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Crude Oil Price Movements between Fundamental and Uncertainty: Evidence from Frequency Causality Tests

Amine Mounir*

ESCA Ecole de Management, Lot 67-3, Finance City (CFC), Bd de l'Aéropostale, Casablanca 20250 Morocco.
*Email: ammounir@esca.ma

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ABSTRACT

This paper studies the cyclo-stationary causality of crude oil price movements using (1) net inventory withdrawals as a fundamental related factor and (2) the VIX index as an uncertainty/financial related factor. It uses frequency causality tests to assess their predictive power for crude oil movements with different time cycles. Results show that WTI crude oil prices had a quick reaction to oil net inventory withdrawals movements and a lesser extent to VIX before 2010. However, this result reversed after, revealing no predictive power of the fundamental related factor while the VIX is observed as a persistent leading indicator with high frequencies over the period 2010:12-2022:06.

Keywords: Oil Prices, Frequency Causality Tests, VIX, Frequency Domain
JEL Classifications: C22, C32, C53, E32, Q47

1. INTRODUCTION

The crude oil market is one of the most scrutinized markets worldwide by politicians, investors, and academics. Crude Oil price movements have a tremendous impact on the growth and production of developed and developing countries leading to a particular interest of governments and politics. The intensification of international trade around the world and the great uncertainty of the crude oil market made the latter at the heart of investors, companies, governments, and scholars' attention.

From the academic perspective, a tremendous number of articles studied the impact of oil price shocks on macroeconomic and/or financial variables. The impact on gross domestic product (GDP), for example, has been extensively studied by researchers (Hamilton, 1983; Guo and Kliesen, 2005). Others explored the impact of crude oil price shocks on exchange rates (Adeniyi et al., 2012), stock market price movements (Basher et al., 2012), and budget and government revenue (Zakaria and Shamsuddin, 2017).

While existing literature is abundant in contributions with one direction impact studies and analysis (i.e., the impact of crude oil price movements on economic and financial variables). Few articles pay attention to the impact in the reverse direction (i.e., the impact of economic and financial variables on crude oil price movements). Based upon demand factors represented by GDP expectations and geopolitics events for example, some contributions study their impact on crude oil price movements (Coleman, 2012; Khan et al., 2021). Others use supply factors like inventories, expected petroleum producer decisions and importer refiner acquisition cost, or even a mix of factors related to fundamentals and financial/uncertainty indicators to assess their impact on crude oil price (Dutta et al., 2021b; Ozcelebi, 2021; Zhao et al., 2022).

It is common in the existing literature to refer to VAR techniques or related variations to explore the impact of different variables on crude oil prices or vice versa. This application is meant to describe the short-run dynamic relation between variables unless the long-run equilibrium is the objective, then a vector error correction model (VECM) or other variations are used. In both time scales, those techniques do not consider differences in cycle lengths where several endogenous variables may have a persistent predictive power on the exogenous variable. Moreover, the long-run equilibrium within the cointegration framework is a concept tightly related to the study period, i.e., one may detect a long-run equilibrium between crude oil price and real GDP quarterly data for a given country from 2005 to 2010, it is difficult to imagine that this result will hold for another time frame and/or time-frequency unit.

Considering the cyclical features of the crude oil markets, this article explores the predictive power of (1) crude oil net inventory withdrawals as a fundamental related factor and VIX as a financial factor for WTI crude oil price movements. It uses the frequency causality test proposed by Geweke (1982), Hosoya (1991) and refined by Breitung and Candelon (2006).

This test presents, first, a consistent measure of causality in nonlinear and/or cyclical variables dynamic setting. Second, it decomposes the causality strengths and predictive power of variables over different frequencies ranging from low to high frequency. This decomposition is important to assess the predictive power of fundamental and financial-related factors for crude oil over different cycle lengths.

The rest of the paper is organized as follows. Section 2 discusses the state of the art related to crude oil-related factors. Section 3 presents data and lays the foundations of the frequency causality tests. Section 4 presents the results of the empirical study. Finally, Section 5 summarizes our conclusions.

