International Journal of xxxxxx
Vol. x, No. x, (20xx), pp. xx-xx

Dynamic Connectedness between commodities, forex exchanges, equity markets, and uncertainty: Evidence from the US and Australia

Chi Cuong Nguyen [1], Albert Sundjaja [1] and Marin Stoyanov [1]

[1] *WorldQuant University*

anthony.nguyen.dn5@gmail.com
albertsundjaja@gmail.com
phdmarinstoyanov@gmail.com

Abstract

The financial markets are facing a situation of growing unprecedented uncertainty, supported by various shocks to the system, such as pandemics or energy and inflation pressures. This paper studies the interdependence across extreme quantiles of volatility of related financial markets, such as stocks, foreign exchange, oil, and gold, under the impacts of market sentiment. Time-Varying Parameter Vector Autoregression (TVP-VAR) is employed by the project as a new approach that is superior to the traditional mean-based measures. This model performs well in extreme market conditions to check for dynamic spillovers related to return and energy shocks. The study shows the extent of connectedness of the network not only on average but also at the peaks of the market volatility levels. The 2008 financial crisis or COVID-19 and the Russia-Ukraine war are considered the major events where heightened connectedness was experienced. It is found that the WTI and Brent crude prices help in the spread of shocks in the entire financial network, while gold still acts as safe haven in times of stress. Moreover, the stock and the foreign exchange markets are clear systemic shock net transmitters, with their EPU and OPU sentiment measures leading to their market expectations. These findings will be critical for investors, financial markets, fund managers, and policymakers regarding the management of risks, especially at times when there are significant disruptions in the market.

Keywords: *TVP-VAR, uncertainty, interdependence, extreme market conditions, network connections, significant disruptions, extremes of market volatility, shock events*

1. Introduction

In the last decades, the growing interconnectedness of financial and economic variables, including those of commodity prices, stock markets, and macroeconomic indicators, makes knowledge about systemic risk necessary. Global crises like the 2008 financial crisis, COVID-19, and geopolitical tensions like the Ukraine-Russia conflict, increase market volatility and risk levels, which lead to the need to investigate these relations via the proxies of market uncertainty sentiment indices. While several pieces of literature have researched conventional financial assets, such as the equity market and forex (Barunik et al., 2017; Chow, 2021; Wang et al, 2023), those papers might not include the effects of commodities on the whole system. For instance, the two most

ISSN: XXXX-XXXX IJXX

important commodities that strictly influence the financial and macroeconomic systems are crude oil and gold. Their nature of characteristics, for instance, oil is used in production and energy markets, and gold is acting as a safe-haven asset (Baur and McDermott, 2010). These are very critical to understanding how the shocks spread across the economy, especially in the US and Australia as comparison case studies.

However, conventional methodologies of risk assessment, such as correlation analysis or traditional VaR, usually focus on average market conditions while failing to conduct necessary studies on the varying dynamics that occur under different quantile levels, such as extreme market conditions. Thus, there is a need for a more appropriate and accurate approach to examine how these economic variables interact under normal and extreme conditions.

2. Theoretical Framework

Chisti et al. (2) researched an empirical inquiry into how various economic indicators, specifically foreign institutional investments, exchange rates, and crude oil prices, are interrelated and impact stock market performance in relation to the Nifty 50 index in the Indian financial system[10]. Neely researched the impact of the Russia–Ukraine war on the prices of oil and other sanctioned commodities, as did Qi Zhang et al. They all come to the conclusion that when such a big exporter goes offline either because of sanctions or because of infrastructural problems, this inevitably affects the supply of oil [1],[2]. Khan et. al (4) go one step further and analyze how extreme geopolitical events affect freight prices, which are a very important part of pricing commodities [19]. Hung (60) combined wavelet coherence analysis with a multivariate DCC-GARCH model to analyze the time-frequency dynamics between exchange rates, stock markets, and international commodities markets, in particular, gold and oil [12]. Reddy et al. (599) analyzed six macroeconomic indicators, namely inflation, interest rates, gold, silver, crude oil, and exchange rates, for their effects on sectoral performance and pointed out the complex interrelationship among various dimensions of macroeconomic factors and the outcomes in sectors. Rehman and Vo (3) examined the returns integration between commodities in precious metals, energy, and industrial metals, in an attempt to reveal the interconnectivity and interdependencies among these categories of commodities [15]. Shah et al. (2) conducted an in-depth study into the dependence between crude oil, precious metals (including gold), and foreign exchange markets using both time and frequency domains [14]. Finally, making a more solid empirical analysis, Tiwari et al. (1) evaluated the systemic risk and interdependencies across stock market indicators with the oil market of G7 economies [13]. Lastly, Wei et al. (24) combine wavelet techniques with statistics of long memory to explore long-term correlations among Chinese stock market indices and crude oil futures, looking at the effects of more recent financial crises [17]. Fu et al. (2) use wavelet analysis and Non-linear distributed lag modeling (NARDL) to study the relationship between subjective factors, consumer sentiment and inflation expectations, and energy prices, focusing on Brent crude and natural gas. Their study revealed that there is a negative relationship between consumer sentiment and energy prices and a positive relationship between inflation expectations and energy prices [20]. Shang and Hamori (1) analyzed the relationship and spillover effect between crude oil, gold, financial markets and macroeconomic indicators using a quantile time-frequency connectedness approach. Kalman filter was used within the Time-Varying Parameter Vector Autoregression (TVP-VAR) model to estimate the time-varying parameters and later apply the model for forecasting purpose suggestions [21].

In recent years, quantile connectedness has become the focus of academic inquiry. This is due to the ability to detect specific associations in different quantile tails. and severe market conditions. This method is extremely valuable for analyzing financial markets and a wide range of indicators. Such detailed analysis enhances risk assessment and facilitates, as well as supports, the development of bespoke risk management strategies tailored to different market stress levels (Ando and Bai 270) [3]. Connectedness analysis, such as the TVP-VAR analysis, not only helps investors detect early signs of market downturns and upswings, also serves as an advanced forecasting tool for anticipating market fluctuations and major economic changes. This novel approach helps protect portfolios and capitalize on emerging opportunities. In the same manner, policymakers can also leverage this approach to design responsible policies that adapt to fluctuating market conditions (Ando et al. 2402). This will increase the ability of investors, central banks and government agencies to make informed and flexible decisions. which promotes economic stability... Moreover, time-varying connectedness analysis has proven effective in assessing rare but high-impact tail risks in dynamic enviroments. It provides a comprehensive approach that facilitates dynamic analysis of the market under various situations. The quantitative time-frequency method pioneered by Chatziantoniou et al. (2) shows improved integration of time-frequency quantile exposure methods [9]. This innovative framework was developed by Chatziantoniou et al. (4) and Ando et al. (1) and offered a unique ability to examine relationships within the time-frequency spectrum and across quantile ranges. Doing so, the method provides a comprehensive analysis of the interaction between financial markets and indicators under various conditions, as well as helps to gain a deeper understanding of market changes.

3. Methodology

In this study, we utilize the quantile framework of connections initially designed by Chatziantoniou et al. (4) to scrutinize how the effects are transmitted among the commodity, stock, and foreign exchange at various levels of quantiles [8]. Time-varying parameter Vector Autoregressive (TVP-VAR) models are frequently used in econometrics to research the changing relations between numerous sequential data sets, where variables available vary over the years. The concept of 'linkages' in this scenario basically refers to how two or more variables or even financial assets possibly relate to each other as time passes and has often been used as an important concern in the context of systemic risk in finance.

This approach is also referred to as the time-frequency connectedness in quantiles, and it enhances the framework of connectedness hence proposed by Diebold and Yilmaz (60), Baruník and Křehlík (41) and Ando et al. (3) [22][6][3]. To put it into the context further, Diebold and Yilmaz (60) laid the foundation of the methodology centered on the multivariate time series analysis, which employs generalized variance decomposition, which overcomes these limitations [22]. Antonakakis et al. (5) then developed a relevant further method using time-dependent parameter vector autoregressive (TVP-VAR) models within the broader theoretical framework of Koop and Korobilis (105) that combines structural and Bayesian techniques [23][24].

In advancing this conception, Baruník and Křehlík (2018) devised means to probe connectedness over various frequency bands and across time, especially in terms of dissecting short-term (high-frequency) and long-term (low-frequency) connectedness. Ando et al. (3) unlocked themselves from the above challenges by coming up with the quantile connectedness method – a method that measures the association/dependency between variables at different levels of quantile, thus, a detailed analysis of extreme events and their impact on the interconnectedness is possible [3].

The quantile connectedness analysis is highly useful in assessing the extent of market connectedness during all forms of market regimes: norm (average market activity), high quantile (bullish market), and low quantile (bearish market activity). This assists in estimating how strong the impacts of some in terms of magnitude and direction of market shocks or price jump events. Such an approach allows one to better understand how market overtone transformations operate under the influence of crisis situations.

3.1. Model

TVP-VAR model for time series variables at time t can be written as

$$Y_t = \Phi_t Y_t - 1 + \varepsilon_t Y_t = \varphi_t Y_{t-1} + \varepsilon_t Y_t = \Phi_t Y_t - 1 + \varepsilon_t$$

Where

- Y_t : K x 1 vector of endogenous variables
- ϕ_t : K x K time-varying coefficient matrix changing over time
- ϵ_t : K x 1 vector of error terms, assumed to follow a multivariate normal distribution with mean = 0 and time-varying covariance matrix Σ_t

3.2. Time-Varying Parameter Evolution

The time-varying coefficient matrix ϕ_t follows a stochastic process, which is modelled as a random walk:

$$\phi_t = \phi_{t-1} + \eta\, t$$

Where

- $\eta\, t$: K x K matrix of innovations associated with the time-varying parameters, which is assumed to be normally distributed

3.3. Variance Decomposition (Forecast Error Variance Decomposition - FEVD)

$$\theta^H_{ij}(t) = \frac{\sigma^{-1}_{ii} \sum_{h=0}^{H-1} (e'_i A_h(t) \Sigma_t e_j)^2}{\sum_{h=0}^{H-1} (e'_i A_h(t) \Sigma_t A'_h(t) e_i)}$$

Where

- $\theta^H_{ij}(t)$: portion of the H-step ahead forecast error variance of variable i attributable to shocks of variable j at time t
- $A_h(t)$: time-varying coefficient matrix for the h-th lag in the moving average representation of TVP-VAR
- Σ_t : time-varying covariance matrix of the innovations ε_t
- e_i and e_j are the selection vectors of the i-th and j-th variables

- H : forecast horizon

3.4. Connectedness Measures

3.4.1 Total Connectedness Index (TCI)

TCI measures the overall degree of connectedness in the system. Total connectedness at time t, which represents the average percentage of forecast error variance due to shock from other variables of the model, is defined as:

$$TCI_t = \frac{1}{K}\sum_{i=1}^{K}\sum_{j=1,\, i\neq j}^{K} \theta^{H}_{ij}(t)$$

3.4.2 Directional Connectedness (from and to others)

The connectedness from variable i to others can be calculated as

$$C_{i\rightarrow}(t) = \sum_{j=1,\, j\neq i}^{K} \theta^{H}_{ji}(t)$$

While the connectedness to the variable i from others can be calculated as:

$$C_{i\leftarrow}(t) = \sum_{j=1,\, j\neq i}^{K} \theta^{H}_{ij}(t)$$

3.4.3 Net Pairwise Connectedness

The net connectedness between two variables i and j can be calculated as:

$$C^{H}_{ij}(t) = \theta^{H}_{ij}(t) - \theta^{H}_{ji}(t)$$

3.4.4 Net Total Directional Connectedness

$$Net\,C_{i}(t) = C_{i\leftarrow}(t) - C_{i\rightarrow}(t)$$

3.5. Dynamic Connectedness Measures

In the TVP-VAR framework, connectedness measures change over time due to the fundamental interconnectivity of the associated variables. This dynamicity allows the examination of such correlations as systemic risk, contagion and co-movements within the financial markets.

The equations provided in previous sections can be used to analyze the time-varying connectedness in the context of systemic risk, macroeconomic policy and financial markets. It is the nature of what happens to the transmitted shock wave as deviation is induced by comparison model sizes.

4. Data

The data in this paper were collected from publicly available online sources, including Federal Reserve Economic Data, investing.com and policyuncertainty.com. The variables used in this research are monthly prices for WTI crude oil, gold, S&P500, USD index, US uncertainty market sentiment, oil uncertainty market sentiment, Brent crude oil, gold, ASX50, AUD index, AU uncertainty market sentiment, and oil uncertainty market sentiment. The data ranges from October 2004 to July 2023. The following table describes in detail the data attributes, sample periods, and data sources of each variable used in the study.

Table 1: Data description

Variable	Sample Period	Description	Data Sources
WTI	2004M10-2023M7	West Texas Intermediate (WTI) crude oil spot price returns	Federal Reserve Economic Data
Gold	2004M10-2023M7	Gold price returns	Investing.com
S&P500	2004M10-2023M7	The Standard and Poor's 500 returns	Investing.com
USDI	2004M10-2023M7	US dollar index returns	Investing.com
EPU	2004M10-2023M7	US Uncertainty Market Sentiment	policyuncertainty.com
OPU	2004M10-2023M7	Oil Uncertainty Market Sentiment	policyuncertainty.com
Brent	2004M10-2023M7	Brent crude oil spot price return	Federal Reserve Economic Data
Gold	2004M10-2023M7	Gold price returns	Investing.com
ASX50	2004M10-2023M7	The ASX 50 index returns	Investing.com
AUDI	2004M10-2023M7	Australia Dollar index returns	Investing.com
EPU	2004M10-2023M7	AU Uncertainty Market Sentiment	policyuncertainty.com
OPU	2004M10-2023M7	Oil Uncertainty Market Sentiment	policyuncertainty.com

To ensure consistency and ease of comparison, all variables were scaled and measured on returns. This transformation was done to retain the relative differences while making them suitable for comparison analysis. Meanwhile, the EPU and OPU variables were kept on a scale over 100 as the source.

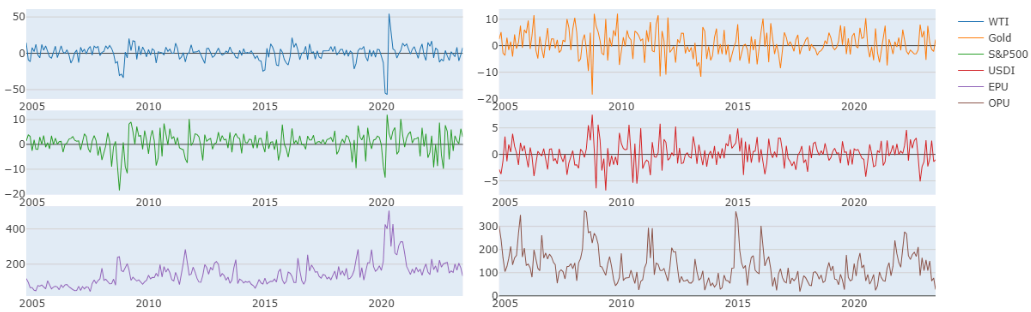
5. Results

5.1 US Data

5.1.1 Raw Data

	WTI	Gold	S&P500	USDI	EPU	OPU
2004-10-01	14.52	2.43	1.39	-2.84	118.34	300.81
2004-11-01	-9.20	5.09	3.79	-3.71	96.70	242.97
2004-12-01	-11.19	-2.80	3.19	-1.19	66.53	163.93
2005-01-01	7.79	-3.68	-2.56	3.34	66.73	104.66
2005-02-01	2.38	3.03	1.87	-1.31	51.70	126.60
2023-02-01	-1.67	-5.37	-2.65	2.68	152.97	155.26
2023-03-01	-4.73	7.42	3.45	-2.28	200.49	109.07
2023-04-01	8.08	1.10	1.45	-0.83	165.42	150.42
2023-05-01	-10.43	-1.38	0.25	2.59	205.18	64.43
2023-06-01	-1.88	-2.20	6.27	-1.37	179.31	77.11
2023-07-01	7.96	2.30	3.07	-1.03	132.71	27.48

The table above shows a sample of what the raw data looks like for the US market.



