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Examining the Time-Varying Causality Between Oil Returns and Stock Returns in Norway

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This study examines the time-varying causality between oil returns and stock returns in Norway. We find that data frequency determines the direction of causality between oil returns and stock returns. A bidirectional causality exists between oil returns and stock returns in the daily data, while a unidirectional causality runs from stock returns to oil returns in the weekly and monthly data. Time-varying causality also exists between these series.

I. Introduction

Current events in the global arena, such as the emergence of the COVID-19 pandemic and the Russia-Ukraine War, have affected both the financial and energy sectors in different countries and have sparked renewed interest in the relationship between two market indicators—oil and stock returns.

The advent of the COVID-19 pandemic and the containment measures taken by governments across the world have caused significant disruptions to the global economy, especially the global financial and oil markets (Iyke & Ho, 2021; Raifu, 2022). Specifically, on April 21st, 2020, West Texas Intermediate (WTI) oil price recorded a negative price of $36.98 per barrel, falling from $18.31 per barrel the previous day.[1] Similarly, Brent crude oil price fell by 47.47% from $17.36 per barrel on April 20th, 2020 to $9.12 per barrel on April 21st, 2020.[2] In the global financial market, Dow Jones, NASDAQ 100 and S&P 500 share prices declined on average by 0.56%, 0.27% and 0.53%, respectively, between March 11th and March 31st, 2020.[3] Conversely, the current war between Russia and Ukraine has led to a significant spike in the prices of crude oil occasioned by crude oil supply disruption. Before the beginning of the war on February 24th, 2022, WTI and Brent crude oil prices stood at $92.77 per barrel and $99.29 per barrel, respectively.[4] Within a month, WTI and Brent crude oil prices rose significantly to $116.2 per barrel and $122.67 per barrel, respectively—a historical rise in oil returns since the Global Financial Crisis (GFC).[5]

Theoretically, there is a negative relation between oil prices and stock returns through the cash flow channel (Jones & Kaul, 1996). However, the empirical evidence, in terms of impact and direction of causality, appears inconclusive (see Smyth & Narayan, 2018, for a review). Besides, global occurrences, such as the GFC, COVID-19 pandemic, and Russia-Ukraine War, do influence how oil prices affect different sectors of the economy. Such occurrences of global crises do cause a structural shift in the relationship between oil returns and stock returns, thereby affecting the directions of causality over time. Thus, failure to account for such structural changes when modelling the causality between oil returns and stock returns could lead to a spurious conclusion (Salisu & Fasanya, 2013).

In light of this, we hypothesize that there is no time-varying causality between oil returns and stock returns in Norway—the largest crude oil exporter in Europe (Singhal et al., 2021). To test this null hypothesis against the alternative, we use a time-varying causality method developed by Shi, Hurn, and Phillips (2018). This method has a couple of advantages. The most important of them is that it allows for changes in the causal directions, dating of economic crisis, and instability in the relationship between variables (Shi et al., 2018). Several studies have examined the causal relationship between oil returns and stock re-

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1 See https://www.eia.gov/dnav/pet/hist/RWTCD.htm

2 See https://www.eia.gov/dnav/pet/hist/RBRTED.htm

3 *investing.com*

4 See https://www.eia.gov/dnav/pet/hist/RWTCD.htm, https://www.eia.gov/dnav/pet/hist/RBRTED.htm

5 See https://www.eia.gov/dnav/pet/hist/RWTCD.htm, https://www.eia.gov/dnav/pet/hist/RBRTED.htm

turns in Norway (see e.g., Bjørnland, 2009; Singhal et al., 2021), but none has examined the time-varying causal relation between oil returns and stock returns. In addition, this study examines the time-varying causality between oil returns and stock returns using daily, weekly, and monthly data of oil returns and stock returns.

The remaining sections are organised as follows: Section 2 presents the methodology and data sources. Section 3 presents findings, while Section 4 concludes.