2. LITERATURE REVIEW

In attempts to explain crude oil variations, several authors used different factors. A large part of the literature focuses on fundamental factors (Kilian, 2009; Jing et al., 2019; Coleman, 2012; Khan et al., 2021) related to supply, demand, global economic growth, and geopolitics. The second bunch of literature tackles the crude oil price movements from an uncertainty point of view. Kang et al. (2017) explore the dynamic effects of US and non-US oil production shocks on economic policy uncertainty using a structural VAR model. Their findings support a strong relationship between EPU and crude oil. Ozcelebi (2021) uses US government bond yields and Global Economic Policy Uncertainty (GEPU) to explore their effects on oil prices. Using the quantile cointegration test, Ozcelebi (2021) finds long-term nonlinear relationships among variables. Bekiros et al. (2015) compare the forecastability of real oil returns using economic policy uncertainty (EPU) data. They find information on EPU does matter in predicting oil returns out-of-sample. Liu et al. (2013) investigate cross-market uncertainty using the crude oil volatility index (OVX), stock market volatility index (VIX), and gold price volatility index (GVZ). Their findings suggest that there is no long-run equilibrium between the volatility indices. In the same spirit, Dutta et al. (2021a) use symmetric and asymmetric GARCH models to capture the predictive power of the crude oil volatility (OVX) index for crude oil returns. In sum, A growing interest in literature focuses on complex uncertainty information and data related to the surrounding crude oil price features or at least having, intuitively, an impact on such a complex market (Dutta et al., 2021b; Zhao et al., 2022; Li et al., 2022).

It is worth noting that while a large part of the literature is concerned with crude oil-related factors, very few explore the relationship features that exist between these variables and crude oil prices. Bekiros et al. (2015) find that economic policy uncertainty (EPU) information helps forecast real oil returns when accounting for nonlinearities between these two variables. Li et al. (2022) explore the cross-correlation between crude oil and three volatility indices and find that there are nonlinear and multifractal relationships among these variables. Similarly, Ozcelebi (2021) results support nonlinear relationships between WTI crude oil, 10 years of US government bond yields, and GEPU.

While oil price literature is abundant of valuable contributions, a large part shares the same technical framework relying upon VAR modeling and/or variation to describe relationships between crude oil prices and other factors. Unfortunately, such a framework does not help to disentangle the short- and long-term effects that factors may have on crude oil prices with accurate time cycle lengths. It is difficult to believe that some specific factor will have a permanent impact on the crude oil market. Baumeister and Kilian (2012) oil price forecasting model, for example, performs well during the period when economic fundamentals show persistent movements, between 2002 and 2011, but less well during other periods.

3. DATA AND METHODOLOGY

3.1. Data

Conventional oil market VAR models contain 4 variables: oil price, inventories, world economic activity, and production[1]. Our concern in this article is to shed the spotlight on the predictive power of some exogenous variables for WTI crude oil future movements over different time scales. While world economic activity and production demonstrate a long-term impact on crude oil prices with the cointegration framework, the short-run impact with other variables is less discussed in the literature. We extend the latter using the financial-related factor VIX index[2] describing uncertainty in the American financial markets and the crude oil net inventory withdrawals[3] translating the net balance between the worldwide supply and demand of WTI crude oil. The last variable is a fundamental related factor acting as a proxy for differences between economic activity as the demand factor and production as the supply factor.

WTI crude oil spot prices, the crude oil net inventory withdrawals data along with the VIX index price are used as data for the tests. The period study ranges from January 1997 to June 2022[4].

1 Other articles explore the importer refiner acquisition cost as a predictor of oil price (Baueimster and Kilian, 2015)

2 VIX Index data are extracted for SIX Financial Database.

3 Crude oil spot prices and net inventory withdrawals data are extracted from U.S. Energy Information Administration (EIA).

4 The period study is constrained by the availability of net inventory withdrawals data that starts from 1997.

It is worth highlighting that any change in the data-generating process during the sample period will result in biased estimates. Thus, we apply the multiple break test (Bai and Perron, 1998; Bai and Perron, 2003) which aims to determine the timing of the breakpoints due to a shift in the data-generating process. Moreover, splitting the overall period into subperiods will help to study the dynamic of causality. Table 1 shows 4 subperiods resulting from the multiple break test with 3 breaks and a trimming value of 20% on the crude oil time series.

