Energy Economics 33 (2011) 497–503

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis

Xiaodong Du [a,*], Cindy L. Yu [b,1], Dermot J. Hayes [c,2]

[a] Department of Agricultural & Applied Economics, University of Wisconsin-Madison, WI, USA
[b] Department of Statistics, Iowa State University, IA, USA
[c] Department of Economics and Department of Finance, Iowa State University, IA, USA

ARTICLE INFO

Article history:
Received 25 September 2009
Received in revised form 29 June 2010
Accepted 29 December 2010
Available online 14 January 2011

JEL classification:
C11
G13
Q4

Keywords:
Ethanol
Gibbs sampler
Petroleum inventory
Stochastic volatility

ABSTRACT

This paper assesses factors that potentially influence 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. Speculation, scalping, and petroleum inventories are found to be important in explaining the volatility of crude oil prices. Several properties of crude oil price dynamics are established, including mean-reversion, an asymmetry between returns 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 can be largely explained by tightened interdependence between crude oil and these commodity markets induced by ethanol production.

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 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 have played 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 et al. (2008) also link the oil price surge to large speculative capital flows that moved into the U.S. oil market. They consider the sharp oil price change (i) an endogenous response of a world economy that tried to increase the global supply of sound and liquid financial assets, and (ii) resulting from excess asset demand from emerging markets such as China and the East Asian economies.

Agricultural commodity prices have displayed similar behavior. The Chicago cash corn price rose to over $3.00/bushel to reach $7.20/bushel in July 2008. It then fell to $3.60/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.

The rapid growth of index investment in commodities has an indirect but significant impact on futures markets including crude oil and agricultural commodity markets. The two most popular commodity indices are the Goldman Sachs Commodity Index (GSCI) and the Dow Jones-UBS Commodity Index (DJ-UBS). The financial institutions who sell the index instruments typically purchase futures contracts of commodities linked to an index in order to offset their financial exposure. As index traders operate only on futures markets, additional demand for commodity futures deviates from the

* Corresponding author. 405 Taylor Hall, Department of Agricultural & Applied Economics, University of Wisconsin-Madison, Madison, WI 53705, USA. Tel.: +1 608 262 0699; fax: +1 608 262 4376.
E-mail addresses: xdu23@wisc.edu (X. Du), cindyyu@iastate.edu (C.L. Yu), dhayes@iastate.edu (D.J. Hayes).
[1] Tel.: +1 515 294 3319.
[2] Tel.: +1 515 294 6185.

0140-9883/$ – see front matter © 2011 Elsevier B.V. All rights reserved.
doi:10.1016/j.eneco.2010.12.015

fundamental supply and demand relationship in cash markets and may contribute substantially to the increase of price volatility in future markets. In addition, the recent surge of index investments in futures markets induces commodity prices to be increasingly exposed to market-wide shocks, such as shocks to the exchange rate and stock market, and to be more closely interconnected with each other (Tang and Xiong, 2010).

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 seek 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 investigating 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) 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. Kaufmanna 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 et al., 1990; Ewing et al., 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 chemicals and fertilizer. The effect of an oil price shock 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 some latent stochastic process in SV models. ARCH-type models are relatively easy to estimate and remain popular (see Engle, 2002 for a recent survey). More importantly, SV models fit more naturally with a wide range of applications, including option and other derivative pricing, much of which is based on continuous models. While directly connected to diffusion processes, SV models provide greater flexibility in describing stylized facts about returns and volatilities (Shephard, 2005) and their linkages to other observable determining factors, which are the main reasons why we focus on the SV model in the current study. In ARCH models, given past information, variance is deterministic and can be readily estimated via maximum likelihood-type techniques. In contrast, volatility in SV models is latent and relatively difficult to estimate. 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 et al., 2002, 2006; Jacquier et al., 1994, 2004; Kim et al., 1998).

Oil price dynamics are characterized by high volatility with 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, an asymmetry between returns and volatility,[3] is found to provide superior forecasting results for crude oil price changes (Morana, 2001).[4] To fully capture the stylized facts of oil price dynamics, we adopt a stochastic volatility model with Merton jump in return (SVMJ). 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 jump sizes that follow a normal distribution.

The applied SVMJ model belongs to the class of affine jump-diffusions (AJD) models (Duffie et al., 2000), which are tractable and capable of capturing salient features of price and volatility in a parsimonious fashion. The AJD model allows us to combine into a single model time-varying volatility, the leverage effect, and jumps. It also has the advantage of ensuring that the volatility process can never be negative or reach zero in finite time, and it provides closed-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 AJD 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.

