t=1}^{T}$. Model parameters are $\Theta=\{\mu,\kappa,\theta,\beta,\sigma_v,\rho,\lambda_y,\mu_y,\sigma_y\}$.

2.1.1 Bayesian Inference

Conditioning on the latent variables, v_t and J_t^y, $y_{t+1}-y_t$ and $v_{t+1}-v_t$ follow a bivariate normal distribution:

$$\begin{bmatrix} y_{t+1}-y_t \\ v_{t+1}-v_t \end{bmatrix} | v_t, J_t^y \sim N\left[\begin{pmatrix} \mu + J_t^y \\ \kappa(\theta - v_t) + Z_{t+1}\beta \end{pmatrix}, v_t \begin{pmatrix} 1 & \rho\sigma_v \\ \rho\sigma_v & \sigma_v^2 \end{pmatrix}\right]. \qquad (2)$$

So the joint distribution of the returns, $Y=\{y_t\}_{t=1}^{T+1}$, the volatility, $V=\{v_t\}_{t=1}^{t+1}$, the jumps, $J=\{J_t^y\}_{t=1}^{T}$, and the parameters Θ is:

$$\begin{aligned} p(\Theta,V,J\,|\,Y) &\propto p(Y,V\,|\,J)\,p(J\,|\,\Theta)\,p(\Theta) \\ &\propto \prod_{t=0}^{T-1}\frac{1}{\sigma_v v_t\sqrt{1-\rho^2}}\,\text{ex}\left\{-\text{p}\frac{1}{2(1-\rho^2)}\left((\varepsilon_{t+1}^{y})^2-2\rho\varepsilon_{t+1}^{y}\varepsilon_{t+1}^{v}+(\varepsilon_{t+1}^{v})^2\right)\right\} \\ &\quad \times\prod_{t=0}^{T-1}\frac{1}{\sigma_y}\exp\left(-\frac{(\xi_t^y-\mu_y)^2}{2\sigma_y^2}\right)\times\prod_{t=0}^{T-1}\lambda_y^{J_{t+1}^y}(1-\lambda_y)^{1-J_{t+1}^y}\times p(\Theta) \end{aligned} \qquad (3)$$

where $\varepsilon_{t+1}^{y} = (y_{t+1} - y_t - \mu - J_t)/\sqrt{v_t}$ and $\varepsilon_{t+1}^{v} = \left(v_{t+1} - v_t - \kappa(\theta - v_t) - Z_{t+1}\beta\right)/(\sigma_v\sqrt{v_t})$.

Following the literature, we employ the following convenient conjugate and proper priors: $\mu \sim N(0,1)$, $\kappa \sim TN_{(0,\infty)}(0,1)$, $\theta \sim TN_{(0,\infty)}(0,1)$, $\mu_y \sim N(0,100)$, $\sigma_y^2 \sim IG(5,1/20)$, and $\lambda_y \sim beta(2,40)$, where $TN_{(a,b)}(\mu,\sigma^2)$ denotes a normal distribution with mean μ and variance σ^2 truncated to the interval (a,b), and IG and $beta$ represent the inverse gamma and beta distribution, respectively. Similar to Jacquire, Polson, and Rossi (1994), (ρ,σ_v) are re-parameterized as (ϕ_v,ω_v), where $\phi_v = \sigma_v\rho$ and $\omega_v = \sigma_v^2(1-\rho^2)$. The priors of the new parameters are chosen as $\phi_v \mid \omega_v \sim N(0,1/2\omega_v)$ and $\omega_v \sim IG(2,200)$.

2.1.2 The Gibbs sampler

The complete model is given by the equation (3) together with the prior distribution assumptions. The model is fitted using recent advances in MCMC techniques, namely, the Gibbs sampler. Given the conditionally conjugate priors, the posterior simulation is straightforward and proceeds in the following steps.

Step *1.* $\mu \mid \cdot \sim N(S/W, 1/W)$

where $W = \frac{1}{1-\rho^2}\sum_{t=0}^{T-1}\left(\frac{1}{v_t}\right) + \frac{1}{M^2}$, $S = \frac{1}{1-\rho^2}\sum_{t=0}^{T-1}\frac{1}{v_t}\left(C_t - \rho\frac{D_t}{\sigma_v}\right) + \frac{m}{M^2}$,

$C_t = y_{t+1} - y_t - N_t^y\xi_t^y$, and $D_t = v_{t+1} - v_t - \kappa(\theta - v_t) - Z_{t+1}\beta$. m and M are the hyperparameters for the prior of the corresponding parameter (the same hereafter).

Step 2. $\mu_y \mid \cdot \sim N(S/W, 1/W)$

where $W = \frac{T}{\sigma_y^2}$, $S = \frac{\sum_{t=0}^{T-1}\xi_t^y}{\sigma_y^2} + \frac{m}{M^2}$.

