Volatility Spillovers and Nexus across Oil, Gold, and Stock European Markets

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ABSTRACT

This paper utilises a trivariate VAR-BEKK-GARCH model to investigate the dynamic relationships between global oil price, gold price, and European stock markets. This paper observes weak return spillover effects from the oil market to 6 European stock markets (Netherlands, Lithuania, Portugal, Czech Republic, Romania, and Slovenia) and from gold to Iceland, while there is no evidence of return spillovers from stock markets to oil and gold. The non-existence of return linkages between gold and stock (oil) suggests that the gold market plays a haven role. With reference to volatility spillovers, the results show obvious asymmetric bidirectional volatility interaction between the European stock markets and the global oil/gold markets. Stronger shock and volatility contagions from the European stock market to both oil and gold markets are observed compared with the opposite direction. For the volatility nexus between oil and gold, weak and moderate evidence of shock and volatility transmission from gold to oil markets is reported. Additionally, the study documents important and effective empirical implications for portfolio management and investment hedge strategies: firstly, adding European stock markets to a diversified oil/gold portfolio can achieve the expected returns while reducing risk; and secondly, the European investors can use the gold and oil markets to hedge against their stock market portfolio.

KEYWORDS

Volatility Spill Overs and Nexus Across Oil, Gold, and Stock Markets, European Countries

INTRODUCTION

The commodity markets' rapid growth has led to intensified investments in recent decades. As such, these markets have demonstrated elevated variations in price behaviour, leading to upward and downward fluctuations. In general, price increases resulted from factors such as tightness in markets due to unfavourable weather conditions and macroeconomic events worldwide, such as the Global Financial Crisis (GFC) in 2008, causing a deep recession for many economies with a similar effect on the commodity markets. Consequently, it became crucial for investors to seek alternative options to diversify portfolio risk, leading to heightened investment activities in the commodity markets in recent years. Given the abrupt and volatile nature of commodity markets (such as oil and precious metals) and stock markets, it is pertinent for investors, portfolio managers and policymakers to comprehend the influential interdependencies between commodities, precious metal prices and the stock market, signaling a more profound analysis of the return and volatility amongst these markets (e.g., Ahmed & Huo, 2020; Ahmed & Huo, 2021). Since gold is often treated as a safe haven investment against movements occurring in the stock market, it is pertinent to further explore their links with the equity market as well as other commodities such as oil.

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The general belief is that returns of the stock and commodity markets are not correlated or negatively correlated and therefore lead to possible diversification benefits (Daskalaki & Skiadopoulos, 2011; Gorton & Rouwenhorst, 2006), which represents an important topic in recent years. Some empirical studies point out that the inclusion of commodities in investors' stock portfolios can have a hedging effect (e.g., Jensen et al., 2000). As this effect is realised over time, investors will transfer portions of their investment into commodity markets and hence increase the liquidity and capital inflows in those markets (Belousova & Dorfleitner, 2012). Recent research has suggested the interdependencies between commodity and stock markets have become stronger following the GFC (Aboura & Chevallier, 2015; Creti et al., 2013; Delatte & Lopez, 2013; Jain & Biswal, 2016; Kanjilal & Ghosh, 2017). Investors were induced to invest in precious metals and energy markets due to the stock market's heightened volatility in the aftermath of the GFC (Bampinas et al., 2019). Gold and oil are two of the most traded commodities and followed economic indicators, and many investors perceive them as an imperative safe haven to hedge against risk exposure in stock markets and an essential element of an investment strategy (Baur & McDermott, 2010; Chkili, 2016; Delatte & Lopez, 2013; Khalfaoui et al., 2015). Subsequently, the large inflow of commodity index trades has caused oil and gold markets to be more sensitive to the sentiment of financial markets (Büyükşahin & Robe, 2014).

The substantial literature on this topic mainly examines the volatility linkages between commodity variables (e.g., oil prices or precious metals) and stock markets (see Akkoc & Civcir, 2019; Basher & Sadorsky, 2016; Hamdi et al., 2019; Jain & Biswal, 2016; Lin & Su, 2020; Morema & Bonga-Bonga, 2020; Singhal & Ghosh, 2016). Particularly, scholars tend to focus on the return spill overs and heterogeneity of the commodity market's contagion impacts on the emerging economies or a single developed country. Yet few explicit attempts have been made to simultaneously investigate both return spill overs and volatility transmissions among oil, gold, and the developed and region-specific equity market at an aggregate level considering broad country samples together with implications for asset allocation and portfolio management. Addressing this domain is essential to gain a better understanding of the multilateral dimensions of the effect of oil/gold on the different levels of the real economy. Considering the economic significance of the European stock markets and the inadequacies of the extant literature, this study explores the time-varying return and volatility transmission between oil returns, gold returns, and European stock markets consisting of a large sample of 24 European countries based on a more efficient trivariate VAR-BEKK-GARCH model.

This study also closely examines whether gold and oil can still be utilised to diversify and hedge against investment portfolio and uncover possible reflections on optimal investment decisions, hedging portfolio asset allocation, and risk management to safeguard the economic environment. It uses the daily data expanding through the last decade, from 5 January 2009 to 28 June 2019, encompassing several unstable periods of the commodity and European stock markets, such as post-GFC, the 2009 European sovereign debt crisis and the period following this. In terms of the sample countries, I include the southern European GIIPS (Greece, Ireland, Italy, Portugal, and Spain) group, the largest European stock market (UK), the biggest economy (Germany), the Nordic equity markets and the Baltic markets. Through the analysis of different types of European markets over the turbulent period, this study provides a more holistic understanding of the contagion and interdependency across international commodity markets and European stock returns during the European sovereign debt crisis period. Moreover, the Brent oil price is used to represent the international crude oil market since it has been broadly regarded as a benchmark for global oil markets (Arouri, Jouini, et al., 2011), and the LBMA (London Bullion Market Association) gold price proxies for the global gold market. The results indicate that the oil and gold markets are more sensitive to any fluctuation in the European stock markets; nevertheless, the oil and gold markets still play vital roles in predicting the volatility of some European stock markets. Moreover, the empirical results show there is no evidence of shock spillover effects from oil to gold markets, while the shock spillover effects from gold to oil markets are weak.

As well, it observes weak and moderate evidence of shock and volatility transmission from gold to oil markets. Furthermore, a hedging effect is present when European stocks are added into a well-diversified gold or oil portfolio, and the same impact exists for the opposite. effect for most cases, implying that the negative volatility spillovers overshadow good volatility spillovers.

This paper contributes to the existing literature in four ways. First, to the best of my knowledge, this is the first study to analyse the volatility spillover and interactions between oil, gold, and the entire European stock market, which represents a sizable proportion of the global markets. More specifically, this paper extends a specific perspective on the contagion effects from commodity markets (oil and gold) to the developed regional stock markets using the cases of 24 typical European countries. Second, this research employs the trivariate VAR-BEKK-GARCH model to examine this profound spillover effect. Third, it reports unique asymmetric bidirectional volatility transmissions between the European stock markets and the global gold/oil markets during the most unstable eurozone crisis period. Fourth and lastly, the empirical results from the interaction between the commodity and European stock markets indicate obvious benefits for risk management, portfolio diversification, and hedging, showing that adding the European market to a diversified oil/gold portfolio can lead to better performance. Furthermore, the findings demonstrate huge hedging efficiency that European investors can achieve when using the gold and oil markets to hedge against their equity portfolio. The remainder of this paper is structured as follows. Section 2 contains the literature review and section 3 presents the data. Section 4 outlines the methodological framework. The empirical results and findings are analysed in section 5, and lastly, section 6 concludes the paper.

LITERATURE REVIEW

There is a vast amount of literature on the relationship between commodity markets and stock markets, especially on volatility and return. Yun and Yoon (2019) study the impact of changes in oil prices on the stock price and volatility of airlines in China and South Korea using the VAR-GARCH-BEKK model. The findings show the spillover effect for volatility is much stronger compared to the return spillover effect. Jung and Park (2011) examine the reactions of aggregate stock returns and their volatility to oil price shocks in small open economies, namely the Norwegian and South Korean markets. They establish that the aggregate stock returns and volatility responses vary considerably, depending on two things: the underlying origin of the oil price rise and whether the economy is an oil importer or exporter. In addition, Tchatoka et al. (2019) assess the correlation between oil price shocks and stock market returns and discover that large positive oil price shocks frequently lead to higher market returns for both oil exporting and importing countries when their stock markets perform well. Samanta and Zadeh (2012) find that the possibility of cointegration amongst several macro-variables such as crude oil price, stock price, exchange rate, and gold price are minimal when investigating their co-movement. Xu et al. (2019) research the link between oil and stock markets from the time-varying asymmetric volatility spillover aspect, employing a quantitative approach. They report the evidence of asymmetric spillover effect for most cases, implying that the negative volatility spillovers overshadow good volatility spillovers.

Raza et al. (2016) investigate how gold and oil prices and their volatilities influence emerging markets. The results reveal that gold prices have a positive impact on the BRICS stock market prices whereas the oil prices negatively influence all emerging stock markets. Furthermore, the volatilities of the oil and gold adversely affect all the emerging stock markets in their study. Whilst measuring the volatility behaviour of gold, silver and copper, Hammoudeh and Yuan (2008) discover that past positive oil shocks have a cooling impact on current gold and silver volatilities but no effect on copper volatility. Ahmadi et al. (2016) also note significant differences for gold, silver and copper's responses

to oil price shocks, but find speculative demand shocks weaken the volatility of silver and improve the volatility of copper.

Furthermore, Bjørnland (2009) explores the effects of oil price shocks on Norway's stock returns using a structural VAR model. As an oil exporting country, Norway's economy reacts to heightened oil prices by increasing aggregate demand which can immediately increase its stock market return by 2-3% following a 10% increase in oil prices. As the oil market is often regarded as a leading economic indicator, rising oil prices caused by increased oil demand suggests a higher stock market return (Park & Ratti, 2008). On the other hand, the research conducted by Cunado and Perez de Gracia (2014) finds a strong negative impact of oil price changes on most European stock market returns when investigating the effect of oil price shocks on the stock returns of twelve oil importing economies in Europe based on VAR (Vector Autoregressive model) and VECM (Vector Error Correction Models). For the Chinese market, oil price shocks and volatility do not demonstrate a notable impact on the stock returns for major market indices in China, while an increase in oil volatility can potentially increase market returns in the mining and petro-chemicals indices (Cong et al., 2008). Emphasising the return and volatility link between the Pakistan Stock Exchange and Brent oil prices, Malik and Rashid (2019) could not find any evidence of volatility spillover between Brent oil and the Pakistan stock market in both the short- and long-term using bivariate VAR-AGARCH model. Moreover, Kilian and Park's (2009) and Kilian's (2009) studies suggest that the reactions of U.S. stock returns to oil price shocks vary depending on whether they are propelled by oil supply shocks or oil demand shocks. The analysis by Henriques and Sadorsky (2008) shows that technology stock price shocks have a more significant impact on alternative energy stock prices compared to oil price shocks.

Due to differences in the stock and commodities markets, it is expected that there exists to some extent diversification benefits for investors when including commodity assets into their portfolios (Hammoudeh et al., 2014). Gorton and Rouwenhorst (2006) discover that commodity futures and stocks have a negative correlation, indicating that investors can select these commodities for potential diversifying benefits. Akbar et al. (2019) investigate the correlation between stock prices, gold price, the exchange rate and interest rate in Pakistan. The findings demonstrate an inverse bilateral relationship between stock and gold prices, indicating that as stock prices decrease, gold prices have the contrasting effect, and therefore suggest gold not only is a safe haven but also as an alternative investment option during adverse stock price movements. Jiang et al.'s study (2019) uses a DCC-GJR-GARCH model to explore the connection between the international oil market and Chinese commodity markets. Their results show that the link between oil-commodity sectors can help investors develop excellent portfolios that can help to reduce risks. Maghyereh et al. (2019) examine the link amongst Sukuk, Islamic equities and gold and their research discovers that gold has a hedging and diversification effect for both Sukuk and Islamic stocks. Tursoy and Faisal (2018) examine the associations between Turkish stock prices, gold prices and crude oil prices. Their short-term and long-term analysis results confirm a negative correlation between the stock and gold prices, but the opposite is the case for between stock and oil. Sadorsky (2001) finds that exchange rates, crude oil prices and interest rates, crude oil price and exchange rate all have substantial effects on stock price returns in the Canadian oil and gas industry based on a multifactor market model. Moreover, as the oil and gas sectors display a pro-cyclical nature and less risky nature, the study suggests that these two commodities may not have a hedging effect against inflation, which contradicts what most of the literature contends.

