Evidence for Oil Market Risk Sharing From A Bayesian Perspective

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Overview

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Motivation

- Crude oil is ubiquitous in modern life - used in everything from refined fuels to fertilizers
- Trading is mainly done via the futures market because spot market necessitates physical delivery
- Important for companies and other economic agents to hedge against risks in the oil market, for example airlines
- However, risk dynamics in the oil market have changed since around 2000, when academics agree commodity markets first became financialized (Cheng and Xiong, 2014)

Theory — What is Financialization?

- While many papers have discussed the implication of financialization, the term itself remains vague and can only be broadly defined as the acceptance of an asset by a wider set of market participants than before (Fattouh, Kilian and Mahadeva, 2013)
- Financialization also brings with it increased levels of speculation, though the pricing implications of such speculation in the commodity market are unknown (ibid)
- Like financialization, speculation is also somewhat of a vague concept, but can generally be defined as the volume of trading above volume needed to hedge spot positions (Working, 1960)

Theory — What is Financialization?

- Working's T index captures our definition of speculation by calculating volume of futures trading above volume for hedging

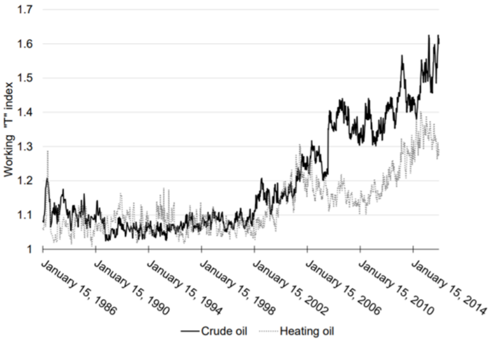


Figure: (Isleimeyyeh, forthcoming)

Theory — Effects of Financialization

- **Asset Price Bubbles:** Financialization and associated speculation causes asset price bubbles as speculators decouple expectations from fundamentals (Brown and Sarkozy, 2009).
- **Information Discovery:** Financialization reduces informational friction in the oil market, leading to heterogeneous expectations globally. Hence, oil futures returns can be a 'barometer' for global economic strength (Cheng and Xiong, 2014).
- **Risk Sharing:** Financialization causes investors to reallocate part of their portfolio into the oil market, causing increased integration with traditionally segmented markets and consequently less diversification benefits (Silvenoinen and Thorp, 2013).

Research Questions

Although the aforementioned effects are somewhat interlinked by their common cause, my research focuses explicitly on the risk sharing element of financialization. While past studies like Silvenoinen and Thorp (2013), and more recently Isleimeyyeh (forthcoming) gives good evidence of increasing co-movements between oil and the stock market, frequentist regression models are used and as such cannot capture detailed time-variance at monthly or even annual intervals. I hope to use Bayesian modelling to test the following:

Research Questions

1. Does the risk sharing theory hold between the oil and equity markets?
2. How has the risk sharing relationship changed over time?
3. Does risk sharing encompass short-term shocks, or solely long-term co-movements?

Model — Co-movement

Traditionally, systematic risk is defined as co-movement between an asset and a wider market. For the following let z be the return of oil and x the return of an external market.

Co-movement Model

$z = \beta x + \epsilon$

Derivation From CAPM

$z - r_f = \alpha + \beta(x - r_f) + \epsilon$

Assume inter-period risk free rate is negligible...

$z = \beta x + \epsilon$

Derivation From Proportionality

$z \propto x$

$z = \beta x$

Add market noise...

$z = \beta x + \epsilon$

Model — Impulse Response

Silvenoinen and Thorpe (2013) suggest that risk-sharing may also occur with short-term shocks, which we can test with an impulse response function.

Impulse Response Model - adapted from Kilian (2008)

$z_t = \Sigma_{h=0}^{1} \beta_{t-h} S_{t-h} + \epsilon_t$

I use a simple distributed lag model to calculate the impact response to shock variable S at horizons 0, 1.