3.2. Methodology

This section summarizes the foundations of frequency causality tests proposed by Geweke (1982), Hosoya (1991) and refined by Breitung and Candelon (2006).

Following the notation of (Breitung and Candelon, 2006), let $Y_t=(x_t,y_t)'$ be a two-dimensional stationary vector of length T. The vector has the following finite-order VAR(p) representation:

$$\Theta(L)\,Y_t=\varepsilon_t \tag{1}$$

Where $\Theta(L)=I_2-\Theta_1L-\Theta_2L^2-\cdots-\Theta_pL^2$ has L as a lag operator such as $LY_t=Y_{t-1}$. ε_t is assumed to be white noise with mean zero $E(\varepsilon_t)=0$ and covariance matrix $\Sigma=E(\varepsilon_t\varepsilon_t')$. Since Σ is positive, semi-definite, and symmetric, applying Cholesky decomposition, $G'G=\Sigma^{-1}$ (where G is a lower-triangular matrix), we can rewrite the finite-order VAR(p), in equation (1) as the following moving-average representation:

$$\Phi(L)\varepsilon_t=\begin{bmatrix}\Phi_{11}L & \Phi_{12}L\\ \Phi_{21}L & \Phi_{22}L\end{bmatrix}\begin{bmatrix}\varepsilon_{1t}\\ \varepsilon_{2t}\end{bmatrix}=\Psi(L)\eta_t$$

$$=\begin{bmatrix}\Psi_{11}L & \Psi_{12}L\\ \Psi_{21}L & \Psi_{22}L\end{bmatrix}\begin{bmatrix}\eta_{1t}\\ \eta_{2t}\end{bmatrix} \tag{2}$$

Where $\eta_t=G\varepsilon_t$, $E(\eta_t\eta_t')=I$, $\Phi(L)=\Theta(L)^{-1}$, and $\Psi(L)=\Phi(L)G^{-1}$.

Applying Fourier transformations to the moving-average representation system in (2) leads to the following spectral density of y_t:

$$f_x(\omega)=\frac{1}{2\pi}\left\{\left|\Psi_{11}(e^{-i\omega})\right|^2+\left|\Psi_{12}(e^{-i\omega})\right|^2\right\} \tag{3}$$

From equation (3) Geweke (1982) derived the causality measure from x_t to y_t at frequency ω as follows:

$$M_{x\to y}(\omega)=\log\left\{1+\frac{\left|\Psi_{12}(e^{-i\omega})\right|^2}{\left|\Psi_{11}(e^{-i\omega})\right|^2}\right\} \tag{4}$$

According to this measure if $|\Psi_{12}(e^{-i\omega})|^2=0$, then $M_{x\to y}(\omega)=0$ i.e., x_t does not cause y_t at frequency ω. Testing the null hypothesis H_0: $M_{x\to y}(\omega)=0$ is difficult because the distribution of Wald statistic is a nonlinear function of the VAR parameters. Breitung and Candelon (2006) proposed a simple approach to test the null hypothesis conditioned by:

$$\left|\Theta_{12}(e^{-i\omega})\right|=\left|\sum_{k=1}^{p}\theta_{12,k}\cos(k\omega)-\sum_{k=1}^{p}\theta_{12,k}\sin(k\omega)i\right|=0 \tag{5}$$

Where $\theta_{12,k}$ is the (1,2)-element of Θ_k. The sufficient condition to (5) is:

$$\begin{cases}\sum_{k=1}^{p}\theta_{12,k}\cos(k\omega)=0\\ \sum_{k=1}^{p}\theta_{12,k}\sin(k\omega)=0\end{cases} \tag{6}$$

Breitung and Candelon (2006) reformulated the relation between x_t and y_t, by imposing the restrictions in (6) in the following VAR(p) model:

$$y_t=c_1+\alpha_1y_{t-1}+\cdots+\alpha_py_{t-p}+\beta_1x_{t-1}+\cdots+\beta_px_{t-p}+\varepsilon_{1t} \tag{7}$$