II. Methodology and Data Sources

To model the time-varying causality between oil returns and stock returns in Norway, we use daily, weekly, and monthly data on Brent crude oil price and the OSLO All-Share index. The Brent crude oil price is obtained from the Energy Information Administration, while the OSLO All-Share index is sourced from *https://www.investing.com*. The data covers the period from 2011 to 2021. Figure 1 shows the trends of the daily, weekly, and monthly series of oil and stock prices. The returns to oil and stock are computed as follows:

$$\text{Oil returns: } \ln\left(\frac{olp}{olp_{t-1}}\right) * 100 \tag{1}$$

$$\text{Stock returns: } \ln\left(\frac{stp}{stp_{t-1}}\right) * 100 \tag{2}$$

The time-varying causality test developed by Shi et al. (2018) begins by specifying a lag-augmented VAR (LA-VAR) suggested by Toda and Yamamoto (1995). Assume a bivariate case of x_{it} and x_{2t}, the LA-VAR model can be specified as:

$$\begin{aligned} x_{it} &= \alpha_{10} + \alpha_{11t} + \sum_{i=1}^{k+d} \beta_{1i} x_{1t-i} + \sum_{i=1}^{k+d} \delta_{1i} x_{2t-i} + \varepsilon_{1t} \\ x_{2t} &= \alpha_{20} + \alpha_{21t} + \sum_{i=1}^{k+d} \beta_{2i} x_{2i1t-i} + \sum_{i=1}^{k+d} \delta_{2i} x_{2t-i} + \varepsilon_{2t} \end{aligned} \tag{3}$$

where k is the lag length, d is the maximum order of integration, and t is the time trend. The null hypothesis of no Granger causality between x_{1t} and x_{2t} is specified as:

$$H_0 : \delta_{11} = \cdots = \delta_{1k} = 0$$

The alternative hypothesis is specified as:

$$H_0 : \delta_{11} \neq \cdots \neq \delta_{1k} \neq 0$$

Given this LA-VAR framework, Shi et al. (2018) developed three supremum *Wald* tests that can be used to assess the time-varying causality between variables. These three supremum *Wald* tests include the forward recursive test of Thoma (1994), the rolling window test of Swanson (1998), and the recursive evolving algorithm test of Phillips, et al. (2015). Following Shi et al. (2018), the forward recursive algorithm *Wald* statistic $[f_1, f_2]$ with a small simple size fraction $f_w = f_2 - f_1 \geq f_0$ is given as $W_{f_2}(f_1)$ and the supremum *Wald* statistic version is given as:

$$sw_F(f_0) = \frac{\sup}{(f_1, f_2 \in \wedge_0, f_2 = f)} \{W_{f_2}(f_1)\}. \tag{4}$$

Here $\wedge_0 = \{(f_1, f_1); 0 \prec f_0 + f_1 \leq 1, \text{ and } 0 \leq f_1 \leq 1 - f_0\}$ for the small sample size $f_0 \in (0, 1)$ in the regression. Shi et al. (2018) state that the forward expanding and rolling window are special cases of recursive evolving procedures, which have $f_1 = 0$ and sets $f = f_1$. The rolling window itself has a fixed window width $f_w = f_2 = f_1 = f_0$ and window initialisation $f_1 = f_2 - f_1$. The dating rules, especially in a simple switch case, are given for the three causality tests procedures as follows:

$$\begin{aligned} \text{Forward: } \hat{f}_e &= \frac{\inf}{f \in [f_0, 1]} \{f : W_f(0) > cv\} \\ \text{and } \hat{f}_f &= \frac{\inf}{f \in [f_e, 1]} \{f : W_f(0) > cv\} \end{aligned} \tag{5}$$

$$\begin{aligned} \text{Rolling: } \hat{f}_e &= \frac{\inf}{f \in [f_0, 1]} \{f : W_f(f - f_0) > cv\} \\ \text{and } \hat{f}_f &= \frac{\inf}{f \in [f_e, 1]} \{f : W_f(f - f_0) > cv\} \end{aligned} \tag{6}$$

$$\begin{aligned} \text{Recursive: } \hat{f}_e &= \frac{\inf}{f \in [f_0, 1]} \{f : SW_f(f_0) > scv\} \\ \text{and } \hat{f}_f &= \frac{\inf}{f \in [f_e, 1]} \{f : SW_f(f_0) > scv\} \end{aligned} \tag{7}$$

where cv and scv are critical values of W_f and SW_f statistics, respectively. The indicators $\hat{f}_e$ and $\hat{f}_f$ are estimated chronologically and their test statistics can exceed or fall below the critical values for the beginning and endpoints in the causal nexus.