Step 3. $\sigma_y^2 \mid \cdot \sim IG\left(\frac{T}{2} + m, \frac{1}{1/2\sum_{t=0}^{T-1}(\xi_t^y - \mu_y)^2 + 1/M}\right)$

Step 4. $\lambda_y \mid \cdot \sim beta\left(\sum_{t=0}^{T-1} N_t^y + m, T - \sum_{t=0}^{T-1} N_t^y + M\right)$

Step 5. $\theta \mid \cdot \sim TN_{(0,\infty)}(S/W, 1/W)$

where $W = \frac{\kappa^2}{\sigma_v^2(1-\rho^2)}\sum_{t=0}^{T-1}\frac{1}{v_t} + \frac{1}{M^2}$, $S = \frac{\kappa}{(1-\rho^2)\sigma_v}\sum_{t=0}^{T-1}\frac{1}{v_t}\left(\frac{D_t/\sigma_v - \rho C_t}{v_t}\right) + \frac{m}{M^2}$,

$C_t = y_{t+1} - y_t - N_t^y \xi_t^y$, and $D_t = v_{t+1} + (\kappa - 1)v_t - Z_{t+1}\beta$.

Step 6. $\kappa \mid \cdot \sim TN_{(0,\infty)}(S/W, 1/W)$

where $W = \frac{\kappa^2}{\sigma_v^2(1-\rho^2)}\sum_{t=0}^{T-1}\frac{(\theta - v_t)^2}{v_t} + \frac{1}{M^2}$,

$S = \frac{\kappa}{(1-\rho^2)\sigma_v}\sum_{t=0}^{T-1}\left(\frac{(\theta - v_t)(D_t/\sigma_v - \rho C_t)}{v_t}\right) + \frac{m}{M^2}$, $C_t = y_{t+1} - y_t - N_t^y \xi_t^y$, and

$D_t = v_{t+1} - v_t - Z_{t+1}\beta$.

Step 7. $\omega_v \mid \cdot \sim IG\left(\frac{T}{2} + m, \frac{1}{1/2\sum_{t=0}^{T-1} D_t^2 + 1/M - S^2/2W}\right)$ and $\phi_v \mid \omega_v \sim N(S/W, \omega_v/W)$

where $W = \sum_{t=0}^{T-1} C_t^2 + 2$, $S = \sum_{t=0}^{T-1} C_t D_t$, $C_t = (y_{t+1} - y_t - N_t^y \xi_t^y)/\sqrt{v_t}$, and

$D_t = (v_{t+1} - v_t - \kappa(\theta - v_t) - Z_{t+1}\beta)/\sqrt{v_t}$.

Step 8. $\xi_{t+1}^y \mid \cdot \sim N(S/W, 1/W)$

where $W = \frac{(N_t^y)^2}{(1-\rho^2)v_t}$, $S = \frac{N_t^y}{(1-\rho^2)\sigma_v}\sum_{t=0}^{T-1}\left(C_t - \rho D_t/v_t\right) + \frac{\mu_y}{\sigma_y^2}$, $C_t = y_{t+1} - y_t - \mu$, and

$D_t = v_{t+1} - v_t - \kappa(\theta - v_t) - Z_{t+1}\beta$.

Step 9. $N_{t+1}^y \mid \cdot \sim Bernoulli\left(\frac{\alpha_1}{\alpha_1 + \alpha_2}\right)$

where $\alpha_1 = \exp\left\{-\frac{1}{2(1-\rho^2)}\left[A_1^2 - 2\rho A_1 B\right]\right\}\lambda_y$,

$\alpha_2 = \exp\left\{-\frac{1}{2(1-\rho^2)}\left[A_2^2 - 2\rho A_2 B\right]\right\}(1-\lambda_y)$, $A_1 = (y_{t+1} - y_t - \mu - \xi_t^y)/\sqrt{v_t}$,

$A_2 = (y_{t+1} - y_t - \mu)/\sqrt{v_t}$, and $B = (v_{t+1} - v_t - \kappa(\theta - v_t) - Z_{t+1}\beta)/(\sigma_v\sqrt{v_t})$.

