

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

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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 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.

Keywords: Gibbs sampling, Merton jump, leverage effect, stochastic volatility.

JEL Classification: G13; Q4.

1. Introduction

Crude oil prices exhibited exceptional volatility throughout 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 (2009) 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. The Chicago cash corn price rose over \$3/bushel to reach \$7.2/bushel in July 2008. It 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. With 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 crops by not only increasing 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 spill over 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 for 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 corn ethanol production has affected agricultural commodity price formation.

A considerable body of research 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 European 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 the 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 are 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 shocks on U.S. agricultural employment is investigated by 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 Markov chain Monte Carlo (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,¹ high volatility, and jumps, and are accompanied by underlying fundamentals of oil supply and demand markets (Askari and Krichene 2008). The recent jumps in oil prices could possibly be explained by demand shocks together with sluggish energy production and lumpy investments (Wirl 2008). Incorporating the leverage effect, a negative correlation

¹ An augmented Dickey-Fuller test indicated that the crude oil price over the sample period possessed a unit root, while changes in oil prices were stationary.

between price and volatility, is found to provide superior forecasting results for crude oil price changes (Morana 2001).² 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 a jump size that follows a normal distribution.

The applied SVMJ model belongs to the class of affine jump-diffusion models (Duffie, Pan, and Singleton 2000), which are tractable and capable of capturing 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 of 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, the 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 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

² Examples from the literature of modeling leverage effects within an ARCH/GARCH framework include Nelson 1991, Engle and Ng 1993, and Glosten, Jagannathan, and Runkle 1994.

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.

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:

$$\begin{aligned} y_{t+1} &= y_t + \mu + \sqrt{v_t} \varepsilon_{t+1}^y + J_t^y, J_t^y = \xi_t^y N_t^y \\ v_{t+1} &= v_t + \kappa(\theta - v_t) + Z_{t+1} \beta + \sigma_v \sqrt{v_t} \varepsilon_{t+1}^v. \end{aligned} \quad (1)$$

where both ε_{t+1}^y and ε_{t+1}^v are assumed to follow $N(0,1)$ with correlation

$\text{corr}(\varepsilon_{t+1}^y, \varepsilon_{t+1}^v) = \rho$, 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*(λt) 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. $Z_t = (Z_{1t}, Z_{2t}, \dots, Z_{nt})'$ 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:

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

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:

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

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

We assume the parameters, $\Theta = \{\mu, \kappa, \theta, \beta, \sigma_v, \rho, \lambda_y, \mu_y, \sigma_y\}$, are mutually independent. 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 Jacquier, 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 $\phi_v | \omega_v \sim N(0, 1/2\omega_v)$ and $\omega_v \sim IG(2, 200)$.

2.1.2 The Gibbs sampler

The complete model is given by 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. $\mu | \cdot \sim N(S/W, 1/W)$

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

$C_t = y_{t+1} - y_t - N_t^y \xi_t^y$, 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. $\mu_y | \cdot \sim N(S/W, 1/W)$

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

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

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

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

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

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

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

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

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

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

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

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

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

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

$A_2 = (y_{t+1} - y_t - \mu) / \sqrt{v_t}$, 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 $1 < t+1 < T$,

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

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

For $t+1=1$,

$$p(v_1 | \cdot) \propto \frac{1}{v_1} \times \exp \left\{ -\frac{[\zeta_2^y - 2\rho\zeta_2^y \zeta_2^v + (\zeta_2^v)^2]}{2(1-\rho^2)} \right\}.$$

For $t+1=T+1$,

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

It is 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

A minor yet important methodological contribution of this study is the way we estimate the effect of economic variables Z_t on the instantaneous latent volatility. After obtaining simulated draws of the latent variables and other model parameters, we estimate β using the WLS method:

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

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 stochastic volatility model

To investigate possible volatility spillover between crude oil and agricultural commodity markets, we model three pairs of log return of commodity prices in the bivariate stochastic volatility (SV) framework: crude oil/corn, corn/wheat, and crude oil/wheat. We

refer to the first commodity in the pair as commodity 1, and to the second commodity in the pair as 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 $Y_t = (Y_{1t}, Y_{2t})'$ for $t = 1, \dots, T$, i.e., $Y_{it} = \Delta \log P_i = \log P_{i,t} - \log P_{i,t-1}$, $i = 1, 2$.