III. Empirical Results

We conduct both the Augmented Dickey–Fuller and Phillips–Perron unit root tests. The results, presented in Table 1, show that the two oil and stock returns contain a unit root or are not stationary. Having determined the order of integration, we further conducted the structural stability test using the Quandt–Andrews and Bai–Perron structural breakpoint tests. The results from the two tests for all data frequencies are displayed in Table 2. The two tests support the evidence that oil and stock returns are unstable overtime, implying that there is a structural break in the data series, which occurred during the peaks of the COVID-19 pandemic (March and April 2020). For the daily, weekly, and monthly data, structural breaks occurred on 25th March 2020, 15th March 2020, and April 2020, respectively. This finding is in line with what was observed during the pandemic (Zhang et al., 2021).

Table 3 presents the results of the linear and time-varying causality tests between oil returns and stock returns in Norway. For the linear causality, we use the Toda-Yamamoto Granger-non-causality test. The results for the weekly and monthly data show the existence of unidirectional causality running from stock returns to oil returns. However, the results from the daily data show that the causality runs from both sides—that is, from oil returns to stock returns and vice versa. When we apply the time-varying causality test, the results are a bit different for the daily and weekly data but are same for the monthly data irrespective of the algorithm procedures employed. Specifically, the results show that, though causality varies between oil returns and stock returns overtimes, the variability is dominated by unidirectional causality from stock returns to oil returns. This indicates that stock returns have predictive power over oil returns. This could be attributed to the fact that energy companies also trade in the stock market. Hence, whatever happens in the stock market, especially in the course of trading, could affect energy price. For weekly

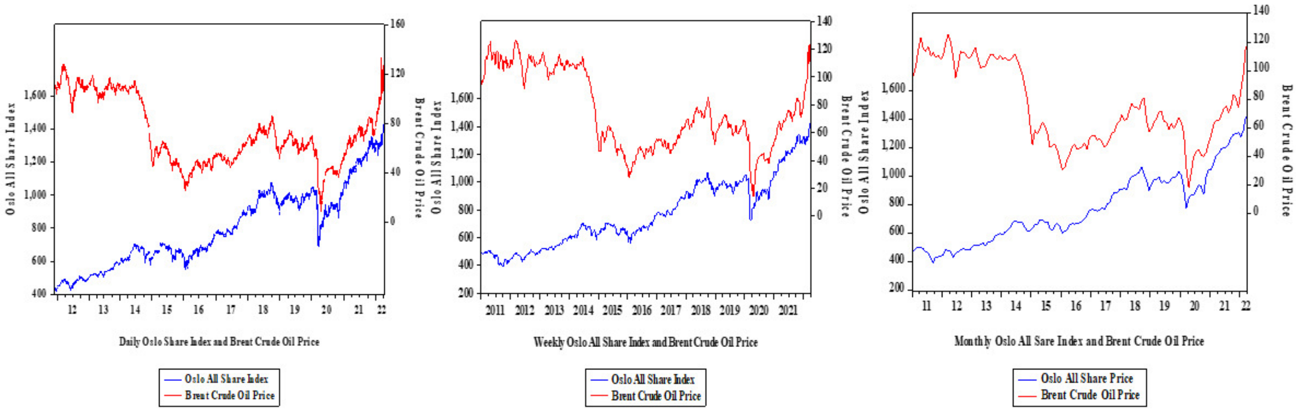

Figure 1. Trends of the daily, weekly, and monthly oil and stock prices

Table 1. Unit Root Test Results

	Level			First Difference			Decision
	WC	WC&T	WDC&T	WC	WC&T	WDC&T	
Augmented Dickey–Fuller Unit Root Test							
Stock Returns	0.163	2.631	2.375	-10.237***	-10.27***	-9.918***	I(1)
Oil Returns	-1.796	-1.302	-0.144	-8.929***	-9.020***	-8.964***	I(1)
Phillips–Perron Unit Root Test							
Stock Returns	0.228	-2.808	2.470	-10.154***	-10.196***	-9.927***	I(1)
Oil Returns	-1.731	-1.409	-0.002	-7.903***	-8.315***	-7.951***	I(1)

