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Forecasting volatility in the biofuel feedstock markets in the presence of structural breaks: A comparison of alternative distribution functions

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ABSTRACT

The need for research on commodity volatility has grown considerably due to the important role and financialization of commodities in global asset markets. This paper examines the volatility forecasting performance of a wide variety of GARCH-based models in the context of biofuel feedstock markets in the presence of structural breaks. Our sample is also extended to several non-renewable energy commodities to evaluate comparatively the volatility forecasting performance across various commodity markets. The model specifications allow for different conditional distribution functions in the rolling window estimations. A break detection algorithm finds significant evidence of structural breaks in the unconditional variance of all commodity returns under study. The out-of-sample analysis, which is based on an up-to-date model comparison testing procedure, reveals that volatility models accommodating structural breaks in the data provide the best volatility forecasts for most cases. Regarding the relevance of distribution functions, the skewed normal distribution dominates in the model confidence sets. Nevertheless, the complex distribution functions do not always outperform simpler ones, although true return distribution is asymmetric and heavy-tailed.

1. Introduction

Research on commodity volatility has been gaining ground due to increasing volatility and the growing role of commodities in global asset markets (see Chkili et al., 2014; Kang and Yoon, 2009; Vivian and Wohar, 2012; among others). As widely documented, accurate volatility forecasts are important inputs for portfolio optimization, option pricing, value-at-risk modeling, and dynamic hedging. The literature on modeling and forecasting volatility in commodity markets has primarily focused on non-renewable energy and precious metal commodities (see, e.g., Arouri et al., 2012; Cheong, 2009; Chkili et al., 2014; Charfeddine, 2014; Charles and Darné, 2017; Gong and Lin, 2017a; Harvey and Sucarrat, 2014; Haugom et al., 2014; Klein and Walter, 2016; Lv and Shan, 2013; Liu et al., 2017; Narayan and Narayan, 2007; Sadorsky, 2006; and Wen et al., 2016). In contrast, there has been relatively little research conducted on modeling and forecasting volatility of biofuel feedstock markets[1] despite the increasing volatility of these markets resulting from biofuel supportive policies around the globe. Furthermore, a substantial motivation behind studying these commodities is the financialization of commodities, which has become even more prominent after the global financial crisis (Cheng and Xiong, 2014). Hence, the main purpose of this study is to add to the limited literature on volatility forecasting performance of biofuel feedstock commodities. In addition, we have extended our sample to include crude oil and gasoline to compare volatility forecasting performance across broader commodity markets.

We have focused on the biofuel feedstock commodities that have highest production volume across the globe. A large number of biofuel plants that operate on a large scale in the US, Brazil, and some Asian countries use palm oil and corn as feedstock (see Serra, 2011; Hasanov et al., 2016). In the US market, the soybean serves as the main feedstock for biofuel production which has surged significantly to 2 BG (billion gallons) by

[1] Biofuel feedstocks are mainly agricultural crops which have both food and energy uses. The usual types of biofuel are bioethanol and biodiesel. Bioethanol is commonly produced from energy crops such as corn, wheat, barley and sugar beet in the US, Brazil, and EU countries. The sugars contained in these crops are altered into ethanol through the fermentation process (The European Renewable Ethanol Association: ePure, n.d.). On the other hand, biodiesel is an alternative fuel similar to conventional mineral diesel. Biodiesel can be produced from edible oils (e.g., palm, rapeseed, and soybean), animal fats, and waste cooking oil.

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2017 from 1 BG in 2012 (Cui and Martin, 2017). The reason of burgeoning trend in biodiesel supply is catalysed by implementation of renewable fuel standards. The rapeseed oil contributes most of the feedstock production in the European Union (accounting for approximately 80% of feedstock). Globally, the palm oil contributes one-third of global vegetable oil production and outperform other vegetable oils in terms of growth rate in the global marketplace (USDA, 2006). Apart from the data of biofuel feedstock commodities, we have also considered the non-renewable energy commodities for comparison purposes. We use unrefined oil (i.e., crude oil) which is main input in the production of petroleum products. Also, we include gasoline in our study as it is one of the refined products. This energy fuel is widely harnessed for the internal combustion engines for transports (e.g., cars, motorbikes, trucks, boats and other transport vehicles).

As commonly noted, the correct specification of the conditional distribution of asset returns is potentially crucial for asset pricing and option valuation. For example, according to Arrow-Pratt's definition of risk aversion, for a given mean and variance, a risk-averse investor does not prefer assets whose return distributions are negatively skewed to those that are positively skewed. However, it remains an open question as to how important alternative conditional distributions are in out-of-sample volatility forecasting. Volatility forecasts can be obtained using different methods, depending on a range of conditional variance specifications and conditional distribution functions.[2] As Chuang et al. (2007) note, an appropriate distribution function should contain the following common features. First, the distribution must sufficiently capture a sizeable range of shapes. Second, shape parameters of a distribution function must reflect the skewness and kurtosis of a return series. Finally, distribution function parameters should be estimable using numerical optimization and/or statistical procedures. Although a sizable number of complex distribution functions are proposed in the literature (see, for example, Aas and Haff, 2006; Fernandez and Steel, 1998; Ferreira and Steel, 2006; Nelson, 1991; Theodossiou, 1998), there have been a limited number of studies that investigate the volatility forecasting performance of GARCH-based variance models combined with various distribution functions in the context of commodity markets (with the notable exception of Giot and Laurent, 2003; Lv and Shan, 2013). Along with the research works by Giot and Laurent (2003) and Lv and Shan (2013), this paper provides one of the first studies on the performance of volatility forecasting for commodities under various conditional distributions. Indeed, our study differs from the aforementioned papers in several ways. First, aforementioned studies used quasi maximum likelihood estimations, which are based on only Gaussian and skewed Student t conditional distributions. In contrast, our study considers eight different conditional densities. Second, their study is based on the common loss measures and superior predictive ability (SPA) test which depend on the benchmark models, while we use a more recent model confidence set (MCS) procedure proposed by Hansen et al. (2011). Third, our primary focus is on the biofuel feedstock markets. Finally, our forecasting experiment accounts for structural breaks.

