



Tail events: A new approach to understanding extreme energy commodity prices



Nicolas Koch*

Mercator Research Institute on Global Commons and Climate Change (MCC), Torgauer Str. 12-15, 10829 Berlin, Germany

ARTICLE INFO

Article history:

Received 11 July 2013

Received in revised form 21 February 2014

Accepted 22 February 2014

Available online 11 March 2014

JEL classification:

G12

G13

Q41

Q43

Q48

Keywords:

Energy futures markets

Financialization

Fundamentals

Trading activity

Liquidity

ABSTRACT

This paper shows that extreme energy price changes, located in the 10% tails of the distribution, cluster across energy futures markets during the boom–bust cycle of 2006 to 2012. Using multinomial logit regressions, we find that the coincidence of such tail events cannot be explained solely by common supply and demand fundamentals. Instead, we provide evidence that the transmission of extreme price changes occurs through a financial demand channel. Specifically, changes in the net long position of hedge funds are associated with a significant increase in the probability of coincident large positive and negative returns across energy markets. Evidence that index investments drive tail events is limited. Further, we identify adverse shocks to speculator funding liquidity as determinant of synchronized price drops across energy markets. The likelihood of extreme negative returns in more than one market significantly increases when the TED spread rises.

© 2014 Elsevier B.V. All rights reserved.

1. Introduction

Over the past decade, energy commodity prices have shown dramatic rises and falls, which have not been observed since the energy crisis of the 1970s (e.g., Creti et al., 2013).¹ At the same time, energy futures markets have experienced an impressive increase in financial investor participation (Rouwenhorst and Tang, 2012), leading to heated debate about the effects of speculative trading on commodity price fluctuations (Fattouh et al., 2013; Irwin and Sanders, 2012). This paper proposes a new approach to understanding extreme events and boom–bust processes in energy markets. We seek to answer the following questions. Can the tail events in energy price innovations be explained by common supply and demand fundamentals? Or is there evidence of an amplification mechanism caused by financial intermediaries and their speculative trading? The relative importance of the explanations is essential to policymakers as well as commodity producers and consumers who are concerned by an anomalous propagation of disruptive tail events.

Using weekly energy futures data for the period June 2006 to July 2012, we find that extreme energy price changes, which are defined as the bottom or top 10% tail of the distribution, cluster across energy commodity markets. Further, we show that the clustering of weeks in which more than one market synchronously experiences tail events cannot be exclusively explained by market fundamentals commonly used to explain commodity performance. Instead, we find strong evidence that the transmission of extreme price changes occurs through a combination of a liquidity channel and financial demand channel. Specifically, speculator funding liquidity and the trading position of two types of financial traders, hedge funds and commodity index traders, are determinants of coincident extreme price changes. This evidence suggests that the propagation mechanism of the recent boom–bust cycle in energy prices is related to the American financialization of commodity futures markets.

To understand the factors that explain the coincidence of extreme price changes across energy markets, we draw upon a recent paper by Liu et al. (2011) for theoretical motivation. Their demand-based commodity pricing model guides our investigation since it predicts that the equilibrium commodity price under large financial investments depends on exogenous financial demand. They argue that the presence of financial investors – who are neither hedgers nor traditional speculators because they trade based on financial factors such as portfolio diversification needs or capital constraints, but not on real demand factors – is key to determining commodity price deviations from fundamentals.

* Tel.: +49 30 338 5537 231; fax: +49 30 338 5537 102.

E-mail address: koch@mcc-berlin.net.

¹ For example, the sharp decline of the crude oil price from an all-time high of \$140/barrel in mid-2008 to \$34/barrel by January 2009 exceeds previous record price drops observed during the energy crisis of the 1970s by a factor of two. Similarly, the recovery rate in 2009 has few rivals in the recent history.

The model predicts that the in and out flow of speculative money exacerbates price volatility. It also suggests that correlations between commodity prices increase if the different commodities are subject to correlated financial demand. The important implication of Liu et al. (2011) is that variables which reflect the financial demand for commodities may explain the coincidence of extreme price changes across markets. In a similar vein, theoretical work by Brunnermeier and Pedersen (2009) highlights that large capital losses or shocks to funding liquidity force financial players to liquidate their holdings in several markets at the same time. This liquidation can amplify shocks and cause commonality in the price fluctuations across different markets. The study predicts that adverse shocks to financial intermediary funding liquidity lead to coincident poor performance of markets in which intermediaries are marginal investors. Because limits to arbitrage for financial investors play an important role in commodity markets (Cheng et al., 2012; Etula, 2013), the predictions are relevant in explaining the clustering of worst energy returns we observe during the recent 2008–09 crisis.