Let $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$, $\mu = (\mu_1, \mu_2)'$, and $V_t = (V_{1t}, V_{2t})'$. The bivariate SV model with possible volatility spillover from one market to the other is specified as

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

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

dependence in returns dependence by the constant correlation coefficient ρ_ε , the

volatility spillover 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 2 market. As ϕ_{21} is different from zero, the cross-

dependence of volatilities is realized via volatility transmission from the commodity 1 to

the commodity 2 market. The matrix Σ_η defines the variation of individual volatility

process as $\begin{pmatrix} \sigma_{\eta_1}^2 & 0 \\ 0 & \sigma_{\eta_2}^2 \end{pmatrix}$.

The model in equation (5) is completed by the specification of a prior distribution

for all unknown parameters $\Theta' = \{\mu_1, \mu_2, \rho_\varepsilon, \phi_{11}, \phi_{12}, \phi_{21}, \sigma_{\eta_1}^2, \sigma_{\eta_2}^2\}$. We assume the model

parameters are mutually independent. The prior distributions are specified as

(i) $\mu_1 \sim N(0, 25)$; (ii) $\mu_2 \sim N(0, 25)$; (iii) $\phi_{11}^* \sim \text{beta}(20, 1.5)$, where $\phi_{11}^* = (\phi_{11} + 1) / 2$;

(iv) $\phi_{22}^* \sim \text{beta}(20, 1.5)$, where $\phi_{22}^* = (\phi_{22} + 1) / 2$; (v) $\phi_{21} \sim N(0, 10)$;

(vi) $\sigma_{\eta_1}^2 \sim \text{IG}(2.5, 0.025)$; (vii) $\sigma_{\eta_2}^2 \sim \text{IG}(2.5, 0.025)$.

After observing the data, the joint posterior distribution of unknown parameters Θ' and the vector of latent volatility $V = (V_0, \dots, V_{T-1})$ is

$$p(\Theta', V | Y) \propto p(Y | \Theta', V) p(\Theta', V) \propto \prod_{t=0}^{T-1} p(Y_t | V_t) \prod_{t=0}^{T-1} p(V_t | \Theta') p(\Theta'). \quad (6)$$

The software package WinBUGS (Bayesian inference using Gibbs Sampling) is employed for the computation of the bivariate SV model (see Meyer and Yu 2004 and Yu and Meyer 2008 for implementation details). It uses a specific MCMC technique to construct a Markov chain by sampling from all univariate full conditional distribution in a cyclic way.

3. Data

Our empirical analysis makes use of weekly average settlement prices of crude oil futures contracts traded on the New York Mercantile Exchange (NYMEX) from November 16, 1998, to January 26, 2009. Similarly, the corn and wheat prices are the weekly average settlement prices of futures contracts traded on 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 forces influencing oil price volatility, the SVMJ model in equation (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 product stocks (excluding the Strategic Petroleum Reserve) were downloaded from the Energy Information Administration Web site.

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:

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

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 spillover 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 during the week of October 23, 2006, the wheat futures prices also have a structure change in the same period. The change points are represented by the vertical lines in the figures. The timing of the structure change is consistent with the finding in the literature (e.g., Irwin and Good 2009). For comparison, we split the sample into two subsamples and estimate equation (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 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 subsequent financial crisis.

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

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

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 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 affected 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 during this time period was a result of price variation in the corn market, which in turn was 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.

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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