Step 10. The posterior distribution of v_{t+1} is time-varying as follows:

For $1 < t+1 < T$,

$$p(v_{t+1}|\cdot) \propto \exp\left\{-\frac{\left[-2\rho\varsigma_{t+1}^y\varsigma_{t+1}^v + (\varsigma_{t+1}^v)^2\right]}{2(1-\rho^2)}\right\} \times \frac{1}{v_{t+1}} \times \exp\left\{-\frac{\left[\varsigma_{t+2}^y - 2\rho\varsigma_{t+2}^y\varsigma_{t+2}^v + (\varsigma_{t+2}^v)^2\right]}{2(1-\rho^2)}\right\},$$

where $\varsigma_{t+1}^y = C_t = (y_{t+1} - y_t - N_t^y\xi_t^y)/\sqrt{v_{t-1}}$, $\varsigma_{t+1}^v = (v_{t+1} - v_t - \kappa(\theta - v_t) - Z_{t+1}\beta)/(\sigma_v\sqrt{v_t})$.

For $t+1=1$,

$$p(v_1|\cdot) \propto \frac{1}{v_1} \times \exp\left\{-\frac{\left[\varsigma_2^y - 2\rho\varsigma_2^y\varsigma_2^v + (\varsigma_2^v)^2\right]}{2(1-\rho^2)}\right\}.$$

For $t+1 = T+1$,

$$p(v_{T+1}|\cdot) \propto \exp\left\{-\frac{\left[-2\rho\varsigma_{T+1}^y\varsigma_{T+1}^v + (\varsigma_{T+1}^v)^2\right]}{2(1-\rho^2)}\right\} \times \frac{1}{v_{T+1}}.$$

It's difficult to sample from this posterior distribution of v_{t+1} because it is time-varying and in complicated forms. We employ the random walk Metropolis-Hasting algorithms (Gelman et al. 2007) to update the latent volatility variables.

Step 11. Estimation method for β

After obtaining simulated draws of the latent variables and other model parameters, we estimate β using weighted least square (WLS) method:

$$\hat{\beta} = (W'W)^{-1}W'G \qquad (4)$$

where $W = \frac{Z_{t+1}}{\sigma_v \sqrt{(1-\rho^2)v_t}}$, $G = \frac{D_t - \rho\sigma_v C_t}{\sigma_v \sqrt{(1-\rho^2)v_t}}$, $C_t = y_{t+1} - y_t - \mu - N_t^y \xi_t^y$, and $D_t = v_{t+1} - v_t - \kappa(\theta - v_t)$.

2.2 The Bivariate SV model

To investigate possible volatility spillover between crude oil and agricultural commody markets, we model three pairs of log return of commodity prices in the bivariate SV framework, crude oil/corn, corn/wheat, and crude oil/wheat. We refer the first commodity in the pair as commodity 1, the second commodity 2. That is to say that crude oil or corn is commodity 1 in each pair, while corn or wheat is commodity 2. We denote the observed log-returns of futures prices at time t by $D_t = (D_{1t}, D_{2t})'$ for $t = 1,...,T$, i.e., $D_{it} = \Delta \log P_i = \log P_{i,t} - \log P_{i,t-1}$, $i = 1,2$. Let $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$, $\mu = (\mu_1, \mu_2)'$, and $V_t = (V_{1t}, V_{2t})'$. The bivariate stochastic volatility model with possible volatility spill-over from one market to the other is specified as

$$
\begin{aligned}
D_t &= \Omega_t \varepsilon_t, \quad \varepsilon_t \overset{iid}{\sim} N(0, \Sigma_\varepsilon), \\
V_{t+1} &= \mu + \Phi(V_t - \mu) + \eta_t, \quad \eta_t \overset{iid}{\sim} N(0, \Sigma_\eta).
\end{aligned} \tag{5}
$$

where $\Omega_t = \begin{pmatrix} \exp(v_{1t})/2 & 0 \\ 0 & \exp(v_{2t})/2 \end{pmatrix}$, $\Sigma_\varepsilon = \begin{pmatrix} 1 & \rho_\varepsilon \\ \rho_\varepsilon & 1 \end{pmatrix}$. While Σ_η describes the returns dependence by the constant correlation coefficient ρ_ε, the volatility spill-over effect is captured by $\Phi = \begin{pmatrix} \phi_{11} & 0 \\ \phi_{21} & \phi_{22} \end{pmatrix}$. We constrain ϕ_{12} to equal zero to exclude the possibility of unrealistic volatility transmission from the market of commodity 1 to the commodity market 2. As ϕ_{21} is different from zero, the cross dependence of volatilities are realized via volatility transmission from the commodity 1 to the commodity 2's market. The matrix Σ_η defines the variation of individual volatility process as $\begin{pmatrix} \sigma^2_{\eta 1} & 0 \\ 0 & \sigma^2_{\eta 2} \end{pmatrix}$. The estimation of the bivariate SV model (5) is implemented in Bayesian inference using Gibbs Sampling (WinBUGS) following the lines of Yu and Meyer (2008).