In recent decades, there is an increasing focus on the relationship among oil, precious metals such as gold and the stock market, and the risk diversification implications and hedging effects. Narayan et al. (2010) suggest that the inflationary pressures due to an increase in the oil price can boost investments in gold which is effectively used to hedge against inflation. Basher and Sadorsky (2016) use the DCC-, ADCC- and GO-GARCH variants to model volatilities and interdependence between

emerging stock market, gold prices, oil prices, VIX, and bond prices. Their hedge ratios estimated using the GO-GARCH model for gold are most effective for hedging emerging market stock prices on several occasions while oil elicits the best hedging effect for most cases. Jain and Biswal (2016) evaluate the financial linkages between the Indian stock market, exchange rate, international oil price and global gold market. The findings stipulate that a drop in gold and crude oil prices leads to a reduced value of the Indian rupee, supporting gold as a hedging asset for investors. While focusing on the relationship between gold and oil market futures and stock returns in the US, Junttila et al. (2018) observe that the correlation between gold and US equities becomes negative, substantiating the safe haven assumption of gold. Bedoui et al. (2019) employed the nested copula-based GJR-GARCH model to study the dependence structure between the US dollar exchange rate, gold, and oil. They subsequently find that the dependence between the three during crisis periods is stronger compared to undisturbed periods.

Singhal et al. (2019) research the relationship among exchange rate, global gold prices, international oil prices and the Mexican stock market index since Mexico is a major oil and gold exporting country. Employing the ARDL Bound testing cointegration approach, they found that oil prices adversely affect both the stock market and exchange rate of Mexico, while international gold prices only have the opposite effect for stock prices but no substantial influence on the exchange rate. In their research, Balli et al. (2019) note that the connections among commodities' uncertainty indices intensified during the GFC and the 2014-2016 oil price collapse. The results of the analysis indicate that as precious metals displayed less correlations with other non-metal commodities, precious metals played a safe haven role during crises. Mensi et al. (2018) investigate the co-movements between the BRIC countries' (Brazil, Russia, India, China and South Africa) stock markets, gold price, WTI (West Texas Intermediate) and Brent crude oil prices but find no market interdependence between the gold and BRIC nations' stock markets, meaning that gold has a hedging effect. Therefore, portfolio risk is impacted by the connectedness between oil and stock markets. Moreover, Elie et al. (2019) confirm the weak roles of crude oil and gold as safe haven assets against overall downward movements in clean energy stock indices.

On the other hand, Kang et al. (2017) explore the spillover effects between rice, wheat corn, WTI crude oil, silver and gold using the multivariate DECO-GARCH model. Their results show a positive equicorrelation between commodity market returns which increases significantly during the financial turmoil periods. It indicates that the diversification advantages of an international portfolio could be reduced. Bouri et al. (2017) contend that the volatilities of gold and oil affect the Indian domestic stock market nonlinearly based on a cointegration and nonlinear causality method using implied volatility indices, as gold and oil are amongst India's top imports. Bassil et al. (2019) observe the sign and magnitude of a long-term relationship between the daily prices of gold and oil are not the same over different regimes, confirming that such a relationship will change over time. Therefore, the oil price, as a biased predictor is not very relevant in estimating future gold prices. Akkoc and Civcir (2019) use different specifications of the SVAR-DCC-GARCH model to examine the volatility spillover from oil and gold to Turkey's stock market following the GFC. Their results confirm the presence of time-varying market interdependence and volatility transmission from the prices of oil and gold to Borsa Istanbul Stock Exchange Index with a stronger influence of gold. From this it emerges that gold may be unable to serve as a bulwark against the market risk. While studying the dynamics between stocks, exchange rates and gold prices, Beckmann et al.'s (2019) findings support the assertion that gold as a safe haven is able to shield investors before the collapse of Lehman Brothers. Nevertheless, the role of gold changes significantly after the Global Financial Crisis in 2008, and the essential implication is that gold is unable to hedge investors' portfolios.

DATA

This paper explores the return and volatility transmissions among oil price, gold price and 24 stock markets in Europe. It employs the raw data of daily price/index of oil, gold and the European stock markets compiled from DataStream. The sample period is between 5 January 2009 to 28 June 2019 and covers several erratic episodes of the commodity and European stock markets. It uses the Brent oil price to represent the international crude oil market, as it is widely viewed as a benchmark of the global oil market, pricing approximately 70% of crude oil traded worldwide (Arouri, Jouini, et al., 2011). LBMA (London Bullion Market Association) gold price is employed to proxy for the global gold market and the most representative stock indices in the EU are used in this research[1]. Since the financial markets are characterised by heterogeneity, the varieties of stock markets selected in this study provide deeper insights into dynamic linkages to different financial markets. The returns used in this study are calculated as 100, multiplying the difference between the natural logarithms of the prices at current and previous periods[2].

Table 1 reports the descriptive statistics of market return for the global oil market, gold market, and the European stock markets. From Table 1, it is easily observed that the average returns for most markets are positive with exceptions of the stock markets in Cyprus, Greece, Luxembourg, Portugal, Slovakia, and Spain. In terms of the standard deviation which measures the unconditional volatility, I observe the highest value in the Cyprus stock market (2.389) with the second highest in the Greece stock market (2.352) while Lithuania's stock market has the lowest risk with a standard deviation of 0.861. The oil and gold markets both have a moderate return and risk level compared with all the European stock markets as reflected by the mean and standard deviation statistics. In addition, most market returns are negatively skewed, highlighting that the return data are distributed asymmetrically. The value of kurtosis ranging from the lowest 5.653 for the German stock market to the highest 523.353 for the Slovenian stock market indicates the return is highly leptokurtic with fat tails compared to a normal distribution. The Jarque–Bera test statistics can reject the null hypothesis of normality for all the market returns at the 1% significance level, confirming the non-normality of market returns. Q(20) - the statistics of the Ljung-Box Q statistic test with 20 lags regarding autocorrelation - is significant at the 10% significance level for the majority of the returns series. It suggests that the market returns exhibit serial correlation and confirm the VAR model's appropriateness. As a result, the preliminary descriptive statistics demonstrate that the market return data is asymmetrically and non-normally distributed with excess kurtosis and autocorrelation, indicating the appropriateness to employ GARCH0-type models accompanied by VAR estimation. This makes it possible to estimate the time-varying conditional variance and covariance.

For stationarity, it employs two different unit root tests: the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1981) and the Phillips-Perron (PP) test (Phillips & Perron, 1988) to verify the order of integration for all the variables. As noted in Table 2, both ADF and PP statistics suggest that all of the price level data have a non-stationary feature while their first differences are stationary. The ADF^L and PP^L values are negative for the oil market, the gold market and all of the European stock markets with the exception of Iceland, which has a positive PP^L value. It can therefore be concluded that the prices for oil, gold and all European stock markets are I(1) since ADF and PP statistics are insignificant for the level data but significant for the first differences. This outcome supports further use of the Johansen and Juselius cointegration test which is discussed in the methodology and findings sections.

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[1] I use AEX Index for Netherlands, ATX for Austria, BEL 20 Index for Belgium, BUX for Hungary, Cyprus General Index for Cyprus, Dax 30 for Germany, CAC 40 Index for France, MIB Index for Italy, ATHEX20 for Greece, IBEX35 for Spain, ISEQ for Ireland, Lux Stock Exchange General Index for Luxembourg, HEX for Finland, OMX Iceland All-Share Index for Iceland, OMX Stockholm 30 for Switzerland, OMX Vilnius_GI for Lithuania, PSI-20 for Portugal, PX Index for Czech Republic, BET Index for Romania, SAX for Slovakia, SBI Top for Slovenia, SMI for Sweden, Warsaw General Index for Poland and FTSE 100 for the UK.
[2] $R_t = 100*ln(P_t/P_{t-1})$, where P_t is the raw data of daily price/index of oil, gold and stock markets in this research at time t.

Table 1. Descriptive Statistics for Market Returns

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	JB	Q(20)
Oil	0.015	0.021	10.867	-11.128	1.857	0.145	6.156	1144	18.554
Gold	0.019	0.017	6.865	-10.162	1.009	-0.548	10.226	6086	39.269
Austria	0.018	0.000	8.709	-9.012	1.367	-0.296	6.390	1349	37.905
Belgium	0.021	0.017	8.955	-6.613	1.098	-0.084	6.882	1720	40.841
Cyprus	-0.100	0.000	16.958	-15.525	2.389	0.135	10.925	7164	67.720
Czech Republic	0.006	0.000	7.249	-7.037	1.101	-0.188	8.164	3054	43.024
Finland	0.017	0.000	7.131	-8.160	1.219	-0.175	6.439	1361	31.632
France	0.018	0.015	9.221	-8.384	1.268	-0.128	6.791	1644	26.905
Germany	0.033	0.054	5.895	-7.067	1.250	-0.224	5.653	824	21.940
Greece	-0.054	0.000	16.374	-17.878	2.352	-0.216	8.993	4113	59.733
Hungary	0.042	0.001	10.674	-7.573	1.339	0.106	7.207	2021	44.802
Iceland	0.033	0.000	4.763	-13.612	0.874	-1.398	28.276	73668	37.175
Ireland	0.033	0.021	7.570	-10.416	1.248	-0.526	8.664	3781	39.723
Italy	0.002	0.011	10.684	-13.331	1.571	-0.354	7.179	2046	32.393
Lithuania	0.048	0.004	10.927	-11.938	0.861	0.077	36.321	126484	118.70
Luxembourg	-0.010	0.000	8.829	-7.441	1.542	-0.005	5.841	920	39.508
Netherlands	0.028	0.044	7.072	-5.873	1.129	-0.173	6.374	1310	22.089
Poland	0.028	0.000	5.799	-6.881	1.063	-0.360	7.190	2059	46.132
Portugal	-0.009	0.007	10.196	-7.247	1.207	-0.226	6.743	1620	67.507
Romania	0.040	0.022	10.565	-13.117	1.301	-0.956	19.065	29818	81.371
Slovakia	-0.001	0.000	11.880	-14.810	1.159	-1.232	26.530	63763	62.005
Slovenia	0.002	0.000	40.474	-40.354	1.391	0.014	523.353	30844921	218.64
Spain	-0.002	0.017	13.484	-13.185	1.405	-0.145	10.367	6192	46.064
Sweden	0.038	0.031	6.114	-8.072	1.134	-0.290	6.776	1663	39.495
Switzerland	0.020	0.021	4.903	-9.070	0.961	-0.607	8.922	4162	29.276
UK	0.018	0.015	5.032	-5.481	0.984	-0.177	5.977	1024	17.731

Note: Each country's name represents its stock market index return. Q(20) is statistically significant at the 10% significance level except for oil, France, Germany, Netherlands and the UK.

Table 2. Unit Root Test Results

	ADF^L	PP^L	ADF^D	PP^D
Oil	*-1.604*	*-1.650*	*-51.934*	*-51.975*
Gold	*-2.408*	*-2.387*	*-52.631*	*-52.643*
Austria	*-2.203*	*-2.078*	*-49.411*	*-49.346*
Belgium	*-1.617*	*-1.538*	*-49.822*	*-50.042*
Cyprus	*-1.351*	*-1.354*	*-48.418*	*-48.423*
Czech Republic	*-2.683*	*-2.697*	*-50.452*	*-50.422*
Finland	*-1.402*	*-1.318*	*-50.586*	*-50.662*
France	*-1.506*	*-1.406*	*-52.157*	*-52.261*
Germany	*-1.198*	*-1.176*	*-51.883*	*-51.896*
Greece	*-1.780*	*-1.687*	*-38.567*	*-49.303*
Hungary	*-0.453*	*-0.326*	*-52.910*	*-53.131*
Iceland	*-0.010*	*0.068*	*-39.135*	*-52.489*
Ireland	*-1.020*	*-1.115*	*-27.055*	*-50.013*
Italy	*-2.740*	*-2.644*	*-53.866*	*-53.907*
Lithuania	*-1.106*	*-1.186*	*-49.208*	*-49.356*
Luxembourg	*-2.103*	*-2.104*	*-56.929*	*-57.038*
Netherlands	*-1.108*	*-1.096*	*-50.710*	*-50.691*
Poland	*-2.020*	*-2.006*	*-48.570*	*-48.440*
Portugal	*-1.886*	*-1.780*	*-47.961*	*-47.850*
Romania	*-1.532*	*-1.532*	*-30.579*	*-51.164*
Slovakia	*-1.457*	*-1.301*	*-57.406*	*-58.953*
Slovenia	*-1.478*	*-1.438*	*-61.288*	*-61.851*
Spain	*-2.843*	*-2.776*	*-50.099*	*-50.116*
Sweden	*-1.252*	*-1.174*	*-52.993*	*-53.349*
Switzerland	*-1.258*	*-1.141*	*-50.041*	*-50.199*
UK	*-1.988*	*-1.905*	*-51.879*	*-52.018*

Note: When conducting ADF and PP tests, an intercept is included in the test equation. ADF^L and PP^L represent level data while ADF^D and PP^D stand for the first difference of the level data. ADF^D and PP^D are all significant at the 1% level while ADF^L and PP^L are not significant.