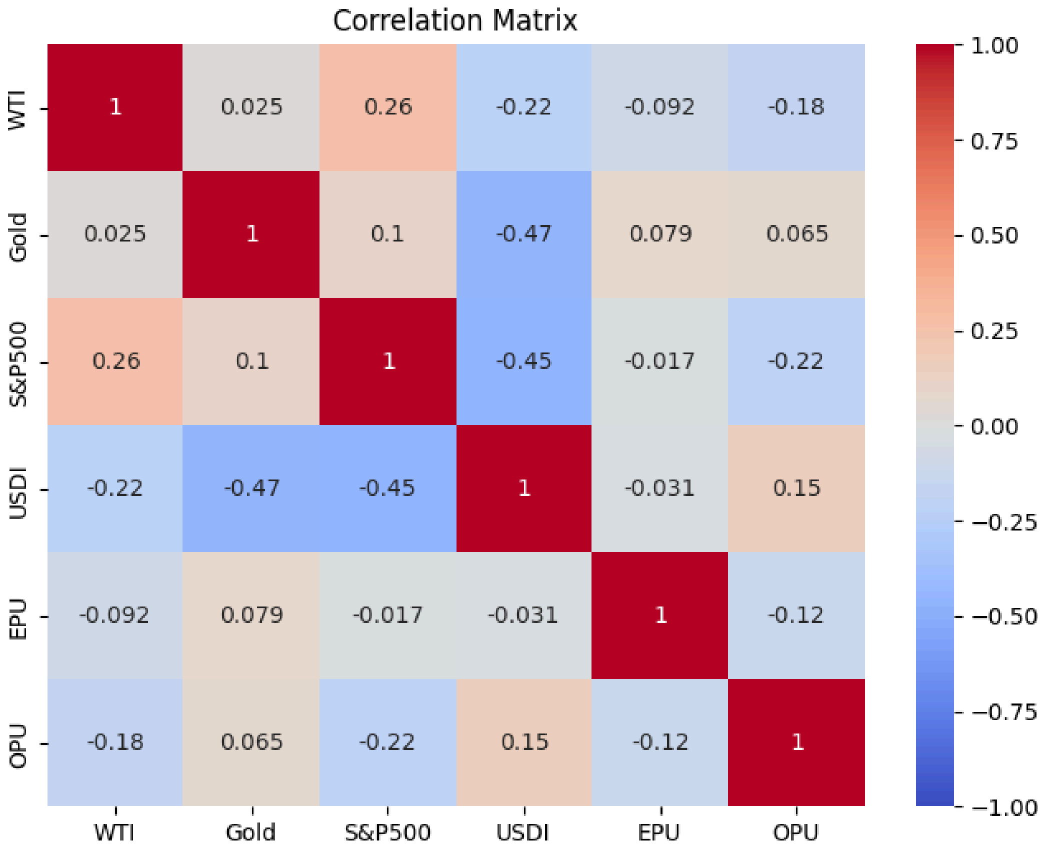
The graph represents the trends for the variables used in the study. The WTI crude oil (top-left) exhibits huge volatility depicted by several spikes. A huge fluctuation in 2020 is caused by the COVID-19 pandemic where the price of oil crashed. The gold price (top-right), S&P500 index (mid-left) and USD index (mid-right) are relatively more stable compared to oil prices but still show some volatility. The EPU and OPU show several peaks depicting significant events such as the 2008 Financial Crisis and the COVID-19 pandemic.

The following table shows the summary statistics of the data. Note that the skewness test is a measure of the bias in the data distribution developed by D'Agostino (680) [25]. As suggested by Anscombe and Glynn (2), the kurtosis test examines whether the distribution is peaked or flat. Proposed by Jarque and Bera (258), the Jarque-bera test addresses the issue of normality of the data [26][27]. The Excess Kurtosis Test, which has been defined by Stock et al. (1), concerns testing of the stability of the distribution [28]. Q(10) is a statistic found in the Ljung-box test that assesses of autocorrelation in a time series at lag 10 with Q2(10) being the q statistic with the longer lags, respectively (Fisher & Gallagher, 2) [29]. Indication of the significance levels are shown by *** for 1% significance level, ** for 5% and * for 10%.

The summary statistics of the raw data are given below.

	WTI	**Gold**	**S.P500**	**USDI**	**EPU**	**OPU**
Mean	0.223	0.684	0.626	0.068	144.846	123.709
Variance	120.736	23.515	19.286	5.021	4760.303	4962.328
Skewness	-0.923***	-0.146	-0.825***	0.102	1.750***	1.219***
	(0.000)	(0.356)	(0.000)	(0.521)	(0.000)	(0.000)
Ex.Kurtosis	7.699***	0.575*	1.735***	0.740**	5.114***	1.503***
	(0.000)	(0.090)	(0.001)	(0.044)	(0.000)	(0.002)
JB	590.309***	3.921	53.988***	5.543*	361.652***	77.237***
	(0.000)	(0.141)	(0.000)	(0.063)	(0.000)	(0.000)
ERS	-2.748***	-5.090***	-5.329***	-2.289**	-2.719***	-1.247
	(0.007)	(0.000)	(0.000)	(0.023)	(0.007)	(0.214)
Q(10)	21.844***	4.973	9.556*	8.481	435.541***	181.575***
	(0.000)	(0.510)	(0.086)	(0.138)	(0.000)	(0.000)
Q2(10)	144.873***	16.374***	50.786***	38.006***	329.334***	126.394***
	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)

Also, the static correlation between variables could be found in the following correlation matrix:



The initial analysis shows that there is no series inter-correlation between variables. Basically, positive linkages could be found between the stock market index returns and other financial assets, such as gold, oil, but a lowly significant negative correlation with the sentiment index could also be documented. Interestingly, there is a negative relationship between the USDI and stock market returns. However, for a more detailed insight in a dynamic relationship between variables, connectedness analysis would be found in the next stages.

Moreover, for more details on the data preprocessing and preliminary analysis, we could refer to appendices 1 (detailed descriptive analysis), 2 (time-series plots), 3 (variable outlier check), 4 (variable distributions), 5 (autocorrelation function analysis), and 6 (stationary test). In short, time-series variables showed low intensity of autocorrelation while unit root tests reported all variables were stationary.

5.1.2 Total Connectedness (TCI)

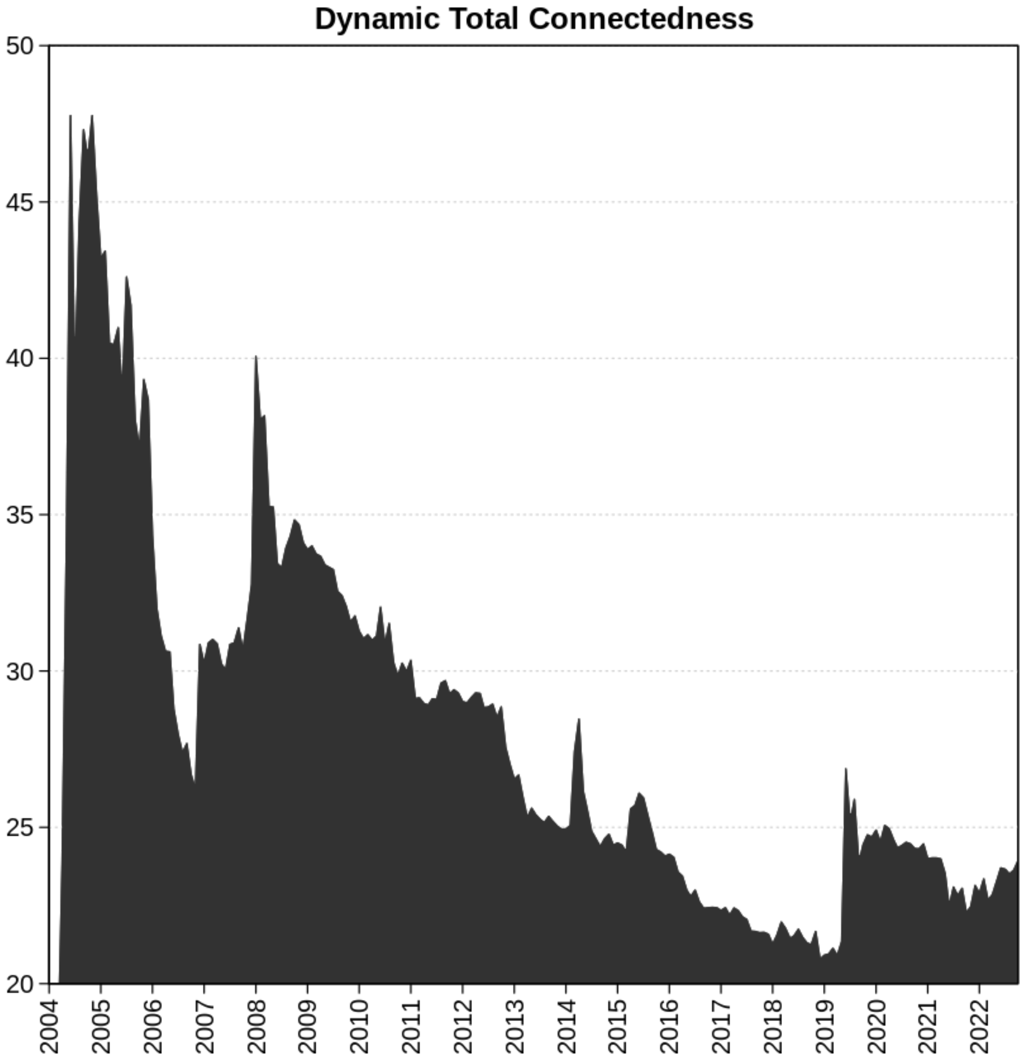


Fig 1. US TCI

The graph above shows the behavior of the Total Connectedness Index (TCI) over the data sample range. The rolling window shows that the TCI is very volatile and shows extreme peaks at certain times. TCI displays a weak downward trend indicating an decrease in connectedness. Spikes can be identified, which can be attributable to geopolitical tensions such as the start of the COVID-19 in the end of 2019, the Russia-Ukraine conflict in 2022. The smoother 200-period window, which represents long-term dynamics, suggests that despite short-term shocks, the overall system dynamic tends to revert to the long-term trend. Overall, the rising trend suggests that markets (the system as a whole) are becoming more interconnected over time and geopolitical tensions or other market shocks have significant effects on interconnectedness.

5.1.3 Directional Connectedness To Others and From Others

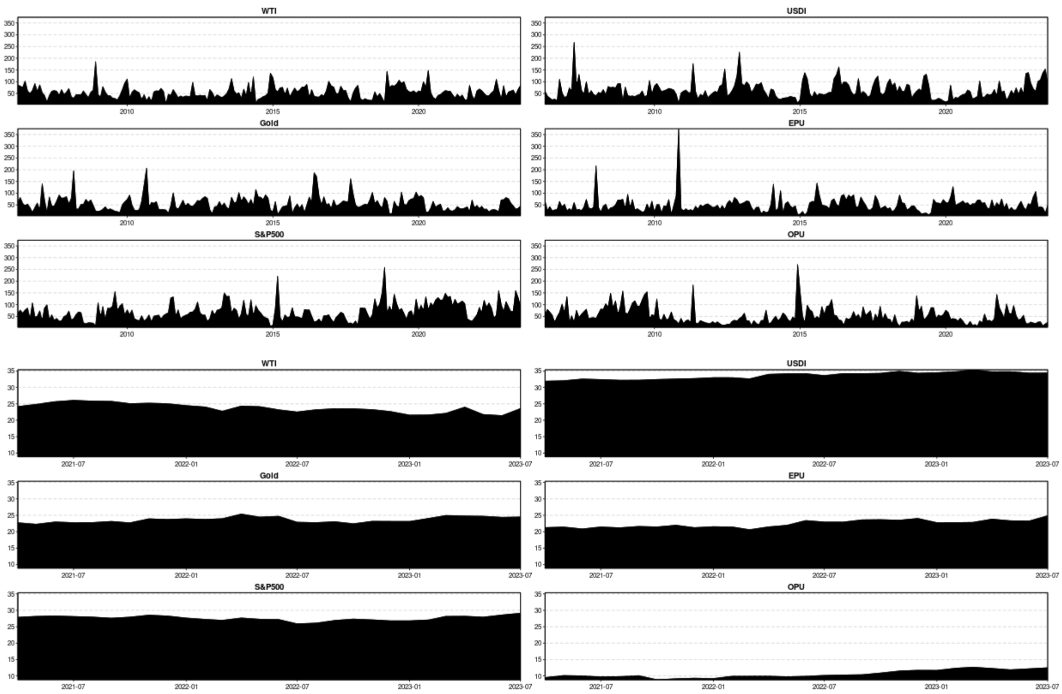


Fig 2. US 20-period (top) & 200-period (bot) directional connectedness to others

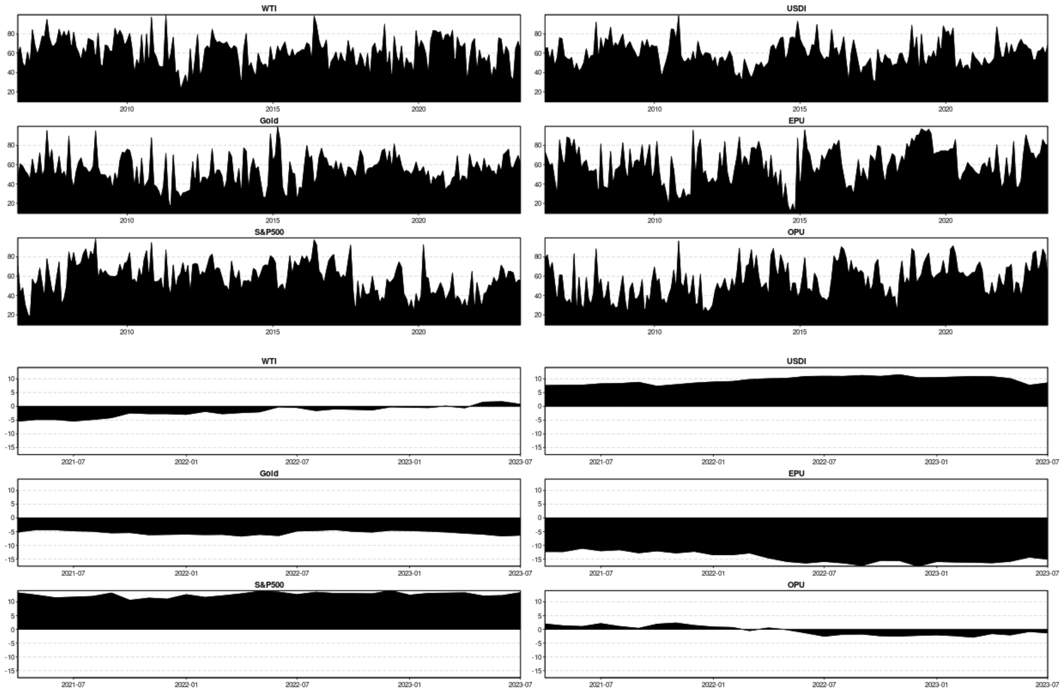


Fig 3. US 20-period (top) & 200-period (bot) directional connectedness from others

Similar to the TCI, the 20-period graph shows more fluctuations compared to the 200-period graph. Sharp spikes can be identified during periods of crises such as during the GFC (2008) and COVID-19 (2020). The spikes suggest that during extreme events, the spillover effects between markets increase, which leads to increased connectedness.

Gold shows a notable distinct pattern from others. It exhibits stable behavior even during extreme market conditions. This shows that gold is acting as a hedge during uncertain periods.