Another important phenomenon in return volatility that needs to be addressed in volatility forecasting is the structural breaks.[3] Numerous theoretical and empirical studies show that estimates of volatility persistence might be spurious if structural changes or regime shifts are evident in the volatility process (see Gong and Lin, 2017b; Hammoudeh and Li, 2008; Lamoureux and Lastrapes, 1990; Mikosch and Stărică, 2004; Wang and Moore, 2009; Wen et al., 2017; among others). In light of the above considerations, Rapach and Strauss (2008) accounted for this phenomenon in the context of conditional variance forecasting for the exchange rate markets. The authors consider various methods of accommodating potential structural breaks in unconditional variance when evaluating exchange rate return volatility forecasts in real time. Moreover, our contribution is broadly connected to the study by Arouri et al. (2012). This paper investigates the relevance of regime shifts and long memory characteristics in modeling and forecasting the conditional variances of oil spot and futures prices utilizing some GARCH-based models. However, in Arouri et al. (2012) and Rapach and Strauss (2008), the model estimations are solely based on a Gaussian distribution function. In contrast, our key emphasis in this study is to evaluate the volatility forecasting performance of conditional variance models estimated assuming a range of distribution functions in the context of biofuel feedstock markets in the presence of structural breaks.

A recent trend in literature has suggested that an appropriate model for the volatility of financial and commodity returns should combine the long-memory and structural change phenomena (e.g., Baillie and Morana, 2009; Belkhouja and Boutahary, 2011; Charfeddine, 2014; Shi and Ho, 2015; Walther et al., 2017). Long-memory behaviour in volatility occurs when the influence of volatility shocks decreases slowly. This behaviour can be observed on the autocorrelation function, which decays slowly to zero at a polynomial rate as the lag increases. In this study, to capture the long-memory feature in the squared returns, we rely on a conditional score model suggested by Harvey and Sucarrat (2014). Two-component conditional score (i.e., Beta-skew-t-EGARCH) model accommodates the conditional skewness and long-memory property by decomposing volatility into the long- and short-term components (see Sucarrat, 2013). Additionally, the parameters are also estimated using the last post-break period to account for structural breaks in out-of-sample forecasting analysis.[4]

The primary objective of this study is to explore the relevance of structural breaks and distribution functions in forecasting the conditional volatility of biofuel feedstock commodities. We address several research questions. First, we investigate whether the forecasting performance of GARCH-based models which take into account the structural breaks in the return series is improved. Second, we analyse the role of a wide range of distribution functions in volatility forecasting performance. The recent literature that addresses forecasting commodity market volatility to some extent ignores the combination of structural breaks, conditional distributions, and asymmetry phenomenon (i.e., the different influences of positive and negative returns of a similar magnitude on conditional volatility). Our paper combines these statistical properties in forecasting the conditional volatility of biofuel feedstock commodities, which include both food and biofuel uses. Finally, a relatively recent conditional score model (i.e., Beta-t-skew-EGARCH) proposed by Harvey and Sucarrat (2014) is employed, which is not investigated in forecasting literature as much as other GARCH-type of models considered in this study.

The remainder of this paper is organized as follows. Section 2 introduces the methodology and methods, including model specifications, conditional distributions, the estimation method, structural break test, out-of-sample testing procedure, and the loss functions. Here, we also briefly present the MCS procedure proposed by Hansen et al. (2011) to assess volatility forecasting performance. Section 3 includes data and descriptive statistics. Section 4 presents the out-of-sample forecasting results and discussion, and robustness checks. Lastly, Section 5 presents the paper's conclusions and implications.

[2] There are many applications in finance that require the correct specification of the conditional distribution of returns. For example, the usual statistical technique in risk management is value-at-risk (VaR) which is used to quantify the level of risk. An appropriate specification of the conditional distribution of returns is important in VaR estimation which critically depends on accurate return and volatility forecasts. The distributions we considered in this study account for the skewness and tail characteristics of asset returns.

[3] The structural breaks might occur in return series due to economic and geopolitical news (e.g., financial crisis in 2008–2009, political turmoil in Lybia in 2012, and crisis in Syria and tropical storm in 2012) especially in the era of rapid and advanced news transmission via current electronic social and commercial media (Belkhouja and Boutahary, 2011; Ewing and Malik, 2017; Ma et al., 2017).

[4] We are grateful to anonymous referees for bringing the importance of long-memory models to our attention.