Table 3. Johansen and Juselius Cointegration Test Results

No. of CE	Trace statistic			Max-Eigen statistic		
	None	At most 1	At most 2	None	At most 1	At most 2
Austria	34.426	16.619	6.688	17.806	9.932	6.688
Belgium	28.207	14.565	5.000	13.642	9.565	5.000
Cyprus	38.078	17.642	7.021	20.436	10.620	7.021
Czech Republic	33.163	18.220	8.310	14.943	9.911	8.310
Finland	34.147	16.176	6.534	17.971	9.643	6.534
France	39.119	15.972	6.584	23.148	9.388	6.584
Germany	28.707	16.019	6.071	12.688	9.948	6.071
Greece	35.347	13.145	5.643	22.203	7.501	5.643
Hungary	37.504	21.448	8.106	16.056	13.343	8.106
Iceland	33.635	15.707	5.655	17.927	10.053	5.655
Ireland	26.074	11.464	3.218	14.610	8.246	3.218
Italy	34.078	14.959	6.542	19.119	8.417	6.542
Lithuania	31.322	14.822	6.122	16.500	8.700	6.122
Luxembourg	31.986	16.990	6.955	14.996	10.035	6.955
Netherlands	36.172	16.441	6.674	19.731	9.767	6.674
Poland	28.288	15.072	5.882	13.216	9.190	5.882
Portugal	38.164	14.575	5.589	23.588	8.986	5.589
Romania	32.566	17.899	5.450	14.667	12.450	5.450
Slovakia	41.837	13.536	4.688	28.302*	8.848	4.688
Slovenia	32.695	12.043	4.781	20.652	7.261	4.781
Spain	31.235	16.184	5.862	15.050	10.323	5.862
Sweden	33.094	16.027	6.157	17.068	9.870	6.157
Switzerland	32.400	16.087	5.747	16.313	10.340	5.747
UK	33.666	16.514	6.433	17.152	10.082	6.433

Note: I allow for a linear deterministic trend in the data with intercept and trend in the cointegration equation when testing the Johansen and Juselius cointegration. ***** represents the rejection of the null hypothesis at the 5% significance level.

METHODOLOGY FRAMEWORK

I use the approach introduced by Johansen and Juselius (1990) to check for cointegration relationship among the price series of $P_t^{oil}, P_t^{gold} \ and \ P_t^{st}$.

The Johansen and Juselius approach use the estimation of the following VAR:

$$P_t = A_0 + \sum_{i=1}^{p} A_i P_{t-i} + \varepsilon_i \tag{1}$$

where $P_t = (P_t^{oil}, P_t^{gold}, P_t^{st})'$

Equation (1) can then be rewritten as:

$$\Delta P_t = A_0 + \Pi P_{t-p} + \sum_{i=1}^{p-1} \Gamma_i \Delta P_{t-i} + \varepsilon_i \qquad (2)$$

where

$$\Pi = \sum_{i-1}^{p} A_i - I \ and \ \Gamma_i = \sum_{i-1}^{p-1} A_i - I$$

Trace and Maximum Eigenvalue statistics which are calculated below are commonly used to identify the existence of cointegrating relationships:

$$\text{Trace statistic: } \lambda_{Trace}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i) \qquad (3)$$

$$\text{Maximum eigenvalue statistic: } \lambda_{Max}(r) = -T \ln(1 - \hat{\lambda}_{r+1}) \qquad (4)$$

where T is the sample size and $\hat{\lambda}_i$ is the ith largest canonical correlation.

Moving to the conditional volatility, General Autoregressive Conditional Heteroskedasticity models were generalised by Bollerslev (1986) based on the Autoregressive Conditional Heteroskedasticity model which was introduced by Engle (1982). After that, these methodologies are widely used to forecast market volatility due to their ability to capture the time-varying conditional variances and consider key features of financial time series (e.g., the volatility clustering effects). Since there are strong interdependencies between different financial markets, multivariate GARCH (MGARCH) models are then developed to capture the dynamics in market volatility among different markets and facilitate research on multidimensional relationships among the financial markets. By specifying the conditional variance and covariance equations, MGARCH models have widely been used to investigate how the correlation and covariance between different variables change dynamically over time. Therefore, it employs the BEKK (Baba, Engle, Kraft and Kroner) multivariate GARCH models (Engle & Kroner, 1995), which are more relevant compared to univariate models when investigating volatility interdependence and transmission mechanisms among different financial time series.

Several empirical studies successfully employing the MGARCH models with BEKK specification indicate the superiority of BEKK GARCH models and their ability to satisfactorily capture the stylised facts of the conditional volatility and dynamics of volatility interaction (see Chang et al., 2011; Chuang et al., 2007; Hassan & Malik, 2007; Huo & Ahmed, 2017; Jouini & Harrathi, 2014; Salisu & Oloko, 2015). There are several advantages of applying VAR-BEKK-GARCH. First of all, it can produce more accurate forecasts than traditional multivariate GARCH which is limited to modelling extreme cases of risk spillovers, such as the GED-GARCH model. Secondly it is more efficient since it requires fewer parameters and less computational complexity when estimating spillover among multi markets. Thirdly, by incorporating the VAR model into BEKK GARCH, it is able to explore the joint evolution of conditional returns and volatility spillover between different markets simultaneously (Yu et al., 2020).

As well as the above benefits of VAR-BEEK-GARCH, I also extend the traditional bivariate model (commonly used by published studies on bilateral volatility transmissions) to a trivariate VAR-BEKK-GARCH, which makes it possible to examine the trilaterial dynamics among oil, gold, and European stock markets at the same time. Thus, when estimating the return and volatility transmission, the trivariate VAR-BEEK-GARCH model is constructed as follows.

The conditional mean model of VAR (1) is given by:

$$R_t = \mu + GR_{t-1} + \varepsilon_t, \varepsilon_t | \Omega_{t-1} \sim N(0, H_t) \tag{5}$$

where R$_t$ denotes a vector of oil market return, gold market return and European stock market return: $R_t = (R_{oil,t}, R_{gold,t}, R_{st,t})'$, G is a (3×3) matrix of VAR coefficients, ε_t is a vector of Gaussian error: $\varepsilon_t = (\varepsilon_{oil,t}, \varepsilon_{gold,t}, \varepsilon_{st,t})'$ and μ represents a vector of constants: $\mu = (\mu_{oil}, \mu_{gold}, \mu_{st})'$.

Moving to the conditional variance, BEKK parameterisation is a more practical and popular parameterisation approach compared to the VECH method. This is because BEKK-GARCH models can simplify the estimation process by computing the reduced number of parameters. In this way, the difficulty in guaranteeing a positive conditional variance and covariance matrix H_t without restrictions on parameters under VECH parameterisation can be overcome. Since the quadratic forms are used to release the positive restriction on the conditional variance matrix in the BEKK-GARCH model and therefore the estimation process can be further simplified.

The conditional variance equation is given as:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{6}$$

where

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{bmatrix}, C = \begin{bmatrix} c_{11} & & \\ c_{21} & c_{22} & \\ c_{31} & c_{32} & c_{33} \end{bmatrix},$$

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \text{ and } B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}.$$

As shown above, A is a 3×3 matrix, capturing the correlation effects between the conditional variances and past shocks. B is also a 3×3 matrix, indicating the effects of past conditional variances on current conditional variances. C is a 3×3 lower triangular matrix with six parameters. The total number of estimated parameters for the trivariate variance equations is 24. The diagonal elements of matrices A (a_{11}, a_{22} and a_{33}) and B (b_{11}, b_{22} and b_{33}) measure the effect of previous shocks and volatility on the current conditional variance, respectively. In contrast, the off-diagonal elements of matrices A (e.g., a_{12}, a_{13} and a_{21}) and B (e.g., b_{12}, b_{13} and b_{21}) are able to reflect the volatility interdependence across the markets. Therefore, the conditional variance for the European stock markets, for example, is not only impacted by its past shocks and conditional variance, but also by those of the oil and gold markets. Indicated here is the existence of direct shocks and volatility transmission between one market and another. Following Hassan and Malik (2007), the conditional variance equation for each market, disregarding the constant coefficients, can be expanded as follows:

$$h_{11,t} = a_{11}^2 \varepsilon_{oil,t-1}^2 + 2a_{11}a_{12}\varepsilon_{oil,t-1}\varepsilon_{gold,t-1} + 2a_{11}a_{31}\varepsilon_{oil,t-1}\varepsilon_{st,t-1} + a_{21}^2 \varepsilon_{gold,t-1}^2 +$$
$$2a_{21}a_{31}\varepsilon_{gold,t-1}\varepsilon_{st,t-1} + a_{31}^2 \varepsilon_{st,t-1}^2 + b_{11}^2 h_{11,t-1} + 2b_{11}b_{12}h_{12,t-1} + 2b_{11}b_{31}h_{13,t-1} +$$
$$b_{21}^2 h_{22,t-1} + 2b_{21}b_{31}h_{23,t-1} + b_{31}^2 h_{33,t-1} \tag{7}$$

$$h_{22,t} = a_{12}^2 \varepsilon_{oil,t-1}^2 + 2a_{12}a_{22}\varepsilon_{oil,t-1}\varepsilon_{gold,t-1} + 2a_{12}a_{32}\varepsilon_{oil,t-1}\varepsilon_{st,t-1} + a_{22}^2 \varepsilon_{gold,t-1}^2 +$$
$$2a_{22}a_{32}\varepsilon_{gold,t-1}\varepsilon_{st,t-1} + a_{32}^2 \varepsilon_{st,t-1}^2 + b_{12}^2 h_{11,t-1} + 2b_{12}b_{22}h_{12,t-1} + 2b_{12}b_{32}h_{13,t-1} +$$
$$b_{22}^2 h_{22,t-1} + 2b_{22}b_{32}h_{23,t-1} + b_{32}^2 h_{33,t-1} \tag{8}$$

$$h_{33,t} = a_{13}^2 \varepsilon_{oil,t-1}^2 + 2a_{13}a_{23}\varepsilon_{oil,t-1}\varepsilon_{gold,t-1} + 2a_{13}a_{33}\varepsilon_{oli,t-1}\varepsilon_{st,t-1} + a_{23}^2 \varepsilon_{gold,t-1}^2 +$$
$$2a_{23}a_{33}\varepsilon_{gold,t-1}\varepsilon_{st,t-1} + a_{33}^2 \varepsilon_{st,t-1}^2 + b_{13}^2 h_{11,t-1} + 2b_{13}b_{23}h_{12,t-1} + 2b_{13}b_{33}h_{13,t-1} +$$
$$b_{23}^2 h_{22,t-1} + 2b_{23}b_{33}h_{23,t-1} + b_{33}^2 h_{33,t-1} \tag{9}$$

The following logarithm likelihood function would be maximised with a normal distribution for the error terms when estimating the above equations:

$$L(\theta) = \sum_{t=1}^{T} L_t(\theta) \tag{10}$$

The log likelihood function of the joint distribution is given as:

$$L_t(\theta) = -\ln(2\pi) - \frac{1}{2}ln|H_t| - \frac{1}{2}\varepsilon_t' H_t^{-1}\varepsilon_t \tag{11}$$

where θ is the vector of parameters to be estimated and T denotes the number of observations.

Since the equation above is non-linear, I use the BFGS (Broyden, Fletcher, Goldfarb, and Shanno) algorithms as the maximisation technique to obtain the initial condition and further estimate the parameters in the variance-covariance matrix.

RESULTS

RESULTS OF COINTEGRATION TESTS

The results of the Johansen and Juselius cointegration test are shown in Table 3. The results suggest there is no evidence of cointegration among the oil market, gold market and all the European stock markets, because both trace and maximum eigenvalue tests results indicate 0 cointegration equation among these variables except in the case of Slovakia[3]. In other words, there is no common driving force for these three variables in the long run. The finding is in line with the work of Sari et al. (2010), who found no evidence of long-term equilibriums among oil prices, precious metal prices, and exchange rates. The nonexistence of a long-term cointegration relationship among the three different markets also supports the idea to investigate their short-term shock and volatility transmissions based on the BEKK GARCH models.

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[3] In the case of Slovakia, only the maximum eigenvalue statistic is significant at the 5% level, demonstrating the existence of 1 cointegration relationship among them. However, the trace test still shows no cointegration among the oil and gold markets and the Slovakian stock market. After considering the results of other cases and the conflicting results in the Slovakian scenario, I tend to use the result of no cointegration which is consistent with other European markets.