5.1.4 Net Total Directional Connectedness

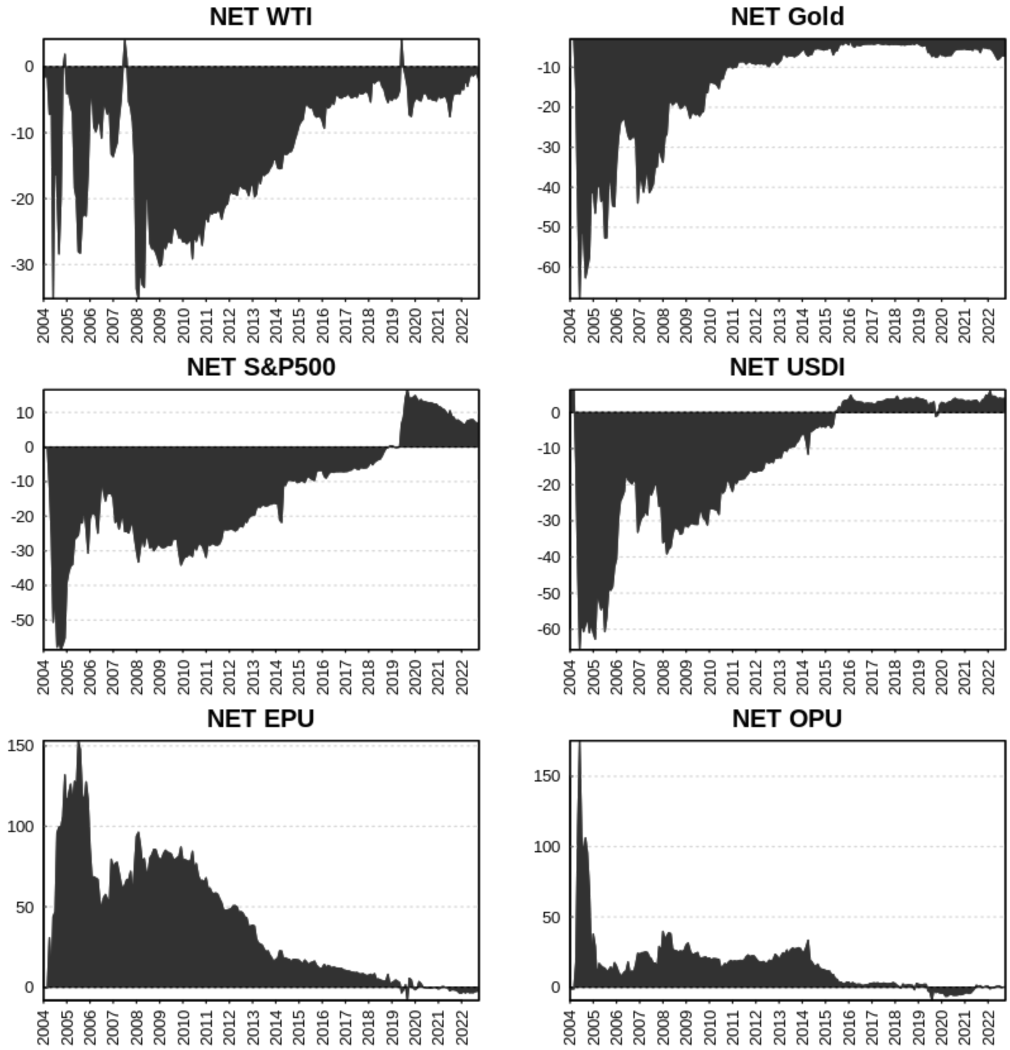


Fig 4. US 20-period (top) & 200-period (bot) net total directional connectedness

Net total directional connectedness shows whether a variable is a net transmitter or a net receiver of shocks. In the short term, the 20-period graph suggests that all of the variables can switch between net transmitter or net receiver depending on the market conditions at the time. However, in the long term, we can see that WTI, gold, EPU and OPU are net receivers, while USDI and S&P500 are net transmitters.

We can conclude that the equity markets (S&P500) and currency markets (USDI) are the key variables that influence the whole market.

5.1.5 Net Pairwise Directional Connectedness

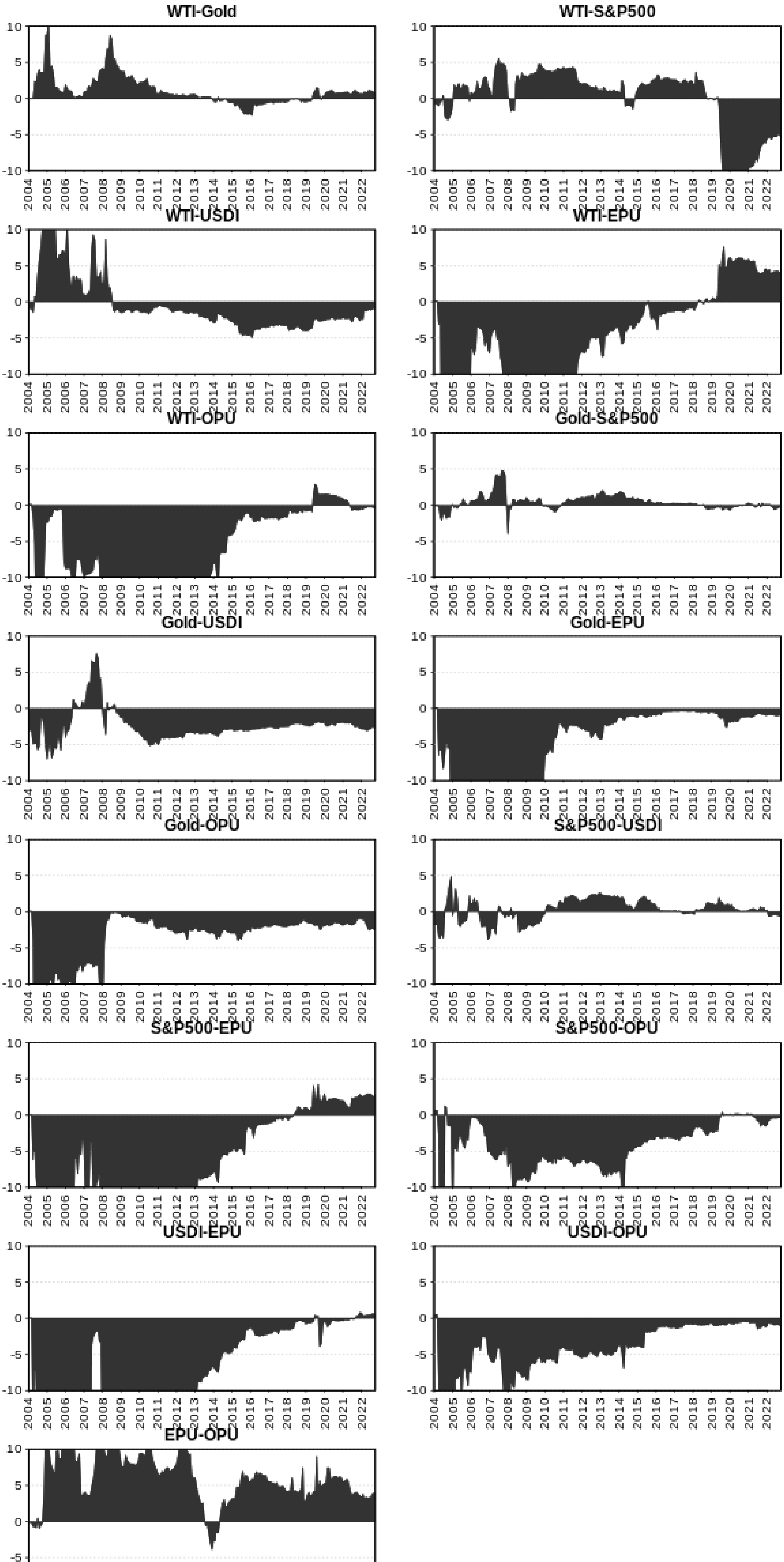

WTI-Gold
WTI-S&P500
WTI-USDI
WTI-EPU
WTI-OPU
Gold-S&P500
Gold-USDI
Gold-EPU
Gold-OPU
S&P500-USDI
S&P500-EPU
S&P500-OPU
USDI-EPU
USDI-OPU
EPU-OPU
10
5
0
-5
-10
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022

Fig 5. net pairwise directional connectedness

As expected the shorter period of connectedness shows more spikes in the net connectedness. This suggests that, in the short term, the interconnectedness between markets can shift very quickly. In the long term, interconnectedness is more stable but major events certainly cause shifts in the connectedness between markets.

From the graph, EPU shows that this variable has a persistent interconnectedness in all of the markets. The pairwise connectedness between EPU and S&P500, WTI and USDI is constantly high across the data range, and spikes can be seen during periods of political uncertainty. This suggests that the market sentiment index can be a good indicator of the state of the market.

5.1.6 Dynamic Pairwise Connectedness

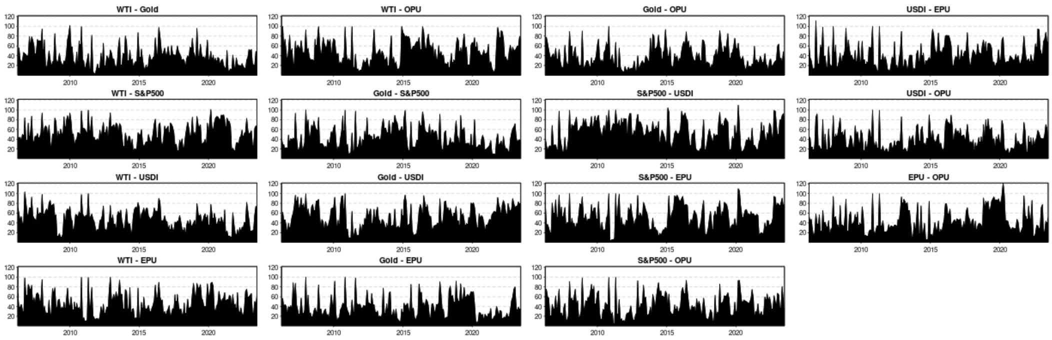


Fig 6. Dynamic pairwise connectedness

5.1.7 Network Plot and Dynamic Connectedness

	WTI	Gold	S&P500	USDI	EPU	OPU	FROM
WTI	"69.18"	" 1.10"	" 6.63"	" 5.33"	" 8.54"	" 9.21"	"30.82"
Gold	" 2.14"	"69.99"	" 1.39"	"13.90"	" 7.51"	" 5.08"	"30.01"
S&P500	" 6.71"	" 1.81"	"61.81"	"11.37"	"11.86"	" 6.44"	"38.19"
USDI	" 5.09"	"11.46"	"11.69"	"54.49"	"11.32"	" 5.95"	"45.51"
EPU	" 2.48"	" 0.42"	" 2.69"	" 0.49"	"91.20"	" 2.72"	" 8.80"
OPU	" 2.26"	" 0.68"	" 2.04"	" 0.90"	" 8.68"	"85.44"	"14.56"
TO	"18.68"	"15.46"	"24.45"	"32.00"	"47.90"	"29.40"	"167.90"
NET	"-12.14"	"-14.55"	"-13.74"	"-13.51"	" 39.10"	" 14.84"	"TCI"
NPDC	" 2.00"	" 1.00"	" 1.00"	" 2.00"	" 5.00"	" 4.00"	"27.98"

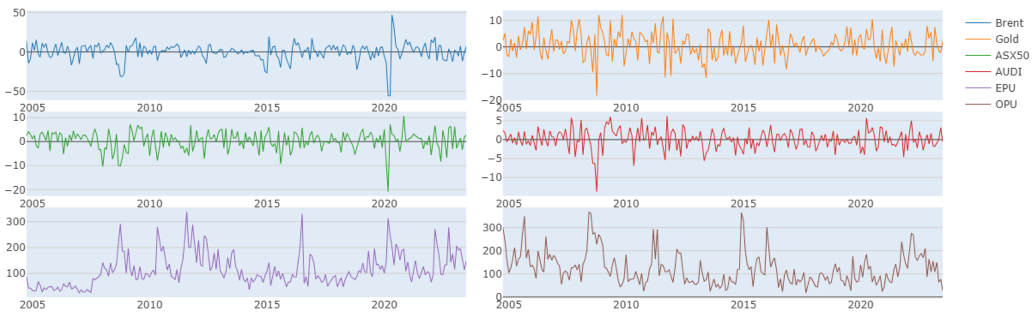
In both the short and long term, the S&P500 and USDI appear to be the central variables that transmits and receives shocks to and from other variables. EPU and OPU were net transmitters (39.1 and 14.84, respectively), while the financial asset returns were net receiver. It suggests that the sentiment variables are leading indicators while financial assets play as lagging indicators. This also shows that policy changes (uncertainty) ad energy uncertainty represent effects on changes in the financial market, and policymakers should put more focus on the S&P500 and USD index when considering policy changes as it can cause spillover effects to others and also be affected by other markets.

5.2 AUS Data

5.2.1 Raw Data and Time-series plots:

	Brent	Gold	ASX50	AUDI	EPU	OPU
2004-10-01	14.18	2.43	2.38	2.46	88.76	300.81
2004-11-01	-14.39	5.09	4.23	1.76	43.55	242.97
2004-12-01	-8.49	-2.80	2.96	-0.63	43.85	163.93
2005-01-01	11.69	-3.68	1.13	0.47	34.66	104.66
2005-02-01	2.16	3.03	2.61	1.42	32.41	126.60
2023-02-01	0.11	-5.37	-2.78	-1.60	206.17	155.26
2023-03-01	-5.17	7.42	-0.86	-1.79	190.03	109.07
2023-04-01	7.62	1.10	1.47	-0.83	194.66	150.42
2023-05-01	-11.47	-1.38	-3.35	0.00	148.30	64.43
2023-06-01	-0.84	-2.20	1.91	3.18	113.89	77.11
2023-07-01	6.80	2.30	2.57	-0.65	149.33	27.48

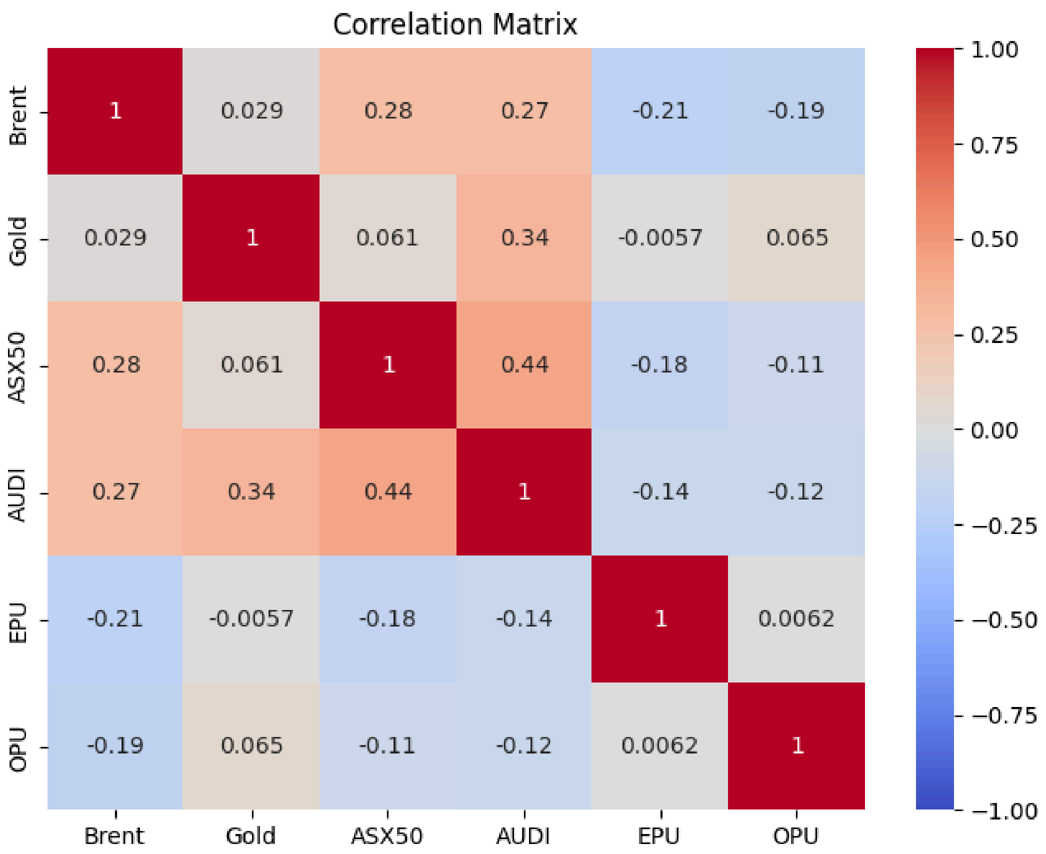
Similar to the US data, the graph represents the trends for the variables used in the study. However, the Brent crude oil (top-left) was instead used as a proxy of global crude oil returns for the Australian market. In a similar fashion, the time-series plot also represents strong volatility, which coincided with the period of the financial crisis (at the end of 2008) or the COVID-19 pandemic (in 2020), the time when the price of oil was severely impacted by the market risk aversion. Similar to the US data, the equity market index (ASX50) and AUD index were more stable with smaller spikes. The EPU of Australia also shows several peaks corresponding to significant risk-aversion events such as the 2008 Financial Crisis or the COVID-19 periods.



