Robust Estimation of Conditional Risk Measures for Crude Oil and Natural Gas Futures Prices in the Presence of Outliers

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/CLZ19
Light Sweet Crude Oil Fut...
58.13
Share
30m
Style
Drawings
Studies
Patterns
/CLZ19 10 D 30m
D: 9/23/19 11:30 PM
O: 58.13
H: 58.13
L: 58.11
C: 58.13
R: 0.02
Volume
16
62
61
60
59
58.13
57
56
55
54
Tue
Wed
Thu
Fri
Sun
Mon
Tue
Wed
Thu
Fri
Sun
Mon
Drawing set: Default

Figure:


/CLZ19
Light Sweet Crude Oil Fut...
58.13
-.29
-0.50%
B: 58.14
A: 58.15
Share
Style
Drawings
Studies
Patterns
/CLZ19 1 Y 1D
D: 9/24/19
O: 58.21
H: 58.26
L: 58.04
C: 58.13
R: 0.22
Volume
2,074
OpenInterest
277,306
72
70
68
66
64
62
60
58.13
56
54
52
50
48
46
44
Oct
Nov
Dec
19
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Drawing set: Default

Figure:

Why outliers?

- Commodity prices have been identified as one of the significant market risks for banks by the revised market risk framework, Basel III (2019).
- World Economic Forum's Global Risk Perception Survey (GRPS) of leading global businesses, academics, Non-Government Organizations (NGOs), and others place Oil and Gas prices spikes, extreme energy and agriculture volatility, and severe energy price shocks in their top 5 risks in terms of global impact 5 of the last 11 years, and if we include Environment and Societal risks like extreme weather, natural disasters, and climate change that will influence prices, then all of the past 11 years include these risk.
- Outliers?
  - On September 16, 2008 the OPEC cartel lowered its forecast for oil demand that year due to slowing economic growth.
  - On July 15, 2008, President Bush lifted nearly two decades of executive orders banning drilling for crude oil and natural gas off the country shoreline.

Why outliers?

Our methodology is potentially relevant when researching the following issues in commodity risk management:

1. Biased statement of risk.
2. Inaccurate cost to hedge the risk.
3. Inappropriate and inadequate hedges.
4. Misstatement of risk associated with extreme events.
5. Poor scenario and sensitivity analysis.

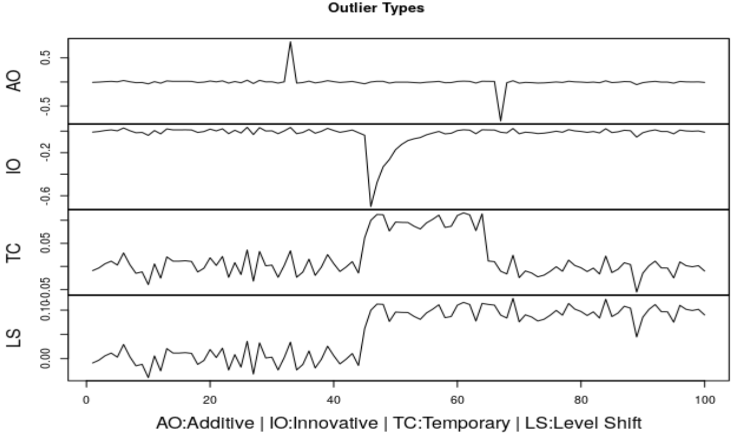
Industry motivation

- Commodity firms like British Petroleum and financial firms like Goldman Sachs, hold commodity portfolios that contain open transactions numbering in the millions of dollars.
- The quantity of risk factors associated with the company's portfolios measure in the hundreds and even thousands. Each of these risk factors is part of a risk model that price outliers can influence.
- Outliers could cause these diversification effects of commodity hedges to be incorrectly measured and hence costly for this firm.

