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Affiliations & Keywords

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Keywords

VaR and ES estimation, PCA, joint semiparametric regression, stress testing, oil markets

Objective

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Research Objective

Introduce a novel framework for the joint estimation of **Value at Risk (VaR)** and **Expected Shortfall (ES)** in Brent crude oil futures markets.

Methodology Overview

Methodology

- Semi-parametric regression integrating key market risk factors:
  - **PCA volatilities** (level, slope, curvature) from futures markets
  - **Implied volatility (OVX)** from options markets
- Fully aligned with **Basel Committee's revised market risk framework**
- Supports **scenario analysis** and **stress testing**

Back-Testing & Validation

- Comprehensive evaluation of VaR and ES performance
- Incorporates **novel validation techniques** ensuring regulatory compliance

Key Findings & Impact

Key Findings

- Outperforms traditional benchmark models
- Higher predictive accuracy and robust risk measurement
- Facilitates direct transition to stress testing of risk factors

Impact

Enhances **interpretability, practicality, and robustness**, providing a valuable tool for **market participants, regulators, and policymakers**.

Historical Context of Oil Market Shocks

Figure: Key Events Influencing Oil Markets Over Time

Components of the Oil Futures Curve Changing Over Time

- Upward sloping (Contango), Downward sloping (Backwardation)
- Level
- Slope
- Curvature

What Drives the Oil Futures Curve?

- Expected supply and demand conditions
- Expectations Inventory Levels
- Expectations OPEC Policies
- Expectation Geopolitical regime
- Risk aversion in the market

Futures Prices and Curves Over Time

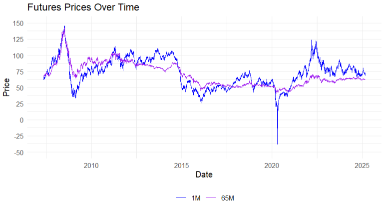

Figure: Futures Prices Over Time (1M vs 65M)

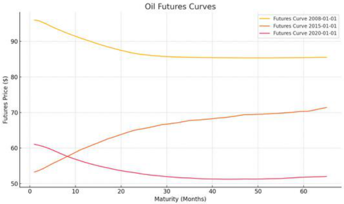

Figure: Oil Futures Curves at Different Dates

What is Oil OVX?

- A measure of implied volatility for crude oil prices, derived from options
- Reflects market expectations of future price fluctuations in oil
- Gauges the risk and uncertainty in oil markets
- Higher OVX values indicate greater expected price volatility
- Used by traders, risk managers, and analysts to hedge or speculate

Background: Risk in Energy Futures Positions

- The global oil market is highly sensitive to external shocks, such as geopolitical events, climate change, or pandemics.
- Traditional risk models often focus on specific spot- or short-term futures price (uni-variate), **failing to adequately account for risks associated with the full futures curve and maturity mismatches**.
- This oversight can lead to extreme losses when market conditions shift abruptly. Historic cases like **Metallgesellschaft (1993)** and **Amaranth Advisors (2006)** illustrate the catastrophic consequences of ignoring maturity risk.

Regulatory Context & Our Approach

1. Shift focus from Value at Risk (VaR) to Expected Shortfall (ES)
2. Specification of the risk factors that are driving VaR and ES
3. Scenario analysis and stress testing of risk factors
4. Back testing procedures for VaR and ES

Note on Industry Regulation

Industry firms are not regulated like bank and financial institutions the same way, but they tend to look to this sector for "state of the art" financial risk management.

Our Modeling Scope

In the paper we model **1% and 2.5% for 1M, 4M, 12M, 65M**.

Our Proposed Solution: A Semi-Parametric Framework

Methodology

We use a semi-parametric approach for the joint estimation of Value at Risk (VaR) and Expected Shortfall (ES), building on recent academic work by Fissler and Ziegel (2016) and Bayer and Dimitriadis (2019).

Key Innovations

- **Captures Curve Risk:** We employ Principal Component Analysis (PCA) to model the full futures curve dynamics, moving beyond simple, single-point risk metrics.
- **Augmented Volatility:** The model incorporates both backward-looking (PCA) and forward-looking (OVX) volatility measures, directly linking risk estimates to observable market factors.
- **Tail Risk Focus:** It moves away from the assumption of normally distributed profits and losses to better capture extreme tail events.

Data Description

Dependent variables

Y's: Returns WTI Oil 1M, 2M, . . . , 65M

Independent risk factors/variables

- $\mathbf{X_1}$: EWMA volatility future curve level (PCA1)
- $\mathbf{X_2}$: EWMA volatility future curve slope (PCA2)
- $\mathbf{X_3}$: EWMA volatility future curve curvature (PCA3)
- $\mathbf{X_4}$: VIX volatility index Futures Options WTI Oil (OVX)

Data Period & Details

- **Period:** 11 May 2007 – 28 Feb 2025
- **Contracts:** 1M to 65M
- **Observations:** 4,646
- Returns with roll-over correction
- **Special note:** Replace 1M return with 2M return on 20 April 2020 (price