3. Data

Our empirical analysis makes use of weekly average settlement prices of crude oil futures contracts traded on New York Mercantile Exchange (NYMEX) from November 16, 1998 and January 26, 2009. Similarly, the corn and wheat prices are the weekly average settlement prices of futures contracts traded in the Chicago Board of Trade (CBOT) over the same period. The futures prices are taken from the corresponding nearest futures contracts, which are the contracts closest to their expiration. Figure 1 presents the logarithm of crude oil prices and the log returns over the sample period.

To investigate the influencing forces for oil price volatility, the SVMJ model in eqn. (1) relates price volatility to a set of explanatory economic variables Z_t. Each of the included variables, its hypothesized relationship with oil price variability, and the related data sources are discussed in detail as follows.

3.1 Scalping

Scalping refers to activities that open and close contract positions within a very short period of time so as to realize small profits. It typically reflects market liquidity. Focusing on taking profits based on small price changes, scalpers may allow prices to adjust to information more quickly and assumedly increase price variability. A standard measure of scalping activity in futures markets is the ratio of volume to open interest. We construct the proxy for scalping activities in crude oil futures market using weekly average trading volume and open interest of nearest futures contracts in the NYMEX market.

3.2 Crude oil inventory

The volatility of a commodity price tends to be inversely related to the level of stocks. A significant negative relationship between crude oil inventory and price volatility has been documented in Geman and Ohana (2009). Total U.S crude oil and petroleum products stocks (excluding the Strategic Petroleum Reserve) were downloaded from the EIA website.

3.3 Speculation index

The speculation index is intended to measure the intensity of speculation relative to short hedging.. For traders in the futures market who hold positions in futures at or above specific reporting levels, the U.S. Commodity Futures Trading Commission (CFTC) classifies their futures positions as either “commercial” or “noncommercial”. By definition, commercial positions in a commodity are held for hedging purposes, while noncommercial positions mainly represent speculative activity in pursuit of financial profits. So the speculation index is constructed as the ratio of noncommercial positions to total positions in futures contracts using the following:

$$\begin{cases} 1+\dfrac{SS}{HS+HL} & \text{if } HS > HL; \\ 1+\dfrac{SL}{HS+HL} & \text{if } HS < HL. \end{cases}$$

where $SS(SL)$ represents speculative short (long) positions in the crude oil futures market, while $HS(HL)$ represents short (long) hedged positions. These weekly position numbers are obtained from Historical Commitments of Traders Reports (CFTC 1998-2009). All independent variables Z_t are centralized by subtracting the means.

To facilitate the analysis of volatility spill-over between crude oil and corn markets, we apply the algorithm, which is proposed in Bai (1997) and implemented in Zeileis et al. (2002), to test for possible structural change of corn and wheat prices over the sample period. The test results presented in figures 2 and 3 indicate that while the pattern of corn futures prices changed in the week of Oct. 23, 2006, the wheat prices has structure change in the same period, the week of Oct. 30, 2006. The change points are represented by the vertical lines in the figures. The timing of structure change is consistent with the finding in the literature (e.g., Irwin and Good 2009). For comparison, we thus split the sample to two subsamples and estimate eqn. (5) repeatedly to estimate for possible volatility spillover among crude oil, corn and wheat markets.

4. Empirical Results

First, we coded the Gibbs sampler of the univariate SVMJ model introduced in Section 2 in Matlab and ran it for 50,000 iterations on generated data. The generated data experiment was done to test the reliability of the estimation algorithm. Inspection of the draw sequences satisfied us that the sampler had converged by iteration 20,000. The results indicate that our algorithm can recover the parameters of the data generating process sufficiently. Then we run the estimation for 50 times with 30,000 iterations each time on the collected data described in Section 3. For each run, we discard the first 20,000 runs as a "burn-in" and use the last 10,000 iterations in MCMC simulations to estimate the model parameters. Specifically, we take the mean of the posterior distribution as a parameter estimate and the standard deviation of the posterior as the standard error.

The estimated volatility over the sample period is plotted in figure 4. From an examination of figure 3, it is clear that there exists volatility clustering, i.e., when volatility is high, it is likely to remain high, and when it is low, it is likely to remain low. Also, it can be seen that volatility peaked around March 2003, the time of the Iraq invasion. The other period with high price variation is December 2008, that is coincident with the recent oil price surge and following financial crisis.

The posterior estimates of the SVMJ models reported in table 1 indicate:

(1) Mean-reversion in the behavior of volatility: the speed of mean reversion (κ) is 0.49 with the long-run mean return 0.0056*52=0.29;

(2) A negative leverage effect; the negative correlation between instantaneous volatility and prices, $\rho = -0.1187$;

(3) Infrequent compound Poisson jumps: the estimate of λ suggests on average 0.0035*52=0.182 jumps per year.