Table 1 reports the results of the unit root tests from the Augmented Dickey-Fuller and Phillips–Perron unit root tests. The indicators WC, WC&T, and WDC&T denote unit root tests with constant, with constant and trend and without constant and trend, respectively. ***: p<0.01; **: p<0.05.

data, only the rolling algorithm procedure shows bidirectional causality between oil returns and stock returns. The recursive expanding algorithm procedure results show the existence of unidirectional causality that runs from oil returns to stock returns. However, the forward expanding algorithm procedure shows that there is no causality between oil returns and stock returns. For the daily data results, both the forward and rolling algorithm procedures support a bidirectional causality between oil returns and stock returns, while the recursive expanding algorithm procedure supports a unidirectional causality that runs from stock returns to oil returns (see Appendix for the time-varying causality graphs, which show the periods of causality).

IV. Conclusion

This study investigates the time-varying causality between oil returns and stock returns in Norway taking into consideration the data frequencies (daily, weekly, and monthly data). We find that data frequency determines the direction of causality between oil returns and stock returns. Specifically, we establish the existence of a bidirectional causality between oil returns and stock returns in daily data. In weekly and monthly data, we find the existence of a unidirectional causality that runs from stock returns to oil returns. Above all, we establish a time-varying causality between oil returns and stock returns, thereby rejecting the null hypothesis of no time-varying causality between the two variables. This study only assesses a time-varying causality between oil returns and stock returns in Norway. Future studies should include top global crude oil-exporting countries. We conclude that a strong policy is fundamental to building oil and stock markets' resilience to the pandemic.

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Table 2. Structural Stability Test

Quant–Andrews Unknown Breakpoint Test Null Hypothesis: No breakpoints within 15% trimmed data	
Statistical Test	**Result (p-values)**
Daily Data	
LR F-Stat (25/03/2020)	176.120***
LR Wald-Stat (25/03/2020)	352.240***
Expo LR F-Stat	81.313***
Expo LR Wald–Stat	169.048***
Ave LR F-Stat	43.456***
Ave LR Wald–Stat	86.912***
Weekly Data	
LR F-Stat (15/03/2020)	23.946***
LR Wald-Stat (15/03/2020)	47.891***
Expo LR F-Stat	6.123***
Expo LR Wald–Stat	17.943***
Ave LR F-Stat	1.758
Ave LR Wald–Stat	3.516
Monthly Data	
LR F-Stat (2020M04)	14.501***
LR Wald-Stat (2020M04)	29.003***
Expo LR F-Stat	2.8039***
Expo LR Wald–Stat	9.969***
Ave LR F-Stat	0.717
Ave LR Wald–Stat	1.435
Bai-Perron Breakpoint Test	
Daily Data	
Schwarz criterion selected breaks	1 (25/03/2020)
LWZ criterion selected breaks	1 (25/03/2020)
Weekly Data	
Schwarz criterion selected breaks	1 (15/03/2020)
LWZ criterion selected breaks	0 (15/03/2020)
Monthly Data	
Schwarz criterion selected breaks	1 (2020M04)
LWZ criterion selected breaks	0 (2020M04)

Table 2 reports the results from Quant–Andrews Unknown Breakpoint Test. ***: p<0.01; **: p<0.05. L-R denotes likelihood ratio.