Why do we care? We find:

- Results using 14 years of daily settlements for commodity instruments from the CME group, show that a robust estimation (after properly modeling outliers) leads to an increase or decrease of VaR metrics.
- The analysis showed that risk metrics like VaR and CVaR can be inaccurately reported, which could impact hedging cost and hedging decisions.
- Risk metrics of VaR and CVaR generally decreased implying risk could be overstate, but ...
- Increases in VaR occurred in 5% of crude oil contracts and 5.5% for natural gas contracts. These cases could potentially cause serious problems for a commodity trading firm.
  - Why? Expected loss if VaR is exceeded could be much larger than anticipated.
  - These larger losses would require immediate risk capital to be deployed.

Example of outlier types



Methodology

We follow Chen and Liu (1993) and use a nonseasonal case without a constant term:

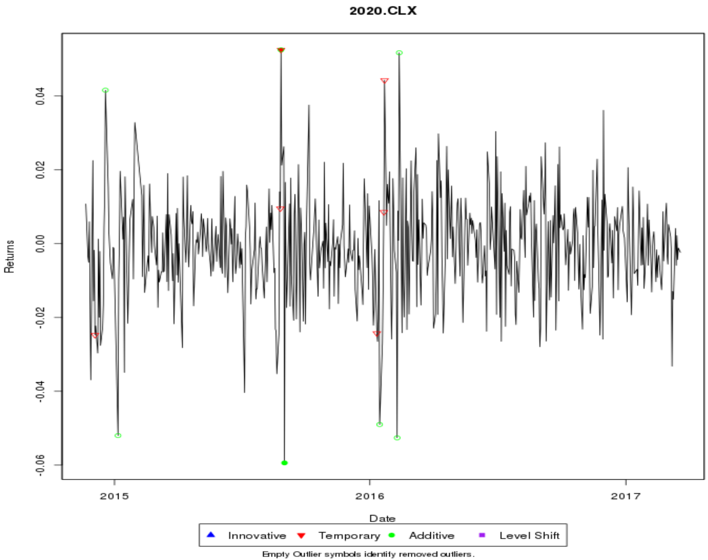
- Let Y_t be a time series following ARMA process without drift or trend:

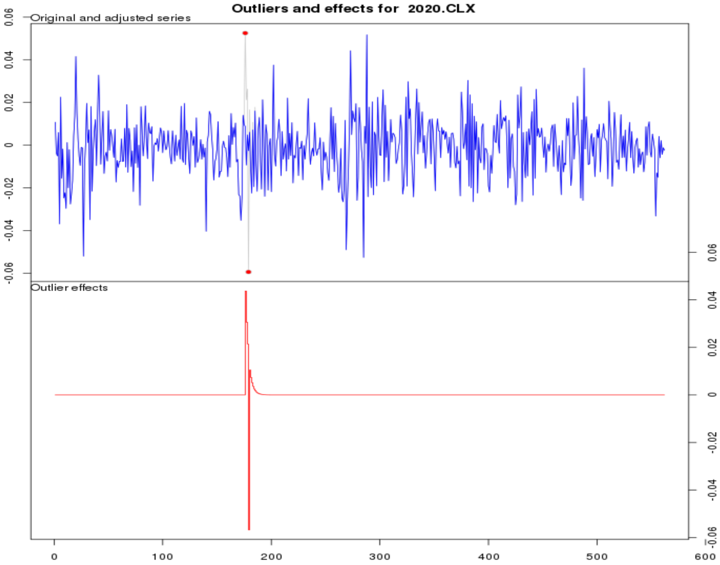
$$Y_t = \frac{\theta(B)}{\varphi(B)\cdot\alpha(B)} a_t, t = 1, \cdots, n \tag{1}$$

- Where n is the number of observations,
- B is the back shift operator,
- $\theta(B)$ is a moving average component, roots outside of the unit circle,
- $\varphi(B)$ is an auto regressive component, roots outside of the unit circle and
- $\alpha(B)$ is a difference component, roots on the unit circle.
- a_t are Normal(0,σ_a^2) IID.