All the explanatory variables included in the time-varying volatility have the hypothesized sign. The posterior standard deviations associated with these coefficients are quite small relative to their means. While scalping activity increases the crude oil price volatility, petroleum inventory negatively affects the price variability. More importantly, speculation in the crude oil futures market is found to increase up oil price variation in a significant manner.

We ran Winbugs codes for the bivariate SV model for 30,000 iterations with the first 20,000 iteration discarded as burn-in. The estimation results for volatility spillover between crude oil and corn markets are presented in table 2, while table 3 shows those for oil/wheat and corn/wheat markets. The spillover effects are not significantly different from zero in the first subsample period, November 1998 - October 2006. In the second subsample period, October 2006 – January 2009, the estimate of $\phi_{21} = 0.13$ in table 2 indicates a significant volatility spillover from crude oil market to corn market. This result supports the hypothesis that higher crude oil prices led to forecasts of a large corn ethanol impact on corn prices which in turn impacted corn price formation. The estimation result of $\phi_{21} = 0.16$ for the model of corn and wheat markets indicates that a significant portion of the price variation in the wheat market in this time period was a result of price variation in the corn market which in turn were due to price variation in the crude oil market. These results make sense when one considers that corn and wheat compete for acres in some states.

The correlation coefficient between crude oil and corn markets in table 2 increases from 0.13 to 0.33 in the second period, while that for crude and wheat markets increases from 0.09 to 0.28, as presented in table 3. These results indicate a much tighter linkage between crude oil and agriculture commodity markets in the second period.

5. Conclusion

In this study, we show that various economic factors including scalping, speculation, and petroleum inventories explain crude oil price volatility. After endogenizing these economic factors, the model with both diffusive stochastic volatility and Merton jumps in returns adequately approximates the characteristics of recent oil price dynamics. The Bayesian MCMC method is shown to be capable of providing an accurate joint identification of the model parameters. Recent oil price shocks appear to have triggered sharp price changes in agricultural commodity markets, especially the corn and wheat market, potentially because of the tighter interconnection between these food/feed and energy markets in the past three years.

References

Askari, H, Krichene, N. 2008. Oil price dynamics (2002-2006). *Energy Economics* 30:2134-2153.

Babula, R, Somwaru, A. 1992. Dynamic impacts of a shock in crude oil price on agricultural chemical and fertilizer prices. *Agribusiness* 8:243-252.

Baele, L. 2005. Volatility spillover effects in European equity markets. *Journal of Financial and Quantitative Analysis* 40:373-401.

Bai, J. 1997. Estimation of a change point in multiple regression models. *Review of Economics and Statistics* 79:551-563.

Caballero, RJ, Farhi E, and Gourinchas, P. 2008. Financial crash, commodity prices, and global imbalances. Working Paper 14521, National Bureau of Economic Research (NBER).

CFTC (U.S. Commodity Futures Trading Commission). 1998-2009. Historical Commitments of Traders Reports. Available at http://www.cftc.gov/marketreports/commitmentsoftraders/, last visited 03/31/2009.

Cheong, CW. 2009. Modeling and forecasting crude oil markets using ARCH-type models. *Energy Policy*, forthcoming.

Chib, S, Nardari, F, Shephard, N. 2002. Markov chain Monte Carlo methods for stochastic volatility models. *Journal of Econometrics* 116: 225-257.

Duffie, D, Pan, J, and Singleton, K. 2000. Transform analysis and asset pricing for affine jump-diffusions. *Econometrica* 68: 1343-1376.

Engle, RF. 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica* 50: 987-1008.

--. 2002. New frontiers for ARCH models. *Journal of Applied Econometrics* 17: 425-446.

Ewing, B, Malik, F, Ozfidan, O. 2002. Volatility transmission in the oil and natural gas markets. *Energy Economics* 24:525-538.

Gelman, A, Carlin, J, Stern, H, Rubin, D. 2007. *Bayesian Data Analysis*, Chapman & Hall/CRC: Boca Raton, FL.

Geman, H, Ohana, S. 2009. Forward curves, scarcity and price volatility in oil and natural gas markets. *Energy Economics*, forthcoming.

Hamao, Y, Masulis, R, Ng, V. 1990 Correlation in price changes and volatility across international stock markets. *Review of Financial Studies* 3:281-307.

Hamilton, JD. 2008. Oil and the macroeconomy. In *The New Palgrave Dictionary of Economics,* 2nd edition, ed. Durlauf, S. and Blume, L. New York: Palgrave Macmillan.

---. 2009. Understanding crude oil prices. *Energy Journal* 30:179-206.

Heston, S. 1993. A closed-form solution for options with stochastic volatility with applications to bond and currency options. *Review of Financial Studies* 6:327-343.

