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Time-variations in commodity price jumps☆

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ABSTRACT

In this paper, we study jumps in commodity prices. Unlike assumed in existing models of commodity price dynamics, a simple analysis of the data reveals that the probability of tail events is not constant but depends on the time of the year, i.e. exhibits seasonality. We propose a stochastic volatility jump–diffusion model to capture this seasonal variation. Applying the Markov Chain Monte Carlo (MCMC) methodology, we estimate our model using 20 years of futures data from four different commodity markets. We find strong statistical evidence to suggest that our model with seasonal jump intensity outperforms models featuring a constant jump intensity. To demonstrate the practical relevance of our findings, we show that our model typically improves Value-at-Risk (VaR) forecasts.

1. Introduction

Models of commodity price dynamics proposed recently feature continuous and discontinuous components. While the continuous component has been extensively studied, it is somewhat surprising that little attention has been paid to the modeling of the discontinuous components, i.e. price jumps. Current models of commodity prices implicitly assume a constant probability of jumps. There are, however, reasons to question the validity of this assumption. This is because many commodities display seasonal demand and/or supply patterns. For example, the demand for heating oil peaks during the winter and bottoms out during the summer. Hence, it is natural to expect a higher number of price shocks during the cold months, when demand for energy peaks, than during the summer months.

This paper studies the dynamics of jump events in commodity markets. In doing so, we make three important contributions to the literature on commodity price modeling. First, we analyze the distribution of extreme commodity returns over time. Specifically, we extract the top and bottom 2.5% returns of the heating oil, natural gas, soybeans and corn markets. We examine the distribution of these returns over time and find important variations in the probability of jumps. This result has a profound implication. It suggests that the assumption of constant jump intensity, implicit in existing models of commodity price dynamics, is not supported by the data.

Second, this observation inspires us to propose and estimate a stochastic volatility jump–diffusion model to capture this time-variation. The novel feature of our model is a time-varying probability of jump occurrences, which we model in an intuitive and parsimonious way. Using a Markov Chain Monte Carlo (MCMC) based approach, we estimate our model for the four markets considered using more than 20 years of data. Our parameter estimates unequivocally point to significant time-variations in the probability of

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jumps, confirming the results of our preliminary analysis. We relate these fluctuations to seasonal stages of demand and supply cycles, suggesting that our findings are not only statistically significant but also economically plausible. For example, our model suggests that the intensity of jumps in energy markets rises substantially during the cold months relative to the summer months, when the demand for energy commodities is typically low.

Third, we assess our newly proposed model in detail, drawing on statistical and economic loss functions. We compare all models based on Deviance Information Criterion (DIC) scores, which take into account model complexity. We show that the model with time-varying jump intensity always achieves a smaller DIC score than its competitor, demonstrating its superiority from a statistical point of view. In order to establish the practical relevance of our study, we assess all models on their ability to improve risk-management decisions. With a view to doing this, we estimate the Value-at-Risk (VaR) and conduct a comprehensive backtesting analysis. The results show that capturing time-variations in the probability of jumps typically improves VaR forecasts.

Our work relates to the literature on asset price modeling. This literature dates back to the seminal work of Black & Scholes (1973), who model prices as a diffusion process with constant volatility. Hull & White (1987) and Heston (1993) extend this model and specify the volatility of the underlying as a mean-reverting stochastic process. These models crucially hinge on the counterfactual assumption that asset prices follow continuous processes. For example, such an assumption is difficult to reconcile with the large fluctuations of October 1987.[1] In light of this, Bates (1996) proposes a stochastic volatility model with jumps in returns, and empirically confirms the superiority of his model. Bakshi et al. (1997) echo these conclusions. Duffie et al. (2000) propose two jump–diffusion models. The first model features simultaneous jumps in returns and volatility and correlated jump sizes. The second model features independent jump arrivals and sizes. These models are comprehensively analyzed by Eraker et al. (2003), who convincingly show that stochastic volatility jump–diffusion models capture the dynamics of equity indices better than standard models, such as those of Black & Scholes (1973), Merton (1976) and Heston (1993).

In contrast to the literature concerned with equity price dynamics, the literature on commodity price modeling is somewhat scant. Hilliard & Reis (1998) and Karali et al. (2011) estimate jump–diffusion models, originally developed for equity prices, in commodity markets. Sørensen (2002), Back et al. (2013), Brooks & Prokopczuk (2013) and Schmitz et al. (2014) propose a variety of models that capture seasonal variations in commodity returns and volatility. But none of these studies considers the time-varying probability of jumps.

The remainder of this paper proceeds as follows. Section 2 describes our dataset and documents important time-variations in the probability of extreme returns. Section 3 presents our model and explains our estimation approach. Section 4 discusses our parameter estimates. Section 5 assesses the importance of our proposed model. Section 6 analyzes the robustness with respect to the model specification. Finally, Section 7 concludes.

2. Data and preliminary analysis

This section first provides a detailed account of our dataset of commodity prices. We then conduct a preliminary analysis of extreme returns over time.

2.1. Data

We obtain daily futures settlement prices for the heating oil, natural gas, corn and soybeans futures markets from the Commodity Research Bureau (CRB). Our sample period extends from January 2, 1991 to December 30, 2011. The futures contracts on all four commodities trade on the Chicago Mercantile Exchange (CME). Energy futures, i.e. heating oil and natural gas, follow a monthly expiration cycle. Corn futures contracts are available for the following months: March, May, July, September and December. Finally, soybeans futures expire in January, March, May, July, August, September and November.

Our interest in the heating oil, natural gas, corn and soybeans futures markets is not coincidental. Several reasons motivate our focus on these four commodities. First, these markets rank high among the most liquid commodity markets. Obviously, fair transaction prices are important to obtain economically meaningful parameter estimates. Second, the heating oil, natural gas, corn and soybeans futures markets display important seasonal patterns at the intrayear level (Karali et al., 2011; Schmitz et al., 2014). These seasonal fluctuations are important because they are likely to introduce time-variations in the probability of jumps, which we analyze in this paper.

Because investments in commodity markets typically involve rolling over futures contracts, one should be cautious of the computation of commodity returns, making sure that information from two different contracts are not used to compute returns. In computing commodity returns, we distinguish between two cases. First, suppose that we are interested in computing returns on the business day immediately following the expiration of the previous prompt contract, i.e. the rollover date. We compute the return on a specific commodity as the logarithm of the ratio of the price of the current front-month contract over the second-nearby contract on the rollover day. More formally, we compute commodity returns as follows:

$$r_{t+1} = \log \frac{F_{t+1}^{(1)}}{F_t^{(2)}} \tag{1}$$

where r_{t+1} denotes the commodity return at time $t + 1$. $F_{t+1}^{(1)}$ refers to the price of the first nearby contract at time $t + 1$. Finally, $F_t^{(2)}$ is the price of the second nearby contract at time t. Note that the first nearby contract at time $t + 1$ was the second nearby contract at time t. Thus, the return in Eq. (1) is based on prices of the same contract at different points in time.

[1] See Roll (1988) for an interesting discussion of these events.