Algorithm for detecting and correcting outliers

- **Stage 1.** Outlier detection is performed estimating ARIMA models and checking for significant outliers at different times based on t-statistics from the parametric estimation.
- **Stage 2.** Filter outliers by joint estimation of ARIMA models with results from Stage 1. Outliers found to be insignificant are dropped from the initial set based on t-statistics by parameter estimation.
- **Stage 3.** Iterate over Stages 1 and 2 to determine the intervention modeled series and the final outlier effects.


2020.CLX
Returns
0.04
0.02
0.00
-0.02
-0.04
-0.06
2015
2016
2017
Date
Innovative
Temporary
Additive
Level Shift
Empty Outlier symbols identify removed outliers.


Outliers and effects for 2020.CLX
Original and adjusted series
Outlier effects
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
0
100
200
300
400
500
600

Outlier detection process

- The algorithm for managing outliers will select parametric ARIMA models with outlier effects based on the minimization of Akaike (AIC) and Bayesian (BIC) information criterion statistics.
- The algorithm will return :
  1. the final outlier set,
  2. the regression coefficients,
  3. intervention modeled data series,
  4. regression residuals, and
  5. outlier impacts.
- Our analysis utilizes the *R* Analytical software and statistical packages for outliers and forecast developed by Lopez-de Lacalle (2016) and Hyndman (2017), for estimating the initial and final outliers in each time series.
- Parametric specifications of the time series components of the log returns of commodity prices are returned if outliers are found:
  - an ARIMA model specification of the log returns and functional specifications for outliers with a decay rate of $\delta = 0.7$.
  - Only the ARIMA specification is returned if no outliers are found, and this is the best fit model of the time series.

Analysis of crude oil (CL) and natural gas (NG) futures prices – data description

- The data for this analysis is from the CME Group daily settlements for commodity instruments.
- The specific CME instruments are outright futures contracts for natural gas (NG) and crude oil (CL).
- The data starts on 2003-12-31 and ends on 2017-03-20.
- The contracts are monthly for each commodity.
- The CME Group lists CL future contracts 9 forward years with monthly listing for the current year and following 5 years.
- Year 6 and out are listed for June and December contract monthly.
- Additional months are added annually when the December contract expires to keep 9 years of the combination of monthly and biannual contracts listed.
- NG is listed monthly for the current year plus the following 12 calendar years with a new year added when the December contract expires for the current year.

Summary statistic comparison of log returns of the raw and outlier intervention modeled CL and NG commodity contracts

CL				NG			
Contracts	198	Min	Max	Contracts	276	Min	Max
Observations	196,301	79	2,213	Observations	376,429	75	2,232
	Average	Range			Average	Range	
			Raw (Base) Data				
Mean(%)	-0.02	-0.12	0.12	Mean(%)	-0.06	-0.29	0.09
Annualized Mean(%)	-7.06	-44.89	45.22	Annualized Mean(%)	-22.70	-104.81	32.21
Median(%)		-0.14	0.17	Median(%)		-0.09	0.07
StDev(%)	1.50	0.97	2.42	StDev(%)	1.06	0.56	2.14
Annualized StDev(%)	23.78	15.42	38.43	Annualized StDev(%)	16.77	8.83	33.92
Skewness		-1.40	0.91	Skewness		-1.751	1.123
Kurtosis		-0.56	11.10	Kurtosis		1.009	22.773

Summary statistic comparison of log returns of the raw and outlier intervention modeled CL and NG commodity contracts

				Intervention Model			
Mean(%)	0.00	-0.20	0.14	Mean(%)	-0.14	-2.32	0.14
Annualized Mean(%)	-0.68	-72.74	49.93	Annualized Mean(%)	-52.58	-847.9	52.32
Median(%)		-0.06	0.18	Median(%)		-2.28	0.12
StDev(%)	1.40	0.82	2.33	StDev(%)	0.95	0.45	1.97
Annualized				Annualized			
StDev(%)	22.27	13.02	36.92	StDev(%)	15.13	7.19	31.19
Skewness		-1.03	0.32	Skewness		-0.58	1.02
Kurtosis		-0.56	7.97	Kurtosis		0.03	9.64

Analysis of the number and percentage of futures contracts that failed to reject normality