Irwin, S, Good, H. 2009. Market instability in a new era of corn, soybean, and wheat prices. *Choices* 24: 6-11.

Jacquier, E, Polson, N, Rossi, P. 1994. Bayesian analysis of stochastic volatility models. *Journal of Business and Economic Statistics* 12:371-389.

--. 2004. Bayesian analysis of stochastic volatility models with fat-tails and correlated errors. *Journal of Econometrics* 122:185-212.

Kaufmann, R., Ullman, B. 2009. Oil prices, speculation, and fundamentals: interpreting causal relations among spot and futures prices. *Energy Economics*, forthcoming.

Kilian, L. 2008. The economic effects of energy price shock. *Journal of Economic Literature* 46:871-909.

Li, H, Wells, M, Yu, C. 2008 A Bayesian analysis of return dynamics with Levy Jumps. *Review of Financial Studies* 21:2345-2378.

Morana, C. A semiparametric approach to short-term oil price forecasting. *Energy Economics* 23:325-338.

Sadorsky, P. 2006. Modeling and forecasting petroleum futures volatility. *Energy Economics* 28: 467-488.

Shephard, N. 2005. *Stochastic volatility: Selected Reading*. New York: Oxford University Press.

Taylor, SJ. 1994. Modeling stochastic volatility. *Mathematical Finance* 4:183-204.

Uri, N. 1996. Changing crude oil price effects on U.S. agricultural employment. *Energy Economics* 18:185-202.

Wirl, F. 2008. Why do oil prices jump (or fall)? *Energy Policy* 36:1029-1043.

Yu, J, Meyer, R. 2008. Multivariate stochastic volatility Models: Bayesian estimation and model comparison. *Econometric Reviews* 25:361-384.

Zeileis, A, Leisch, F, Hornik, K, Kleiber, C. 2002. Strucchange: an R package for testing for structural change in linear regression models. *Journal of Statistical Software* 7:1-38.

Table 1. SVMJ model parameter posterior mean and standard deviations

Variable	Mean	Std. dev.
μ	0.0056	0.0001
μ_y	0.1256	6.8448
σ_y	2.1821	0.0630
λ_y	0.0035	0.0001
θ	0.0106	0.0001
κ	0.4900	0.0092
σ_v	0.0576	0.0004
ρ	-0.1187	0.0050
β_1	0.0031	0.0002
β_2	-0.0034	0.0004
β_3	0.0029	0.0003

Table 2. Bivariate (Oil/Corn) SV model estimation results

Variable	11/1998 - 10/2006		10/2006 – 01/2009	
	Mean	Std. Dev.	Mean	Std. Dev.
μ_1	-5.94	0.22	-5.94	0.35
μ_2	-8.42	0.22	-7.60	0.25
ϕ_1	0.96	0.002	0.98	0.02
ϕ_2	0.86	0.05	0.79	0.11
ϕ_{21}	-0.049	0.06	0.13	0.09
ρ	0.13	0.05	0.33	0.09
σ_1	0.19	0.03	0.17	0.04
σ_2	0.50	0.08	0.14	0.06

Table 3. Bivariate (Oil/Wheat and Corn/Wheat) SV model estimation results

Variable	Oil and Wheat Markets				Corn and Wheat Markets			
	11/1998-10/2006		10/2006-01/2009		11/1998-10/2006		10/2006-01/2009	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
μ_1	-6.12	0.14	-5.99	0.45	-6.89	0.18	-6.08	0.29
μ_2	-6.39	0.23	-5.89	0.28	-6.55	0.17	-6.08	0.35
ϕ_1	0.90	0.06	0.98	0.02	0.88	0.04	0.91	0.09
ϕ_2	0.94	0.04	0.85	0.11	0.91	0.09	0.86	0.12
ϕ_{21}	-0.07	0.05	0.04	0.05	0.04	0.05	0.16	0.17
ρ	0.09	0.05	0.28	0.09	0.63	0.03	0.60	0.06
σ_1	0.20	0.05	0.19	0.05	0.36	0.07	0.16	0.07
σ_2	0.12	0.04	0.13	0.05	0.12	0.03	0.12	0.04