The applied Bayesian method extracts information about the distribution of the latent state variables, X, model parameters, Θ, from observed prices, Y, and results in the so-called posterior distribution, $p(\Theta, X|Y)$ (Johannes and Polson, 2003). The MCMC algorithm repeatedly samples from the posterior distributions, which generates a Markov chain over (Θ, X), until converging to the equilibrium/stationary posterior distribution, $p(\Theta, X|Y)$. Compared with other estimation methods of stochastic volatility models such as efficient method of moments (EMM), simulated maximum likelihood (e.g., Brandt and Santa-Clara, 2002), and generalized method of moments (GMM) (e.g., Pan, 2002), the Bayesian method is particularly suitable and has been proven to perform well and produce relatively accurate results. It is worth noting that the Kalman filter block updating method is difficult to the model in the current study, not only because the square-root volatility process is non-linear, but also because our model contains jumps, which are not easy to deal with in the Kalman filter framework.

To the best of our knowledge, our study is the first to apply an SVMJ model to empirically examine crude oil price and volatility dynamics allowing for mean-reversion, the leverage effect, and Merton jumps. Our results suggest that volatility peaks are associated with significant political and economic events. The explanatory variables we include have the hypothesized signs and can explain a large portion of the price variation. Scalping and speculation are shown to have had a 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 timing of large-scale production of ethanol.

In the following section, we describe the model and the associated Bayesian analyses for the stochastic volatility models. Details of the MCMC algorithm are deferred to the Appendix. Section 3 describes our data, while Section 4 presents the empirical results. Concluding remarks are presented in Section 5.

2. The model

Our empirical models consist of (i) a univariate SVMJ model for crude oil prices and associated latent volatility, and (ii) a bivariate model for oil prices and agricultural commodity prices, specifically corn and

[3] Here, the asymmetry refers to the fact that large negative returns tend to be associated with higher future volatility rather than with positive returns (Nelson, 1991).

[4] Examples from the literature of modeling leverage effects within an ARCH/GARCH framework include Nelson (1991), Engle and Ng (1993), and Glosten et al. (1993).

wheat prices, to quantify the possible volatility transmission among these markets.

2.1. The univariate SVMJ model

Let P_t denote crude oil prices and y_t denote the corresponding logarithm of prices, i.e., $y_t = \log P_t$. The dynamics of y_t are characterized by the discretized SVMJ model as follows[5]:

$$
\begin{aligned}
y_{t+1} &= y_t + \mu\Delta + \sqrt{v_t\Delta}\varepsilon^y_{t+1} + J^y_t, J^y_t = \xi^y_t N^y_t \\
v_{t+1} &= v_t + \kappa(\theta - v_t)\Delta + \mathbf{Z}'_{t+1}\boldsymbol{\beta} + \sigma_v\sqrt{v_t\Delta}\varepsilon^v_{t+1}
\end{aligned}
\tag{1}
$$

where both ε^y_{t+1} and ε^v_{t+1} are assumed to follow $N(0, 1)$ with correlation ρ, i.e., $\mathrm{corr}(\varepsilon^y_{t+1}, \varepsilon^v_{t+1}) = \rho$, which measures the dependence 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 proposed in Heston (1993). While J^y_t represents a jump in return, the jump time N^y_t is assumed to follow a $Poisson(\lambda_y\Delta)$ with the probability $P(N^y_t = 1) = \lambda_y\Delta$ for small Δ, and the jump size ξ^y_t follows the distribution of $N(\mu_y, \sigma^2_y)$. Both jump time and size are assumed to be independent of ε^y_{t+1} and ε^v_{t+1}.

The symbol μ measures the mean return, θ is the unconditional mean of the stochastic volatility, κ is the speed of mean reversion of volatility, while σ_v represents the volatility of the volatility variable. $\mathbf{Z_t} = (Z_{1t}, Z_{2t},..., Z_{nt})'$ is an $n \times 1$ vector of n explanatory variables at time t, whose effects on volatility are represented by the parameter vector $\boldsymbol{\beta}$. All variables $\mathbf{Z_t}$ are centralized by subtracting the means. For this process, we have observations $\{y_t\}^{T+1}_{t=1}$ and $\{\mathbf{Z_t}\}^{T+1}_{t=1}$, latent volatility variables $\{v_t\}^{T+1}_{t=1}$, latent jump times $\{N^y_t\}^T_{t=1}$, and sizes $\{\xi^y_t\}^T_{t=1}$. Model parameters are $\Theta = \{\mu, \kappa, \theta, \boldsymbol{\beta}, \sigma_v, \rho, \lambda_y, \mu_y, \sigma_y\}$.