Summary statistics:

	Brent	Gold	ASX50	AUDI	EPU	OPU
Mean	0.273	0.684	0.387	0.036	114.387	123.709
Variance	120.31	23.515	15.862	6.707	3831.12	4962.328
Skewness	-1.126***	-0.146	-1.033***	-0.703***	1.127***	1.219***
	(0.000)	(0.356)	(0.000)	(0.000)	(0.000)	(0.000)
Ex.Kurtosis	6.474***	0.575*	2.954***	2.902***	1.228***	1.503***
	(0.000)	(0.090)	(0.000)	(0.000)	(0.005)	(0.002)
JB	442.480***	3.921	122.367***	97.941***	62.035***	77.237***
	(0.000)	(0.141)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-2.720***	-5.090***	-4.501***	-3.400***	-3.169***	-1.247
	(0.007)	(0.000)	(0.000)	(0.001)	(0.002)	(0.214)
Q(10)	23.208***	4.973	3.562	2.675	254.129***	181.575***
	(0.000)	(0.510)	(0.735)	(0.864)	(0.000)	(0.000)
Q2(10)	146.816***	16.374***	9.394*	15.441***	120.734***	126.394***
	(0.000)	(0.003)	(0.092)	(0.004)	(0.000)	(0.000)

the static correlation between variables could be found in the following correlation matrix:



The initial analysis shows that there is no series inter-correlation between variables.

Similar to the correlation results in the US market, positive linkages could be found between the stock market index returns and other financial assets, such as gold, oil, and the domestic currency exchange rate returns, but lowly significant negative correlation with the sentiment index could also be documented. However, for a more detailed insight in dynamic relationship between variables, connectedness analysis would be found in the next stages.
Similar to the US market analysis, for more details on the data preprocessing and preliminary analysis, we could refer to appendices 1 (detailed descriptive analysis), 2 (time-series plots), 3 (variable outlier check), 4 (variable distributions), 5 (autocorrelation function analysis), and 6 (stationary test). In short, time-series variables showed low intensity of autocorrelation while unit root tests reported all variables are stationary.

5.2.2 Total Connectedness (TCI)

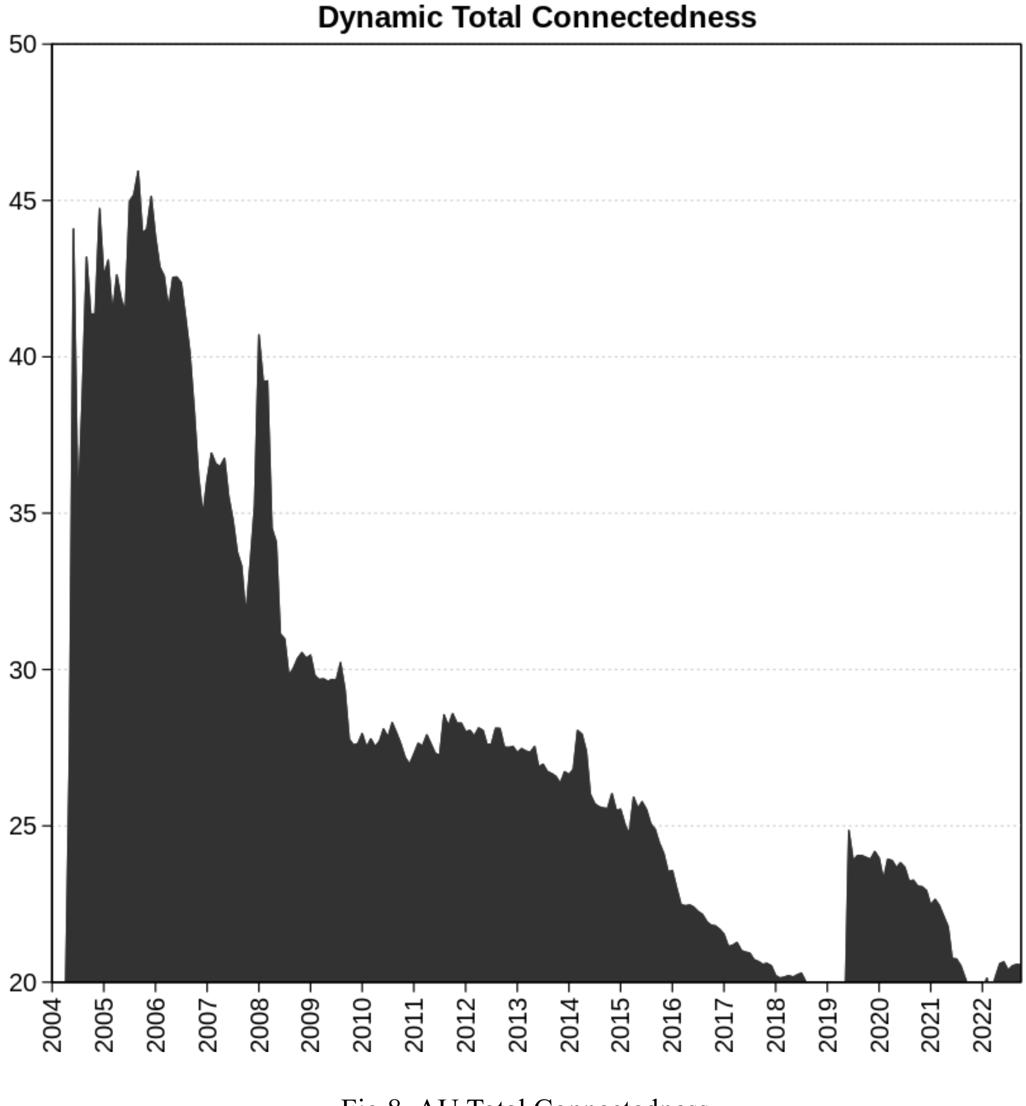


Fig 8. AU Total Connectedness

The situation is analogous compared with the US market connectedness, and here the chart yet again shows relatively high volatility with almost identical extreme spikes due to the same COVID-19 exposure and later the Russia-Ukraine war. The relatively high connectedness intensity is also found in the 2008-2009 global financial crisis period.

5.2.3 Directional Connectedness To Others and From Others

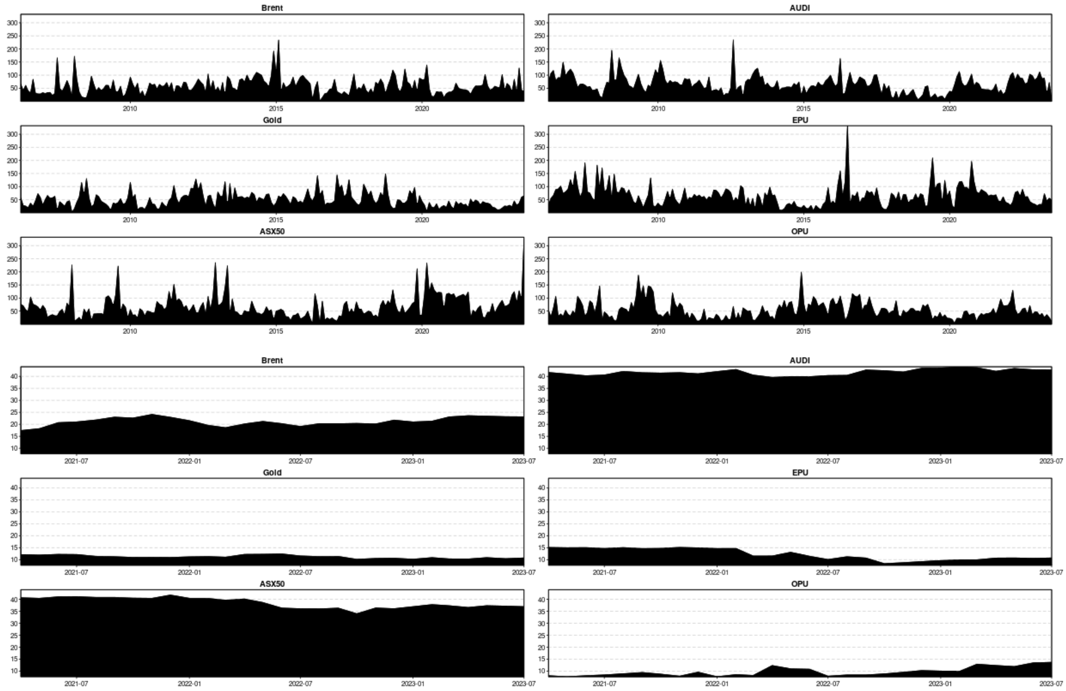


Fig 9. AU 20-period (top) & 200-period (bot) directional connectedness to others

The 20 rolling graph is more volatile compared to the 200 rolling one and this is quite normal because the more granular the data is (the 20 moving average) the more details are visible and the chart becomes more serrated while the higher time frame (200 moving average) the smoother the chart becomes.

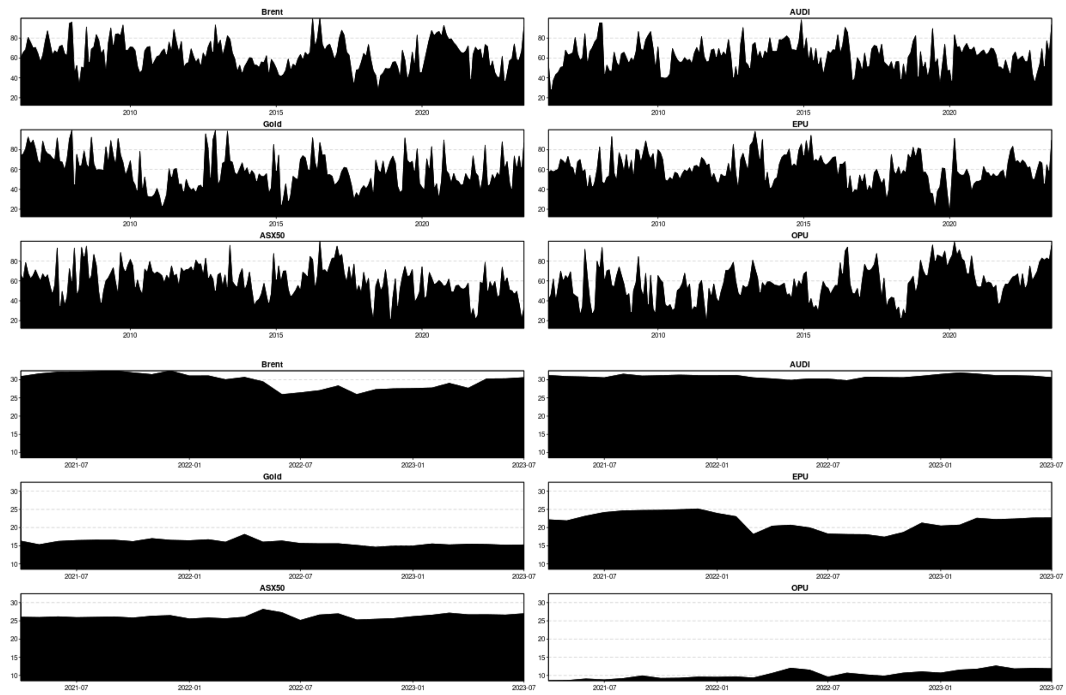


Fig 10.AU 20-period (top) & 200-period (bot) directional connectedness from others

5.2.4 Net Total Directional Connectedness

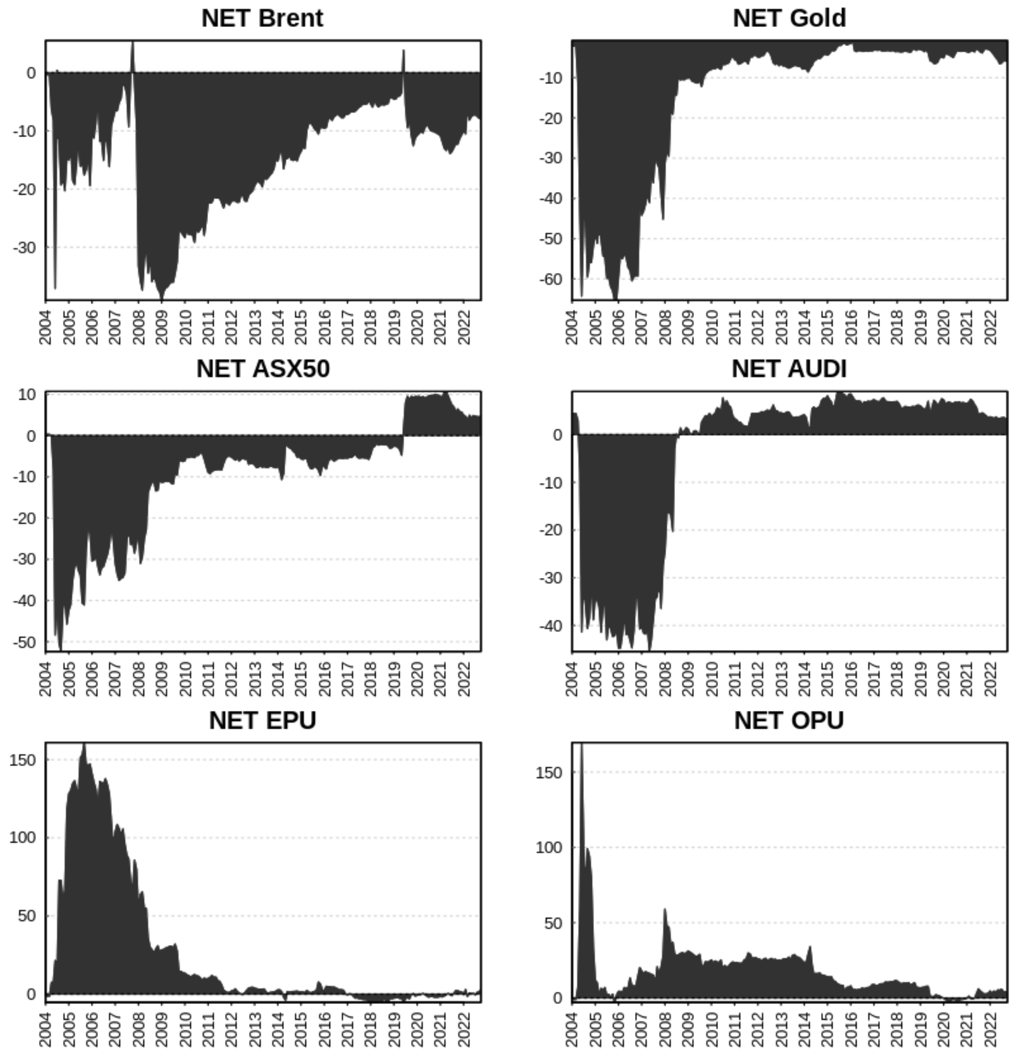


Fig 11. AU net total directional connectedness

Yet again, the total net directional connectedness shows which variables are the receiver or transmitter of shocks. The same logic applied to the Australian dollar shows that the 20-period graph suggests that all of the variables can switch between net transmitter or net receiver depending on the market conditions at the time. Looking at the long term 200-period charts shows that EPU and OPU are net receivers while AUDI and ASX50 are net transmitters.
This is nothing new considering that the Australian dollar is commodity pegged, and it is expected to have deeper dependencies with commodities like gold, oil and other metals.