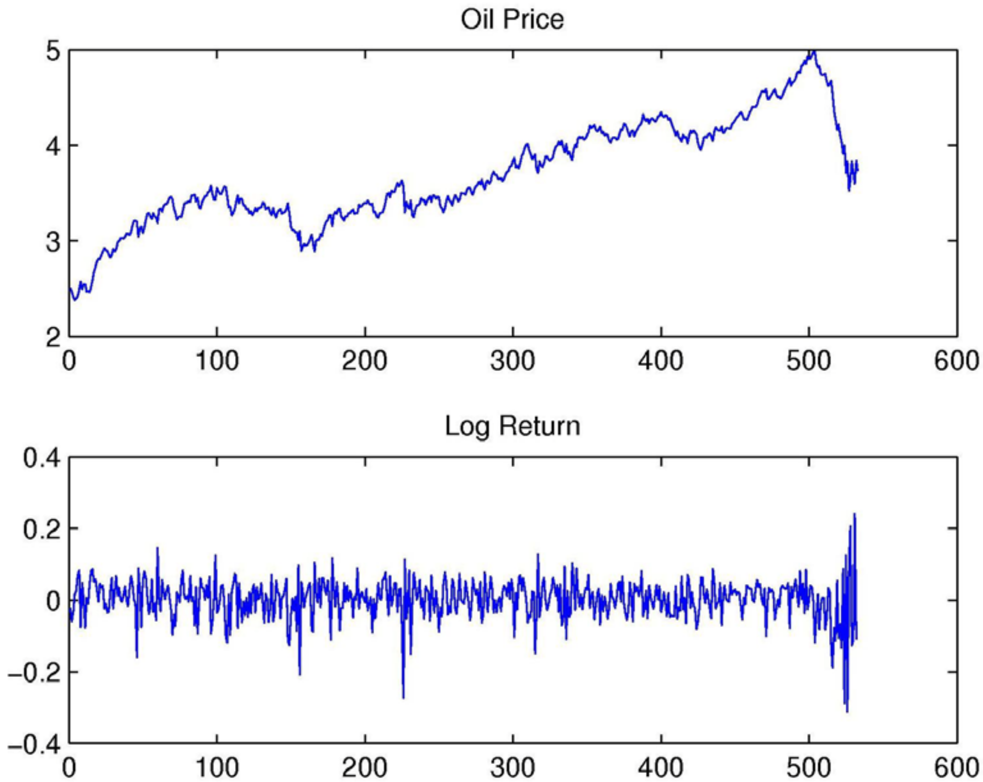

Figure 1. The log and log-return of crude oil prices (11/1998-01/2009).

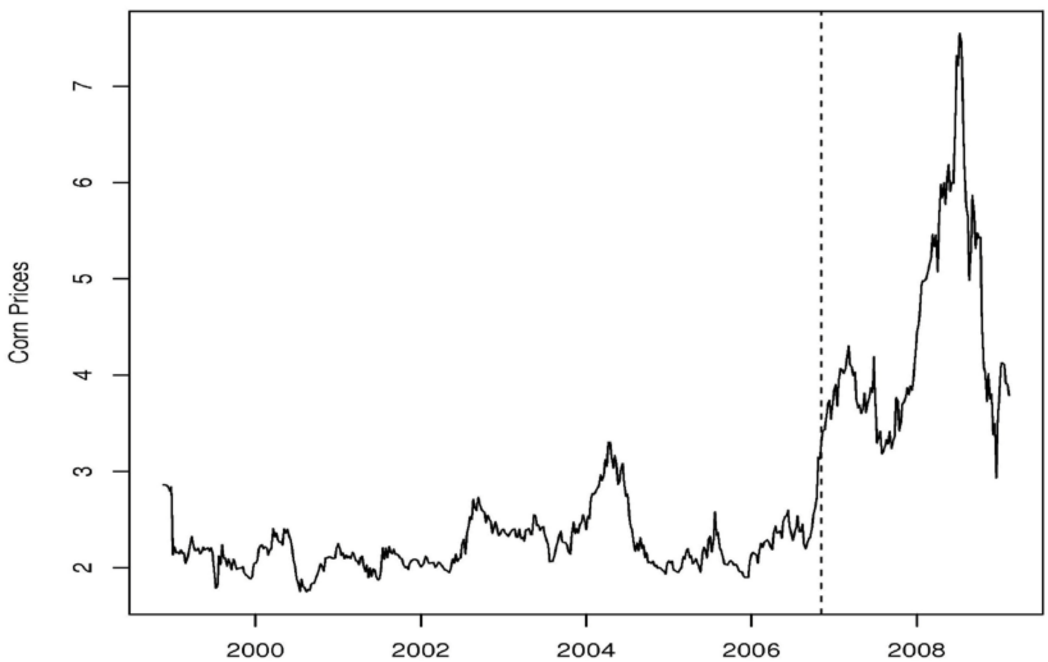

Figure 2. Structure change test of corn futures prices (11/1998-01/2009).