The employed SVMJ model for crude oil prices includes two important components: (i) the jump-diffusion model of Merton (1976), which assumes that crude oil prices exhibit both continuous, diffusive movements modeled by Brownian motion, and large, discontinuous jumps, modeled by the Poisson process; and (ii) the stochastic volatility model of Heston (1993), which allows oil price volatility itself to follow a separate diffusion process.

We employ Bayesian MCMC methods to estimate the univariate SVMJ model. For the parameter vector $\Theta = \{\mu, \kappa, \theta, \boldsymbol{\beta}, \sigma_v, \rho, \lambda_y, \mu_y, \sigma_y\}$, we assume the parameters are mutually independent. Following the literature, we employ the convenient conjugate and proper priors for the parameters[6]: $\mu \sim N(0, 1)$, $\kappa \sim TN_{(0,\infty)}(0, 1)$, $\theta \sim TN_{(0,\infty)}(0, 1)$, $\mu_y \sim N(0, 100)$, $\sigma^2_y \sim IG(5, 1/20)$, $\lambda_y \sim Beta(2, 40)$, and $\beta_i \sim N(0, 1)$, $i = 1, 2, 3$. Similar to Jacquier et al. (1994), (ρ, σ_v) are re-parameterized as (ϕ_v, ω_v), where $\phi_v = \sigma_v\rho$ and $\omega_v = \sigma^2_v(1-\rho^2)$. The priors of the new parameters are chosen as $\phi_v|\omega_v \sim N(0, 1/2\omega_v)$ and $\omega_v \sim IG(2200)$.

Conditioning on the latent variables, the current period's volatility v_t, and jump J^y_t, increments of the next period's price and volatility, $y_{t+1} - y_t$ and $v_{t+1} - v_t$, follow a bivariate normal distribution:

$$
\begin{bmatrix} y_{t+1} - y_t \\ v_{t+1} - v_t \end{bmatrix} | v_t, J^y_t \sim N\left[\begin{pmatrix} \mu\Delta + J^y_t \\ \kappa(\theta - v_t)\Delta + \mathbf{Z}'_{\mathbf{t}+1}\boldsymbol{\beta} \end{pmatrix}, v_t\Delta\begin{pmatrix} 1 & \rho\sigma_v \\ \rho\sigma_v & \sigma^2_v \end{pmatrix}\right]. \tag{2}
$$

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, $J = \{J^y_t\}^T_{t=1}$, and the parameters Θ are

$$
\begin{aligned}
& p(\Theta, v, J|y) \propto p(y, v|J)p(J|\Theta)p(\Theta) \\
& \propto \prod_{t=0}^{T-1} \frac{1}{\sigma_v v_t \Delta\sqrt{1-\rho^2}}\, exp\left\{-\frac{1}{2(1-\rho^2)}\left((\varepsilon^y_{t+1})^2 - 2\rho\varepsilon^y_{t+1}\varepsilon^v_{t+1} + (\varepsilon^v_{t+1})^2\right)\right\} \\
& \times \prod_{t=0}^{T-1} \frac{1}{\sigma_y}\, exp\left(-\frac{\left(\xi^y_t - \mu_y\right)^2}{2\sigma^2_y}\right) \times \prod_{t=0}^{T-1} \lambda_y^{J^y_{t+1}}\left(1-\lambda_y\right)^{1-J^y_{t+1}} \times p(\Theta)
\end{aligned}
\tag{3}
$$

where $\varepsilon^y_{t+1} = (y_{t+1} - y_t - \mu\Delta - J_t)/\sqrt{v_t\Delta}$ and $\varepsilon^v_{t+1} = (v_{t+1} - v_t - \kappa(\theta - v_t)\Delta - Z_{t+1}\beta)\ /\ (\sigma_v\sqrt{v_t\Delta})$, while $p(\Theta)$ denotes the joint prior distribution of model parameters.

The complete model is given by Eq. (2), 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, we extend the approach suggested by Li et al. (2008); the essential steps of the Gibbs sampler are fully described in the Appendix.