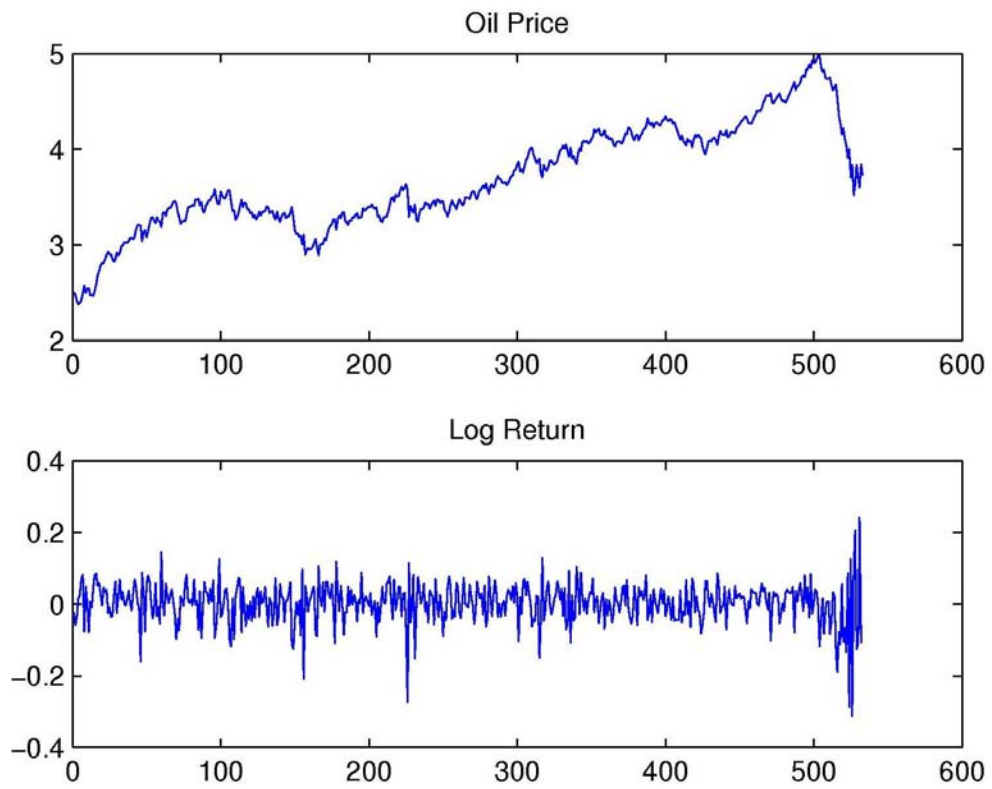


Figure 1. The log and log-return of crude oil prices (11/1998–01/2009)

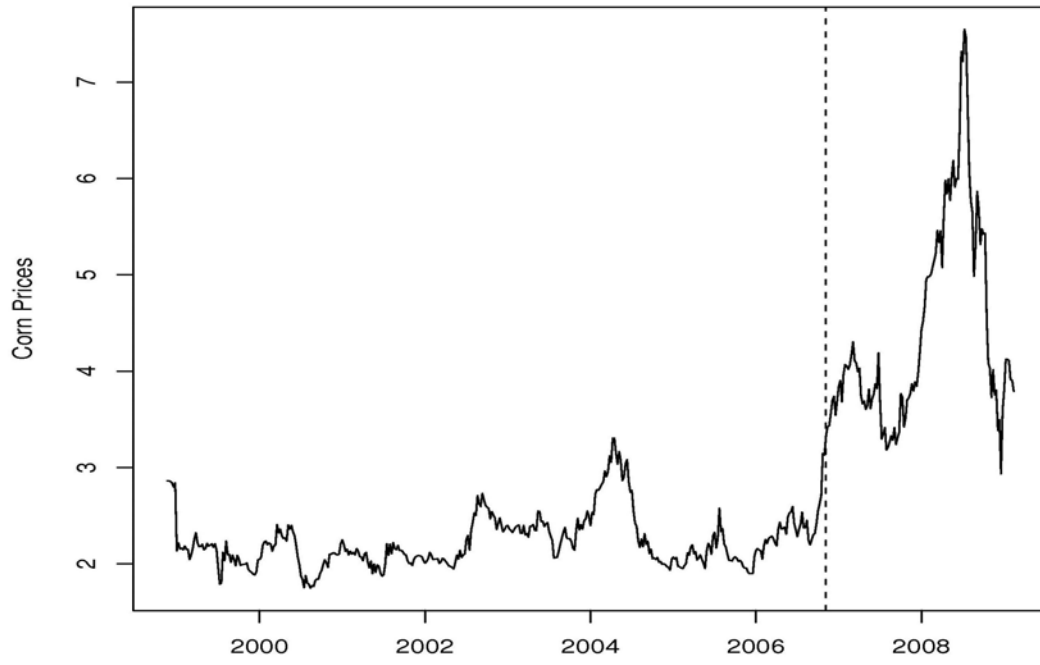


Figure 2. Structure change test of corn futures prices (11/1998–01/2009)