5.2.5 Net Pairwise Directional Connectedness

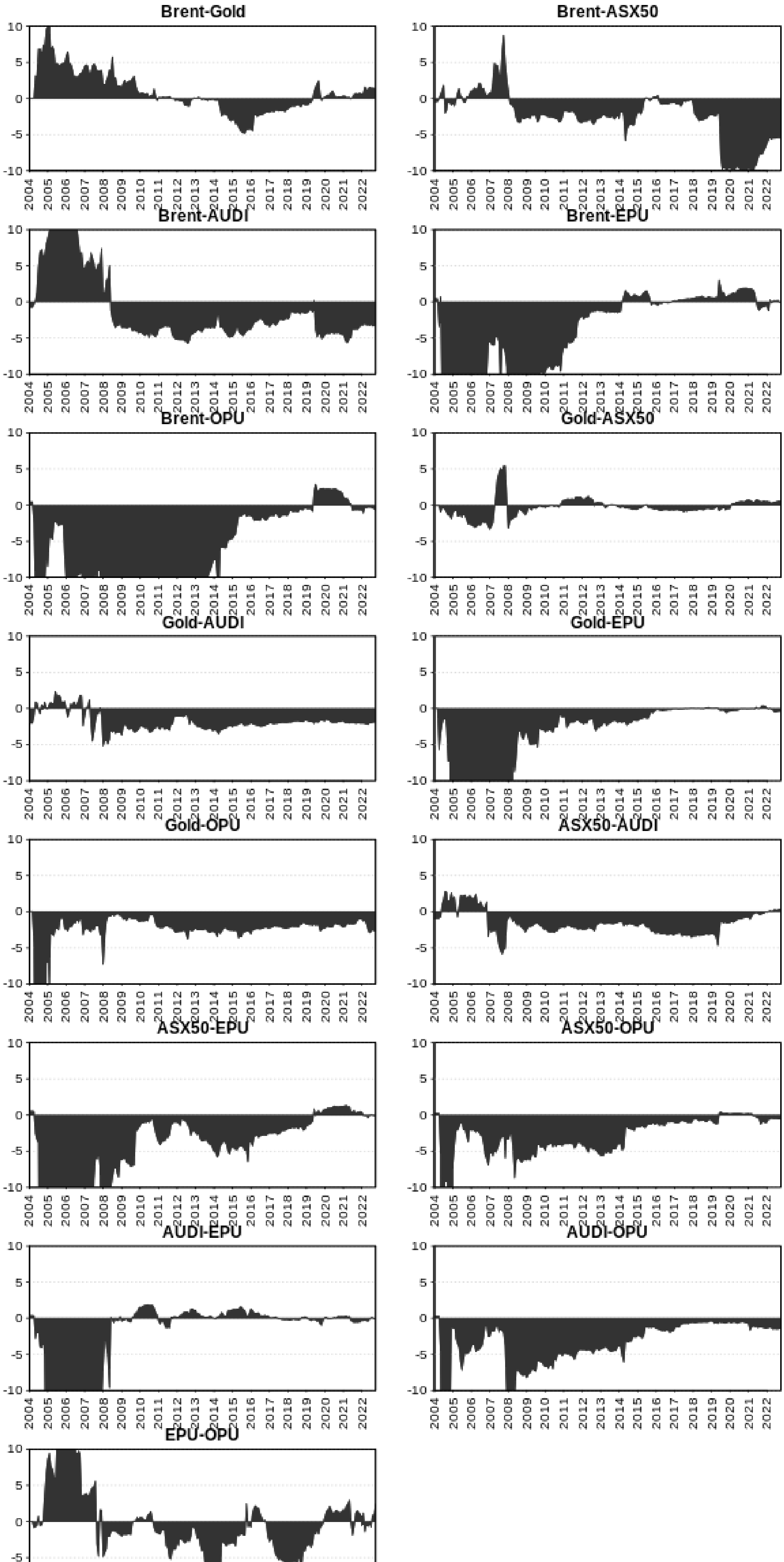

Brent-Gold
Brent-ASX50
Brent-AUDI
Brent-EPU
Brent-OPU
Gold-ASX50
Gold-AUDI
Gold-EPU
Gold-OPU
ASX50-AUDI
ASX50-EPU
ASX50-OPU
AUDI-EPU
AUDI-OPU
EPU-OPU

Fig 12. AU net pairwise directional connectedness

In the short term, every pair fluctuates between the net transmitter and receiver of the pair. However, we can see that during crises, there are some significant spikes which show that connectedness strength changes during market events.

Over the long term, each pair, except Brent and OPU, hold their direction of relationship. It is the strength that changes.

5.2.6 Dynamic Pairwise Connectedness

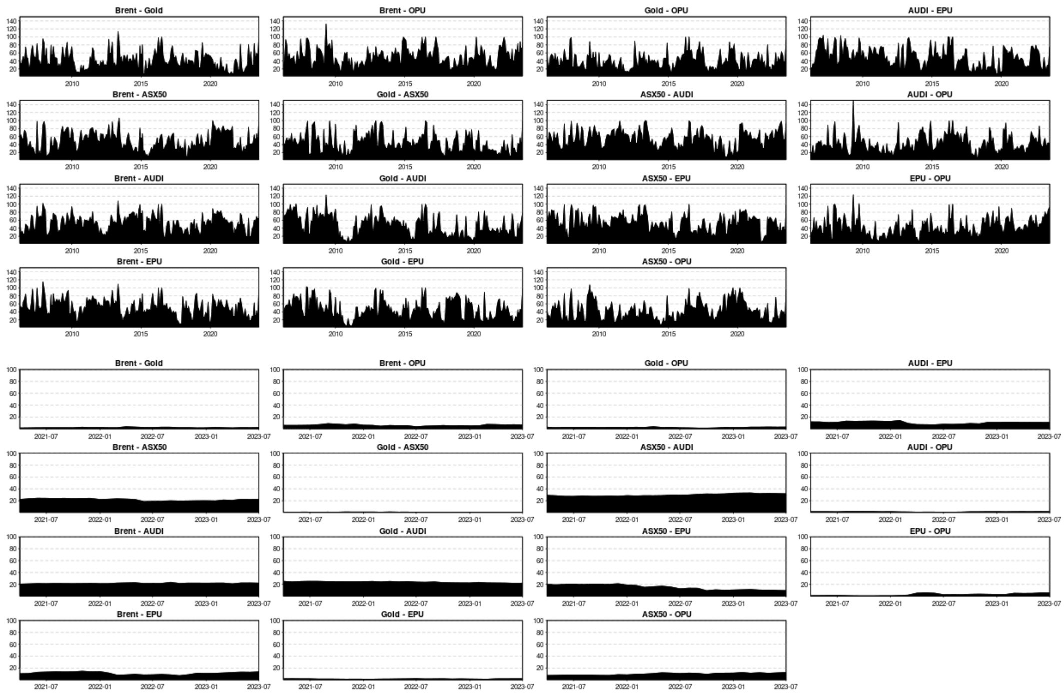


Fig 13. AU 20-period (top) and 200-period (bot) dynamic pairwise connectedness

5.2.7 Dynamic Connectedness

Table. AU average connectedness table

	Brent	Gold	ASX50	AUDI	EPU	OPU	FROM
Brent	"63.44"	" 2.08"	" 6.98"	" 8.74"	" 9.84"	" 8.92"	"36.56"
Gold	" 2.87"	"71.57"	" 1.23"	"11.46"	" 8.68"	" 4.18"	"28.43"
ASX50	" 4.54"	" 0.95"	"67.49"	"11.31"	"11.52"	" 4.19"	"32.51"
AUDI	" 7.85"	" 9.64"	" 9.74"	"59.48"	" 8.66"	" 4.63"	"40.52"
EPU	" 3.84"	" 0.41"	" 4.16"	" 4.39"	"82.00"	" 5.21"	"18.00"
OPU	" 2.64"	" 0.83"	" 1.07"	" 0.77"	" 5.04"	"89.65"	"10.35"
TO	"21.75"	"13.91"	"23.18"	"36.66"	"43.75"	"27.12"	"166.36"
NET	"-14.82"	"-14.52"	" -9.33"	" -3.86"	" 25.75"	" 16.78"	"TCI"
NPDC	" 1.00"	" 0.00"	" 2.00"	" 3.00"	" 4.00"	" 5.00"	"27.73"

In both the short and long term, EPU and OPU are net transmitters. Changes in these variables have an impact on other variables, making them suitable as leading indicators. Meanwhile, Brent Oil, Gold, ASX50 index, and AUDI are displayed as net receivers. This shows that policy changes and energy uncertainty sentiments transmit shocks fast to the market behavior. When making policy changes, it is important to focus more on the effect of policy uncertainty and energy market stability because they are the net transmitters in the system.

5. Findings

By investigating the various interaction channels between markets, the study provides insights into the intricacies of global and regional economic cooperation, especially during times of increased instability. The study conducted in both the US and Australia shows that the volatility of oil prices is subject to great variations, with major bursts happening at critical points such as the 2008 Financial Crisis, the COVID-19 pandemic, and the Russia-Ukraine conflict. The Brent crude oil and WTI crude oil prices which were used as proxies for global oil returns in the Australian and US markets, respectively, have led to the sizable flow-on of the financial assets into other markets. Through these intensifications in connectedness, it is proved that the oil markets have got a bigger part to play in spreading the shocks to the other parts of the financial systems.

Thus, in the U.S. market, Sharp fluctuations around the 2008 Financial Crisis, the COVID-19 pandemic, and the Russia-Ukraine conflict clearly reflect the volatility of WTI crude oil, while gold, the S&P 500, and the USD index only surge at periods. Economic Policy Uncertainty and Oil Price Uncertainty peak with most events as indications of tension in these markets. The Total Connectedness Index (TCI) suggests that over time, the financial markets in the United States are becoming more connected. Short-term connectedness, on the other hand, is erratic, with sharp increases discernible in the graphs during crises. However, long-term dynamics illustrate a return to longer-term behavioral trend lines that are less volatile. In addition, equity markets (S&P 500) and the USD index are net shock transmitters, further proving their importance in market dynamics. On the other hand, WTI crude oil, gold, EPU and OPU are net shock absorbers indicating their vulnerability to systemic shocks. During times of uncertainty, gold almost always behaves as a hedge and does not fluctuate much, even in extreme conditions. In the pairwise connectedness analysis, it is proven that the S&P 500, WTI and USD index are affected by EPU all the time, therefore bringing significance to EPU as a sentiment index. The network analysis points out that the S&P 500 index and the USD index are the most dominant indices, which both send and receive shocks within the economy. Therefore these results show that managing systemic risk requires the surveillance of major stock and currency markets.

The Australian context exhibits comparable tendencies with Brent crude oil acting as a representative of global oil return trends. While the ASX 50 index as well as the AUD index remain fairly constant, the Brent crude oil and Economic Policy Uncertainty (EPU) indicators are volatile during turbulent periods, particularly the COVID-19 pandemic and the Global Financial Crisis of 2008. The Total Connectedness Index captured the essence of the US market, revealing high volatility and the increasing connectedness of markets over time. Within the context of Australia, the AUD index and ASX 50 are considered shock net senders, the same as Brent crude oil, gold and EPU are net receivers. This aspect shows the typical commodity-based economy of Australia where the AUD appears to have significant attachments to the world commodity market, oil and gold inclusive. Political and energy uncertainty indices, in particular, the EPU and OPU, act as net transmitters underlining their importance as a leading indicator in the system.

After all, the findings imply that, in the US and Australian markets, linkages between the two are extended over time, thus the effect of shock transfer intensifies during the crisis, so there is a need to monitor the key sources of it such as the stock and foreign exchange markets.

6. Conclusion

This study utilized a lot of valuable data about linkages of plunging from one market to another and the interaction of markets, especially in a brief unstable period. Through the strategy of rolling windows, the comparison of the US and Australian markets points out that both WTI and Brent oil prices exhibit high volatility during several important events, such as the 2008 Financial Crisis, the COVID-19 pandemic, and the Russia-Ukraine crisis. The S&P500 and USD index in the U.S. and the ASX50 and AUD index in Australia are the main transmitters of market shocks, while Economic Policy Uncertainty (EPU) remains a net receiver as it reacts to broader market conditions.

Furthermore, it is also indicated that the US-Australian financial institutions are becoming more connected as the periods of crisis lengthen. This brings attention to the aspects of equity and forex markets such as the S&P 500, USD index, ASX 50, AUD index and sentiment indices like EPU, and OPU that need to be monitored at all times. Attention should be paid by policymakers to the issues of energy and political risk since the two factors are key in the operation of markets and can spread across financial systems and cause shocks.

Expanding on these results, the examined research gives some practical lessons for investors and policymakers. The research employs the Time-Varying Parameter Vector Autoregression (TVP-VAR) method to show in particular how extreme market events and sentiment shifts are observed across various asset classes. These findings are essential to come up with risk management strategies that are safe in different market scenarios, whether it is a high time or a crisis.

To summarize, the present study demonstrates the growing integration of financial markets and the importance of systemic risk in the transmission of alloyed assets and indices. Having learned this, investors and policymakers will be able to cope better during high-risk-intensity times and know how to strengthen the financial systems in the ever more globally economically integrated world.

7. Source Codes

Please view the current state of the Source Code and preliminary findings of descriptive analysis - EDA results, and Connectedness analysis for the US Data from the following link: Source Code US

Or:
https://colab.research.google.com/drive/1NS7pJYp4LMYpnsSB2rZaWPDO4b4L0uAL?usp=sharing

For the Australian market data from the following link: Source Code AU

Or:
https://colab.research.google.com/drive/1ErxAEcT_PIIgwTwRxT4Soyc_3GAi5GsS?usp=sharing

References

1. Christopher J. Neely, The Russian Invasion, Oil and Gasoline Prices, and Recession, ECONOMIC Synopses, 2022
2. Zhang, Q., Hu, Y., Jiao, J. *et al.* The impact of Russia–Ukraine war on crude oil prices: an EMC framework. *Humanit Soc Sci Commun* 11, 8 (2024). https://doi.org/10.1057/s41599-023-02526-9
3. Ando, T., M. Greenwood-Nimmo, and Y. Shin. "Quantile Connectedness: modelling tail behaviour in the topology of financial networks. Available at SSRN 3164772." (2018).
4. Ando, Tomohiro, and Jushan Bai. "Quantile co-movement in financial markets: A panel quantile model with unobserved heterogeneity." *Journal of the American Statistical Association* 115.529 (2020): 266-279.
5. Ando, Tomohiro, Matthew Greenwood-Nimmo, and Yongcheol Shin. "Quantile connectedness: modeling tail behavior in the topology of financial networks." *Management Science* 68.4 (2022): 2401-2431.
6. Baruník, Jozef, Evžen Kočenda, and Lukáš Vácha. "Asymmetric volatility connectedness on the forex market." *Journal of International Money and Finance* 77 (2017): 39-56.
7. Baur, Dirk G., and Thomas K. McDermott. "Is gold a safe haven? International evidence." *Journal of Banking & Finance* 34.8 (2010): 1886-1898.
8. Chatziantoniou, Ioannis, David Gabauer, and Alexis Stenfors. "Interest rate swaps and the transmission mechanism of monetary policy: A quantile connectedness approach." *Economics Letters* 204 (2021): 109891.
9. Chatziantoniou, Ioannis, et al. "Quantile time–frequency price connectedness between green bond, green equity, sustainable investments and clean energy markets." *Journal of Cleaner Production* 361 (2022): 132088.
10. Chisti, Khalid Ashraf, Saila Shakeel, and Khursheed Ali Ganai. "An Analysis of Interaction among Macroeconomic Variables through Cointegration and Causality Approach." *Journal of Economics and Business* 3.2 (2020).
11. Chow, Hwee K. "Connectedness of Asia Pacific forex markets: China's growing influence." *International Journal of Finance & Economics* 26.3 (2021): 3807-3818.
12. Hung, Ngo Thai. "Analysis of the time-frequency connectedness between gold prices, oil prices and Hungarian financial markets." *International Journal of Energy Economics and Policy* 10.4 (2020): 51-59.
13. Tiwari, Aviral Kumar, et al. "Systemic risk spillovers between crude oil and stock index returns of G7 economies: Conditional value-at-risk and marginal expected shortfall approaches." *Energy Economics* 86 (2020): 104646.
14. Shah, Adil Ahmad, et al. "Dynamics of connectedness across crude oil, precious metals and exchange rate: Evidence from time and frequency domains." *Resources Policy* 73 (2021): 102154.
15. Rehman, Mobeen Ur, et al. "Modelling the quantile cross-coherence between exchange rates: Does the COVID-19 pandemic change the interlinkage structure?." *Journal of International Financial Markets, Institutions and Money* 76 (2022): 101495.
16. Wang, Gang-Jin, et al. "Interconnected multilayer networks: Quantifying connectedness among global stock and foreign exchange markets." *International Review of Financial Analysis* 86 (2023): 102518.
17. Wei, Yu, et al. "Oil price fluctuation, stock market and macroeconomic fundamentals: Evidence from China before and after the financial crisis." *Finance research letters* 30 (2019): 23-29.
18. Wen, Tiange, and Gang-Jin Wang. "Volatility connectedness in global foreign exchange markets." *Journal of Multinational Financial Management* 54 (2020): 100617.
19. Khan K, Su CW, Tao R (2021) How do geopolitical risks affect oil prices and freight rates? Ocean Coast Manag 215:105955
20. Fu, Lianlian, et al. "Asymmetric Dynamic Linkage between Consumer Sentiment, Inflation Expectations, and International Energy Prices: Evidence from Time-Frequency Wavelet and

Nonlinear Analysis." *PLOS ONE*, vol. 19, no. 9, Public Library of Science, Sept. 2024, https://doi.org/10.1371/journal.pone.0308097.

