The Cost Implications of Managing Outliers in Energy Commodity Prices

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Overview

In this study, we employ statistical procedures to identify outliers in the prices for all crude oil and natural gas futures contracts traded on the CME over the period of 2003 through March 2017. We present new propositions based on Frances (2008) to aid in removing the effects of outliers in commodity price time series and apply them to the contracts studied. Empirical results for crude oil and natural gas futures contracts show that outliers can have a large impact on the estimation of various risk metrics including Value At Risk (VaR), expected shortfall (ES), and probability of outperforming a benchmark. Our research demonstrates that it is crucial to work with the correct processes when estimating different risk metrics.

Methods

The major advancement in outlier research was the ability to quantitatively classify types of outliers and how they impact a data generating process, DGP. The outliers studied include level shift or change (LS), temporary change (TC), additive outlier (AO), and innovative outlier (IO). The LS is a special type of AO where the innovation occurs and the level remains. The AO outliers are often data errors. AO outliers require intervention or adjustment and IO do not require adjustment (see Tsay (1988), Chen and Lui (1993) and Frances (2008)). Chen and Lui (1993) add that IO are not independent of the model and will decay with time for a stationary process. However, for a non-stationary process, it may have an initial effect at the time of the intervention and a level shift from the second period of the intervention.

We modify the propositions of Frances (2008) to be more suitable for commodity research. Our new propositions are:

Proposition 1. If only once in a while an IO occurs at a forecast origin, it will be handled so as to avoid a less accurate forecast, while decreasing residual variance or forecast error.

Proposition 2. If only once in a while an AO occurs at the forecast origin, adjustments will be made to the additive event so as to decrease residual variance.

Proposition 3. If only once in a while a LS occurs at a forecast origin, it will be handled so as to avoid a less accurate forecast, while decreasing residual variance or forecast error.

Proposition 4. If only once in a while a TS outlier occurs at a forecast origin, it will be handled so as to avoid a less accurate forecast, while decreasing residual variance or forecast error.

The general algorithm for detecting and correcting outliers used in this research is: Stage 1. Initial detecting and locating of potential outliers based on the ARIMA specification. Stage 2. Joint estimation of outliers effects and parameter estimation and outlier removal. Stage 3. Detection of outliers by iterating over stages 1 and 2 to determine the adjusted series. This algorithm will return the final outliers set, the regression coefficients, adjusted data series, regression residuals, and outlier impacts. Sanchez and Pena (1997) highlight how this iterative process improves on the determination and overcomes limitations previously mentioned. Our analysis utilizes the R Analytical software and statistical packages for outliers and forecast developed by Lopez-de-Lacalle (2016) and Hyndman (2017), respectively, for estimating the initial and final outliers in each time series. The software filters seasonal ARIMA components.

Results

We compute different risk metrics in order to illustrate the impact of the outliers. We provide results for Value at Risk, expected shortfall and probability of outperforming a benchmark. We will use one of the Natural Gas contracts for the risk metrics computation. It is contract 2017.NGJ. The original annualized statistics are:

Mean (%)	Standard Deviation (%)	Skewness	Kurtosis
-11.1911	16.7462	-0.4692	6.9828

The outlier detection algorithm identified and removed 10 AO, 5 TC, 0 LS and 5 IO. The total number of outliers is 20. The clean data series has the following annualized statistics:

Mean (%)	Standard Deviation (%)	Skewness	Kurtosis
0.0047	14.7110	0.0075	1.6180

To model the original data series, we assume that it comes from a mixture of two Normal distributions. We can design a mixture of two normal distributions in order to create a distribution that has four target moments. Solving a nonlinear system of equations gives the values for the parameters of the mixture. Monte Carlo Simulation from the estimated normal mixture of distributions with 100,000 scenarios resulted in 95% VaR = -1.6197% and 99% VaR = -3.1148%. Monte Carlo simulation from a Normal distribution with mean and standard deviation equal to the values obtained after outlier removal, resulted in 95% VaR = -1.5204% and 99% VaR = -2.1544%. The percentage change reduction in 95% VaR between the original and clean data processes is 6% and for the 99% VaR is 30%. Keeping in mind that we computed daily VaR, the changes are substantial.

In order to obtain estimates for the ES, we set up the value of the benchmark equal to the 95% VAR obtained in the earlier simulation = -1.5204% . Using the same simulated 100,000 scenarios from the mixture of normal distributions produced ES = 0.04%. The simulation from the clean normal resulted in ES = 0.01%. The percentage change reduction in the ES between the original and clean data processes is 75%.

This example illustrates that it is very important to work with the correct process when estimating different risk metrics. The computations for the NG contract showed that when outliers are removed, VaR and ES lowered. This is not surprising; outliers cause heavier tails and the risk metrics computed are higher.

We also analyze the impact of outliers on the modified VaR and ES. The risk metrics were calculated based on a Cornish-Fischer approximation. VaR and CvaR decreased on average of 8.6% to 8.9% with NG decreasing on average of 14.4% to 16.7%. These changes in risk metrics indicate that outlier adjustment is relevant. To get a holistic appraisal of the impact a VaR (ES), we compute the Volatility Elasticity. This elasticity is the percentage change in each risk measure divided by the percentage change in residual volatility. We show that on average for CL the elasticity is 0.90% to 0.94%, or for a 1% change in volatility, risk decrease by 0.009 to 0.0094. NG elasticity for a 1% change in volatility is 1.2% to 1.3%.

Conclusions

We show that detecting outliers is an important step in identifying the true DGP from a risk measurement point of view. We followed our Propositions I through IV for handling outliers using an adaptation of previous outlier detection algorithms. The algorithm was able to address common issues with outliers of masking/shadowing as seen by the substantial reduction in each contacts set of final outliers from the initial set. The analysis demonstrated that risk could be separated between the DGP and outlier impacts. The analysis showed that risk metrics like VaR and ES can be inaccurately reported, which could impact hedging cost and hedging decisions from the changes in residuals 2nd, 3rd, and 4th moments. These results are consistent with Jorion's (2007) approaches where large observations can be viewed as outliers, and that aspects of non-normality can impact risk. This research also shows that Jorion's viewpoints could be convoluted by outliers, causing difficulty in separating the two.

Selected References

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