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 SV framework, as proposed in Yu and Meyer (2008): 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 $\mathbf{Y_t} = (Y_{1t}, Y_{2t})'$ for $t = 1,..., T$, i.e., $Y_{it} = \Delta \log P_{it} = \log P_{i,t} - \log P_{i,t-1}$, $i = 1, 2$. Let $\boldsymbol{\varepsilon_t} = (\varepsilon_{1t}, \varepsilon_{2t})'$, $\boldsymbol{\mu} = (\mu_1, \mu_2)'$, and $\mathbf{V_t} = (V_{1t}, V_{2t})'$. The bivariate SV model with possible volatility spillover is specified as

$$
\begin{aligned}
\mathbf{Y}_t &= \boldsymbol{\Omega_t}\boldsymbol{\varepsilon_t}, \boldsymbol{\varepsilon_t} \overset{iid}{\sim} N(0, \boldsymbol{\Sigma}_\varepsilon), \\
\mathbf{V_{t+1}} &= \boldsymbol{\mu} + \boldsymbol{\Phi}(\mathbf{V}_t - \boldsymbol{\mu}) + \boldsymbol{\eta_t}, \boldsymbol{\eta_t} \overset{iid}{\sim} N\left(0, \Sigma_\eta\right)
\end{aligned}
\tag{4}
$$

where $\boldsymbol{\Omega_t} = \begin{pmatrix} exp(v_{1t})/2 & 0 \\ 0 & exp(v_{2t})/2 \end{pmatrix}$, and $\boldsymbol{\Sigma_\varepsilon} = \begin{pmatrix} 1 & \rho_\varepsilon \\ \rho_\varepsilon & 1 \end{pmatrix}$. While $\boldsymbol{\Sigma_\varepsilon}$ describes the dependence in returns by the constant correlation coefficient ρ_ε, the variation of individual volatility process is defined by the matrix $\boldsymbol{\Sigma_\eta}$ as $\begin{pmatrix} \sigma^2_{\eta 1} & 0 \\ 0 & \sigma^2_{\eta 2} \end{pmatrix}$.

The volatility spillover effect is captured by $\boldsymbol{\Phi} = \begin{pmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{pmatrix}$

where $\phi_{ij}(i, j = 1,2)$ denotes the spillover effect from market of commodity i to market of commodity j. While ϕ_{12} and ϕ_{21} are different from zero, the cross-dependence of volatilities is realized via volatility transmission between the two commodity markets. In other words, model (4) describes the cross-dependence of two markets both in the returns and in the volatilities, where the cross-dependence of volatilities is realized via volatility spillover and clustering jointly.

The model in Eq. (4) is completed by the specification of a prior distribution for all parameters, $\Theta' = \{\mu_1, \mu_2, \rho_\varepsilon, \phi_{11}, \phi_{12}, \phi_{21}, \phi_{22}, \sigma^2_{\eta 1}, \sigma^2_{\eta 2}\}$. In this study, we assume that the model parameters are mutually independent. Following Yu and Meyer (2008), the convenient conjugate and proper priors for the parameters are specified as $\mu_1 \sim N(0,25)$; $\mu_2 \sim N(0,25)$; $\phi^*_{11} \sim Beta(20,1.5)$, where $\phi^*_{11} = (\phi_{11}+1)/2$; $\phi^*_{22} \sim Beta(20,1.5)$, where $\phi^*_{22} = (\phi_{22}+1)/2$; $\phi_{12} \sim N(0, 10)$; $\phi_{21} \sim N(0,10)$; $\sigma^2_{\eta 1} \sim IG(2.5,0.025)$; and $\sigma^2_{\eta 2} \sim IG(2.5,0.025)$.

[5] In this study, we apply the first order Euler discretized version of the continuous SVMJ models on weekly data with the discretization interval $\Delta = 52/250$.

[6] The symbol $TN_{(a, b)}(\mu, \sigma^2)$ denotes a normal distribution with mean μ and variance σ^2 truncated to the interval (a, b), while IG and $Beta$ represent the inverse gamma and beta distributions, respectively.

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

$$p(\Theta', V \mid Y) \propto p(Y \mid \Theta', V)\, p(\Theta', V) \propto \prod_{t=0}^{T-1} p(Y_t \mid V_t) \prod_{t=0}^{T-1} p(V_t \mid \Theta')\, p(\Theta'). \quad (5)$$

The software package WinBUGS (Bayesian inference using Gibbs Sampling) is employed for the computation of the bivariate SV model.[7] It uses a specific MCMC technique to construct a Markov chain by sampling from the univariate conditional distribution of each unknown parameter.

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.