See table 6 of Paper

All Reject Normality

	Contracts	Jarque Bera	Shapiro Wilk	% of Contracts Jarque Bera	% of Contracts Shapiro Wilk
		Raw (Base) Data			
CL	198	31	42	16%	21%
NG	276	0	0	0%	0%
		Intervention Model			
CL	198	45	47	23%	24%
NG	276	22	31	8%	11%
	Initial	% Total	Final	% Total	% Change
CL	13481	6.87%	1357	0.69%	-89.93%
NG	15079	4.01%	3071	0.82%	-79.63%

Lower part of table: 13,481 potential outliers for CL and 15,079 for NG. Almost 7% of CL data and 4% for NG data. Well within common Extreme Value Theory observations of 5% to 15% of data. Final outliers 1357 (0.69% CL) and 3071 (0.82% NG).

Summary of initial and final outliers by type

See Table 7 of paper

		Additive	Innovative	Level Shift	Temporary	Total
CL	Initial	4,575	0	4,827	4,079	13,481
	Final	703	310	33	311	1,357
	Change	-85%		-99%	-92%	-90%
NG	Initial	6,054	0	3,435	5,590	15,079
	Final	1,465	618	62	926	3,071
	Change	-76%		-98%	-83%	-80%

The final set of outliers is reduced by 85% for CL and 76% for NG. Interestingly, IO are not detected in the first stage but the final set includes 310 IO for CL and 618 for NG. Biggest reduction in # of outliers is for LS (99% for CL and 98% for NG).

So why do we care? Computing VaR and CVaR puts it in $$ terms

- We compute Gaussian VaR and CVaR and Modified VaR and CVaR. Modified risk calculations are based on incorporating skewness and kurtosis via an analytical estimation using a Cornish-Fisher (special case of a Taylor) expansion.
- CL VaR and CvaR decreased on average of 8.6% to 8.9% with NG decreasing on average of 14.4% to 16.7%.
- Some contract's Risk metrics increased.
- Each risk measure is stand alone for a long position in each contract based on 1,000,000 bbls of CL and 1 BCF (1,000,000 mmBTU) of NG.

Percentage change in VaR and CVaR metrics

Risk Metric	Average	Min		Max	
Crude Oil					
Gaussian VaR	-8.66%	-27.19%	2022.CLF	4.23%	2008.CLM
Modified VaR	-8.91%	-40.39%	2015.CLG	7.47%	2008.CLV
Gaussian CVaR	-8.58%	-26.83%	2022.CLF	3.10%	2008.CLM
Modified CVaR	-8.66%	-26.64%	2022.CLF	12.08%	2008.CLV
Natural Gas					
Gaussian VaR	-15.00%	-48.94%	2029.NGZ	4.80%	2007.NGN
Modified VaR	-16.85%	-65.43%	2029.NGX	6.26%	2022.NGK
Gaussian CVaR	-14.37%	-47.04%	2029.NGZ	4.37%	2007.NGN
Modified CVaR	-14.98%	-56.55%	2029.NGX	4.74%	2010.NGJ

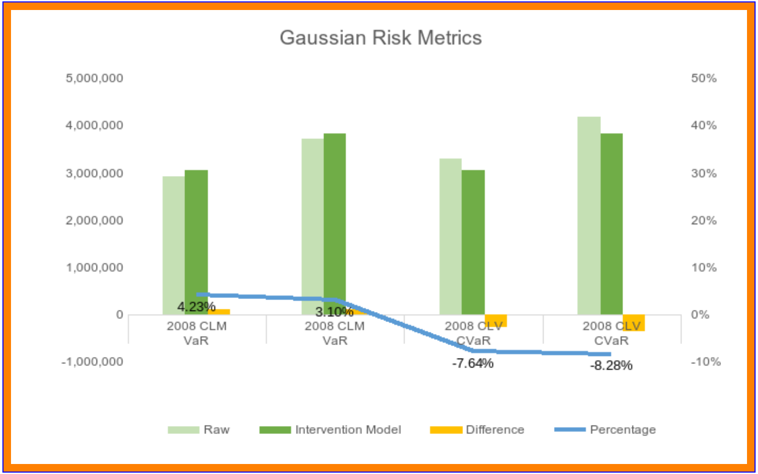
Analysis of risk metrics that increased after outlier adjustments