Table 3. Linear and Time Varying Causality Tests

Null Hypothesis	Test Results	Decision
Linear Granger-Causality Test		
Daily Data		
Oil returns → Stock Returns	35.796***	Bidirectional Causality
Stock Returns → Oil returns	94.423***	
Weekly Data		
Oil returns → Stock Returns	11.173	Unidirectional Causality from Stock returns to oil returns
Stock Returns → Oil returns	80.742**	
Monthly Data		
Oil returns → Stock Returns	0.768	Unidirectional Causality from Stock returns to oil returns
Stock Returns → Oil returns	38.076***	
Time-Varying Causality Test		
Null Hypothesis	**Wald Test**	**Finding/Decision**
Daily Data		
Oil returns → Stock Returns	Forward Expanding	Granger Caused
Stock Returns → Oil returns		Granger-Caused Bidirectional Causality
Oil returns → Stock Returns	Rolling	Granger Caused
Stock Returns → Oil returns		Granger-Caused Bidirectional Causality
Oil returns → Stock Returns	Recursive Expanding	No Causality
Stock Returns → Oil returns		Granger-Caused Unidirectional Causality
Weekly Data		
Oil returns → Stock Returns	Forward Expanding	No causality
Stock Returns → Oil returns		No Causality
Oil returns → Stock Returns	Rolling	Granger-Caused
Stock Returns → Oil returns		Granger-Caused Bidirectional Causality
Oil returns → Stock Returns	Recursive Expanding	Granger-Caused/Unidirectional Causality
Stock Returns → Oil returns		No Causality
Monthly Data		
Oil returns → Stock Returns	Forward Expanding	No Causality
Stock Returns → Oil returns		Granger-Caused/Unidirectional Causality
Oil returns → Stock Returns	Rolling	No Causality
Stock Returns → Oil returns		Granger-Caused/Unidirectional Causality
Oil returns → Stock Returns	Recursive Expanding	No Causality
Stock Returns → Oil returns		Granger-Caused/Unidirectional Causality

Table 3 reports the results of the linear and time-varying causality between oil returns and stock returns in Norway. Note: → indicates the null hypothesis that the first variable does not Granger-cause the second one. *** denotes 1% level of significance