To investigate the forces influencing oil price volatility, the SVMJ model in Eq. (1) relates crude oil price volatility to a set of explanatory economic variables $\mathbf{Z}=\{Z_1, Z_2, Z_3\}$. 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 in order to possibly realize small profits. It typically reflects market liquidity. A standard measure of scalping activity in futures markets is the ratio of volume to open interest. Volume refers to the number of futures contracts traded in a market during a given period of time, while open interest is defined by the total number of "open" contracts that have not been settled at the end of each day. Focusing on taking profits based on small price changes, scalpers may allow prices to adjust to information more quickly and assumedly increase price variability (Brorsen, 1991). Goodwin and Schnepf (2000) confirm that in the corn and wheat futures markets, the extent of scalping or daily trading tends to have a significant positive influence on price variability. We construct a proxy for scalping activities in the 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 theory of storage, introduced among others by Kaldor (1939) and Working (1948, 1949), states that holding some inventory allows firms to respond quickly and efficiently to demand and supply shocks and thus to earn a "convenience yield." The relationship between inventory and price volatility has been investigated by a number of studies (e.g., Williams, 1986; Fama and French, 1987). The basic consensus is that the volatility of a commodity price tends to be inversely related to the level of stocks. On the one hand, a positive price shock increases the opportunity cost of holding inventories and thus encourages reducing inventory level. On the other hand, rational agents will respond to a negative price shock by increasing inventories. A significant negative relationship between crude oil inventory and price volatility has been documented in Geman and Ohana (2009). In this study, total U.S. crude oil and petroleum product stocks (excluding the Strategic Petroleum Reserve) were downloaded from the Energy Information Administration (EIA) website.

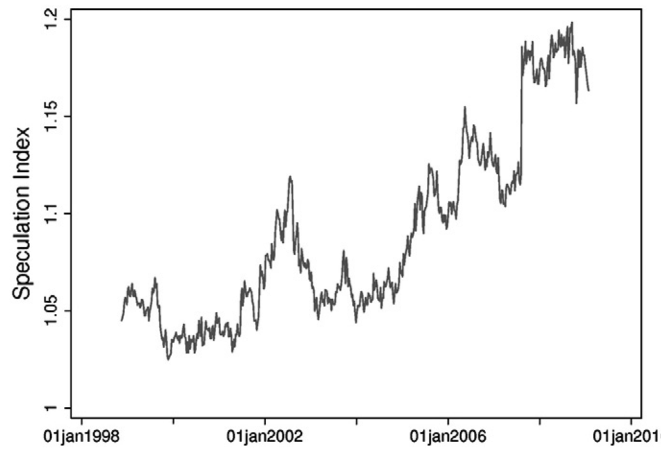

Fig. 1. Weekly speculation index in the crude oil futures market (November 1998–January 2009).

3.3. Speculation index

In this study, we adopt the speculation index developed in Working (1960) to measure the intensity of speculation relative to short hedging. The index is defined as the ratio of speculation short or long positions depending on their relative volumes to total hedging positions. 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 T is constructed using CFTC trader position data:

$$T = \begin{cases} 1 + \dfrac{SS}{HS + HL} \text{if } HS > HL; \\ 1 + \dfrac{SL}{HS + HL} \text{if } HL > HS \end{cases} \quad (6)$$

where $SS(SL)$ represents speculative (noncommercial) short (long) positions in the crude oil futures market, while $HS(HL)$ represents short (long) hedged (commercial) positions. If speculative or hedging cover all categories of positions in the futures market, the relation between short and long positions must hold as $SS+HS=SL+HL$ (Sanders et al., 2010). When long and short hedging positions don't offset each other, speculation is economically necessary to absorb the residual hedging position (Peck, 1980). The speculation index T in Eq. (6) measures the extent by which speculation exceeds the minimum level necessary to offset hedging positions. Considering an extreme case where $HL>HS=0$, the minimum and necessary level of speculation is HL, at which the speculation index $T$is equal to 1.[8]

For calculation, weekly hedging and speculative position numbers are obtained from Historical Commitments of Traders reports (CFTC, 1998–2009). Fig. 1 presents the trajectory of the speculation index over the sample period. From 1998 through early 2005, the average speculation index was about 1.05. In contrast, after August 2007, the index was around 1.18 persistently, which indicates a significantly higher level of speculative position in the crude oil futures market.

[7] See Meyer and Yu (2004) and Yu and Meyer (2008) for implementation details.

[8] Note that in this case, $T=1+SL/(HL+HS)=SS/HL$.

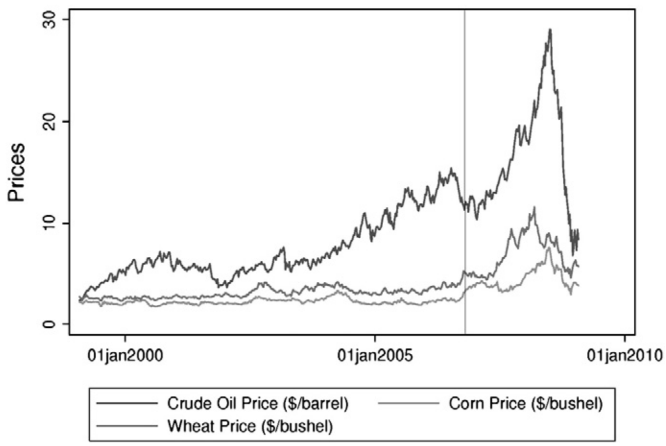

Fig. 2. The log and log-return of weekly crude oil prices (November 1998–January 2009). Note: Crude oil price is multiplied by 0.2 in order to fit together with other price series.