VAR-BEKK-GARCH RESULTS

The estimation results of VAR(1)-BEKK-GARCH (1,1) are shown in Table 4 which consists of two sections. The first part provides the VAR results based on the estimation of conditional mean equations which can examine the return spillovers among these markets. The second part indicates the results from the conditional variance equations modelled by MGARCH with BEKK specifications which can analyse the volatility spillovers.

RETURNS SPILLOVERS BASED ON VAR ESTIMATIONS

Firstly, I discuss the return behaviours for the three variables based on the conditional mean equations estimation results. I observe that the AR(1) parameter g_{33} for stock market returns is statistically significant for 11 groups[4] at least at the 10% significance level. Consequently, the stock market return has an autoregressive feature in these countries, suggesting the short-term predictability which means one-period lagged returns can significantly influence current values in the above stock markets. Furthermore, the current values of these European stock markets are largely influenced by their previous values. However, it cannot observe serial correlation features in oil and gold markets, as the corresponding AR(1) coefficients g_{11} and g_{22} are not statistically significant, implying that it is difficult to use their own lagged returns to forecast their current returns.

When moving to the return spillover effects, this paper can only find unidirectional mean spillovers from the oil market to several European stock markets (Netherlands, Lithuania, Portugal, Czech Republic, Romania, and Slovenia). This signifies that the lagged values of returns in the oil market can significantly influence the current returns of these stock markets as the coefficient g_{31} is statistically significant for these countries. This result demonstrates that some European stock markets strongly depend on past returns in the oil market. However, most European stock markets do not rely on the past value of the oil market return. The results partly support the findings of Basher and Sadorsky (2006) who indicate that oil price increases have a positive impact on excess stock market returns in emerging markets, since similar return spillover effects can be found flowing from the oil market to 6 European emerging stock markets in this study. The reason could be the strong dependence of those economies on the oil market, which is the world's leading economic indicator, as a result the change of oil prices could reflect the expectation of future higher economic growth and further impact their stock market returns. However, in the opposite direction, a very weak return spillover from the European stock market to the oil market can be observed, since the coefficient g_{13} is not statistically significant for all groups, apart from Ireland and Slovenia. As a result, the oil market in general tends to behave independently from the European stock markets. The findings are consistent with some previous studies which find no evidence of return spillovers from international crude oil returns to the stock market returns (Arouri, Lahiani, et al., 2011; Cong et al., 2008; Singhal & Ghosh, 2016).

Looking at the gold side, I can only observe a weak return spillover effect from the gold market to the Iceland stock market since the corresponding coefficient g32 is statistically significant at least at the 10% level. Except for the case of Iceland, there are no return interrelations between the gold market and other European stock markets. The lagged values of returns in the stock market do not affect the current returns of the gold market, the exception being Slovenia's stock market, as the coefficient g23 is statistically insignificant for any of the other European markets. Moreover, the parameters g21 and g12 are statistically insignificant for all scenarios, showing no evidence of return spillovers from the oil market to the gold market, or from the gold to oil market. The lack of dependence between gold and stock and gold and oil markets indicate that the gold market plays a safe haven role as suggested by Baur and McDermott (2010). In summary, the results regarding their

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[4] g33 is significant for Austria, Belgium, Cyprus, Italy, Greece, Lithuania, Portugal, Romania, Slovakia, Switzerland, and Poland.

market returns can only imply weak integration between the oil market and 6 European stock markets (and between gold and the Iceland stock market), demonstrating potential diversification benefits among others.

VOLATILITY SPILLOVERS BASED ON BEKK GARCH

This paper next analyses the volatility spillovers among the Brent oil market, gold market and the European stock markets, since market volatility is strongly affected by the information flow and treated as an accurate measure of information transmission rate (Ross, 1989). Thus, it is possible that the linkages across financial markets not only exist in the returns but also in market volatility. As observed in Table 4, the estimated coefficients for ARCH and GARCH effects [A(1,1), A(2,2), A(3,3) and B(1,1), B(2,2), B(3,3)] in the conditional variance equations for all groups are statistically significant at the 1% significance level, suggesting that the oil, the gold and all the European stocks have significant ARCH and GARCH effects. That implies that the conditional variances of the financial markets in the research are significantly influenced by their own lagged shocks and lagged conditional variance. The outcome is consistent with the work done by Beirne et al. (2013) who provide strong evidence of ARCH and GARCH effects in emerging markets and emphasise the appropriateness of the GARCH models in capturing the key features of financial time series. Furthermore, the estimated ARCH coefficients [A(1,1), A(2,2), A(3,3)] are relatively small in size compared to the GARCH coefficients [B(1,1), B(2,2), B(3,3)], inferring that the conditional volatility of these markets is expected to fluctuate gradually over time rather than change rapidly if there is a shock. In addition, the results indicate a more crucial role of their own volatility in forecasting the future conditional variance compared with their own shocks.

   To examine volatility transmissions, I first look at the nature of spillover mechanisms between the oil and gold markets. By analysing the statistical significance of the off-diagonal coefficients in the matrices A and B from the BEKK model's variance equation (Eq(6))[5], I can perceive that the shocks and volatility spillovers from the gold to oil markets are more obvious than the opposite direction. I find no evidence of shock spillover transmissions from the oil market to the gold market, as the coefficients A(1,2) are insignificant at the 10% level for most cases except for Iceland. As a result, past shocks in the global oil market do not significantly influence the gold market's volatility across the sample period. Looking at the reverse effect, I note that the shock volatility spillover effect from the gold market to the oil market is intermediate, as the coefficients A(2,1) are significant at the conventional levels for 10 groups[6]. In terms of the volatility spillovers, I only observe a weak volatility spillover effect from the oil market to the gold market, since the coefficient B(1,2) is only significant at the 10% level in 5 groups[7]. Conversely, the coefficient B(2,1) is statistically significant for 13 cases (more than half)[8], so it concludes that the volatility spillovers from the gold market to the oil market are moderate. The results demonstrate a unidirectional shock spillover from the gold market to the oil market but a bi-directional volatility spillover between gold and oil markets is also evident. However, the influence of the gold market in terms of both shock and volatility is stronger than that derived from the oil market.

   I next analyse the shock and volatility spillover between the oil and the stock markets in Europe. As reported in Table 4, the off-diagonal elements of matrix A---A(1,3) are statistically significant at the 10% level for 8 stock markets (i.e., Belgium, Ireland, Luxembourg, Iceland, Czech Republic, Romania,

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[5] The off-diagonal elements of matrix A(ij) capture the shock spillover effects from market i to market j. Similarly, the volatility spillovers are measured by the off-diagonal elements of matrix B(ij).

[6] A(2,1) is statistically significant at 10% for Belgium, Hungary, Greece, Spain, Ireland, Luxembourg, Iceland, Lithuania, Slovenia and Switzerland groups.

[7] B(1,2) is statistically significant at 10% for Hungary, Ireland, Iceland, Lithuania and Switzerland groups.

[8] B(1,2) is statistically significant at 10% for Netherlands, Belgium, Hungary, France, Spain, Ireland, Luxembourg, Sweden, Lithuania, Czech Republic, Romania, Slovenia and the UK groups.

Slovakia, and Poland), suggesting evidence of shock spillovers from the oil market to these countries' stock markets. The highest absolute value of coefficient A(1,3) is 0.056 for Iceland at the 1% significance level, implying the Iceland stock market is the most sensitive one to the shocks from the international oil market. This result is similar to that of Arouri, Lahiani, et al. (2011) who also discover that past oil shocks wield significant effects on stock market volatility for 13 GCC countries. Regarding the off-diagonal elements of matrix B---B(1,3), very similar results can be observed since the volatility spillovers from the oil market to the stock market only exist in a few countries[9] due to the significance of corresponding coefficient B(1,3) at the 10% significance level. The findings support previous empirical research which reports that oil price volatility can significantly influence the stock markets (Jammazi, 2012; Park & Ratti, 2008; Yu et al., 2020). Conversely, I find strong evidence of both shock and volatility spillover effects from the oil market to most European stock markets. For shock spillovers, given that A(3,1) is statistically significant at the 10% level for most European stock markets, the shocks can spill over to the oil market from most European countries. Similarly, the volatility spillover effects also exist from most European markets to the oil market, as B(3,1) is statistically significant for most groups at a conventional level. This is similar to Malik and Hammoudeh (2007) who reveal strong volatility spillover effects from the US and Saudi Arabian stock markets to the price of oil (also see Mensi et al., 2013). Therefore, the European stock markets exert a very powerful impact on the oil market, as they are based in countries that are major oil importers with consumers who can significantly influence the oil market. This is not surprising since most European equity and oil markets are well integrated and can be affected by the same business cycle, thus the volatility transmission channel can be strengthened. I clearly observe that the nexus between the European stock markets and the global oil markets is asymmetric where the causality from equity to the oil market is more pronounced, whereas the transmission from oil to the equity markets is less significant since the European countries are significant oil importers and have influences on global commodity prices. These interesting results are consistent with Jouini and Harrathi (2014) who indicate that volatility transmissions run more from the stock markets to the oil prices rather than the other way around.

Moving to the interdependence between the gold market and the European stock markets, there is strong evidence of shock and volatility spillovers between the gold price and most European stock markets due to the significance of coefficients A(2,3), A(3,2), B(2,3) and B(3,2). The volatility spillovers between the gold and European stock markets are very strong, showing good market integration among them. Specifically, I observe shock and volatility spillovers from the gold to stock markets in 12 and 19 European markets, respectively, whereas similar spillover effects from the stock markets to the gold market exist in 21 and 22 groups, respectively. Overall, it reports an interesting phenomenon, that is, shocks and volatility in the gold market can be transmitted to the European markets and shocks from both gold and European stock markets should be considered when predicting future volatility of market returns. The findings are logical and consistent with several studies which report strong evidence of volatility spillover effects between the international gold price and stock markets in the US, Japan, China, South Africa and Nigeria (Adewuyi et al., 2019; Arouri et al., 2015; Mensi et al., 2017) Overall, the spillover effects regarding shocks and volatility are observed to be stronger from the European stock markets to the gold market, indicating that gold is very sensitive to the shocks and fluctuations from the European capital markets. Information from the gold market and European equity markets is observed to be useful in showing that past shocks from most European stock markets play a crucial role in forecasting the time-dynamics of conditional volatility in the gold price.

The results demonstrate that the oil and gold markets are more sensitive to fluctuations in the European stock markets. However, the result implies that the oil and gold markets still have economically and statistically significant predictive power for the dynamics of volatility of some

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[9] B(1,3) is statistically significant at 10% for Hungary, Ireland, Luxembourg, Lithuania, Portugal and Romania.

European stock markets, which supports recent findings by Ahmed and Huo (2020) despite some variances across countries. Moreover, this empirical study cannot find any evidence of shock spillover effects from oil to gold markets, whereas the weak shock spillover effects from the gold to oil markets can be observed. It also finds weak and moderate evidence of shock and volatility transmission from gold to oil markets. The insignificant spillover effects between the oil and gold markets suggest their interdependence. The outcomes of the study are different from previous literature who suggest significant correction between gold and oil returns (Ewing & Malik, 2013; Zhang & Wei, 2010). Interestingly, volatility spillover effects are not homogenous across different financial markets. The varying results on volatility transmissions can be attributed to the different levels of financial integration of these European stock markets with the oil and gold markets, which in turn depends on differences in the sizes of the economy, the demand and supply, institutional development as a form of market regulation and supervision effectiveness and financial system efficiency and other country-specific features.

As far as the economic interpretation is concerned, the main findings highlight that the European markets have been found to interact with oil and gold markets. Empirical evidence of strong volatility contagions and shock from the European stock market to oil and gold should not be surprising given the important role this developed market played in the commodity markets. This suggests that we cannot ignore the impacts from the European region in influencing the volatility of commodity markets. In addition, as a result of the financialization of the commodity markets, both gold and oil have spillover effects on the European equity market due to the importance of oil as a consumption asset to economic activities and of gold as an investment asset for storing value. The result also indicates the linkage between gold and European markets has become stronger. One possible explanation is that at times of uncertainty, especially during financial turmoil, because of its safe haven properties (Baur & McDermott, 2010; Beckmann et al., 2015), gold is becoming an attractive instrument in minimising risk exposure. In examining the transmission of shock and volatility spillovers, the findings show that there is no evidence of return spillovers between gold and oil. Such an observation, from hedging and practical perspectives, is useful for portfolio managers and investors exposed to the stock market crashes and the volatility of the oil market. This means investors can purchase gold related instruments as a diversification tool. Importantly, with the increased integration, policy makers are recommended to closely monitor the contagion to avoid systematic risks.