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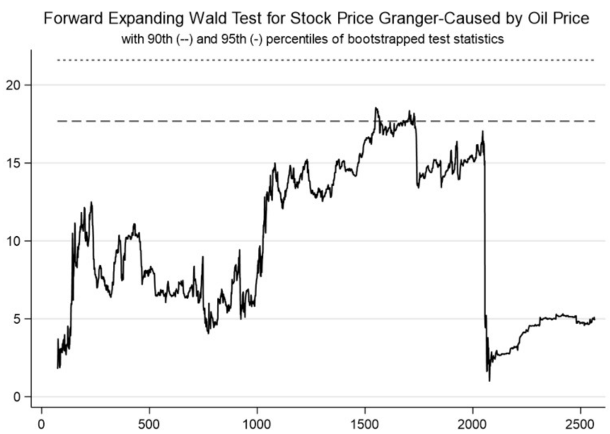
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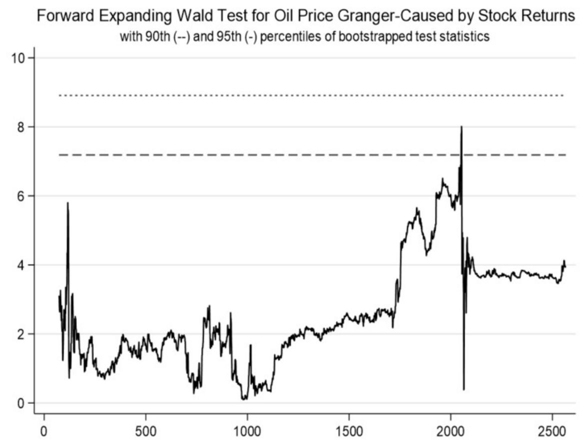
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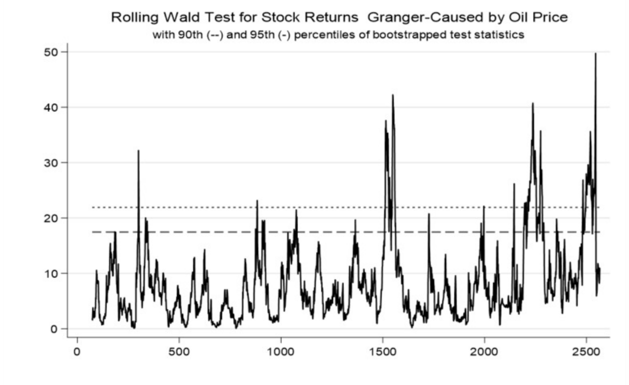
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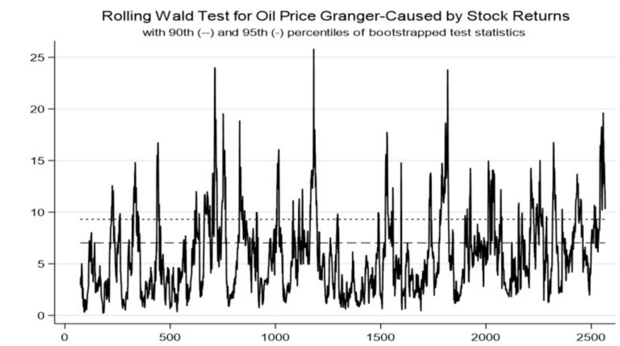
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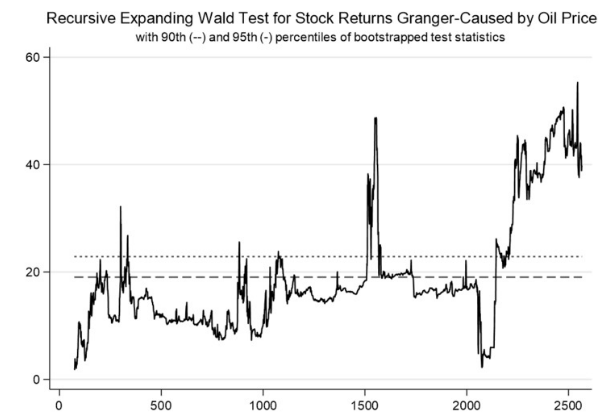
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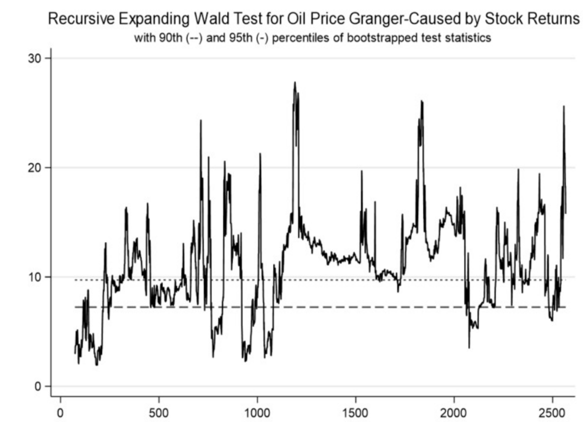
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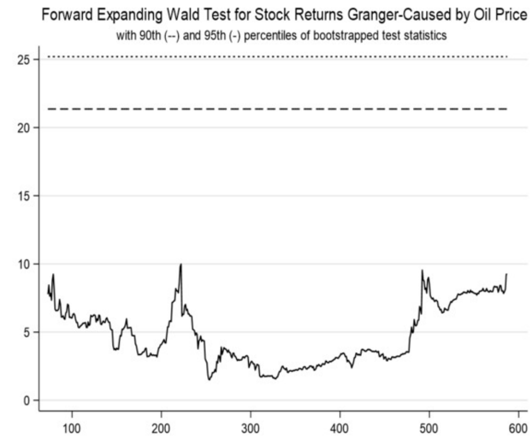
Daily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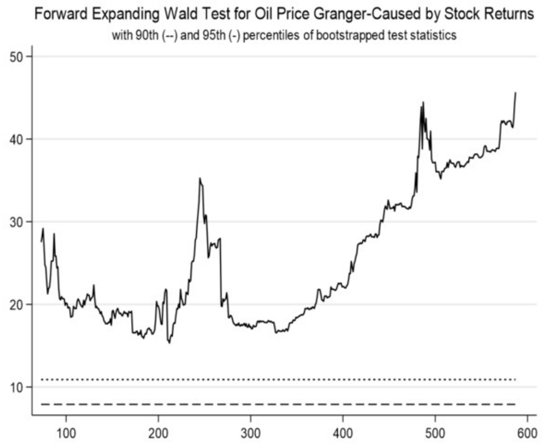
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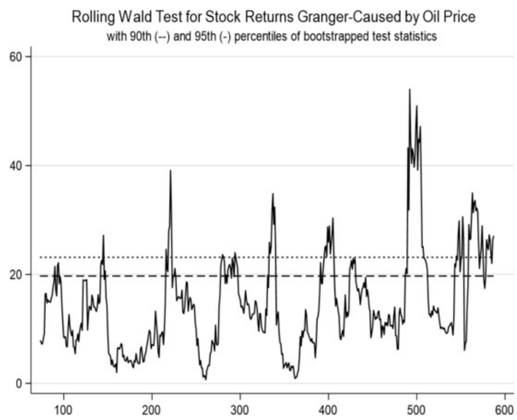