Where $a_j=\theta_{11,j}$ and $\beta_j=\theta_{12,j}$. Testing the null hypothesis of non-predictive power at frequency ω is equivalent to test H_0: $R(\omega)\beta=0$ where $R(\omega)$ is $2\times p$ restriction matrix:

$$R(\omega)=\begin{bmatrix}\cos\omega & \cos 2\omega & \cdots & \cos p\omega\\ \sin\omega & \sin 2\omega & \cdots & \sin p\omega\end{bmatrix} \tag{8}$$

Wald statistic is applied to assess the null hypothesis H_0: $R(\omega)\beta=0$ using γ vector of estimated coefficients from the unrestricted VAR(p) in (7), V residual covariance matrix computed from the same VAR(p) model and Q restriction matrix defined as $Q=\left[0_{2\times(p+1)}\cdots R(\omega)\right]$.

$$W=(Q\gamma)'\left(QVQ'\right)^{-1}(Q\gamma)\sim\chi_2^2 \tag{9}$$

If the Wald statistic at specific frequency ω is higher than a specific critical value of 5% or 1% then the null hypothesis of non-causality is rejected from x_t to y_t and further conclusions can be drawn from the frequency feature as x_t has predictive power for y_t with low, medium, or high cycle length.

Table 1: Subperiods resulting from Bai and Perrons' test

Sub periods	
Period 1	2014:11–2022:06
Period 2	2010:12–2014:10
Period 3	2005:03–2010:11
Period 4	1997:02–2005:02

4. RESULTS

In this section, we use causality tests in the frequency domain to pin out the predictive power of both the crude oil net inventory withdrawals and the VIX index for crude oil price movements. We use monthly data of WTI crude oil spot prices (y_t) as endogenous variable and crude oil net inventory withdrawals (x_{t1}) along with VIX index (x_{t2}) as exogenous variables.

The causality test in the frequency domain requires a stationarity hypothesis. Since we cannot reject the null hypothesis of unit root for crude oil prices[5], we use the first differences of the latter while net inventory withdrawals and VIX data are stationary.

5 The Augmented Dickey-Fuller test statistic is -2.14 for crude oil price on levels

First, we specify a bivariate vector autoregressive model using separately, (1) differentiated crude oil prices with net inventory withdrawals and (2) differentiated crude oil prices with VIX data. This separation is important since we would like to explore the effect of each variable on crude oil independently. VAR specification helps determine the lag length needed for the frequency lag in the causality test. Table 2 reports the Minimum AIC Value along with the corresponding Lag length for Net Inventory Withdrawals and VIX index.

Figure 1 shows the results of the causality tests in the frequency domain. The test statistics represent the Wald test for all frequencies $\omega \in [0,3.14]$. This figure reports also 5% and 10% critical values for the test.

The results show different shapes and behaviors of the test depending on the subperiod. While the test is significant (higher than 5% critical value) for VIX for frequencies in the interval (0.06, 1.7), the net inventory withdrawals do not have any predictive power with 5% critical value for crude oil in period 1. It is important to mention that differences in results through different subperiods are consistent with the precautionary multiple break test applied to suggest that the crude oil prices experienced different regimes during the overall period.

For more details, Table 3 reports frequency bands where variables net inventory withdrawals and VIX are significant and thus have an impact on crude oil prices.

The results from Table 4 show that the net inventory withdrawals do not have any predictive power for crude oil prices with 5% critical value in periods 1 and 2. If we enlarge the confidence interval to 10%, the net inventory withdrawals cause the crude oil with frequencies $\omega \in (0.96, 1.84)$ for period 1 and $\omega \in (0.13, 0.8)$ for period 2.