Risk Metric	Risk Change > 0	Percentage Change
	Crude Oil	
Gaussian VaR	9	4.55%
Modified VaR	10	5.05%
Gaussian CVaR	15	7.58%
Modified CVaR	8	4.04%
Total Contracts	198	
	Natural Gas	
Gaussian VaR	15	5.43%
Modified VaR	17	6.16%
Gaussian CVaR	15	5.43%
Modified CVaR	15	5.43%
Total Contracts	276	

There are cases when the risk metrics increase!

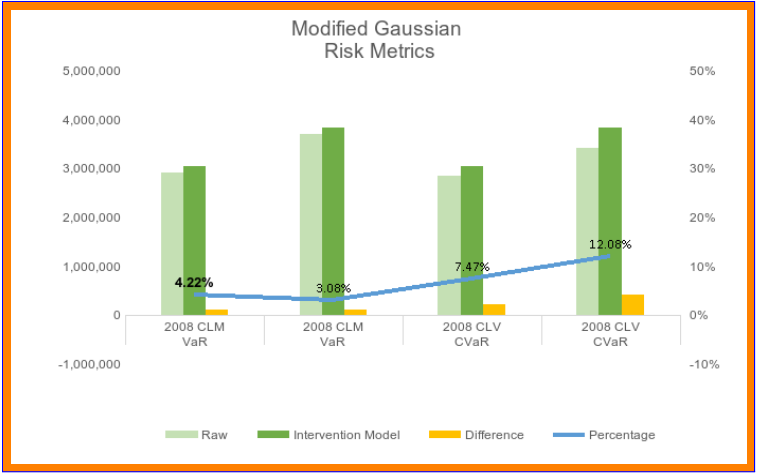
- This occurred for 5% of CL contracts and 5.5% for NG contracts.
- These cases could potentially cause serious problems for a firm.
- Backtests will also suffer showing that the VaR is exceeded, instead of not, more than the predicted number of times per year. This will imply an inadequate risk metric.
- The distributional characteristics will change and the tails will be larger than originally estimated with the raw data. As a result, the expected loss if VaR is exceeded could be much larger than anticipated.
- This larger losses would require immediate risk capital to be deployed, such as a margin call on exchange traded instruments, posting additional capital on over the counter transactions, or being in violation of credit arrangements resulting in technical default.

CL and NG VaR metrics for contracts with significant increases from raw and intervention modeled risk metrics
Slide 1 of 4

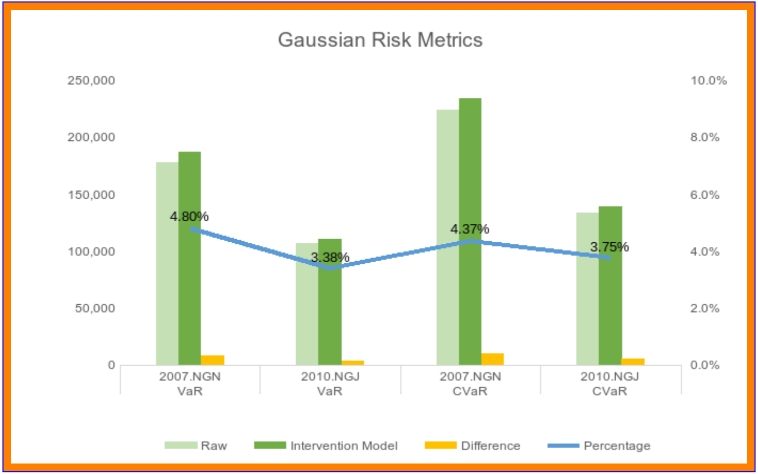


CL and NG VaR metrics for contracts with significant increases from raw and intervention modeled risk metrics