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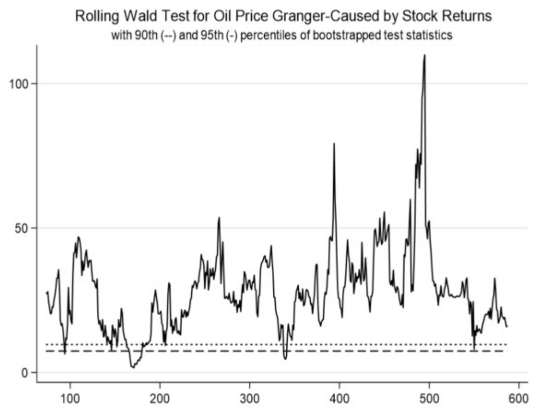
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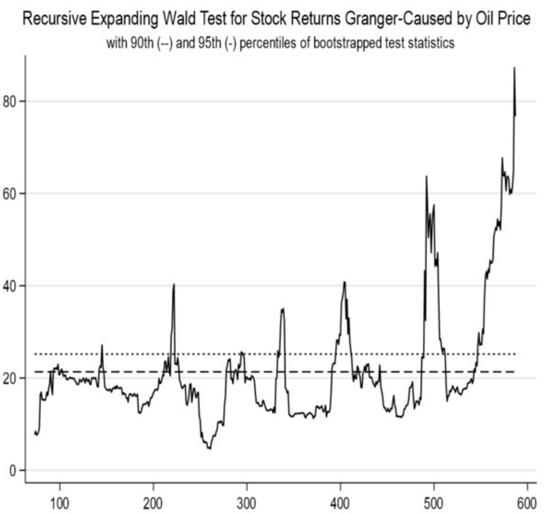
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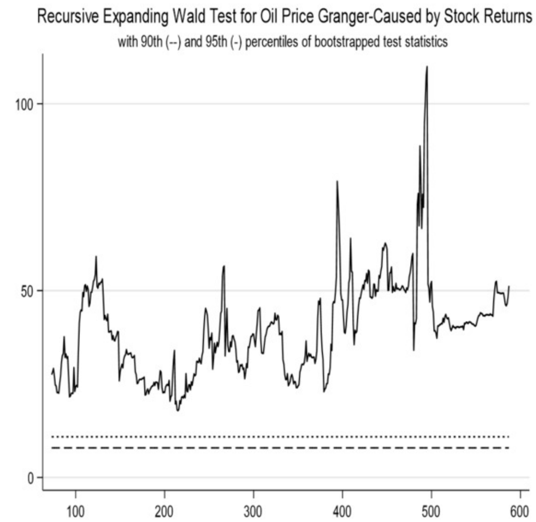
Recursive Expanding Wald Test for Oil Price Granger-Caused by Stock Returns
with 90th (--) and 95th (-) percentiles of bootstrapped test statistics

Weekly

Monthly

Figure 1A. Forward expanding, rolling window and recursive expanding Granger causality between oil returns and stock returns for daily, weekly and monthly data respectively in Norway

The graphs displays the forward expanding, rolling window and recursive expanding Granger causality between oil returns and stock returns based on homoscedastic Wald statistics. — denotes the test statistics sequence; - - - - and …. denote 10% and 5% critical values, respectively.