OPTIMAL PORTFOLIO DESIGNS AND HEDGING RATIOS

Understanding the spillover effects is important for risk management and efficient portfolio diversification. Given the insignificant spillover effects between the European stock markets and the global oil/gold market, potential diversification benefits can be substantial by investing in both oil/gold and European equity markets. To mitigate the risk exposure of the volatile markets and wild price swings, quantifying both optimal weights and hedging ratios is important to minimise the extra risks without decreasing the expected returns. Therefore, portfolio managers can achieve greater diversification gains by investing in both oil and stock or gold and stock markets. To illustrate the implications of the empirical findings on optimal portfolio design and risk hedging, I consider a portfolio of oil and stock (gold and commodity) in mitigating the risk exposure to both the international oil and gold markets. Based on the estimation results of the trivariate VAR-BEKK-GARCH model, I therefore calculate the optimal portfolio weights as well as the optimal hedge ratios.

I apply the method developed by Kroner and Ng (1998) and compute the optimal portfolio weights by constructing a risk minimised portfolio without reducing expected returns. The optimal portfolio weight of the holdings of two assets (e.g., oil and stock or gold and stock) is given by:

$$W_{oil-st} = \frac{h_{33,t}-h_{13,t}}{h_{11,t}-2h_{13,t}+h_{33,t}} \tag{12}$$

$$W_{gold-st} = \frac{h_{33,t}-h_{23,t}}{h_{22,t}-2h_{23,t}+h_{33,t}} \tag{13}$$

where $W_{i-j} = \begin{cases} 0, & if \ W_{i-j} < 0 \\ W_{i-j}, & if \ 0 \le W_{i-j} \le 1 \\ 1, & if \ W_{i-j} > 1 \end{cases}$, represent the weight of asset i in a one-dollar portfolio of

asset i and asset j at time t, and W_{oil-st} refer to the weight of oil market in a one-dollar portfolio of oil and stock while $W_{gold-st}$ is the optimal weight of gold in the considered portfolio of gold and stock.[10]

I also compute the optimal hedge ratio for the portfolio based on the method developed by Kroner and Sultan (1993). In order to make the risk of this portfolio minimal, a long position of one dollar in the oil/gold market needs to be hedged by a short position of βᵢ dollar in the European stock markets. The formulas of the hedge ratio are shown below:

$$\beta_{st-oil} = \frac{h_{13,t}}{h_{33,t}} \tag{14}$$

$$\beta_{st-gold} = \frac{h_{23,t}}{h_{33,t}} \tag{15}$$

The average values of optimal portfolio weights and hedging ratios for the 24 European stock markets are provided in Table 5.

Firstly, it looks at the optimal portfolio weights of the European stock markets in a portfolio constituting the European stock and oil holdings. From the results, most European stock market weights are more than 50% except for Greece (38.23%), varying from 89.83% in the UK being the highest to the lowest of 51.53% for Cyprus. This means that 89.83% (51.53%) of the portfolio's value should be invested in the UK (Cyprus) stock market and the remaining 10.17% (48.47%) should be held in the international oil market. It is indicated in these results that the allocation of the European stock markets in a one-dollar portfolio consisting of both stock and oil is more than half for most cases, implying that investors should hold more stock than oil to reduce the portfolio's risk without sacrificing its expected return. However, for Greece, investors are suggested to hold more oil (61.77%) in their portfolio. In terms of the optimal portfolio weights of the stock market for a portfolio constituting the gold and stock holdings, opposite results are observed with the weights less than 50% in most cases except for Czech Republic, Iceland, Lithuania, Switzerland, and the UK. The range runs from a maximum of 64.33% for Lithuania and a minimum of 19.20% for Greece.

The results can be interpreted as that the allocation of the corresponding equity market in a one-dollar portfolio is 64.33 cents and 19.20 cents for Lithuania and Greece, respectively. Additionally, the results indicate that investors need to invest more in the gold market than their local stock markets to reduce risks to their investment portfolios. However, for investors in Czech Republic, Iceland, Lithuania, Switzerland and the UK, allocating more in their local stock markets (compared with gold) can help them better diversify their portfolio. The findings may serve as an incentive to raise the investment in the oil, gold and European stock markets and are in line with the view that investors in Europe will gain diversification benefits if they invest some of their money in the oil or gold markets.

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[10] Since $W_{oil-cm} + W_{cm-oil} = 1 \ and \ W_{st-cm} + W_{cm-st} = 1$, therefore the optimal weight of stock in the considered portfolio of oil and stock is $W_{st-oil} = \frac{h_{11,t}-h_{13,t}}{h_{11,t}-2h_{13,t}+h_{33,t}}$, whereas $W_{st-gold} = \frac{h_{22,t}-h_{23,t}}{h_{22,t}-2h_{23,t}+h_{33,t}}$ represents the optimal weight of stock in the corresponding portfolio of gold and stock.

Moving on to the average hedge ratios calculated using equations (14) and (15), the ratios differ greatly across the European stock markets. I observe positive values of the average hedge ratios for all pairs of oil-stock. The ratio varies from the minimum of 0.0036 for oil-stock (Slovakia) to a maximum of 0.7266 for oil-stock (UK). It can see that the ratios vary over a large range, suggesting different hedging effectiveness of the oil market for the European stock markets. Taking the UK for example, the highest average hedge ratio is observed for the oil-stock (UK) portfolio signifying this is the most expensive hedge. The ratio (0.7266) indicates that hedging a one-dollar long position (buy) in the oil market requires a short position (sell) of 0.7266 cents in the UK stock market. In terms of the average hedge ratios for gold-stock, I observe negative values for some cases. This interesting result shows that the short position should be changed to the long position since the gold market returns are negatively correlated with the returns of these European stock markets, on average, during the sample period. For the remaining commodities, the hedging ratios are positive, implying that gold price risk exposure can be hedged by shorting in those European stock markets. Regarding the absolute value, it ranges from the lowest of 0.0021 for Hungary to the highest of 0.0855 for Poland. The ratios' small size implies that the market movements of the European stock markets are not highly correlated with the gold prices, indicating an effective hedge. For example, for one dollar that is the long position in the gold market, investors should short or sell 0.21 and 8.55 cents in the Hungary and Poland stock markets, respectively.

Figure 1 illustrates the evolutions of the time-varying hedge ratios for both oil-stock and gold-stock pairs over the sample period. The graphs indicate considerable variability across the sample period, implying that investors need to adjust their hedging strategies frequently when market conditions change. More importantly, the patterns for hedge ratios differ throughout Europe, implying that these European stock markets have different functions in the hedge strategy due to their unique characteristics. Overall, the empirical results indicate that the inclusion of the European stock markets in a well-diversified portfolio of oil or gold can reduce risk without sacrificing the return. Additionally, the oil and gold markets can help European investors to hedge their risk exposure from their local stock markets. Consequently, the findings are important for investors to improve risk-adjusted performance by establishing more diversified portfolios and executing the hedging strategy more effectively.
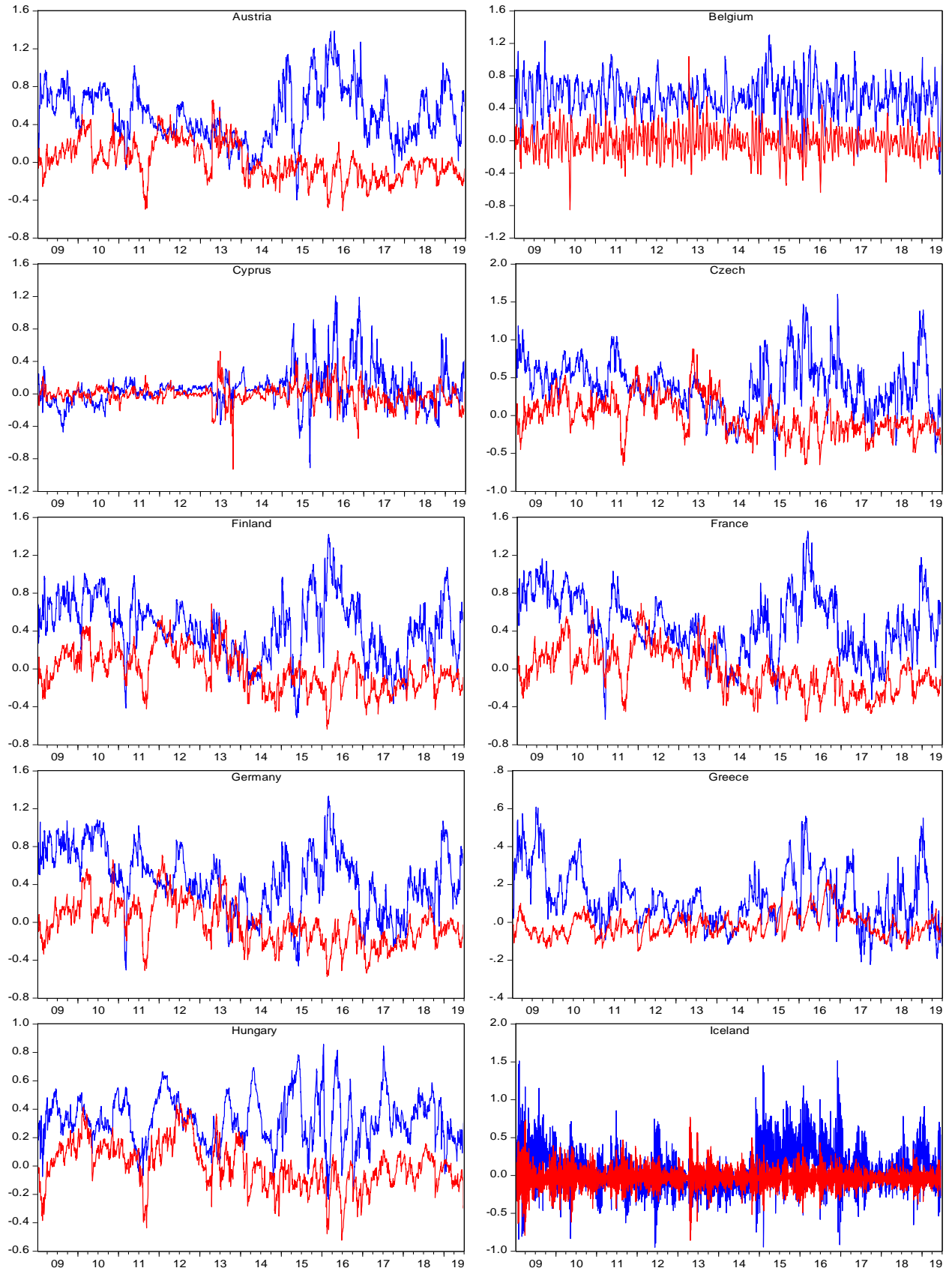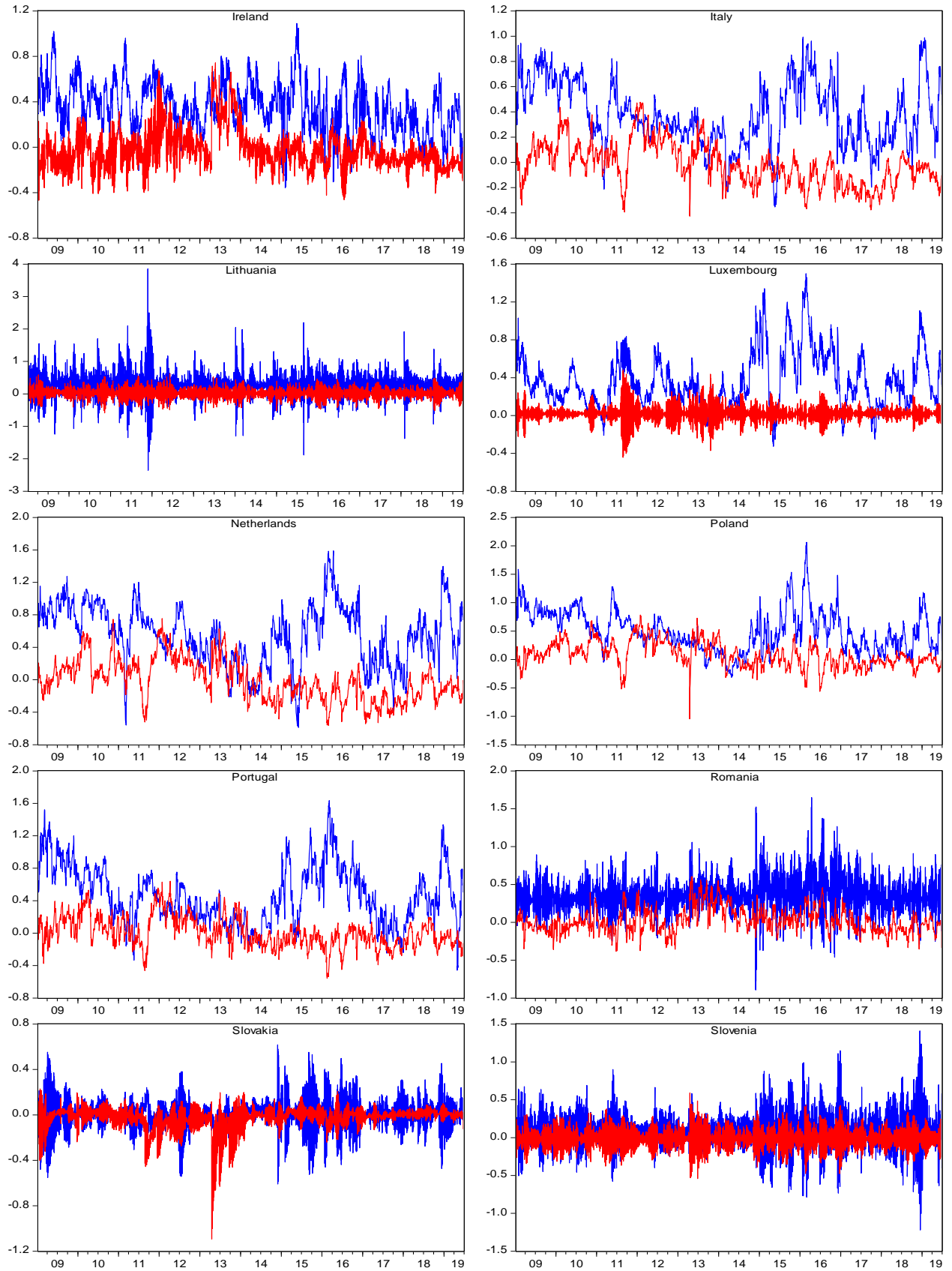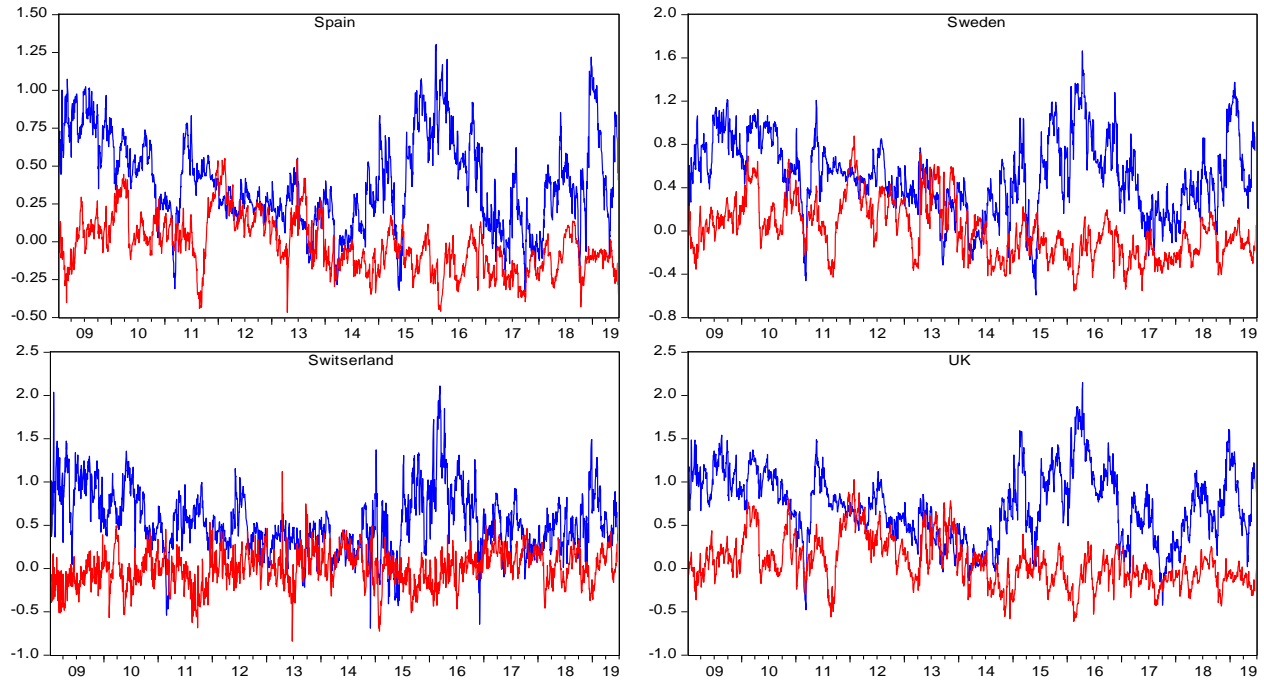
Note: The blue line and red line refer to β_{oil-st} and $\beta_{gold-stl}$, respectively.