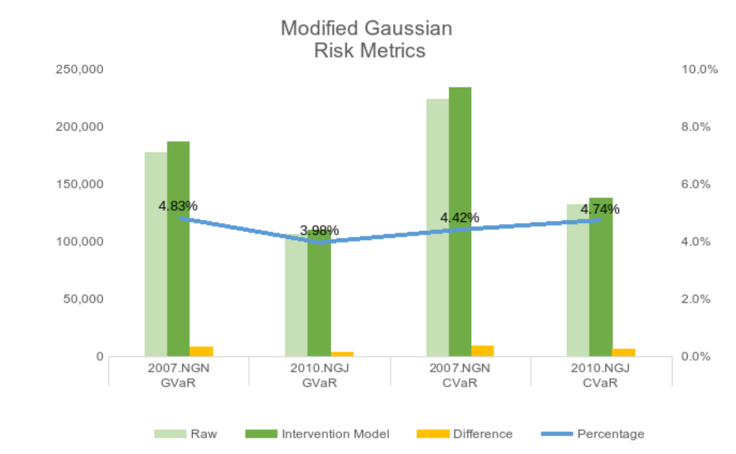
Slide 2 of 4



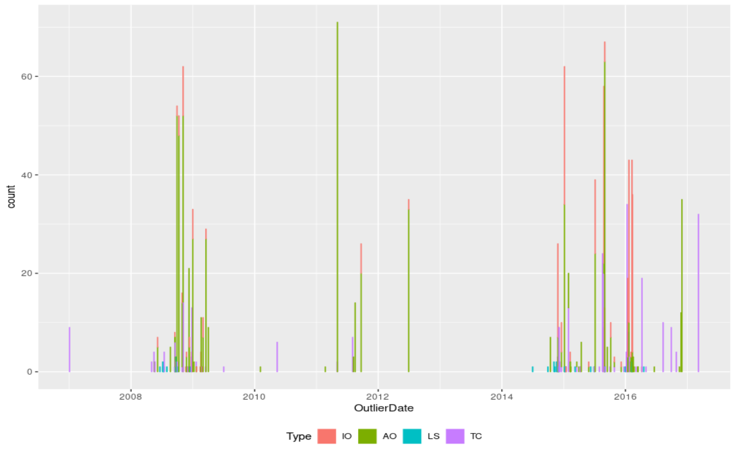
CL and NG VaR metrics for contracts with significant increases from raw and intervention modeled risk metrics
Slide 3 of 4



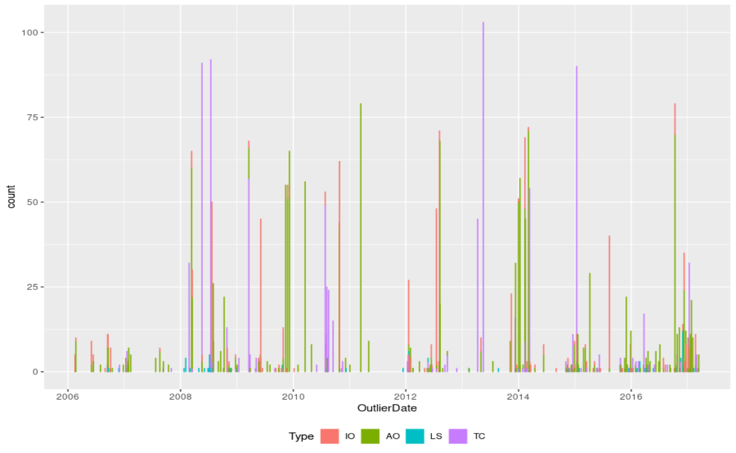
CL and NG VaR metrics for contracts with significant increases from raw and intervention modeled risk metrics
Slide 4 of 4



Number of outliers by each trading day for Crude Oil



Number of outliers by each trading day for Natural Gas



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Conclusion

- We show that detecting outliers is an important step in identifying the true DGP from a risk measurement point of view.
- 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 2nd, 3rd, and 4th moments of the DGP.
- The analysis of residual variance or forecast error was similar to Tsay 1988 findings where the 95th percentile decreased by 50% in his research.