Data Processing Steps

1. Standardized returns matrix
2. Covariance Matrix calculation
3. PCA Analysis
4. Extract first 3 components (~95% variance explained)
5. EWMA Volatilities of PCA components
6. Augment with OVX (Oil Options Volatility Index)
7. Resulting Risk Factors
   - Level Volatility
   - Slope Volatility
   - Curvature Volatility
   - Implied Volatility (OVX)
8. Dynamic Risk Forecast Setting (information at t)

Principal Component Analysis (PCA)

A statistical technique used to reduce the dimensionality of a dataset while retaining as much variability in the data as possible. Transforms a set of possibly correlated variables into a set of linearly uncorrelated variables called Principal Components (PCs). The first PC accounts for the largest possible

EWMA Volatilities of PCA Components

Focus on Volatilities

In the risk analysis, we are not interested in the levels of the PCAs, but the **volatilities of the PCAs**.

- We calculate EWMA for the 3 first components $k = 1,2,3$ (alternative volatility models can be used).

Independent Risk Factors (Revisited)

- $\mathbf{X_1}$: EWMA volatility future curve level (PCA1)
- $\mathbf{X_2}$: EWMA volatility future curve slope (PCA2)
- $\mathbf{X_3}$: EWMA volatility future curve curvature (PCA3)
- $\mathbf{X_4}$: VIX volatility index Futures Options WTI Oil (OVX)

Dynamic Factor Structure

- PCAs using all available data, including future observations that would not be known at the time t, would make the model's performance appear artificially good.

Joint Elicitability of VaR and ES

- VaR can be directly modelled with quantile regression, ES can not.
- ES is **not elicitable** on its own – no valid standalone loss function exists unlike for VaR (minimalization of weighted absolute deviations).
- D&B found though found that the pair (VaR, ES) is **jointly elicitable**.

$$Y_t = \alpha + \beta X_t + \varepsilon_t$$

- $|\varepsilon_1|$ is weighted 0.9
- $|\varepsilon_2|$ is weighted 0.1

Joint Estimation

- **R code** for this estimation in 2023 called `esreg`.
- With this approach, VaR and ES are expressed as linear functions of the risk factors.

Joint Semi-Parametric Regression Model

- In our model Y is the return for a specific oil contract and X are the risk factors (we assume the same for VaR and ES).

Example calculation for 1M at 5%

Quantile Coefficients:

- bq_0: 0.01235
- bq_1: 0.00012
- bq_2: -0.00014
- bq_3: 0.00059
- bq_4: -0.00163

Expected Shortfall Coefficients:

- be_0: 0.01859
- be_1: 0.00013
- be_2: -0.00035
- be_3: 0.00115

Current Risk Factor Values:

PC1_Volatility	PC2_Volatility	PC3_V
123.0207162	31.09358413	10.0865

Benchmark Models & Backtests

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VaR and ES Benchmark models:

- Riskmetrics
- GARCH with N, T, Skew-T, Cornish Fisher, EVT
- Filtered Historical Simulation

VaR and ES Backtests:

- Kupiec (1995)
- Christoffersen (1998)
- McNeil and Frey (2000)
- Nolde and Ziegel (2017)
- Dimitriadis and Bayer (2022, 2023)
    - Version 1, 2, 3

VaR Model Properties

A proper VaR model has:

- The number of exceedances as close as possible to the number implied by the VaR quantile we are trying to model.
- Exceedances that are randomly distributed over the sample (that is no "clustering" of exceedances). We do not want the model to over/under predict in certain periods.

Figure: Example VaR Model Performance (1M Oil Contract, 1% VaR)

Backtesting Results Summary

Backtesting Significance Levels

- 1M Oil Contract, 1% VaR and ES level
- P above 0.10 XXX
- P between 0.05 and 0.10 XX
- P between 0.01 and 0.05 X
- P lower than 0.01 Fail
- (H_0 is a correct risk model, wants to keep H_0)

Key Backtesting Outcomes

- Did this for 1M, 4M, 12M, 65M. 1%, 2.5%, 5%, 95%, 97.5%, 99% level (24 panels).
- **PCA-SemiReg fits excellent VaR and ES for most maturities both left and right tail.**
- FHS and GARCH EVT also perform rather well but not at the same significance levels as PCA-SemiReg for ES tests

Conclusion

Basel Committee's (state of the art) market risk framework emphasizes:

- **More use of expected shortfall as a risk measure**
- **Understanding risk factors**
- **Scenario analysis and stress testing**
- **Robust back-testing procedures for ES**

- Capturing all these issues are often missing in papers on oil price risk management.
- This paper discusses a novel method to jointly estimate Value at Risk (VaR) and Expected Shortfall (ES) using joint semi-parametric approach where risk of oil futures positions is a function of **OVX, and future curve level/slope/curvatures volatilities** (extracted from PCA analysis).
- Preliminary **back-testing** results demonstrate **strong performance** estimation compared to benchmark models.
- Straightforward implementation for **scenario analysis** and **stress testing**.

Future Work

- Complete all back testing of models and conclude.
- Include more risk factors (e.g., skewness from options markets, liquidity measures etc.).
- Other models that capture non-linearity in the tails (machine learning methods).
- Other markets (Commodities, FX, Interest Rates. . .).