We use weekly futures data for six energy commodities with active futures contracts included in the S&P GSCI, Brent crude oil, WTI crude oil, gasoil, heating oil, gasoline and natural gas. Given the rapid growth of commodity index investment, these commodities are particularly well suited to the analysis at hand because financial factors should have a greater impact on indexed commodities (Tang and Xiong, 2012). We first use a VAR framework to estimate filtered returns for each energy market. The pre-filtering of data is intended to prevent the clustering of extreme price changes from being attributed to common risk factors and serial correlation in energy returns. We capture the common exposure by including variables known to predict commodity returns (see Hong and Yogo, 2010), which can be grouped into common macroeconomic predictors (e.g. short rate, yield spread) and commodity-specific predictors (basis, hedging pressure). We subsequently use the residuals from these regressions in our analysis. Next, we identify the extreme returns located in the 10% tails of the distribution for each commodity and count the number of joint occurrences of extreme returns. We treat positive and negative extreme returns separately. We show that the patterns of extreme return clusters are not just a manifestation of positive correlation among energy commodities. Specifically, the frequency of joint large returns cannot be generated from Monte Carlo simulation of the joint return-generation process of the energy return series.

Then, we implement a multinomial logit model (see Bae et al., 2003) to investigate which factors are associated with the propagation of large price changes. The dependent variable is a measure of the intensity of extreme return clustering. The key independent variables are classified into three different transmission channels. (1) The real demand channel refers to the hypothesis that the sharp rise in demand for energy from China and other emerging economies are an important shock to energy markets (Hamilton, 2009; Kilian, 2009). Unexpectedly strong demand may have caused prices to soar before mid-2008 while the sharp price falls may be the result of the world recession with fading demand. (2) The financial demand channel refers to the potential link between extreme energy returns and the increasing flow of money from financial participants into energy futures markets. As measure of speculative financial demand, we use net position changes of two types of financial traders (managed money traders and swap dealers) provided by the US Commodity Futures Trading Commission (CFTC). (3) Finally, the liquidity channel captures the possibility that extreme price movements are likely associated with decreasing funding liquidity. We include the TED spread and changes in repo volume as liquidity proxies. To summarize, the joint occurrences of large price falls are driven mainly by a combination of high TED spreads and reduced net long positions of hedge funds in energy futures. The coincident large price rises, are explained mostly by the net long position of hedge funds and to some extent by index trader positions. These links are however highly non-linear, highlighting that only sufficiently large position changes amplify market movements.

1.1. Related work

Our paper is related to several strands in the literature on the financialization of commodity markets. First, it contributes to the literature on the link between speculative money flows and commodity price behavior. Singleton (2014) finds that the growth of index trader and managed money positions significantly determines crude oil futures price changes. By contrast, Büyüksahin and Harris (2011) find little evidence that hedge funds and swap dealers position changes Granger-cause oil price changes. In sum, evidence remains elusive and controversial (Fattouh et al., 2013). Thus, we abandon the analysis of price levels that previous researchers have centered on to study the impact of speculative trading. Instead, we focus on explaining extreme price innovations to study the impact of speculative trading. While the existence of fat-tails in the distribution of commodity prices are a well-known phenomenon (Mandelbrot, 1963), the driving factors behind disruptive price moves are unknown. Only Candelon et al. (2013) and Joëts (forthcoming) investigate energy price relationships during periods of extreme fluctuations. It turns out that no significant causality exists between markets during regular times whereas price co-movements are higher during extreme periods, most notably, in bear markets. Joëts, 2014 suggests that heterogeneous expectations and market uncertainty may explain the extreme movements.

Second, this paper relates to the literature that analyzes linkages between commodity prices and other financial assets. Tang and Xiong (2012) show that price co-movements between commodities included in commodity indexes increased significantly in recent years. In a similar vein, Silvennoinen and Thorp (2013) and Creti et al. (2013) report increased correlations between commodities and stocks. Büyüksahin and Robe, forthcoming document that the trading position of hedge funds is a significant factor explaining the increase in commodity–stock correlation. A limitation of existing studies is their focus on correlations, which give equal weight to small and large price changes. We abandon the linear correlation framework and focus instead on the evaluation of cross-market linkages in extraordinary market environments with large price changes using a logistic approach.

Third, our analysis is related to several recent papers on the link between financial intermediary funding conditions and commodity prices. Etula (2013) shows that the risk-bearing capacity of broker-dealers is a determinant of commodity risk premia. Cheng et al. (2012) show that financial institutions became consumers rather than providers of liquidity after the recent financial crisis erupted. In addition, Marshall et al. (2013) provide evidence of strong liquidity commonality in commodity markets. Speculators seem to withdraw liquidity in different commodities at the same time following market declines. To the best of our knowledge, this is the first study to evaluate whether funding liquidity acts as a channel to spill over price shocks between commodity markets.

Overall, previous studies make a major contribution to understanding the financialization of energy markets, but none are based on a model flexible enough to disentangle the various driving factors behind disruptive price moves.

2. Extreme energy price changes

In this section we first discuss our data. Next, we filter each raw return series to control for the exposure of energy futures to common risk factors. We then turn to the definition of extreme returns and calibrate their joint occurrence using Monte Carlo simulation.

2.1. Data

We consider weekly data for the sample period from June 14, 2006 until July 25, 2012, a total of 319 observations. The energy futures price data are for four NYMEX contracts (WTI crude oil, heating oil, gasoline and natural gas) and two ICE Futures contracts (Brent crude oil and gasoil). This data set is obtained from Thomson Datastream. The

Download English Version:

<https://daneshyari.com/en/article/5064558>

Download Persian Version:

<https://daneshyari.com/article/5064558>

[Daneshyari.com](https://daneshyari.com)