A high crude oil price, together with federal support policies, encouraged rapid growth of corn ethanol production after late 2006. Feedstock demand pushed up the prices of corn and other agricultural commodities. So there has been a fundamental shift, or structural change, in the market for corn and other major agricultural products. For example, average U.S. corn prices remained below $2.50 per bushel before 2006. But average corn prices have never dropped below $3.00 per bushel since 2006. To facilitate the analysis of volatility spillover between crude oil and agricultural commodity markets, we apply the structural change test algorithm proposed in Bai (1997) to test for possible structural change of corn and wheat prices over the sample period.[9] The test results are presented in Fig. 2, with the structural change points indicated by the vertical line. Fig. 2 indicates that while the pattern of corn futures prices changed during the week of October 23, 2006, the wheat futures prices also have a structural change in the same period. The timing of the structural change in the agricultural prices is consistent with the findings in the literature (e.g., Irwin and Good, 2009). For comparison, we split the sample into two subsamples and estimate model (4) repeatedly to quantify possible volatility spillover among crude oil, corn, and wheat markets.

4. Empirical results

First, we run the Gibbs sampler of the univariate SVMJ model introduced in Section 2 for 30,000 iterations on generated data. The generated data experiment was done to test the reliability of the estimation algorithm. Inspection of the drawn sequences satisfied us that the sampler had converged by iteration 10,000. The results indicate that our algorithm can recover the parameters of the data-generating process sufficiently. Then we ran the estimation for 30,000 iterations on the collected data described in Section 3. The first 20,000 runs were discarded as a "burn-in" and we used the last 10,000 iterations in MCMC simulations to estimate the model parameters. Table 1 reports posterior means, standard deviations, and probabilities of being positive of the model parameters.

The estimated volatility over the sample period is plotted in Fig. 3. From an examination of Fig. 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, which is coincident with the recent oil price surge and subsequent financial crisis.

Table 1
Estimation results of univariate SVMJ model.

Variable	$E(\cdot\,\vert y)$	$Std(\cdot\,\vert y)$	$\Pr(\cdot>0\vert y)$
μ	0.0273	0.0172	0.94
μ_y	4.0610	3.6403	0.91
σ_y	2.2614	0.5992	1.00
λ_y	0.0036	0.0025	1.00
θ	0.0427	0.0049	1.00
κ	2.3012	0.4412	1.00
σ_v	0.2429	0.0188	1.00
ρ	−0.1272	0.1481	0.20
β_1	0.0022	0.0047	0.68
β_2	−0.0067	0.0093	0.23
β_3	0.0037	0.0086	0.66

For most of the parameters of the SV model except μ, μ_y, and ρ, the posterior standard deviations are quite small relative to their means. The results indicate that our SVMJ model successfully captures the major nature of the stochastic volatility. The posterior estimates of the SVMJ models presented in Table 1 indicate

(i) strong mean-reversion in the behavior of volatility: the speed of mean reversion (κ) is 2.30 with the long-run mean return $0.027\times 52=1.42$;
(ii) a negative leverage effect: the negative correlation between instantaneous volatility and prices, $\rho=-0.13$;
(iii) infrequent compound Poisson jumps: the estimate of λ suggests on average $0.0036\times 52=0.19$ jumps per year. The result is consistent with what we observe in the data where we see five or six spikes in about 11 years.

All three explanatory variables included in the time-varying volatility have the hypothesized sign and are consistent with our prior expectations. But the coefficients are generally small in magnitude with relatively large posterior standard deviations. 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.