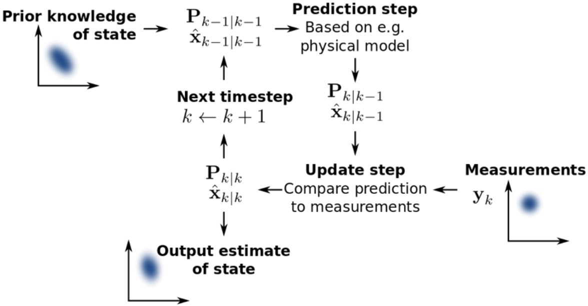
Definition of S

$S_t = \%\Delta V - \%\Delta(\frac{1}{12}\Sigma_{i=1}^{12} V_{t-i})$

Shock is defined as the difference in between the percentage change of some volatility indicator V (e.g. VIX/EWMA volatility) and the percentage change in the rolling 12-month average value of V. Theoretically, S is thus the unexpected portion of percentage change in volatility compared to to expected percentage change in volatility using information from the last 12 months.

Model — State Space Transform

I will transform the β coefficients to be modeled as a state space variable using the Kalman filter. The Kalman filter is a Bayesian modelling technique that updates the most likely position of a state through recursive estimation and observation of priors and posteriors. Kalman filters have already been applied in the modelling of time-varying systematic risk for the equity market (Faff, Hillier and Hillier, 2003).



Model — Kalman Filter

The Kalman filter relies on two sets of equations: namely the prediction and measurement equations. For the following let $\hat{\beta}$ be the state estimate of β coefficients. I model each state to change with time period t.

Kalman Filter Assumptions

$\hat{\beta}_t \sim N(\hat{\beta}_t, \mathbf{P}_t)$
$\mathbf{z}_t \sim N(\mathbf{z}_t, \mathbf{R}_t)$

Prediction Equations

Prediction equations give the prior $\hat{\beta}_{t|t-1}$. As recommended by Faff, Hillier and Hillier (2003) for systematic risk in the equity market, I model the priors as a series of random walks such that:
$\hat{\beta}_{t|t-1} = \hat{\beta}_{t-1|t-1}$
$\mathbf{P}_{t|t-1} = \mathbf{P}_{t-1|t-1} + \mathbf{Q}$

Model — Kalman Filter

Measurement Equations

Measurement equations use the prior $\hat{\beta}_{t|t-1}$ to give the posterior $\hat{\beta}_{t|t}$. In keeping with convention, let $\mathbf{H}$ be the matrix of x values for the following.

$\mathbf{K}_t = \mathbf{P}_{t|t-1}\mathbf{H}_t^\top(\mathbf{H}_t\mathbf{P}_{t|t-1}\mathbf{H}_t^\top + \mathbf{R}_t)^{-1}$

$\hat{\beta}_{t|t} = \hat{\beta}_{t|t-1} + \mathbf{K}_t(\mathbf{z}_t - \mathbf{H}_t\hat{\beta}_{t|t-1})$

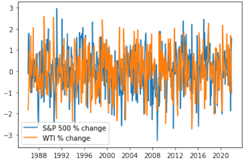
$\mathbf{P}_{t|t} = (I - \mathbf{K}_t\mathbf{H}_t)\mathbf{P}_{t|t-1}$

Implementation

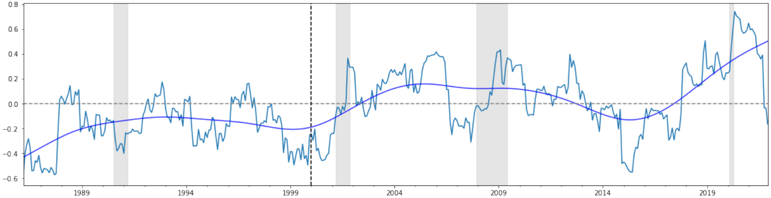
Equations will be implemented in Python via the package 'filterpy' by Labbe (2015). Due to the adaptive nature of the Kalman filter, our initial distributions for $\hat{\beta}_0$ and $\mathbf{z}_0$ matter little, and will be set as diagonal matrices using the historical variance of x. For $\mathbf{Q}$, which regulates the speed of estimate adaption, I use a matrix of the value 0.01 to smooth our results by giving more credibility to the random walk process than new observations.