Table 2: Lag length estimation from Bivariate VAR models along with AIC criterion

Sub period	Net inventory withdrawals		VIX	
	Minimum AIC value	Lag length	Minimum AIC value	Lag length
Period 1	1.4531	4	3.3611	5
Period 2	−1.5222	3	1.1163	3
Period 3	0.0054	7	2.4262	4
Period 4	1.5439	5	1.0237	3

Next, we remark that the net inventory withdrawals had more predictability terms for crude oil in period 3 for frequencies $\omega \in (0.09, 0.63) \cup (1.27, 1.82) \cup (2.55, 3.09)$ and period 4 for frequencies $\omega \in (2.59, 3.10)$ with 5% critical value. Moreover, we notice that the net inventory withdrawals caused crude oil with different frequency bands within the same period as we can see in period 3.

Finally, the VIX seems to have a persistent impact on oil crude through all subperiods with 5% critical value. It bears noting that the contrast between frequency values in different subperiods is misleading since the latter count different observation numbers.

All in all, these results point out, that with relatively high confidence the net inventory withdrawals had more predictive power on crude oil during periods 3 and 4 only. From 2010 to 2022, crude oil supply and demand and hence their balance seem to be disconnected from the crude oil price movements unless we enlarge the confidence interval to 10%. On the other hand, the VIX index representing uncertainty regarding the investment environment had a persistent predictive power for crude oil.

More insights can be drawn from Table 4. The latter reports significant and relevant frequency bands converted to the time scale in months. The second and third column shows the lower (upper) bound of significant frequencies converted to months and represents the lowest (highest) frequency.

Converting significant frequencies to the time scale provides more insights and establishes important findings regarding the predictive power amplitude and time impact of net inventory withdrawals and VIX on crude oil prices. With 5% as a critical value, we find that the net inventory withdrawals enjoyed a small amplitude impact between the lowest and the highest frequency evaluated

Figure 1: Wald test statistics for all frequencies (from ω=0 to ω=3.14) per subperiod

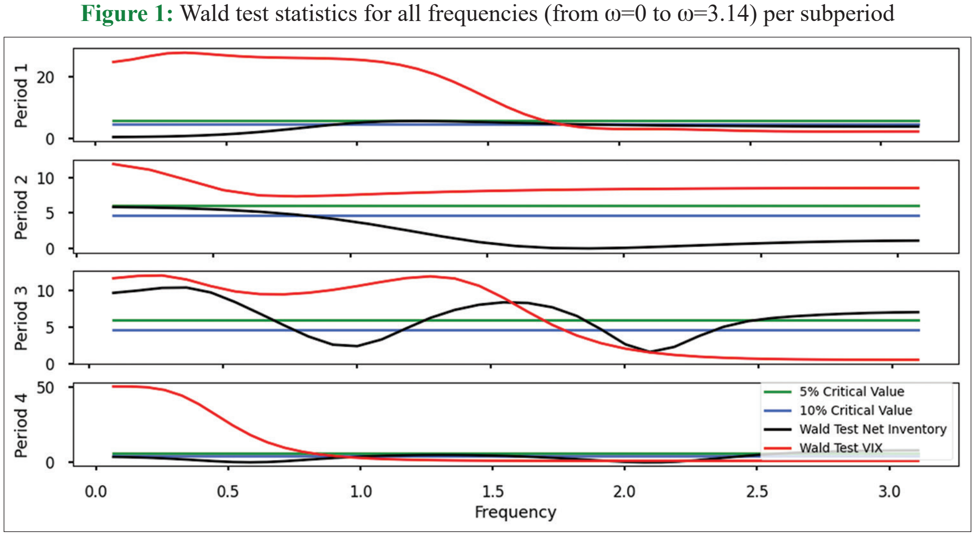

Table 3: Significant frequency bands

	Net inventory withdrawals ($x_{1t} \longrightarrow y_t$)		
	Band 1(*)	**Band 2**	**Band 3**
Period 1	-- (**)		
	[0.96, 1.84] (***)	--	
Period 2	--		
	[0.13, 0.80]	--	
Period 3	[0.09, 0.63]	[1.27, 1.82]	[2.55, 3.09]
	[0.09, 0.72]	[1.18, 1.91]	[2.36, 3.09]
Period 4	[2.59, 3.10]	--	
	[1.16, 1.49]	[2.52, 3.10]	--
VIX ($x_{2t} \longrightarrow y_t$)			
Period 1	[0.06, 1.70]	--	
	[0.06, 1.77]	--	
Period 2	[0.13, 3.07]	--	
	[0.13, 3.07]	--	
Period 3	[0.09, 1.63]	--	
	[0.09, 1.73]	--	
Period 4	[0.06, 0.77]	--	
	[0.06, 0.84]	--	