We ran the bivariate SV model for 50,000 iterations, with the first 40,000 iterations discarded as burn-in. The estimation results for volatility spillover between crude oil, corn, and wheat markets are presented in Table 2. The results indicate some pronounced changes of volatility spillover effects between crude oil and agricultural

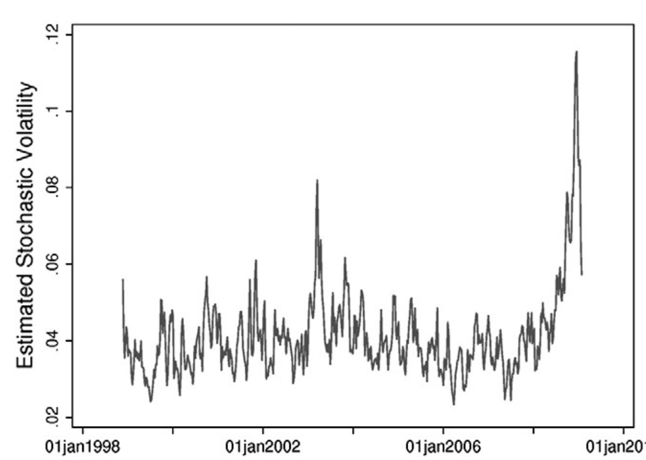

Fig. 3. Estimated volatility of crude oil futures prices (November 1998–January 2009).

[9] The test for structural change is conducted in the framework of a standard linear regression model. Consider the model $y_i=x_i{}'\beta_i+u_i$, $(i=1, 2,..., n)$, where y_i is the commodity price, and $x_i=(1, x_{i1},..., x_{ik})'$ includes a column vector of 1s and observations of k independent variables. The null hypothesis of "no structural change" is $H_0: \beta_i=\beta_0$ $(i=1,..., n)$. In this study, we don't include independent variables except the unit vector for the tests, so that we test for shift of mean in the price series.

Table 2
Estimation results of the bivariate SV Model (standard errors in parentheses).

Variable	Oil and corn markets		Oil and wheat markets		Corn and wheat markets	
	11/1998–10/2006	10/2006–01/2009	11/1998–10/2006	10/2006–01/2009	11/1998–10/2006	10/2006–01/2009
μ_1	−6.06	−6.02	−6.05	−6.13	−6.93	−6.20
	(0.09)	(0.51)	(0.17)	(0.60)	(0.15)	(0.35)
μ_2	−6.82	−7.58	−6.61	−5.98	−6.63	−6.06
	(0.15)	(0.23)	(0.15)	(0.19)	(0.10)	(0.28)
ϕ_1	0.90	0.87	0.77	0.82	0.46	0.82
	(0.07)	(0.09)	(0.10)	(0.15)	(0.12)	(0.14)
ϕ_2	0.66	0.84	0.88	0.83	0.90	0.82
	(0.11)	(0.12)	(0.09)	(0.12)	(0.07)	(0.13)
ϕ_{12}	0.02	0.44	−0.27	0.85	1.24	0.21
	(0.04)	(0.28)	(0.15)	(0.74)	(0.40)	(0.35)
ϕ_{21}	−0.63	0.06	−0.01	0.06	−0.03	0.13
	(0.20)	(0.06)	(0.09)	(0.07)	(0.04)	(0.11)
ρ	0.07	0.34	0.09	0.27	0.60	0.60
	(0.05)	(0.09)	(0.05)	(0.08)	(0.03)	(0.06)
σ_1	0.19	0.12	0.12	0.12	0.13	0.15
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.07)
σ_2	0.13	0.13	0.17	0.11	0.22	0.12
	(0.05)	(0.05)	(0.05)	(0.03)	(0.06)	(0.05)

commodity markets. For example, in the first subsample period, November 1998–October 2006, the price of corn behaved very differently from crude oil prices, which is indicated by a negative spillover coefficient of $\phi_{21}(=-0.63)$. Similarly, we see moderate evidence of negative correlation between price variations in crude oil and wheat markets. It is evident that commodity futures could be included in a portfolio in order to reduce price risk in the energy market. This explains why financial institutions develop and promote agricultural commodity futures as a new asset in their indices, such as GSCI and DJ-UBS, which emerged in recent years. In addition, volatility in the wheat market affected the corn market in a significant manner.

In contrast, in the second subsample period, October 2006–January 2009, agricultural commodity prices and their variations progressively connected with the crude oil price, which may be induced by large-scale ethanol production and the increasing presence of index investors. The positive spillover coefficients for markets of oil/corn ($\phi_{21}=0.06$) and oil/wheat ($\phi_{21}=0.06$) quantify the degree of market co-movement. This 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 $\phi_{21}=0.13$ for the model of corn and wheat markets indicates that a 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. But the evidence for these effects is only moderate given that the posterior standard deviations are of nearly equal magnitude of posterior means.

The correlation coefficient between crude oil and corn markets increases from 0.07 to 0.34 in the second period, while that between crude oil and wheat markets increases from 0.09 to 0.27. 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. 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 estimation of the model parameters. Recent oil price shocks appear to have triggered sharp price changes in agricultural commodity markets, especially in the corn and wheat markets, potentially because of the tighter interconnection between these food/feed and energy markets and the increasing presence of commodity investments in the past three years.