Figure 1. The Time-Varying Hedge Ratios

Table 4. VAR-BEKK-GARCH Results

	Netherlands		Austria		Belgium		Hungary		Cyprus		Germany		France		Italy	
	Mean Equations															
Dependent variable: R_{oil}																
$R_{oil}(-1)$---g_{11}	-0.005	(0.805)	0.008	(0.705)	-0.002	(0.919)	0.018	(0.421)	0.002	(0.947)	0.001	(0.950)	-0.002	(0.907)	0.010	(0.661)
$R_{gold}(-1)$---g_{12}	-0.021	(0.471)	-0.020	(0.520)	0.020	(0.539)	-0.004	(0.910)	-0.004	(0.895)	-0.021	(0.504)	-0.029	(0.341)	-0.020	(0.504)
$R_{st}(-1)$---g_{13}	0.025	(0.422)	-0.023	(0.373)	0.028	(0.399)	0.003	(0.916)	-0.009	(0.447)	-0.007	(0.799)	0.021	(0.450)	-0.005	(0.839)
Constant	0.025	(0.413)	0.029	(0.346)	0.018	(0.559)	0.020	(0.542)	0.012	(0.721)	0.030	(0.320)	0.024	(0.454)	0.030	(0.328)
Dependent variable: R_{gold}																
$R_{oil}(-1)$---g_{21}	0.006	(0.607)	0.000	(0.974)	0.008	(0.493)	0.008	(0.470)	0.008	(0.450)	0.005	(0.606)	0.006	(0.616)	0.005	(0.629)
$R_{gold}(-1)$---g_{22}	-0.008	(0.706)	-0.012	(0.558)	-0.011	(0.632)	-0.010	(0.663)	-0.003	(0.876)	-0.007	(0.765)	-0.009	(0.686)	-0.010	(0.642)
$R_{st}(-1)$---g_{23}	0.002	(0.904)	0.012	(0.437)	-0.009	(0.659)	0.001	(0.939)	0.005	(0.523)	0.005	(0.757)	0.007	(0.691)	0.006	(0.679)
Constant	0.016	(0.390)	0.015	(0.424)	0.011	(0.553)	0.023	(0.233)	0.019	(0.298)	0.011	(0.517)	0.013	(0.473)	0.012	(0.520)
Dependent variable: R_{st}																
$R_{oil}(-1)$---g_{31}	-0.021 *	(0.076)	0.001	(0.915)	-0.017	(0.152)	-0.008	(0.561)	-0.010	(0.334)	-0.019	(0.136)	-0.014	(0.260)	-0.014	(0.392)
$R_{gold}(-1)$---g_{32}	-0.010	(0.630)	-0.004	(0.873)	0.019	(0.371)	-0.003	(0.888)	0.007	(0.705)	-0.002	(0.942)	-0.013	(0.580)	-0.020	(0.502)
$R_{st}(-1)$---g_{33}	0.032	(0.131)	0.042 **	(0.050)	0.060 ***	(0.005)	0.014	(0.532)	0.104 ***	(0.000)	0.003	(0.880)	-0.012	(0.588)	-0.035 *	(0.087)
Constant	0.056 ***	(0.001)	0.047 **	(0.030)	0.026	(0.172)	0.038 *	(0.093)	-0.022	(0.252)	0.071 ***	(0.001)	0.058 ***	(0.004)	0.044 *	(0.097)
	Conditional Variance Equations															
C(1,1)	0.111 ***	(0.000)	0.127 ***	(0.000)	-0.051 *	(0.092)	0.130 ***	(0.000)	-0.105 ***	(0.000)	0.122 ***	(0.000)	0.104 ***	(0.001)	0.134 ***	(0.000)
C(2,1)	0.003	(0.906)	0.003	(0.894)	0.106 ***	(0.001)	0.085 ***	(0.000)	0.014	(0.486)	-0.003	(0.899)	0.020	(0.554)	-0.002	(0.921)
C(2,2)	0.111 ***	(0.000)	0.124 ***	(0.000)	-0.030	(0.666)	0.058 ***	(0.000)	0.104 ***	(0.000)	0.109 ***	(0.000)	0.122 ***	(0.000)	0.125 ***	(0.000)
C(3,1)	0.004	(0.889)	0.013	(0.690)	0.023	(0.802)	-0.128 ***	(0.000)	0.061 ***	(0.006)	0.014	(0.638)	-0.036	(0.425)	-0.010	(0.795)
C(3,2)	-0.084 ***	(0.000)	-0.107 ***	(0.000)	0.155 ***	(0.000)	0.040	(0.202)	-0.077 ***	(0.000)	-0.091 ***	(0.000)	-0.115 ***	(0.000)	-0.157 ***	(0.000)
C(3,3)	0.091 ***	(0.000)	0.125 ***	(0.000)	0.000	(1.000)	0.000	(1.000)	0.000	(1.000)	0.102 ***	(0.000)	0.092 ***	(0.000)	0.128 ***	(0.000)
A(1,1)	-0.177 ***	(0.000)	-0.184 ***	(0.000)	-0.158 ***	(0.000)	-0.133 ***	(0.000)	-0.155 ***	(0.000)	-0.190 ***	(0.000)	-0.175 ***	(0.000)	-0.194 ***	(0.000)
A(1,2)	0.002	(0.801)	0.003	(0.737)	-0.007	(0.463)	-0.001	(0.915)	0.004	(0.556)	0.008	(0.317)	0.004	(0.625)	0.011	(0.152)
A(1,3)	-0.007	(0.501)	-0.017	(0.123)	0.023 **	(0.013)	-0.011	(0.165)	-0.005	(0.530)	-0.010	(0.318)	0.001	(0.957)	-0.020	(0.111)
A(2,1)	0.015	(0.385)	0.029	(0.126)	-0.077 ***	(0.000)	0.083 ***	(0.000)	0.011	(0.496)	0.022	(0.252)	0.026	(0.147)	0.032	(0.106)
A(2,2)	-0.187 ***	(0.000)	-0.206 ***	(0.000)	-0.185 ***	(0.000)	0.188 ***	(0.000)	-0.184 ***	(0.000)	-0.193 ***	(0.000)	-0.197 ***	(0.000)	-0.211 ***	(0.000)
A(2,3)	-0.003	(0.814)	0.011	(0.582)	-0.105 ***	(0.000)	-0.044 **	(0.017)	-0.006	(0.669)	0.013	(0.475)	0.017	(0.390)	0.073 ***	(0.001)
A(3,1)	-0.099 ***	(0.000)	-0.035 *	(0.070)	0.249 ***	(0.000)	0.085 ***	(0.000)	0.016 **	(0.012)	-0.062 ***	(0.002)	-0.075 ***	(0.000)	-0.022	(0.184)
A(3,2)	0.059 ***	(0.000)	0.042 ***	(0.002)	-0.064 ***	(0.001)	-0.034 ***	(0.006)	-0.015 ***	(0.011)	0.052 ***	(0.000)	0.053 ***	(0.000)	0.024 **	(0.033)

A(3,3)	-0.261 ***	(0.000)	-0.227 ***	(0.000)	0.214 ***	(0.000)	0.202 ***	(0.000)	0.349 ***	(0.000)	-0.236 ***	(0.000)	-0.269 ***	(0.000)	-0.239 ***	(0.000)
B(1,1)	0.981 ***	(0.000)	0.980 ***	(0.000)	0.982 ***	(0.000)	0.988 ***	(0.000)	0.986 ***	(0.000)	0.979 ***	(0.000)	0.982 ***	(0.000)	0.978 ***	(0.000)
B(1,2)	0.001	(0.590)	0.001	(0.673)	0.002	(0.535)	-0.002 *	(0.092)	0.002	(0.226)	0.002	(0.240)	0.000	(0.853)	0.002	(0.286)
B(1,3)	-0.001	(0.731)	-0.002	(0.582)	-0.002	(0.586)	0.003 **	(0.039)	0.002	(0.273)	-0.001	(0.637)	0.002	(0.505)	-0.002	(0.567)
B(2,1)	0.007 *	(0.083)	0.007	(0.138)	0.071 ***	(0.000)	-0.006 *	(0.057)	0.003	(0.453)	0.007	(0.104)	0.008 *	(0.077)	0.007	(0.142)
B(2,2)	0.974 ***	(0.000)	0.969 ***	(0.000)	0.964 ***	(0.000)	0.977 ***	(0.000)	0.977 ***	(0.000)	0.973 ***	(0.000)	0.971 ***	(0.000)	0.969 ***	(0.000)
B(2,3)	0.008 **	(0.035)	0.012 **	(0.027)	0.133 ***	(0.000)	0.011 **	(0.013)	0.003	(0.285)	0.008 *	(0.054)	0.014 ***	(0.007)	0.024 ***	(0.000)
B(3,1)	-0.020 ***	(0.001)	-0.007	(0.175)	-0.042 ***	(0.000)	0.006 *	(0.091)	0.000	(0.966)	-0.013 **	(0.016)	-0.015 **	(0.011)	-0.004	(0.459)
B(3,2)	0.016 ***	(0.000)	0.013 ***	(0.001)	-0.121 ***	(0.000)	0.011 ***	(0.000)	0.005 ***	(0.001)	0.016 ***	(0.000)	0.017 ***	(0.000)	0.011 ***	(0.001)
B(3,3)	0.959 ***	(0.000)	0.964 ***	(0.000)	0.952 ***	(0.000)	0.972 ***	(0.000)	0.947 ***	(0.000)	0.965 ***	(0.000)	0.956 ***	(0.000)	0.960 ***	(0.000)