21. Shang, Jin, and Shigeyuki Hamori. "Quantile Time-Frequency Connectedness Analysis Between Crude Oil, Gold, Financial Markets, and Macroeconomic Indicators: Evidence from the US and EU." *Energy Economics*, vol. 132, 2024, 107473, doi:10.1016/j.eneco.2024.107473. Accessed 16 Mar. 2024. *ScienceDirect*, https://www.sciencedirect.com/science/article/pii/S0140988324001816.
22. Diebold, Francis X., and Kamil Yılmaz. "On the network topology of variance decompositions: Measuring the connectedness of financial firms." *Journal of econometrics* 182.1 (2014): 119-134.
23. Antonakakis, Nikolaos, Ioannis Chatziantoniou, and David Gabauer. "Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions." *Journal of Risk and Financial Management* 13.4 (2020): 84.
24. Koop, Gary, and Dimitris Korobilis. "A new index of financial conditions." *European Economic Review* 71 (2014): 101-116.
25. D'Agostino, Ralph B. "Transformation to normality of the null distribution of g1." *Biometrika* (1970): 679-681.
26. Anscombe, Francis J., and William J. Glynn. "Distribution of the kurtosis statistic b 2 for normal samples." *Biometrika* 70.1 (1983): 227-234.
27. Jarque, Carlos M., and Anil K. Bera. "Efficient tests for normality, homoscedasticity and serial independence of regression residuals." *Economics letters* 6.3 (1980): 255-259.
28. Elliott, Graham, Thomas J. Rothenberg, and James H. Stock. "Efficient tests for an autoregressive unit root." (1992).
29. Fisher, Thomas J., and Colin M. Gallagher. "New weighted portmanteau statistics for time series goodness of fit testing." *Journal of the American Statistical Association* 107.498 (2012): 777-787.

Appendices

Appendix 1: Descriptive analysis of variables

Part A - The US market:

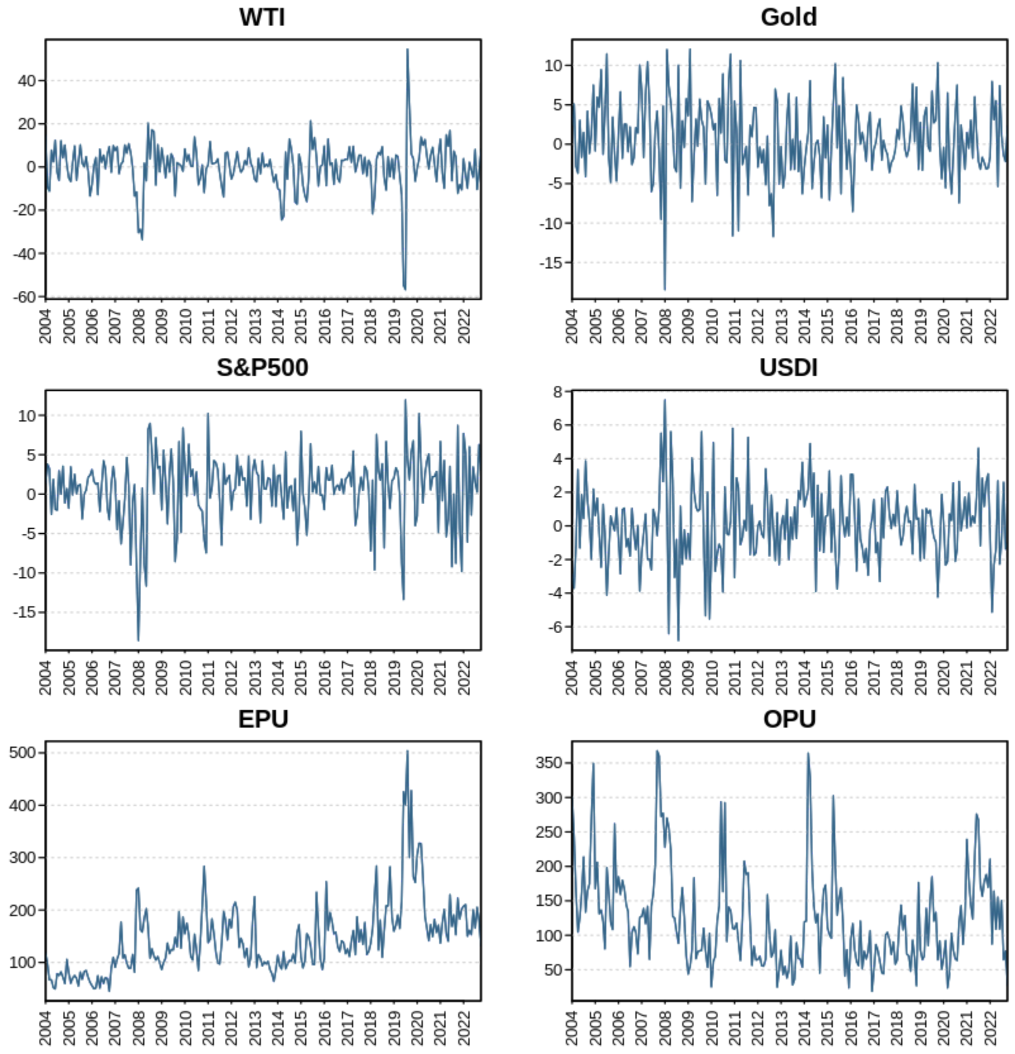
	count	mean	std	min	25%	50%	75%	max
WTI	226.0	0.223053	10.987996	-56.812501	-4.993116	1.466214	6.106317	54.562104
Gold	226.0	0.684405	4.849209	-18.449146	-2.332383	0.351491	3.719395	12.061820
S&P500	226.0	0.626184	4.391617	-18.563649	-1.707072	1.252789	3.276467	11.942090
USDI	226.0	0.067948	2.240677	-6.817635	-1.380627	0.059295	1.466039	7.490780
EPU	226.0	144.846080	68.994952	44.782751	98.331972	133.556701	176.832924	503.963337
OPU	226.0	123.708787	70.443793	18.698283	69.869154	110.215953	160.733398	367.731508

Part B - The Australian market:

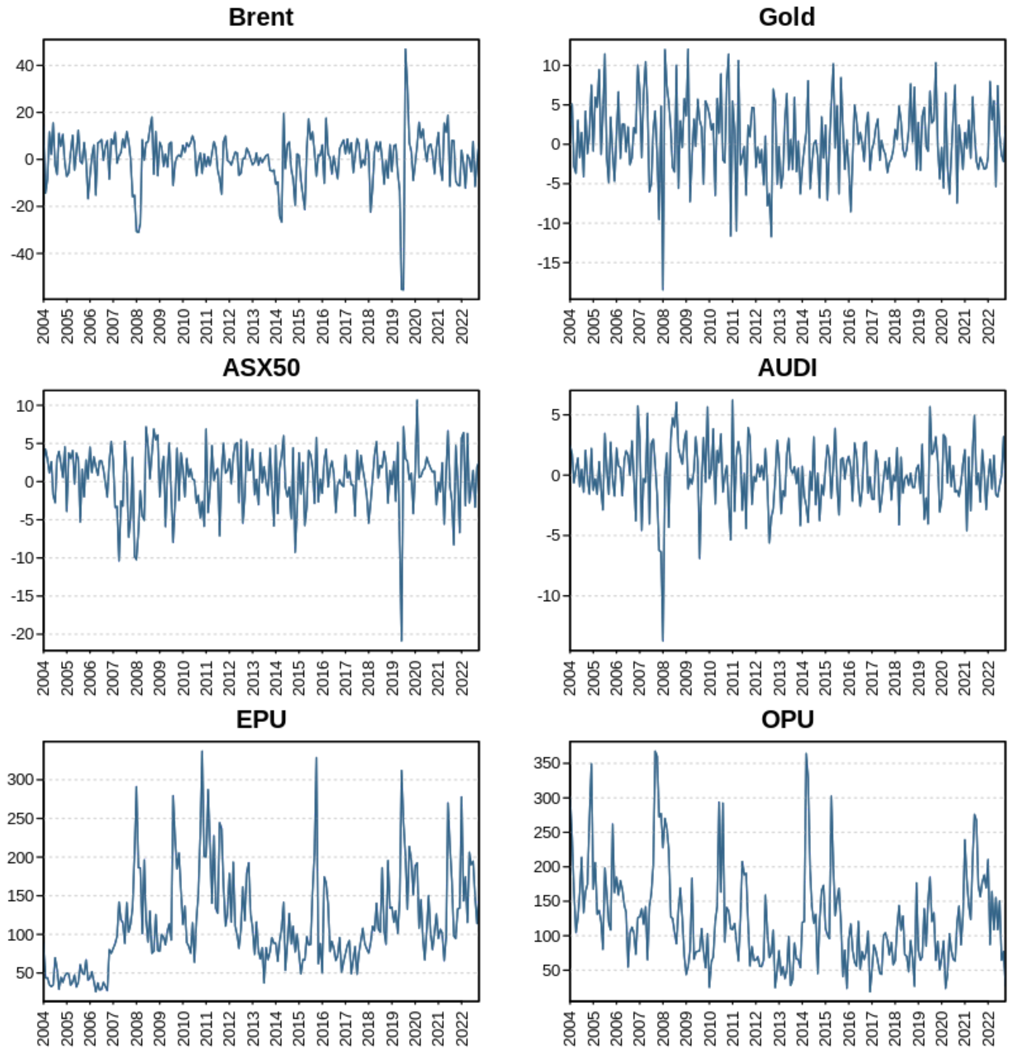
	count	mean	std	min	25%	50%	75%	max
Brent	226.0	0.273230	10.968597	-55.479000	-4.878000	1.662500	6.983500	46.905000
Gold	226.0	0.684405	4.849209	-18.449146	-2.332383	0.351491	3.719395	12.061820
ASX50	226.0	0.387345	3.982654	-20.860000	-1.987500	1.120000	3.050000	10.670000
AUDI	226.0	0.036015	2.589801	-13.722397	-1.502124	0.000000	1.716785	6.215470
EPU	226.0	114.386798	61.896044	25.661973	75.521209	100.498602	141.331937	337.043863
OPU	226.0	123.708787	70.443793	18.698283	69.869154	110.215953	160.733398	367.731508

Appendix 2: Time series plots:

Part A - The US market:



Part B - The Australian market:



Appendix 3: Variable outlier check:

Part A - The US market:

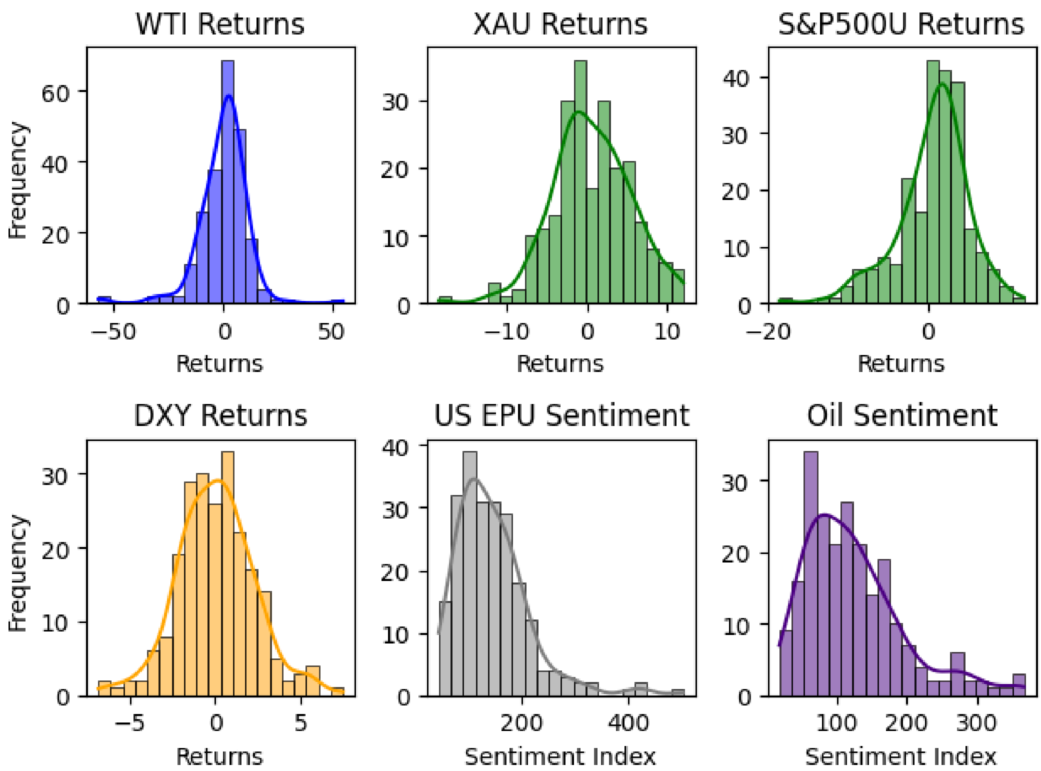
	outlier_counts	outlier_percent
WTI	10.0	4.42
S&P500	8.0	3.54
EPU	8.0	3.54
OPU	7.0	3.10
USDI	4.0	1.77
Gold	3.0	1.33

Part B - The Australian market:

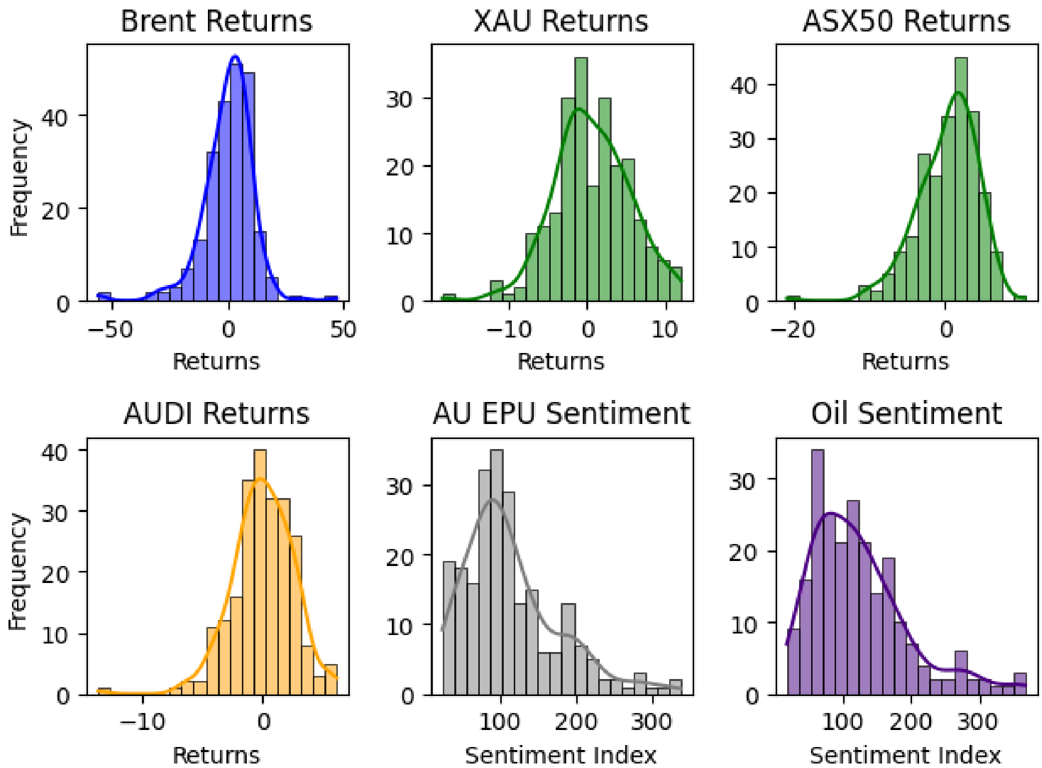
	outlier_counts	outlier_percent
EPU	10.0	4.42
Brent	9.0	3.98
OPU	7.0	3.10
ASX50	5.0	2.21
Gold	3.0	1.33
AUDI	3.0	1.33

Appendix 4: Variable distribution:

Part A - The US market:

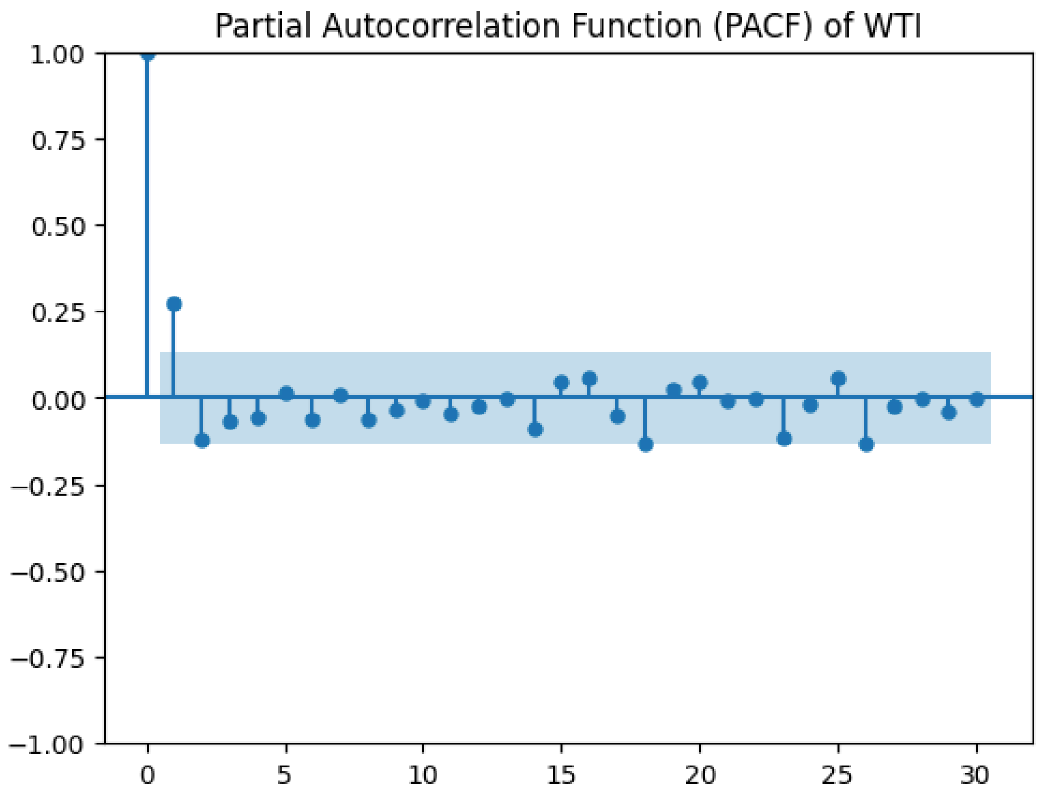


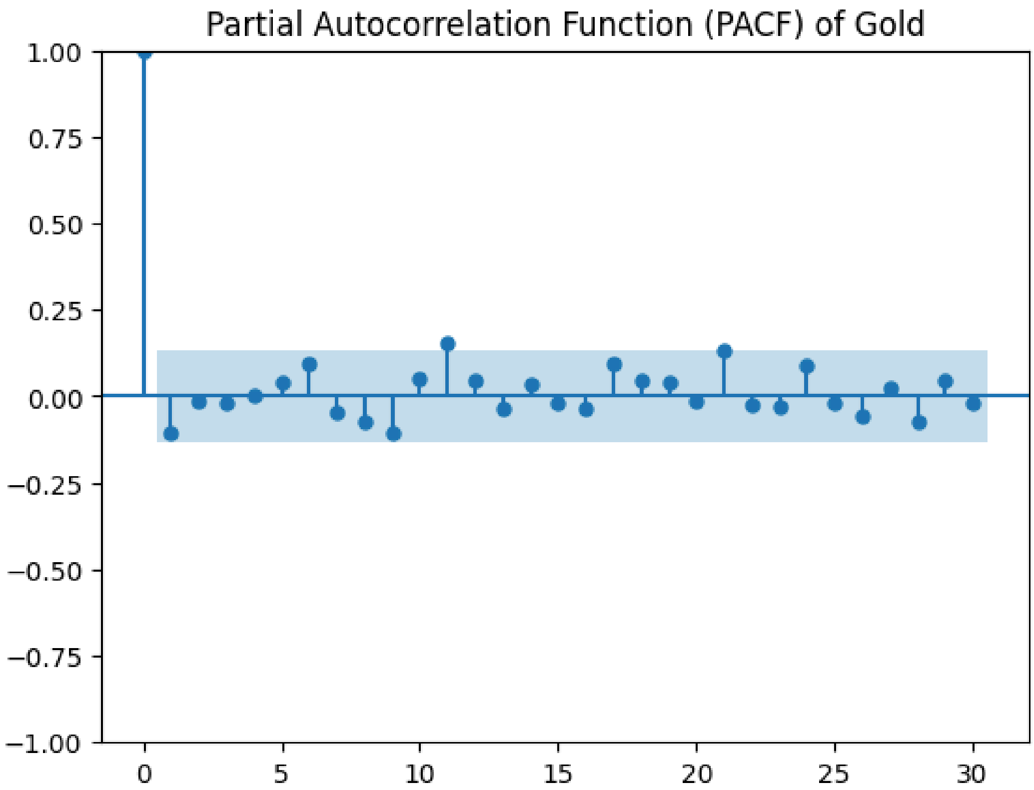
Part B - The Australian market:

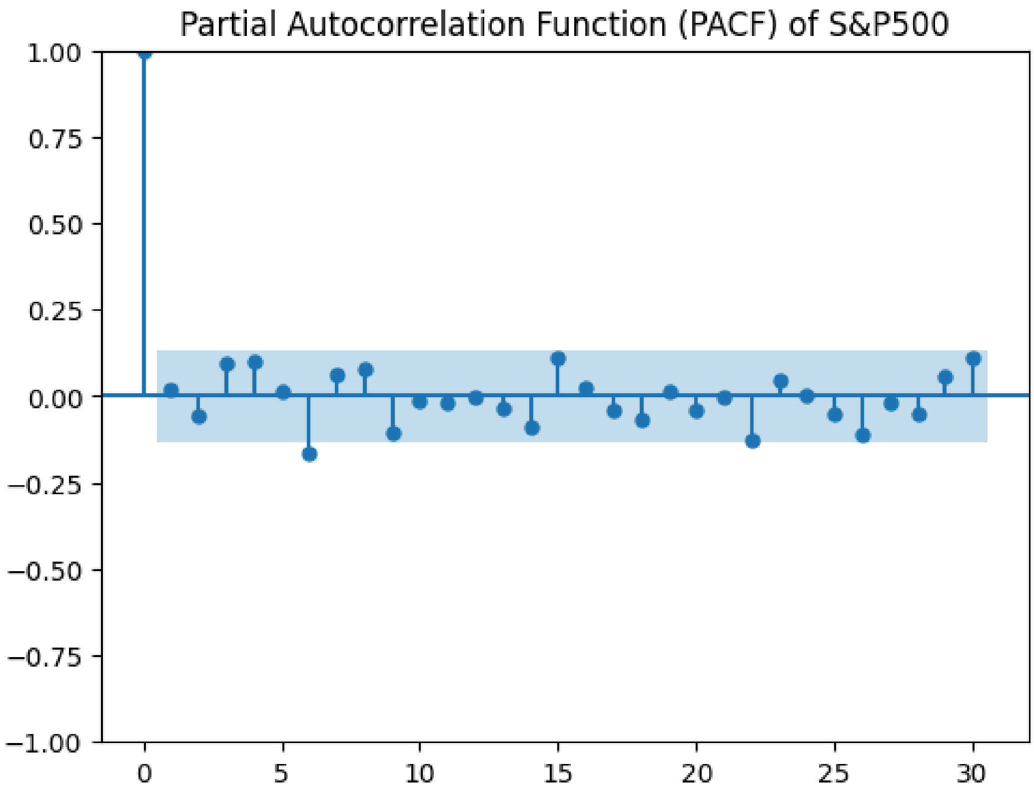


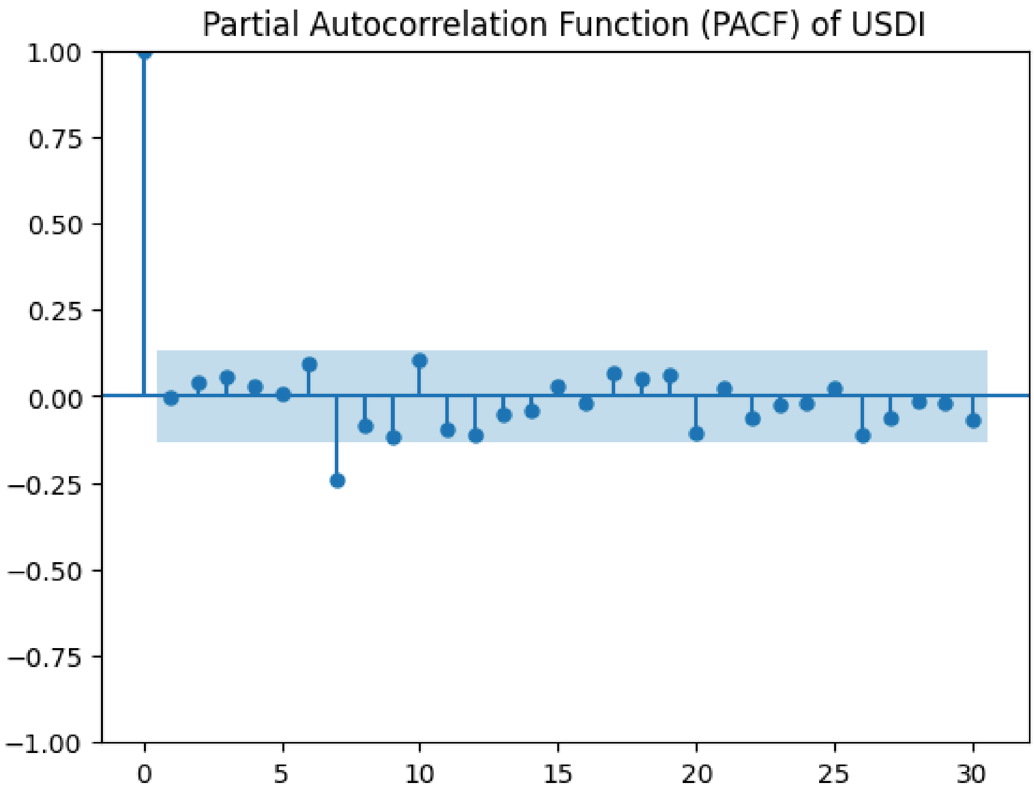
Appendix 5: Variable autocorrelation analysis:

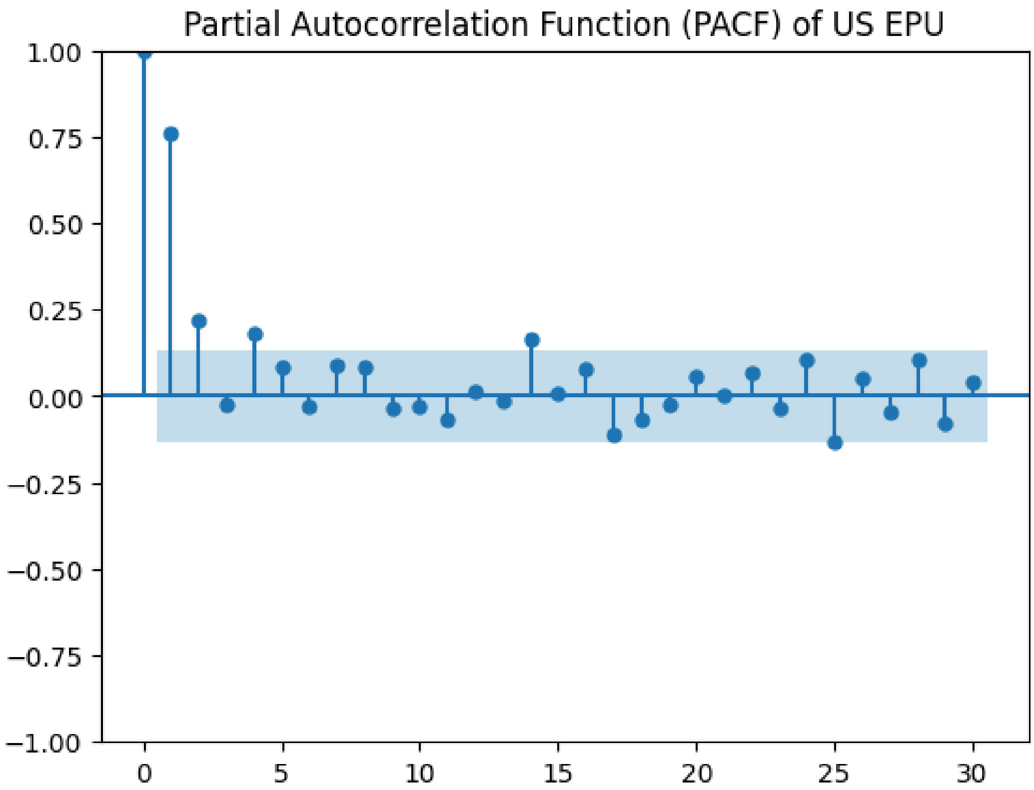
Part A - The US market:

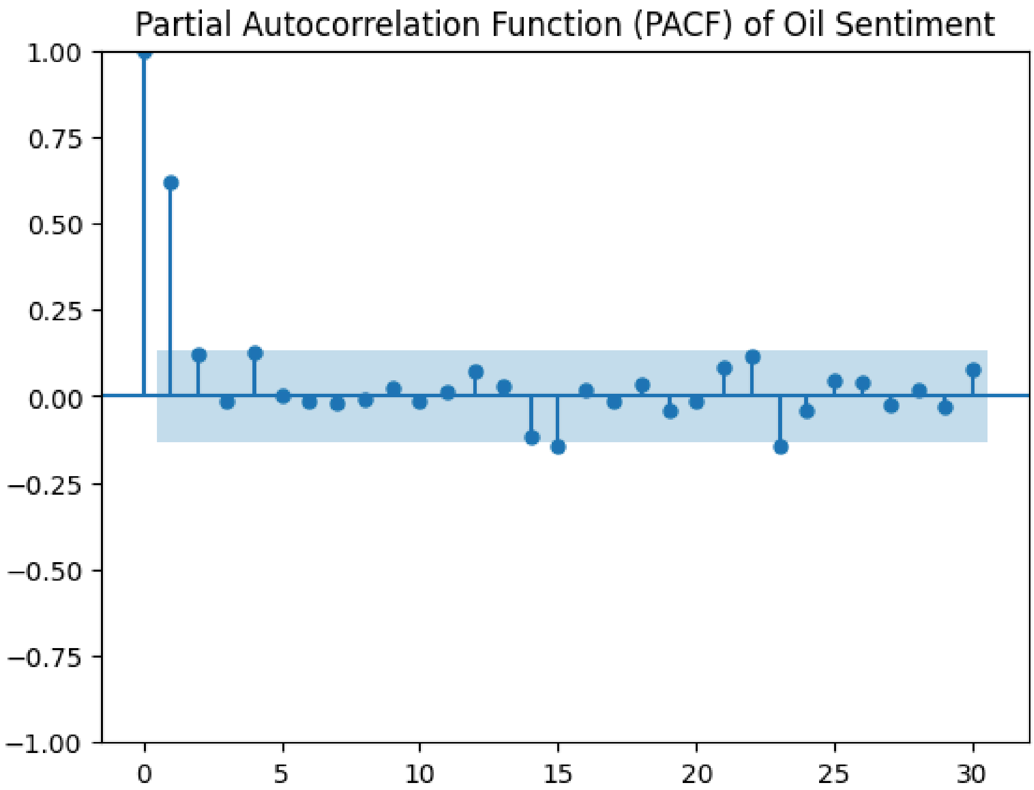



Partial Autocorrelation Function (PACF) of Gold
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25
30

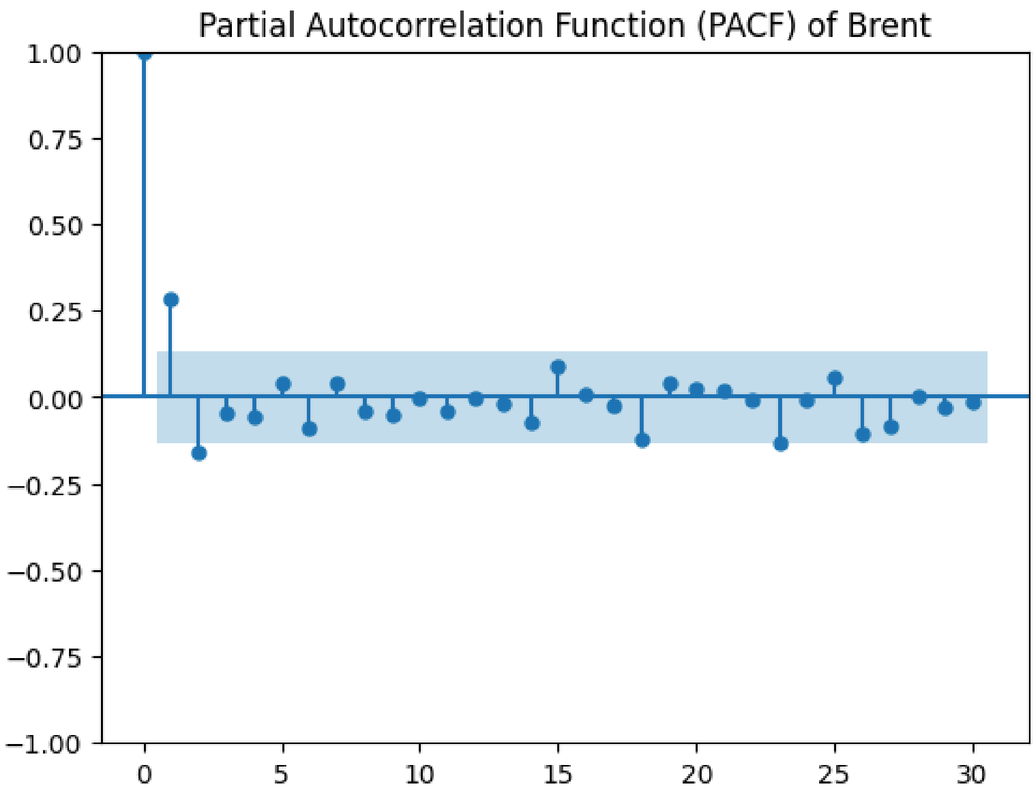

Partial Autocorrelation Function (PACF) of S&P500
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25
30

