TÉCNICO LISBOA

2nd Cycle Integrated Project in Engineering Physics

Predicting Commodity Turning Points with Mixed Causal–Noncausal Models and Exogenous News

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Commodities and Bubbles

- **Commodities** are raw products, such as oil, metals or agricultural goods.
- **Modeling** commodity prices enables producers, investors and policy makers to
  - ↳ anticipate future price movements
  - ↳ manage financial risk
  - ↳ make informed policy decisions

- **Speculative bubbles** are locally explosive rises followed by a sudden crash.
- **Financial instability** arises when bubbles propagate across multiple time series.

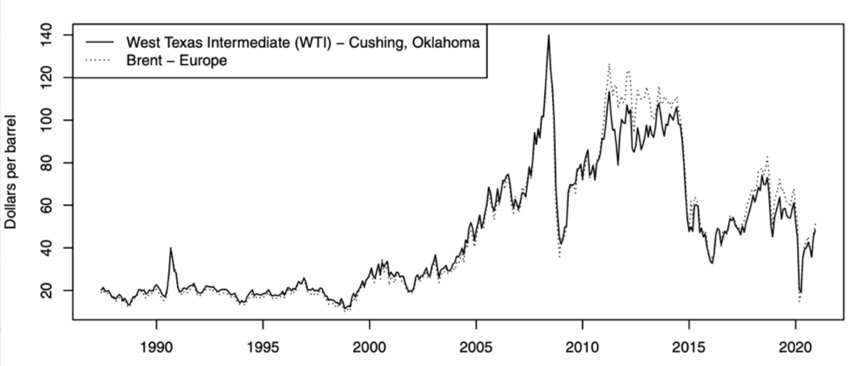

Figure: crude oil monthly price series
(A. Hecq and E. Voison "Predicting crashes in oil prices during the COVID-19 pandemic with mixed causal-noncausal Models", 2021)

Modeling Bubbles

- On **traditional models**, current price depends on **past** prices and innovations
- **Speculative bubbles** are driven by expectations about the **future**
- On **MAR models**, current price depends both on **past** and **future** dynamics

↓

MAR models capture bubble episodes

$$y_t = \underbrace{\phi_1 y_{t-1} + \cdots + \phi_r y_{t-r}}_{\text{Backward-looking (Past Dependent)}} + \underbrace{\psi_1 y_{t+1} + \cdots + \psi_s y_{t+s}}_{\text{Forward-looking (Future Dependent)}} + \underbrace{\varepsilon_t}_{\text{Non-Gaussian Innovation}}$$

Motivation

Commodity prices are strongly influenced by **news and market sentiment.**

Existing MAR studies focus on **price dynamics** and

don't explicitly model the role of news.

↓

How do news affect commodity prices?
Can news improve predictions of bubble crashes?

↓

Incorporate news into MAR models

$$y_t = \phi_1 y_{t-1} + \cdots + \phi_r y_{t-r} + \psi_1 y_{t+1} + \cdots + \psi_s y_{t+s} + \beta' \mathbf{X}_t + \varepsilon_t$$

Objectives

1. Add news exogenous variables to MAR

2. Improve early warning signals of reversals

3. Disentangle surprise vs anticipatory effects

4. Assess news propagation through causal and noncausal channels

Next Steps

1

Model

Build a well-defined MAR model with exogenous variables

2

Estimation

Define functions for parameter estimation and forecasting

3

Test Model

Use Monte Carlo simulations to test model on artificial data

4

Apply to Data

Apply model estimation and forecasting procedure to real commodity data

Thank you!

Extra Slides

AR Models

AR(p) $y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t$

Noncausal AR(r) $y_t = \psi_1 y_{t+1} + \psi_2 y_{t+2} + \cdots + \psi_r y_{t+r} + \varepsilon_t$

MAR(r,s) $y_t = \phi_1 y_{t-1} + \cdots + \phi_r y_{t-r} + \psi_1 y_{t+1} + \cdots + \psi_s y_{t+s} + \varepsilon_t$

- ϕ_i and ψ_j are the lag and lead coefficients, respectively.
- ε_t is the innovation term: Gaussian white noise for causal AR and non-Gaussian i.i.d. distribution for the other two models.

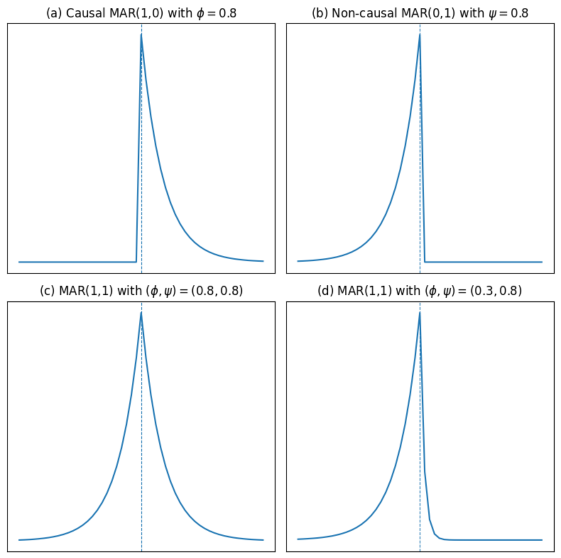

Figure: response of different models to a single local shock.

The Model

MAR(r,s) +
exogenous variables

$$y_t = \Phi(L)^{-1}\Psi(L^{-1})^{-1}\varepsilon_t$$

$$y_t = \Phi(L)^{-1}\Psi(L^{-1})^{-1}(\varepsilon_t + \beta'\boldsymbol{X}_t)$$

- $\Phi(L) = 1 - \phi_1 L - \dots - \phi_r L^r$
- $\Psi(L^{-1}) = 1 - \psi_1 L^{-1} - \dots - \psi_s L^{-s}$
- ε_t follows i.i.d. Student-t distribution
- X_t are weakly exogenous

Parameter Estimation (AML)

$$\hat{L}_T(\theta) = \sum_{t=r}^{T-s} \hat{l}_T(\theta) = \sum_{t=r}^{T-s} \log(f(\varepsilon_t(\theta);\gamma))$$

$$\hat{\theta}_T = \arg\max_{\theta\in\Theta} L_T(\theta)$$

Parameter vector: $\theta = (\phi, \psi, \beta, \gamma, \dots)$
Student-t distribution parameters: $\gamma = (\sigma, \nu)$

Empirical application

- Compare model with MAR benchmarks
- Derive **warning signals of reversals**
  (Rapid growth in $y_t^{noncausal}$)
- Disentangle **surprise and anticipatory effects**
- Assess news propagation through **causal and noncausal channels**

$$y_t^{surp} = \Phi(L)^{-1}\Psi(L^{-1})^{-1}\varepsilon_t$$
$$y_t^{ant} = \Phi(L)^{-1}\Psi(L^{-1})^{-1}\beta'\boldsymbol{X}_t$$

$$y_t^{causal} = \Phi(L)^{-1}\beta'\boldsymbol{X}_t$$
$$y_t^{noncausal} = \Psi(L^{-1})^{-1}\beta'\boldsymbol{X}_t$$