Note: The figures in the brackets are P-values which indicate the statistical significance of the coefficients. ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 4: VAR-BEKK-GARCH Results (Continued)

	Greece		Spain		Ireland		Luxembourg		Finland		Iceland		Sweden		Lithuania	
					Mean Equations												
Dependent variable: R_{oil}																	
$R_{oil}(-1)$---g_{11}	-0.005	(0.799)	0.004	(0.847)	-0.006	(0.769)	0.008	(0.714)	-0.006	(0.773)	0.011	(0.591)	-0.002	(0.925)	0.016	(0.455)
$R_{gold}(-1)$---g_{12}	-0.005	(0.891)	-0.023	(0.450)	0.022	(0.494)	0.012	(0.680)	-0.017	(0.575)	0.016	(0.610)	-0.025	(0.396)	-0.025	(0.450)
$R_{st}(-1)$---g_{13}	0.014	(0.360)	0.017	(0.485)	0.064 **	(0.032)	0.016	(0.496)	0.041	(0.156)	-0.017	(0.664)	0.022	(0.504)	-0.001	(0.981)
Constant	0.046	(0.143)	0.021	(0.501)	0.016	(0.614)	0.037	(0.206)	0.023	(0.467)	0.026	(0.424)	0.014	(0.645)	0.006	(0.859)
Dependent variable: R_{gold}																	
$R_{oil}(-1)$---g_{21}	-0.006	(0.582)	0.008	(0.436)	0.004	(0.686)	0.007	(0.503)	0.007	(0.512)	0.009	(0.415)	0.002	(0.824)	0.006	(0.567)
$R_{gold}(-1)$---g_{22}	0.005	(0.812)	-0.009	(0.660)	-0.012	(0.576)	-0.003	(0.890)	-0.002	(0.928)	0.000	(0.992)	0.000	(0.984)	-0.004	(0.845)
$R_{st}(-1)$---g_{23}	0.005	(0.560)	0.001	(0.944)	-0.012	(0.493)	-0.009	(0.495)	-0.003	(0.850)	0.015	(0.550)	-0.002	(0.935)	-0.001	(0.966)
Constant	0.025	(0.189)	0.010	(0.579)	0.009	(0.638)	0.016	(0.402)	0.014	(0.450)	0.014	(0.478)	0.012	(0.503)	0.018	(0.349)
Dependent variable: R_{st}																	
$R_{oil}(-1)$---g_{31}	0.007	(0.746)	-0.020	(0.173)	-0.003	(0.795)	0.004	(0.818)	-0.006	(0.624)	0.010	(0.305)	-0.001	(0.914)	0.013 **	(0.047)
$R_{gold}(-1)$---g_{32}	0.023	(0.597)	-0.007	(0.782)	-0.008	(0.733)	-0.027	(0.303)	0.007	(0.762)	-0.031 *	(0.079)	-0.011	(0.559)	0.020	(0.121)
$R_{st}(-1)$---g_{33}	0.065 ***	(0.003)	0.035	(0.112)	0.032	(0.136)	0.005	(0.807)	0.031	(0.143)	-0.002	(0.910)	-0.020	(0.358)	0.048 **	(0.032)
Constant	0.041	(0.263)	0.032	(0.164)	0.051 **	(0.011)	0.005	(0.850)	0.040 **	(0.033)	0.047 ***	(0.002)	0.063 ***	(0.000)	0.038 ***	(0.002)
					Conditional Variance Equations												
C(1,1)	0.173 ***	(0.000)	0.127 ***	(0.000)	0.050 *	(0.060)	0.200 ***	(0.000)	0.121 ***	(0.000)	-0.111	(0.695)	0.117 ***	(0.000)	0.476 ***	(0.000)
C(2,1)	0.036 **	(0.021)	0.003	(0.897)	0.145 ***	(0.000)	0.092 *	(0.096)	0.014	(0.579)	-0.049	(0.833)	0.002	(0.930)	-0.056 ***	(0.004)
C(2,2)	0.057 ***	(0.000)	0.114 ***	(0.000)	0.000	(1.000)	0.033	(0.828)	0.118 ***	(0.000)	0.128	(0.166)	-0.111 ***	(0.000)	0.000	(1.000)
C(3,1)	-0.001	(0.969)	-0.031	(0.447)	-0.242 ***	(0.000)	0.046	(0.120)	-0.010	(0.746)	0.063	(0.852)	-0.015	(0.627)	0.036	(0.238)
C(3,2)	-0.026	(0.556)	-0.132 ***	(0.000)	0.000	(1.000)	-0.073 ***	(0.009)	-0.086 ***	(0.000)	-0.217 *	(0.092)	0.081 ***	(0.000)	0.000	(1.000)
C(3,3)	0.093 ***	(0.000)	0.118 ***	(0.000)	0.000	(1.000)	0.000	(1.000)	0.105 ***	(0.000)	0.000	(1.000)	0.103 ***	(0.000)	0.000	(1.000)
A(1,1)	-0.201 ***	(0.000)	-0.189 ***	(0.000)	-0.134 ***	(0.000)	-0.220 ***	(0.000)	-0.186 ***	(0.000)	-0.161 ***	(0.000)	-0.180 ***	(0.000)	-0.205 ***	(0.000)
A(1,2)	0.002	(0.798)	0.006	(0.426)	-0.010	(0.221)	0.005	(0.523)	0.002	(0.797)	0.050 ***	(0.000)	0.000	(0.958)	0.002	(0.775)
A(1,3)	-0.014	(0.463)	-0.010	(0.374)	0.032 **	(0.035)	-0.044 ***	(0.000)	-0.007	(0.460)	-0.056 ***	(0.000)	0.006	(0.534)	0.001	(0.936)
A(2,1)	0.079 ***	(0.000)	0.034 *	(0.073)	-0.034 **	(0.030)	0.125 ***	(0.000)	0.027	(0.166)	0.061 **	(0.021)	0.029	(0.112)	0.057 ***	(0.007)
A(2,2)	0.089 ***	(0.000)	-0.201 ***	(0.000)	-0.156 ***	(0.000)	0.188 ***	(0.000)	-0.203 ***	(0.000)	0.122 ***	(0.000)	-0.194 ***	(0.000)	-0.194 ***	(0.000)
A(2,3)	0.065 **	(0.016)	0.054 **	(0.022)	-0.067 ***	(0.001)	0.038 **	(0.017)	0.006	(0.732)	0.163 ***	(0.000)	-0.002	(0.922)	0.002	(0.861)
A(3,1)	0.006	(0.509)	-0.039 **	(0.025)	0.224 ***	(0.000)	-0.037 **	(0.027)	-0.059 ***	(0.005)	0.063 *	(0.080)	-0.081 ***	(0.000)	-0.068	(0.126)
A(3,2)	0.036 ***	(0.000)	0.036 ***	(0.002)	-0.119 ***	(0.000)	-0.019 ***	(0.026)	0.050 ***	(0.000)	0.096 ***	(0.000)	0.053 ***	(0.000)	0.002	(0.917)

A(3,3)	-0.205 ***	(0.000)	-0.261 ***	(0.000)	0.282 ***	(0.000)	-0.161 ***	(0.000)	-0.236 ***	(0.000)	-0.125 ***	(0.000)	-0.281 ***	(0.000)	0.279 ***	(0.000)
B(1,1)	0.975 ***	(0.000)	0.979 ***	(0.000)	1.004 ***	(0.000)	0.956 ***	(0.000)	0.979 ***	(0.000)	0.940 ***	(0.000)	0.980 ***	(0.000)	0.471 ***	(0.000)
B(1,2)	-0.001	(0.725)	0.001	(0.425)	0.045 *	(0.095)	-0.039	(0.211)	0.001	(0.593)	-0.086 ***	(0.000)	0.001	(0.721)	0.193 ***	(0.000)
B(1,3)	-0.005	(0.299)	0.000	(0.934)	0.019 *	(0.058)	-0.010 ***	(0.005)	-0.001	(0.750)	0.006	(0.688)	0.002	(0.374)	-0.294 ***	(0.000)
B(2,1)	0.004	(0.272)	0.008 *	(0.061)	-0.691 ***	(0.000)	-0.701 ***	(0.000)	0.006	(0.163)	-0.037	(0.720)	0.009 **	(0.043)	0.190 ***	(0.000)
B(2,2)	0.991 ***	(0.000)	0.972 ***	(0.000)	-0.819 ***	(0.000)	-0.963 ***	(0.000)	0.970 ***	(0.000)	0.467 ***	(0.000)	0.973 ***	(0.000)	-0.946 ***	(0.000)
B(2,3)	-0.005	(0.441)	0.022 ***	(0.001)	-0.620 ***	(0.000)	0.001	(0.992)	0.009 *	(0.058)	-0.700 ***	(0.000)	0.009 **	(0.029)	-0.031	(0.343)
B(3,1)	0.004 **	(0.044)	-0.008	(0.119)	-0.226 ***	(0.000)	0.012	(0.431)	-0.010 *	(0.069)	0.585 ***	(0.000)	-0.017 *	(0.010)	1.934 ***	(0.000)
B(3,2)	0.007 ***	(0.000)	0.011 ***	(0.001)	-0.509 ***	(0.000)	0.047	(0.243)	0.014 ***	(0.000)	1.026 ***	(0.000)	0.015 ***	(0.000)	0.288 ***	(0.000)
B(3,3)	0.979 ***	(0.000)	0.956 ***	(0.000)	0.734 ***	(0.000)	0.985 ***	(0.000)	0.965 ***	(0.000)	0.418 ***	(0.000)	0.953 ***	(0.000)	0.670 ***	(0.000)

Note: The figures in the brackets are P-values which indicate the statistical significance of the coefficients. ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 4: VAR-BEKK-GARCH Results (Continued)

