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

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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.

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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

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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).

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