Data

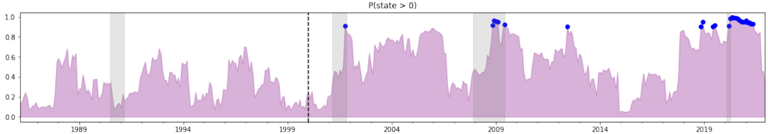
- **Oil Market:** I use rolling front-month West Texas Intermediate (WTI) futures at monthly intervals collected from the US Energy Information Administration (EIA).
- **External Markets:** I collect monthly data on various financial indices from Bloomberg, and commodity prices from the EIA. Key indices used are the S&P 500 index, MSCI global equity indices and the GS Commodity Index.
- **Data Cleaning:** To account for any effects of inflation, I make sure to collect all monetary values in USD, then deflate the data series using monthly US CPI figures from the FRED database. Finally, I calculate the simple returns of the data and standardize annually as well as de-seasonalize the data to arrive at a stationary series.



Co-movement Results — S&P 500

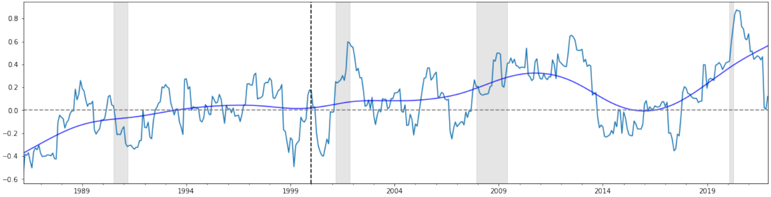


S&P 500 Co-movement Coefficients

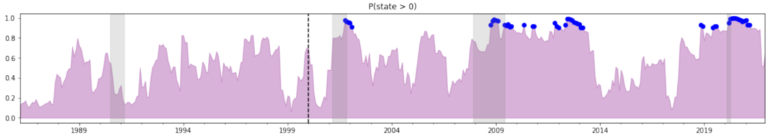


$P(\hat{\beta} > 0)$ for S&P 500 Co-movement Coefficients, $P > 0.9$ Highlighted

Co-movement Results — MSCI World

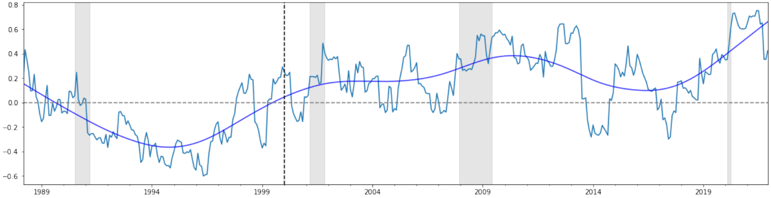


MSCI World Co-movement Coefficients

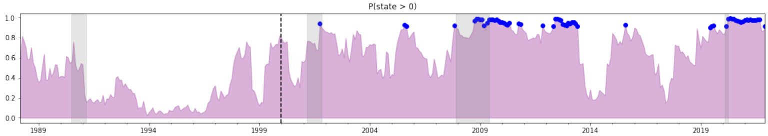


$P(\hat{\beta} > 0)$ for MSCI World Co-movement Coefficients, $P > 0.9$ Highlighted

Co-movement Results — MSCI Emerging Markets



MSCI Emerging Markets Co-movement Coefficients



$P(\hat{\beta} > 0)$ for MSCI Emerging Markets Co-movement Coefficients, $P > 0.9$ Highlighted

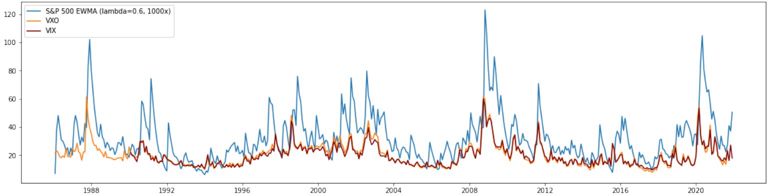
Co-movement Results — Benchmarking

Our results have so far supported the risk sharing theory, but to see if our estimates are plausible, we need to test its performance against OLS (frequentist) and random walk benchmarks. Since the Kalman filter is used for inference rather than prediction, I backtest on in-sample data.