Appendix A. Supplementary data

Supplementary data to this article can be found online at doi:10.1016/j.eneco.2010.12.015.

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.

Brandt, M., Santa-Clara, P., 2002. Simulated likelihood estimation of diffusions with an application to exchange rate dynamics in incomplete markets. Journal of Financial Economics 63, 161–210.

Brorsen, B.W., 1991. Futures trading, transaction costs, and stock market volatility. Journal of Futures Markets 11, 153–163.

Caballero, R.J., Farhi, E., & 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/1998–2009last visited 04/30/2009.

Cheong, C.W., 2009. Modeling and forecasting crude oil markets using ARCH-type models. Energy Policy 37, 2346–2355.

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

Chib, S., Nardari, F., Shephard, N., 2006. Analysis of high dimensional multivariate stochastic volatility models. Journal of Econometrics 134, 341–371.

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

Engle, R.F., 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica 50, 987–1008.

Engle, R.F., 2002. New frontiers for ARCH models. Journal of Applied Econometrics 17, 425–446.

Engle, R., Ng, V., 1993. Measuring and testing the impact of news in volatility. Journal of Finance 43, 1749–1778.

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

Fama, E.F., French, K.R., 1987. Commodity futures prices: some evidence on forecast power, premiums and the theory of storage. Journal of Business 60, 55–73.

Geman, H., Ohana, S., 2009. Forward curves, scarcity and price volatility in oil and natural gas markets. Energy Economics 31, 576–585.

Glosten, L., Jagannathan, R., Runkle, D., 1993. Relationship between the expected value and the volatility of the excess return on stocks. Journal of Finance 48, 1779–1802.

Goodwin, B.K., Schnepf, R., 2000. Determinants of endogenous price risk in corn and wheat futures markets. Journal of Futures Markets 20, 753–774.

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, J.D., 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 (with discussion). Journal of Business and Economic Statistics 12, 371–389.

Jacquier, E., Polson, N., Rossi, P., 2004. Bayesian analysis of stochastic volatility models with fat-tails and correlated errors. Journal of Econometrics 122, 185–212.

Johannes, M., Polson, N., 2003. MCMC method for continuous-time financial econometrics. In: Ait-Sahalia, Y., Hansen, L. (Eds.), Handbook of Financial Econometrics. North-Holland, New York.

Kaldor, N., 1939. Speculation and economic stability. Review of Economic Studies 7, 1–27.

Kaufmann, R., Ullman, B., 2009. Oil prices, speculation, and fundamentals: interpreting causal relations among spot and futures prices. Energy Economics 31, 550–558.

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

Kim, S., Shephard, N., Chib, S., 1998. Stochastic volatility: likelihood inference and comparison with ARCH models. Review of Economic Studies 65, 361–393.

Li, H., Wells, M., Yu, C., 2008. A Bayesian analysis of return dynamics with Levy jumps. Review of Financial Studies 21, 2345–2378.

Merton, R., 1976. Option pricing when the underlying stock returns are discontinuous. Journal of Financial Economic 3, 125–144.

Meyer, E., Yu, J., 2004. BUGS for a Bayesian analysis of stochastic volatility models. Econometrics Journal 3, 198–215.

Morana, C., 2001. A semiparametric approach to short-term oil price forecasting. Energy Economics 23, 325–338.

Nelson, D., 1991. Conditional heteroskedasticity in asset pricing: a new approach. Econometrica 59, 347–370.

Pan, J., 2002. The jump-risk premia implicit in options: evidence from an integrated time-series study. Journal of Financial Economics 63, 3–50.

Peck, A.E., 1980. The role of economic analysis in futures market regulation. American Journal of Agricultural Economics 62, 1037–1043.

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

Sanders, D.R., Irwin, S.H., Merrin, R.P., 2010. The adequacy of speculation in agricultural futures markets: too much of a good thing? Applied Economic Perspectives and Policy. 32, 77–94.

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

Tang, K., & Xiong, W. 2010. Index investing and the financialization of commodities. Working Paper, University of Princeton.

Taylor, S.J., 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.

Williams, J., 1986. The economic function of futures markets. Cambridge University Press, Cambridge.

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

Working, H., 1948. The theory of inverse carrying charge in futures markets. Journal of Farm Economics 30, 1–28.

Working, H., 1949. The theory of the price of storage. American Economic Review 39, 1254–1262.

Working, H., 1960. Speculation on hedging markets. Food Research Institute Studies 1, 185–220.

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