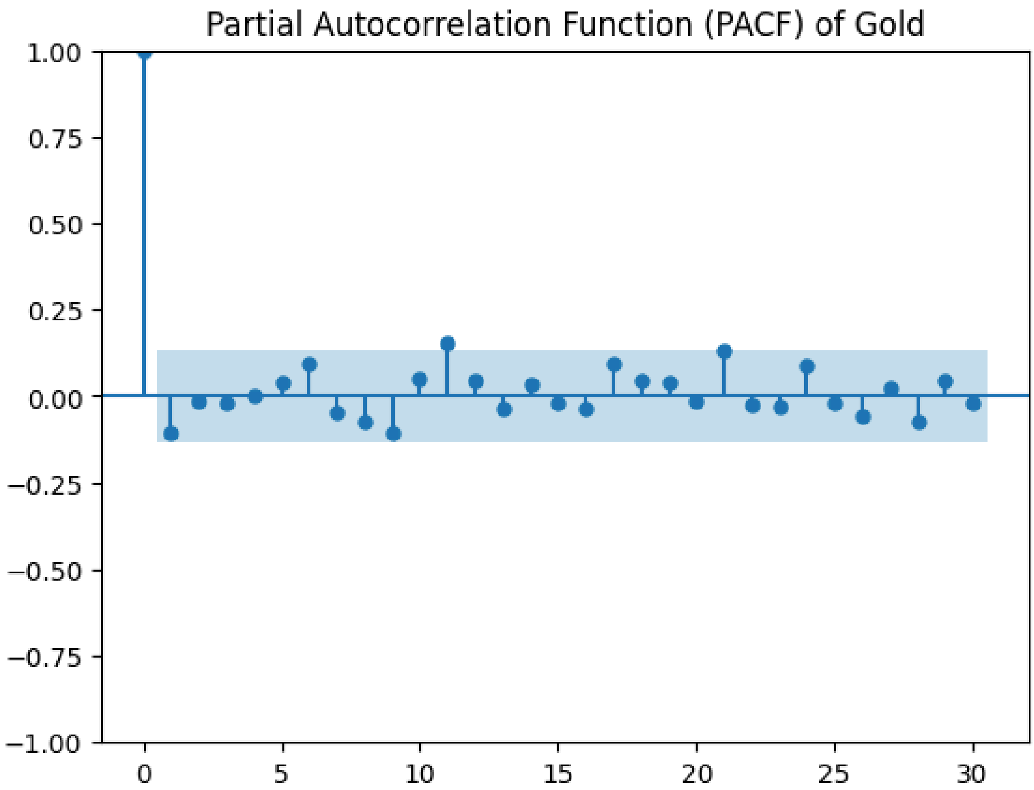

Partial Autocorrelation Function (PACF) of USDI
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25
30

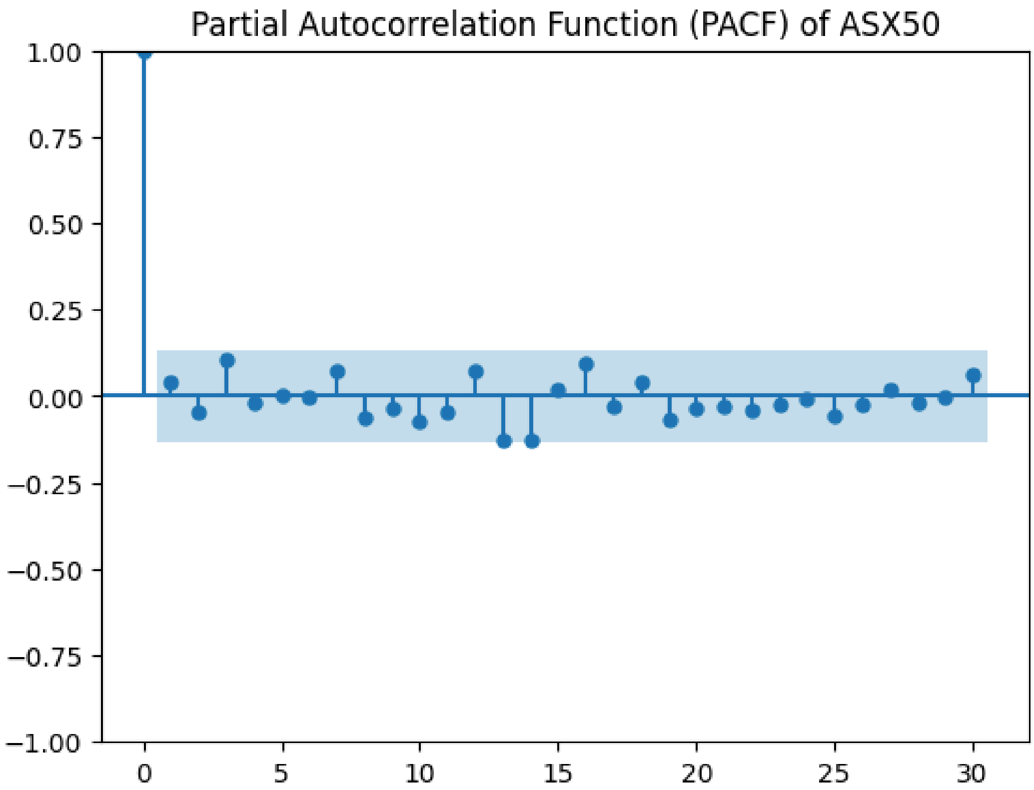

Partial Autocorrelation Function (PACF) of US EPU
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25
30

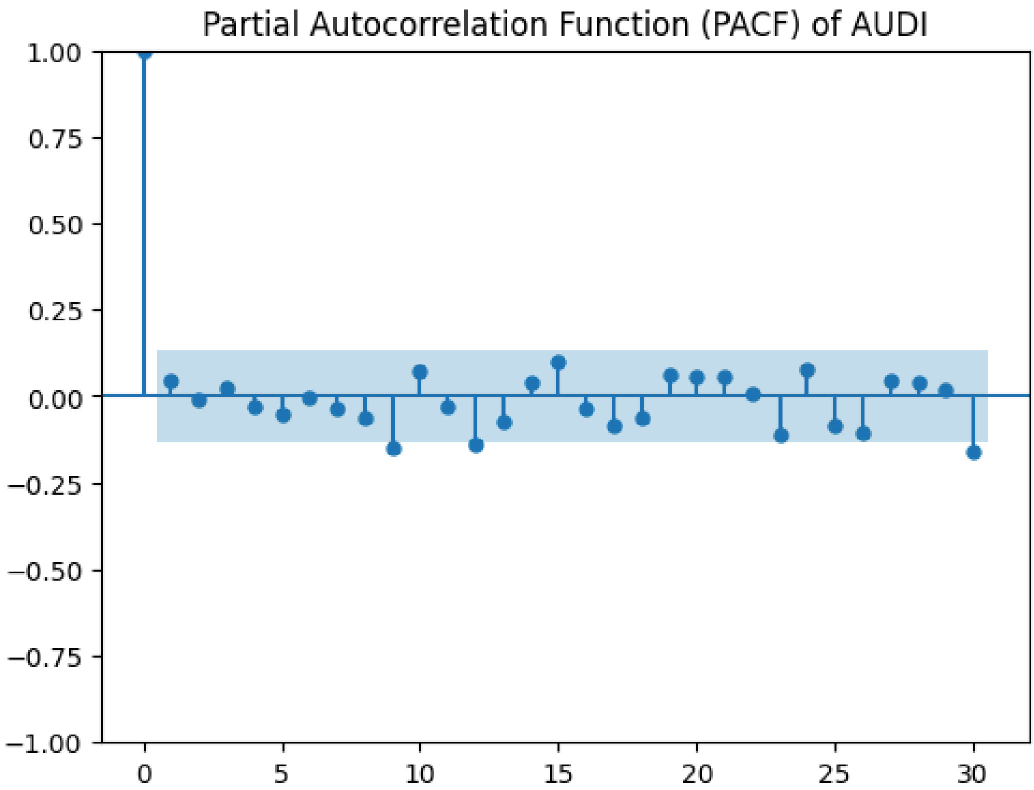


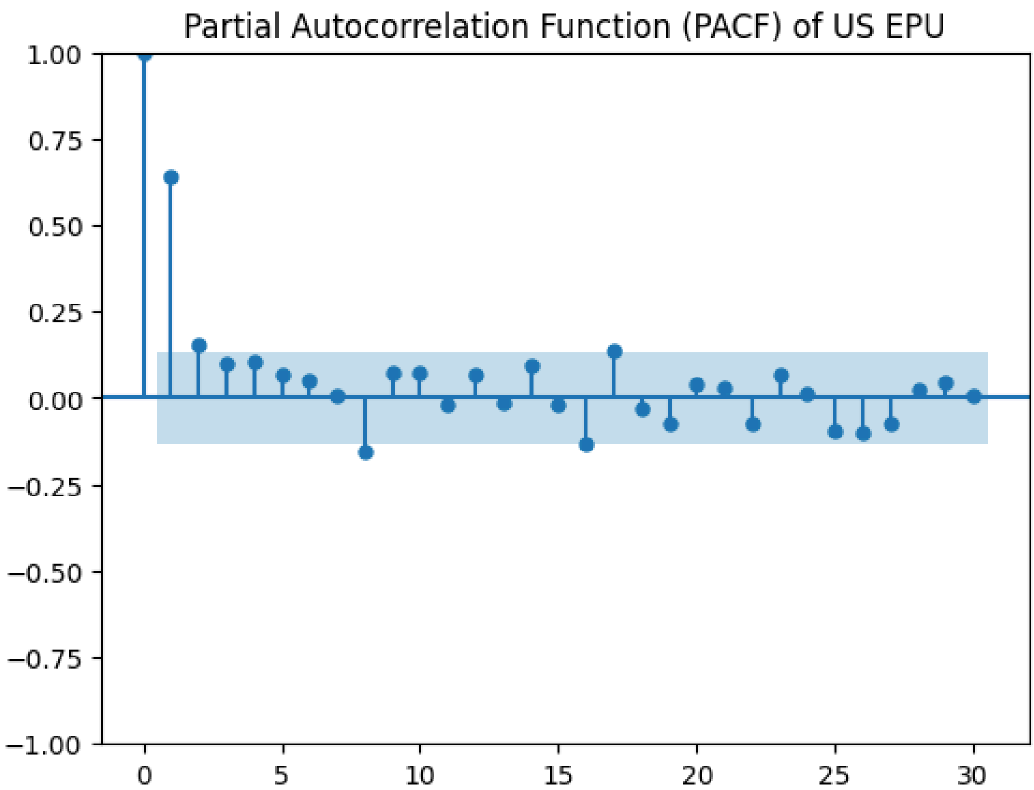
Part B - The Australian market:

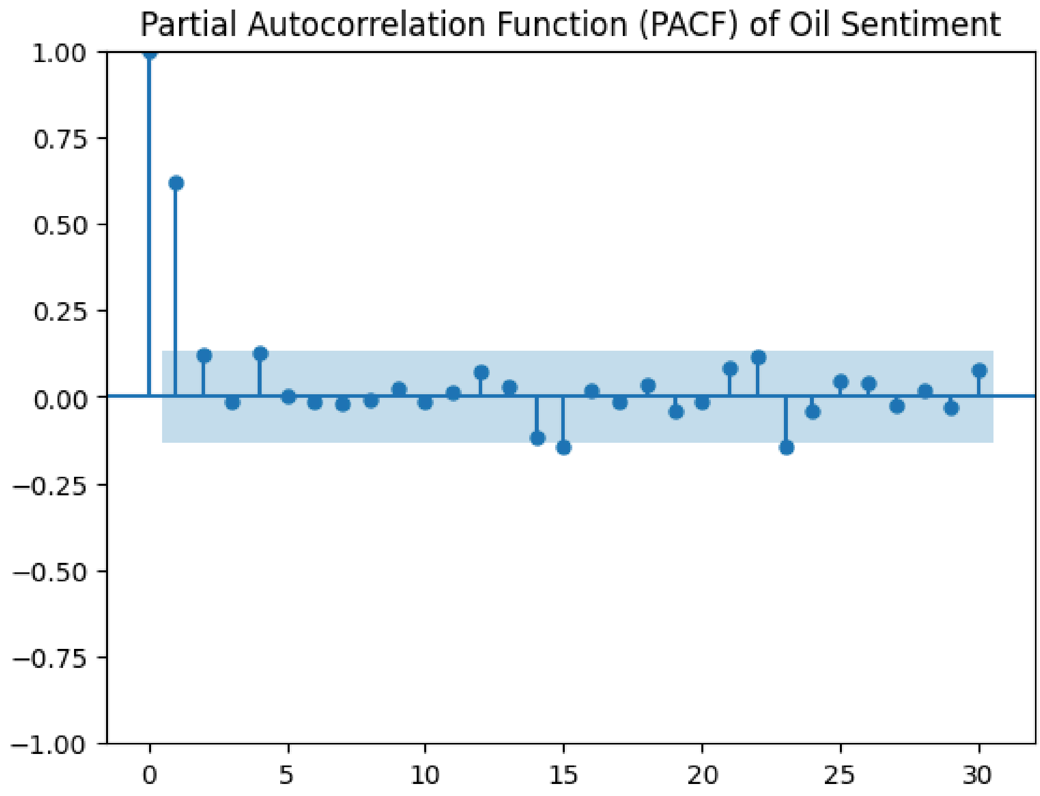



Partial Autocorrelation Function (PACF) of Gold
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25
30


Partial Autocorrelation Function (PACF) of ASX50
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25
30


Partial Autocorrelation Function (PACF) of AUDI
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25
30


Partial Autocorrelation Function (PACF) of US EPU
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25
30



Appendix 6: Stationary (ADF) test:

Part A - The US market:

```
Test Statistic for WTI: -10.1175
p-value for WTI: 0.0000
WTI is likely stationary (rejects unit root).
----------------------------------------
Test Statistic for Gold: -16.6353
p-value for Gold: 0.0000
Gold is likely stationary (rejects unit root).
----------------------------------------
Test Statistic for S&P500: -6.1997
p-value for S&P500: 0.0000
S&P500 is likely stationary (rejects unit root).
----------------------------------------
Test Statistic for USDI: -5.5376
p-value for USDI: 0.0000
USDI is likely stationary (rejects unit root).
----------------------------------------
Test Statistic for EPU: -3.3107
p-value for EPU: 0.0144
EPU is likely stationary (rejects unit root).
----------------------------------------
Test Statistic for OPU: -5.7686
p-value for OPU: 0.0000
OPU is likely stationary (rejects unit root).
----------------------------------------
```

Part B - The Australian market:

```
Test Statistic for Brent: -10.4260
```

```
p-value for Brent: 0.0000
Brent is likely stationary (rejects unit root).
--------------------------------------
Test Statistic for Gold: -16.6353
p-value for Gold: 0.0000
Gold is likely stationary (rejects unit root).
--------------------------------------
Test Statistic for ASX50: -14.3277
p-value for ASX50: 0.0000
ASX50 is likely stationary (rejects unit root).
--------------------------------------
Test Statistic for AUDI: -14.2829
p-value for AUDI: 0.0000
AUDI is likely stationary (rejects unit root).
--------------------------------------
Test Statistic for EPU: -3.9477
p-value for EPU: 0.0017
EPU is likely stationary (rejects unit root).
--------------------------------------
Test Statistic for OPU: -5.7686
p-value for OPU: 0.0000
OPU is likely stationary (rejects unit root).
--------------------------------------
```