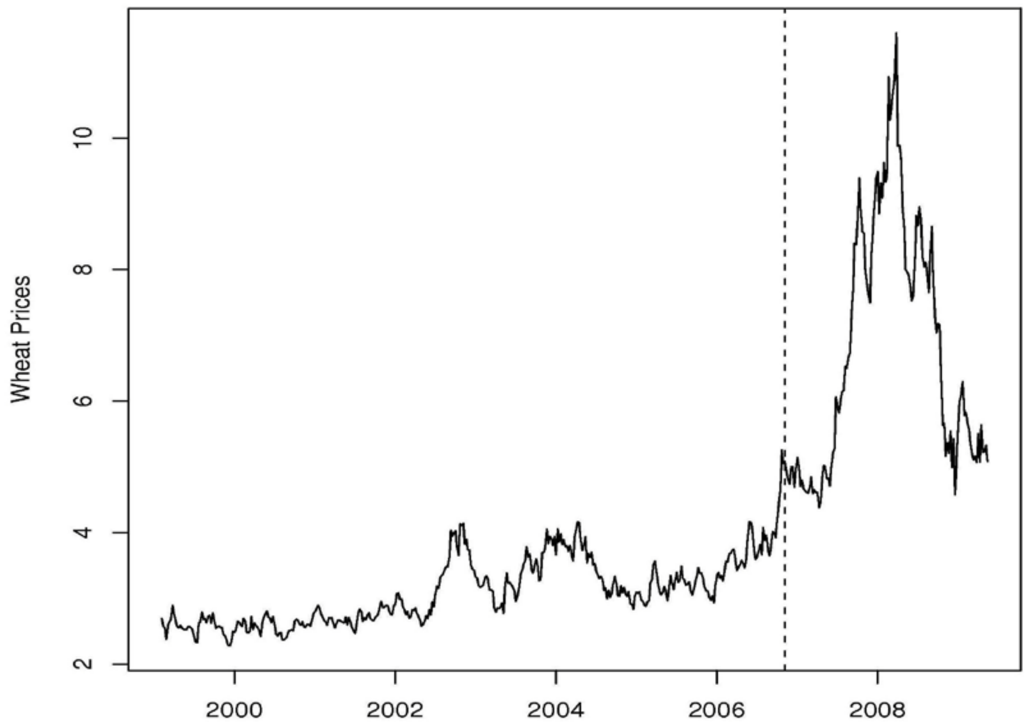

Figure 3. Structure change test of wheat futures prices (11/1998-01/2009).

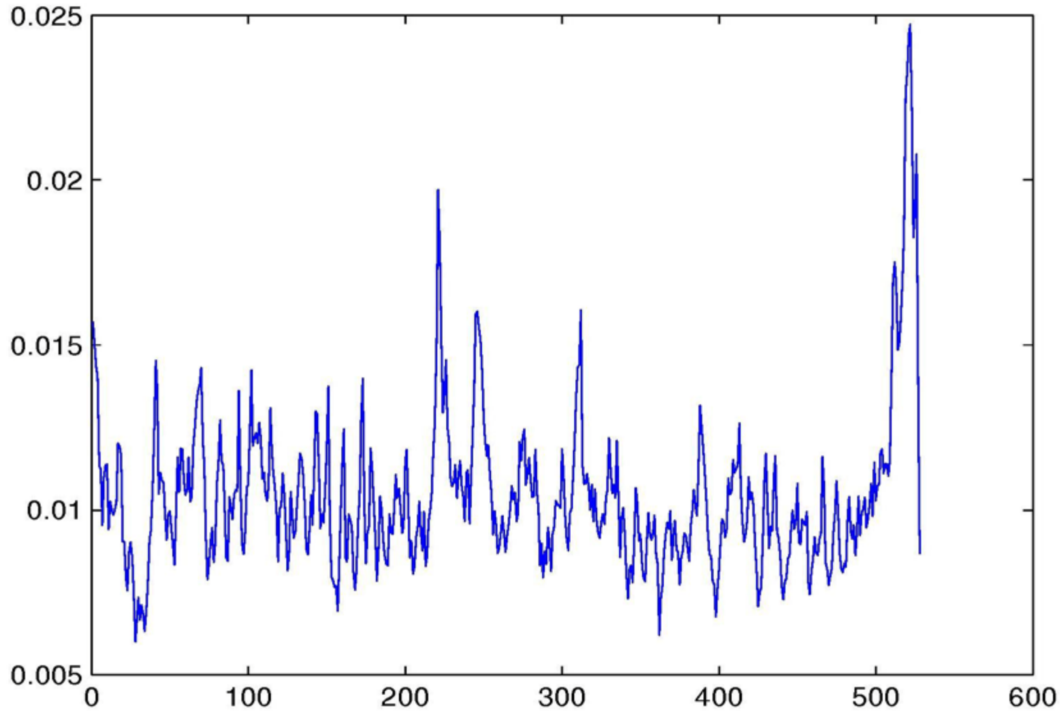

Figure 4. Estimated volatility of crude oil futures prices (11/1998-01/2009).