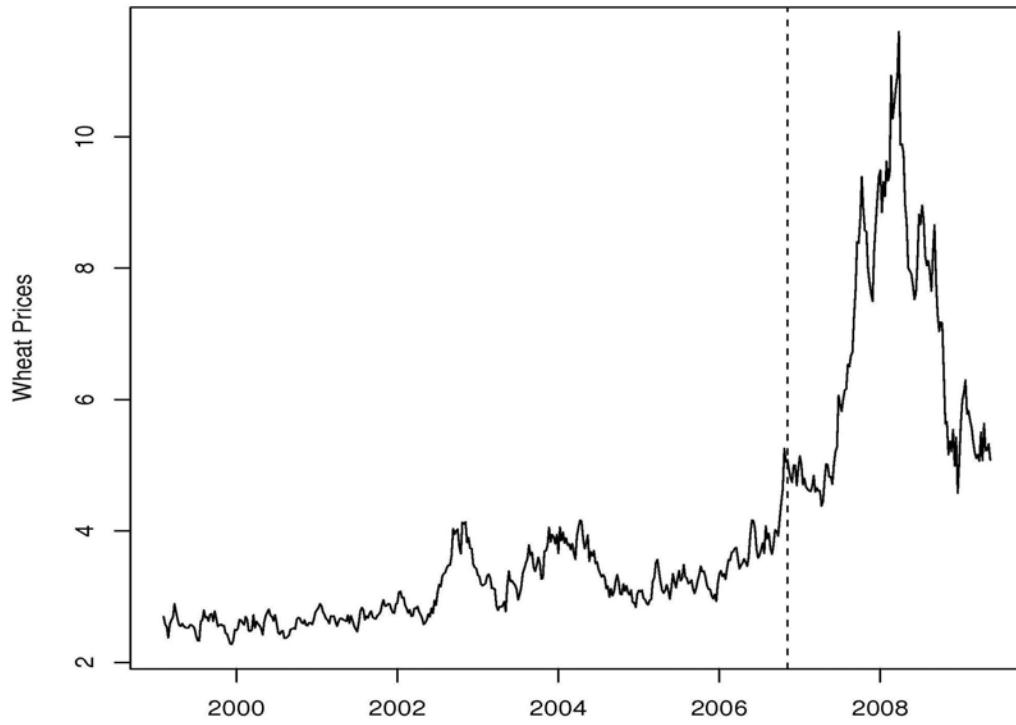


Figure 3. Structure change test of wheat futures prices (11/1998–01/2009)

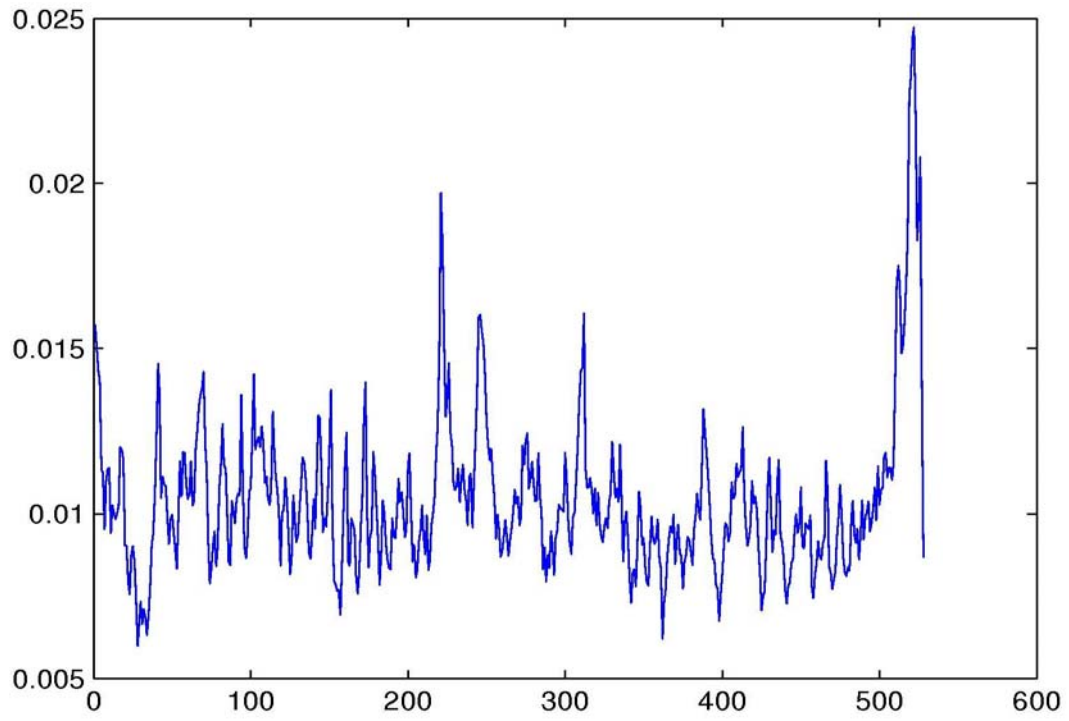


Figure 4. Estimated volatility of crude oil futures prices (11/1998–01/2009)