(*) Bands sorted from low to high frequency, (**) First row: significant with 5% critical value, (***) Second row: significant with 10% critical value

Table 4: Frequency causality with time scale (in months)

	Net inventory withdrawals ($x_{1t} \longrightarrow y_t$)	
	The lowest frequency (*)	**Highest frequency**
Period 1	-- (**)	
	3.28 (***)	1.7
Period 2	--	
	23.5	3.91
Period 3	34.5	1.01
	34.5	1.01
Period 4	1.21	1.01
	2.69	1.01
VIX ($x_{2t} \longrightarrow y_t$)		
Period 1	46	1.84
	46	1.76
Period 2	23.5	1.02
	23.5	1.02
Period 3	34.5	1.91
	34.5	1.81
Period 4	48.5	4.04
	48.5	3.73

(*) Frequencies converted to months, (**) First row: significant with 5% critical value, (***) Second row: significant with 10% critical value

to approximately 6 days[6] for period 4 i.e., any movement in the net inventory withdrawals causes a movement in crude oil prices within a time frame of 1 month (highest frequency) to 1.2 months (lowest frequency). In period 3, we notice that the amplitude increased if we take into consideration the bounds of the lowest frequency and the highest frequency bands only[7]. During this period, the net inventory withdrawals had a predictive power with the highest frequency corresponding to a cycle length of 1 month. During periods 1 and 2, no predictive power of the net inventory variable has been detected with 5% critical value. From 1997 until late 2010, the worldwide supply-demand balance of crude oil had a significant predictive power on crude oil prices with a relatively small amplitude time length and quick impact. However, this ability vanished from 2011 to 2022 unless we increase de confidence interval to 10%.

On the other hand, the VIX index exhibited a persistent predictive power through all subperiods with 5% critical value. The amplitude between the lowest and the highest significant frequencies is high for all subperiods. Finally, the impact of the VIX index movements with the highest frequencies on crude oil becomes shorter through subperiods. From 1997 to 2010 the predictive power of the VIX with the highest frequency was assessed to a cycle length of 3.7 to 4 months while in the more recent period, the impact on crude oil prices with the highest frequency was evaluated to 1 month from the late of 2010 to 2014 and <2 months from 2014 to 2022.

6 The lowest frequency represents 1.21 months and the highest represents 1.01.

7 During period 3 the net inventory withdrawals had predictive power for oil crude movements over 3 separate frequency bands, $\omega \in [0.09, 0.63] \cup [1.27, 1.82] \cup [2.55, 3.09]$

5. CONCLUSION

This article explores the predictive power of VIX as an uncertainty/financial related factor and oil net inventory withdrawals as a fundamental related factor for WTI crude oil price movements using monthly data from 1997 to 2022. It uses frequency causality tests which is consistent with the nonlinear feature of crude oil prices.

Unlike, the conventional VAR modeling framework, the frequency causality tests disentangle short- and long-term effects that net inventory withdrawals and VIX have on crude oil prices with accurate time cycle lengths.

Before frequency causality tests estimation, multiple break test is applied and identifies 3 breaks leading to 4 study periods. Results show that the oil net inventory withdrawals had strong predictive power for WTI crude oil price movements before 2010 consistent with (Baumeister and Kilian, 2012) results. Any change in the net inventory withdrawals causes a movement in the oil prices within time frame of 1 to 1.2 months between 1997 and 2005. This power remained significant for 3 frequency bands from 2005 to 2010. However, the net inventory withdrawals show no predictive power for future crude oil from 2010 to 2022. On the other hand, the VIX index exhibited a persistent predictive power through all subperiods. The impact of VIX movements on crude oil prices becomes quickest. From 1997 to 2010 the predictive power of the VIX with the highest frequency was assessed to a cycle length of 3.7 to 4 months while it is gauged to <2 months between 2010 and 2022.

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