	Portugal	Czech Republic	Romania	Slovakia	Slovenia	Switzerland	Poland	UK
				Mean Equations				
Dependent variable: R_{oil}								
$R_{oil}(-1)$--- g_{11}	-0.004 (0.868)	-0.012 (0.576)	0.001 (0.953)	0.014 (0.496)	0.016 (0.472)	-0.004 (0.861)	0.001 (0.947)	0.001 (0.952)
$R_{gold}(-1)$--- g_{12}	-0.020 (0.514)	-0.015 (0.629)	-0.018 (0.572)	-0.013 (0.676)	0.014 (0.667)	0.014 (0.671)	-0.014 (0.652)	-0.025 (0.405)
$R_{st}(-1)$--- g_{13}	0.044 (0.115)	0.008 (0.809)	0.030 (0.314)	0.010 (0.723)	0.053** (0.023)	0.050 (0.182)	0.010 (0.768)	0.039 (0.282)
Constant	0.024 (0.437)	0.029 (0.386)	0.026 (0.418)	0.012 (0.681)	0.002 (0.953)	0.038 (0.208)	0.025 (0.432)	0.019 (0.535)
Dependent variable: R_{gold}								
$R_{oil}(-1)$--- g_{21}	0.003 (0.760)	0.003 (0.756)	0.004 (0.743)	0.008 (0.468)	-0.001 (0.919)	0.003 (0.796)	0.001 (0.926)	0.004 (0.699)
$R_{gold}(-1)$--- g_{22}	-0.010 (0.632)	-0.013 (0.531)	0.000 (0.985)	-0.002 (0.929)	-0.002 (0.914)	0.001 (0.963)	-0.015 (0.483)	0.000 (0.983)
$R_{st}(-1)$--- g_{23}	0.019 (0.295)	0.000 (0.998)	-0.006 (0.722)	0.008 (0.621)	0.085*** (0.000)	-0.012 (0.614)	0.027 (0.177)	0.005 (0.813)
Constant	0.015 (0.402)	0.014 (0.443)	0.004 (0.821)	0.006 (0.754)	0.007 (0.689)	0.022 (0.269)	0.014 (0.434)	0.014 (0.449)
Dependent variable: R_{st}								
$R_{oil}(-1)$--- g_{31}	-0.024* (0.056)	0.033*** (0.001)	0.026** (0.015)	0.002 (0.876)	0.030*** (0.005)	-0.015 (0.134)	0.003 (0.765)	-0.009 (0.368)
$R_{gold}(-1)$--- g_{32}	0.018 (0.420)	-0.010 (0.604)	0.000 (0.989)	-0.021 (0.361)	-0.019 (0.362)	-0.005 (0.783)	0.020 (0.317)	-0.011 (0.522)
$R_{st}(-1)$--- g_{33}	0.094*** (0.000)	-0.005 (0.810)	0.045* (0.055)	-0.144*** (0.000)	0.030 (0.187)	0.041* (0.070)	0.064*** (0.003)	0.002 (0.929)
Constant	0.024 (0.226)	0.017 (0.313)	0.067*** (0.000)	-0.003 (0.886)	0.018 (0.321)	0.053*** (0.001)	0.032* (0.076)	0.043*** (0.007)
				Conditional Variance Equations				
C(1,1)	0.126*** (0.000)	0.117*** (0.000)	0.103*** (0.002)	-0.139*** (0.000)	0.183*** (0.000)	0.228*** (0.007)	-0.136*** (0.000)	0.100*** (0.001)
C(2,1)	0.037 (0.189)	-0.003 (0.924)	0.082** (0.018)	0.010 (0.658)	0.078*** (0.000)	0.637** (0.011)	0.003 (0.904)	-0.001 (0.969)
C(2,2)	0.107*** (0.000)	0.128*** (0.000)	0.033 (0.689)	0.109*** (0.000)	0.000 (1.000)	0.192 (0.229)	0.122*** (0.000)	0.112*** (0.000)
C(3,1)	-0.105* (0.077)	-0.013 (0.670)	-0.206** (0.014)	-0.012 (0.920)	0.025 (0.599)	0.154 (0.260)	0.012 (0.629)	-0.006 (0.866)
C(3,2)	-0.119*** (0.002)	-0.104*** (0.000)	0.082 (0.693)	-0.080*** (0.001)	0.000 (1.000)	0.259*** (0.000)	-0.096*** (0.000)	-0.097*** (0.000)
C(3,3)	0.129*** (0.000)	-0.076*** (0.000)	0.001 (0.998)	0.000 (1.000)	0.000 (1.000)	0.000 (1.000)	0.115*** (0.000)	0.114*** (0.000)
A(1,1)	-0.183*** (0.000)	0.182*** (0.000)	-0.151*** (0.000)	-0.213*** (0.000)	0.191*** (0.000)	0.196*** (0.000)	-0.199*** (0.000)	-0.178*** (0.000)
A(1,2)	0.005 (0.489)	-0.004 (0.561)	-0.014 (0.010)	0.005 (0.472)	-0.006 (0.271)	-0.023 (0.302)	0.009 (0.230)	-0.002 (0.826)
A(1,3)	0.006 (0.568)	0.022*** (0.005)	0.050*** (0.000)	-0.026*** (0.000)	-0.009 (0.121)	-0.003 (0.768)	-0.015* (0.076)	-0.005 (0.584)
A(2,1)	0.028 (0.106)	-0.028 (0.101)	0.013 (0.466)	0.023 (0.220)	-0.131*** (0.000)	-0.116*** (0.000)	0.025 (0.174)	0.027 (0.117)
A(2,2)	-0.198*** (0.000)	0.198*** (0.000)	-0.149*** (0.000)	-0.220*** (0.000)	-0.238*** (0.000)	-0.194*** (0.000)	-0.210*** (0.000)	-0.195*** (0.000)
A(2,3)	0.037* (0.073)	-0.013 (0.396)	-0.074*** (0.000)	-0.008 (0.549)	-0.008 (0.673)	-0.097*** (0.000)	0.042*** (0.001)	0.017 (0.200)
A(3,1)	-0.054*** (0.005)	0.016 (0.476)	0.115*** (0.000)	-0.001 (0.957)	0.007 (0.247)	0.048 (0.157)	-0.019 (0.366)	-0.096*** (0.001)
A(3,2)	0.060*** (0.000)	-0.082*** (0.000)	-0.019* (0.091)	-0.007 (0.491)	0.012* (0.055)	-0.015 (0.719)	0.047*** (0.005)	0.067*** (0.001)

A(3,3)	-0.293 ***	(0.000)	0.263 ***	(0.000)	0.425 ***	(0.000)	-0.085 ***	(0.000)	0.140 ***	(0.000)	0.352 ***	(0.000)	-0.223 ***	(0.000)	-0.287 ***	(0.000)
B(1,1)	0.979 ***	(0.000)	0.981 ***	(0.000)	-0.994 ***	(0.000)	0.973 ***	(0.000)	0.973 ***	(0.000)	0.982 ***	(0.000)	0.977 ***	(0.000)	0.982 ***	(0.000)
B(1,2)	0.000	(0.919)	0.001	(0.426)	0.012	(0.704)	0.001	(0.885)	-0.012	(0.409)	0.034 **	(0.018)	0.003	(0.133)	0.000	(0.875)
B(1,3)	0.006 *	(0.095)	-0.003	(0.159)	-0.052 ***	(0.000)	-0.028	(0.536)	-0.005	(0.740)	0.010	(0.108)	-0.001	(0.556)	0.002	(0.374)
B(2,1)	0.006	(0.155)	0.007 *	(0.098)	0.626 ***	(0.000)	-0.009	(0.553)	-0.315 ***	(0.000)	-0.041	(0.497)	0.005	(0.267)	0.009 **	(0.037)
B(2,2)	0.972 ***	(0.000)	0.968 ***	(0.000)	0.980 ***	(0.000)	0.952 ***	(0.000)	0.280 ***	(0.000)	0.657 ***	(0.005)	0.968 ***	(0.000)	0.972 ***	(0.000)
B(2,3)	0.018 ***	(0.005)	0.018 ***	(0.000)	0.031 ***	(0.000)	-0.229 ***	(0.002)	-0.973 ***	(0.000)	-0.032	(0.745)	0.019 ***	(0.000)	0.015 ***	(0.000)
B(3,1)	-0.007	(0.273)	-0.005	(0.374)	0.577 ***	(0.000)	-0.117	(0.274)	0.242 ***	(0.000)	-0.050	(0.154)	-0.003	(0.631)	-0.023 **	(0.013)
B(3,2)	0.022 ***	(0.000)	0.020 ***	(0.000)	0.003	(0.750)	-0.145 ***	(0.009)	0.917 ***	(0.000)	-0.246 ***	(0.005)	0.014 ***	(0.007)	0.020 ***	(0.004)
B(3,3)	0.939 ***	(0.000)	0.955 ***	(0.000)	0.900 ***	(0.000)	-0.974 ***	(0.000)	0.247 ***	(0.000)	0.865 ***	(0.000)	0.960 ***	(0.000)	0.942 ***	(0.000)

Note: The figures in the brackets are the P-values which indicate the statistical significance of the coefficients. ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 5. Optimal Portfolio Weights and Hedging Ratios

	W_{oil-st}	$W_{gold-st}$	W_{st-oil}	$W_{st-gold}$	β_{st-oil}	$\beta_{st-gold}$
Austria	0.2873	0.6261	0.7127	0.3739	0.5100	0.0145
Belgium	0.1938	0.5252	0.8062	0.4748	0.5496	-0.0065
Cyprus	0.4847	0.6921	0.5153	0.3079	0.0710	-0.0091
Czech Republic	0.2114	0.4939	0.7886	0.5061	0.4019	-0.0097
Finland	0.2522	0.5691	0.7478	0.4309	0.4339	-0.0098
France	0.2655	0.5861	0.7345	0.4139	0.4717	-0.0217
Germany	0.2543	0.5803	0.7457	0.4197	0.4488	-0.0122
Greece	0.6177	0.8080	0.3823	0.1920	0.1282	-0.0145
Hungary	0.3067	0.6194	0.6933	0.3806	0.3267	0.0021
Iceland	0.1931	0.4219	0.8069	0.5781	0.0780	-0.0315
Ireland	0.2655	0.5618	0.7345	0.4382	0.3515	-0.0240
Italy	0.4004	0.6878	0.5996	0.3122	0.3832	-0.0172
Lithuania	0.1030	0.3567	0.8970	0.6433	0.2630	0.0226
Luxembourg	0.3576	0.6671	0.6424	0.3329	0.3668	0.0204
Netherlands	0.1722	0.5191	0.8278	0.4809	0.5550	-0.0087
Poland	0.1862	0.5019	0.8138	0.4981	0.5025	0.0855
Portugal	0.2534	0.5710	0.7466	0.4290	0.4670	0.0062
Romania	0.2416	0.5123	0.7584	0.4877	0.3604	0.0203
Slovakia	0.3132	0.5801	0.6868	0.4199	0.0036	-0.0282
Slovenia	0.2616	0.5090	0.7384	0.4910	0.0942	-0.0141
Spain	0.3331	0.6348	0.6669	0.3652	0.3965	-0.0233
Sweden	0.1974	0.5162	0.8026	0.4838	0.5183	0.0083
Switzerland	0.1473	0.4306	0.8527	0.5694	0.5499	-0.0042
UK	0.1017	0.4545	0.8983	0.5455	0.7266	0.0716

Note: Optimal portfolio weights---W_{oil-st} and $W_{gold-st}$ are the weights of the oil/gold in a one-dollar portfolio which consists of stock and oil/gold. Therefore, the corresponding weights for the stock market are W_{st-oil}=1-W_{oil-st} ($W_{st-gold}$=1-$W_{gold-st}$). The table only reports the average values of optimal portfolio weights and hedging ratios across the sample period.

CONCLUSION

This paper studies the return and volatility transmissions between oil, gold and the European stock market consisting of 24 European countries, using the trivariate VAR-BEKK-GARCH model. This study uses the data from 5 January 2009 to 28 June 2019, which includes several volatile periods concerning the commodity and European stock markets. The Brent oil price serves to proxy for the international crude oil market while the LBMA gold price data is used to represent the global gold market.

Based on the cointegration test results, there is no cointegration between the gold market, oil market and the stock markets in Europe, with both the trace test and maximum eigenvalue test showing a value of 0 for all countries apart from Slovakia. This suggests there is no evidence of a long-term equilibrium between the three markets.

I measure the return spillovers using the VAR estimations and detect a unidirectional spillover effect from the oil market to some European stock markets (Netherlands, Lithuania, Portugal, Czech Republic, Romania and Slovenia). The findings show that while most European stock markets do not depend on the historic value of oil market return, some markets rely strongly on it. Moreover, return spillover from the European stock markets to the oil market is not observed, suggesting that the global

oil market moves independently of the European stock markets. Referring to the gold market, no return spillover is noted between this market and the European stock markets (and oil market) except in the case of Iceland, suggesting gold plays a safe haven role and this generates diversification benefits. I then employ the GARCH model with BEKK specifications to test the volatility transmissions and discover a one-way shock spillover from the gold to the oil market and a bi-directional volatility spillover between the gold and oil markets. Furthermore, the results indicate that both oil and gold markets are sensitive to fluctuation in the European stock markets.

Regarding the optimal portfolio design and hedging ratios, the results showed that including European stock markets into a well-diversified oil or gold portfolio can diminish risk without reducing the expected return. To sum up, previous empirical studies have investigated the role of oil (Chkili et al., 2014; Khalfaoui et al., 2015; Lin et al., 2014) or gold (Akkoc & Civcir, 2019; Baur & McDermott, 2010; Chkili, 2016) in portfolio diversification and hedging. This study is different in that it analyses the trilateral relationship and finds evidence of hedging effectiveness between gold, oil, and an aggregate regional stock market. It is valuable for investors, asset managers, and policymakers. A comprehensive understanding of spillover effects may help investors to make more diversified portfolios and execute investment hedge strategies more effectively, and policymakers/regulators to develop macroeconomic policies to better manage the financial markets.

However, it should be noted that this study only unravels the connections between oil and gold and stock returns. Future studies should focus on other commodity classes, like silver, platinum, and agricultural commodities (wheat, corn) and their dynamics, which opens plenty of scope for further research. In this study the specific focus was on the European markets, which is the other limitation. Given each regional market shares various credit risk characteristics, market conditions, and institutional environments, the nexus between oil, gold and stock markets could be examined more comprehensively and thoroughly. Research undertaken on the correlations and volatility spillover by incorporating the cross-region and cross-country differences would be useful to investors, policy analysts and policymakers.

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