Variable	OLS estimate	KF mean	RW RMSE	OLS RMSE	KF RMSE
S&P 500	-0.0191	-0.0227	0.9947	0.9945	0.9136
MSCI World	0.0912	0.0848	0.9947	0.9905	0.9065
MSCI EM	0.0911	0.0980	0.9946	0.9954	0.8993

Backtesting shows that the estimated Kalman filter coefficients better fit the in-sample data than random walk or OLS. The mean of the Kalman estimates are also similar to the OLS estimate, indicating that we have successfully extracted a time trend without disturbing the overall relationship.

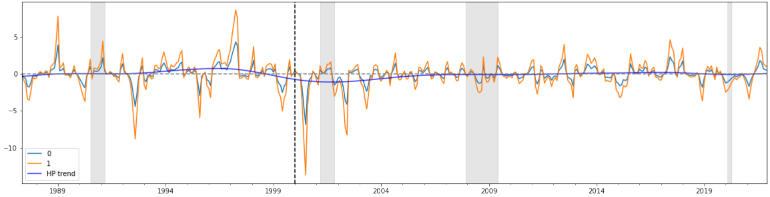
Impulse Response Results — Note on Volatility Measures



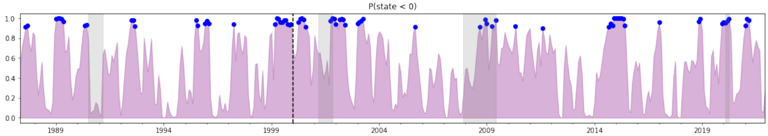
VIX, VXO and S&P 500 EWMA (lambda=0.6)

- VXO is the options implied volatility of the S&P 100 index
- I use VXO rather than the VIX (implied vol on S&P 500) because it stretches back to 1987 rather than 1991 and there's little difference between them
- Realized volatility given by EWMA is fitted to roughly match the VXO using lambda 0.6

Impulse Response Results — S&P 500 EWMA

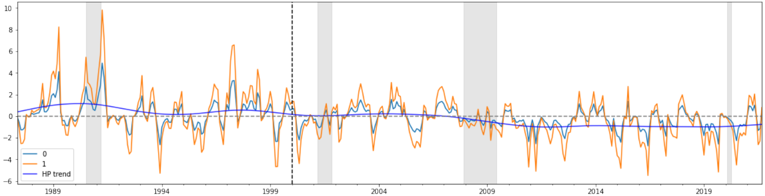


S&P 500 EWMA Impulse Response Coefficients

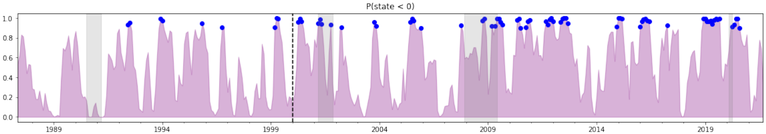


$P(\hat{\beta} < 0)$ for S&P 500 EWMA Impulse Response Coefficients, $P > 0.9$ Highlighted

Impulse Response Results — VXO



VXO Impulse Response Coefficients



$P(\hat{\beta} < 0)$ for VXO Impulse Response Coefficients, $P > 0.9$ Highlighted

Other Results

Type	Dependent (y)	Independent (x)	Trend
Co-movement	GS Commodity Index	Equity Indices (S&P, MSCI)	Increasing
Co-movement	Oil Futures	Natural Gas Futures	Decreasing
Co-movement	Natural Gas Futures	Equity Indices (S&P, MSCI)	No Trend

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