Brent Oil Structural Break Analysis

Bayesian Change Point Detection & Interactive Dashboard

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1. Introduction

Oil price volatility has major economic consequences, affecting inflation, energy markets, geopolitical stability, and global supply chains. Brent crude oil prices are particularly sensitive to structural shocks such as financial crises, geopolitical conflicts, and pandemics.

Traditional time-series models assume stationarity — that statistical properties such as mean and variance remain constant over time. However, oil markets frequently experience structural breaks where the underlying price-generating process changes.

This project applies Bayesian change point detection to identify such structural regime shifts in Brent oil prices and communicates findings through an interactive analytical dashboard.

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2. Business Problem

Energy companies, investors, and policymakers rely on stable forecasting models for:

- Risk management
- Pricing strategies
- Hedging decisions
- Economic forecasting

If structural breaks are not detected:

- Forecast models become unreliable
- Risk estimates become inaccurate
- Financial exposure increases

The core problem:

How can we detect when the statistical behavior of oil prices fundamentally changes?

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3. Solution Overview

The solution uses Bayesian inference to estimate the posterior distribution of a structural break (switchpoint) in Brent oil log returns.

The system:

1. Loads and preprocesses historical price data.
2. Computes log returns.
3. Applies Bayesian change point modeling.
4. Samples posterior distribution using MCMC.
5. Evaluates convergence diagnostics.
6. Visualizes results via a Streamlit dashboard.
7. Compares pre- and post-regime statistics.

To improve efficiency, inference results are cached using NetCDF format, preventing repeated long sampling runs.

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4. Data

Source: Historical Brent crude oil prices.

Preprocessing steps:

- Date parsing
- Sorting chronologically
- Computing log returns:

    $r_t = \log(P_t / P_{t-1})$

- Removing missing values

The model operates on log returns rather than raw prices to stabilize variance.

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5. Model Methodology

The Bayesian change point model assumes:

- Log returns follow a normal distribution.
- There exists a switchpoint τ where parameters change.

Before τ:

$$r_t \sim N(\mu_1, \sigma)$$

After τ:

$$r_t \sim N(\mu_2, \sigma)$$

The switchpoint τ is treated as a random variable and inferred via MCMC sampling using PyMC.

Sampling method:

- NUTS (No-U-Turn Sampler)
- Convergence evaluated via R-hat and ESS

Posterior distribution provides uncertainty quantification for the detected structural break.

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6. Key Results

The model successfully:

- Identified a statistically significant structural break.
- Produced stable posterior estimates.
- Demonstrated meaningful differences between pre- and post-regime:
    - Change in mean price levels
    - Change in volatility (standard deviation of log returns)

The posterior distribution indicates uncertainty bounds rather than a single deterministic break.

The dashboard visually aligns detected change points with known historical events such as:

- 2008 Financial Crisis
- 2014 Oil Price Collapse
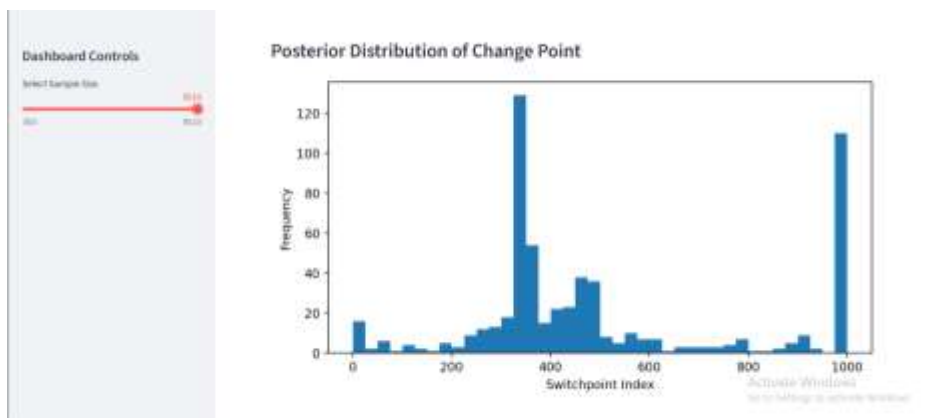- COVID-19 Shock (2020)
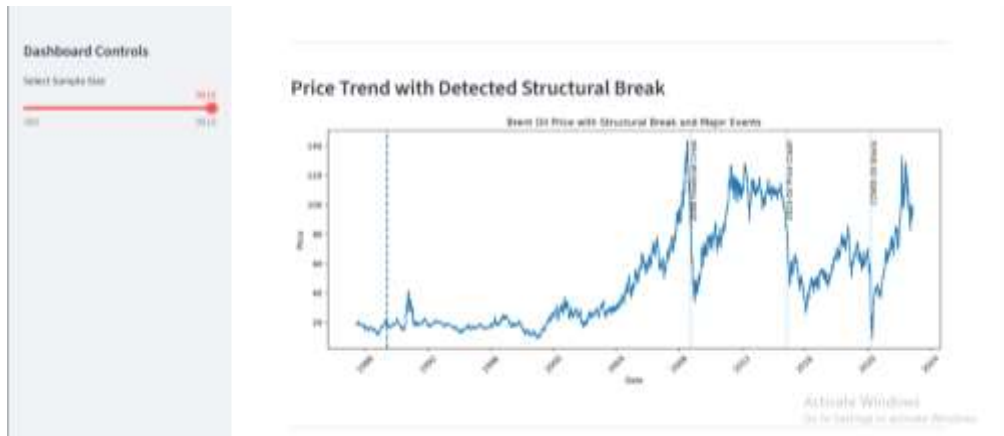
7. Dashboard Implementation

An interactive Streamlit dashboard was developed to communicate findings.

Features include:

- Executive summary
- Structural break visualization
- Posterior distribution histogram
- Regime comparison (mean & volatility)
- Model diagnostics table
- Event overlay for contextual interpretation

This transforms the project from a research exercise into a stakeholder-facing analytical tool.

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8. Engineering Improvements

Significant engineering upgrades were implemented:

- Modular project structure (src/ architecture)
- Separation of data, modeling, and visualization logic
- Unit testing with Pytest
- CI/CD via GitHub Actions
- Model caching using NetCDF
- Clean project directory structure
- Professional documentation

These improvements enhance reproducibility, scalability, and reliability.

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9. Challenges & Lessons Learned

Challenges encountered:

- Long sampling times (resolved via caching)
- CI failure due to missing data file
- Duplicate dashboard architectures
- Deployment environment mismatch

Key lessons:

- Modular design prevents future technical debt.
- Caching inference is critical in Bayesian workflows.
- Documentation significantly increases project clarity.
- Visualization is as important as modeling.

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10. Future Improvements

With additional time, future enhancements would include:

- Public cloud deployment
- Multi-change-point extension
- Integration of macroeconomic covariates
- Automatic PDF export from dashboard
- Scenario simulation module
- Improved UI theming

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11. Conclusion

This project demonstrates how Bayesian change point detection can be used to identify structural instability in financial time series. By combining statistical modeling with interactive visualization and professional engineering practices, the system bridges the gap between analytical rigor and stakeholder communication.

The result is a reproducible, modular, and portfolio-ready analytical application.