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Connectedness and directional spillovers in energy sectors: international evidence

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ABSTRACT

This paper provides a comparative analysis of how the energy-sector stocks of 20 regional blocs (Americas, Australasia, BRIC, Southeast Asia, Scandinavia, Southern Europe, Far East, Europe, European Union, Emerging Europe, Asia, G7, G12, Economic and Monetary Union (EMU), CCARBNS, Latin America, North America, PIIGS, Asia-Pacific and NORCS) are connected from 5 July 1994 to 21 April 2020. It uses various techniques: Diebold and Yilmaz (2014)(DY 2014, hereafter) spillover indices and TVP-VAR, LASSO-VAR. Our main results are as follows: First, the DY approach results show that the biggest net contributor of volatility is the CCARBNS region, followed by the G12 and G7 regions, while the biggest receiver of volatility is the Southeast Asia region. Second, the TVP-VAR and LASSO-VAR results reveal that Scandinavia, Far East, and America's regions are net receivers of energy shocks, with net transmitters being CCARBNS, G7, G12 and Emerging European regions. Third, during the 2007–2008 financial crisis and recent COVID-19 outbreak, energy stock market spillovers have reached unprecedented high levels. Fourth, the world policy uncertainty greatly influenced the magnitude of volatility spillovers across regional energy stock markets.

KEYWORDS
World regional energy markets; spillover analysis TVP-VAR; LASSO-VAR; volatility spillovers

JEL CLASSIFICATION
C01; C22; O57; Q4

I. Introduction

In recent decades, energy has been one of the most important factors that support global economic development (Zhang 2017), and energy stocks and firms have been commonly considered to have good value. The investment community considers energy stocks as barometer stocks following the high level of profits offered by investing in energy stocks. However, as the extensive use of non-renewable energy fuels has aggravated environmental degradation and energy shortages (Xu and Lin 2016), the consumption of non-renewable energy is decreasing, and at the same time, the development of renewable energies is increasing (He et al. 2016). This arrangement has created the notion that the value of non-renewable energy firms will fall while that of clean and alternative new energy firms will rise (Kazemilari et al. 2017; Reboredo 2015). Consequently, investors anticipate greater changes in the structure of energy consumption in the near future, which could lead to shocks and risk in energy markets (Wen et al. 2014). Following that, the socio-economic and financial nature of energy has become increasingly tighter. Studies have suggested that changes in energy stocks could further impact the broader economy and financial markets (Zhang 2017). Thus, fluctuations in energy stocks could bring shocks and risks to stock markets and a broader economy. Therefore, our research extends the literature by focusing on the energy stocks of regional blocs. By identifying influential energy stocks, this study could be helpful for guiding risk management, portfolio management, and option hedging strategies for policymakers and investors interested in energy stocks.

In this paper, we examine the degree of connectedness and directional spillovers across international energy stocks. Early empirical studies have focused on the nature of energy markets and spillovers between energy commodities

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Supplemental data for this article can be accessed here prices (Zhang et al. 2020), energy and stock prices (Le, Abakah, and Tiwari 2021; Sadorsky 2012; Maghyereh et al. 2016) and between specific energy commodities prices and stock price indices (Mensi et al. 2013), with little attention paid to the connectedness between energy-sector stocks of different countries and regional blocs. There is little empirical evidence available regarding the intensity and direction of return and volatility transmission effects across the various regional energy markets, which historically has been segmented due to distances imposed by particular geographical locations. Furthermore, the question of asymmetric information transmission across markets, which is well documented in the finance literature, is still largely unexplored in the area of energy economics. The closest contribution to ours has been provided by Zhang et al. (2020), who analysed spillovers and connectedness effects between natural gas, crude oil and electricity stock indices for North America and Europe. Zhang et al. (2020), using both time-domain approaches, found that total return and volatility spillover are stronger in Europe than in North America. Furthermore, compared to natural gas, crude oil has a greater volatility spillover on the electricity utility stock indices in North America and Europe. Second, in the frequency domain, most of the return spillover occurs in the short term, while that of the volatility spillover occurs over a longer period.

The objective of this paper is to contribute to the growing literature by investigating the connectedness between energy-sector stocks across 20 regional blocs, including Americas, Australasia, BRIC, South East Asia, Scandinavia, Southern Europe, Far East, Europe, European Union, Emerging Europe, Asia, G7, G12, Economic and Monetary Union (EMU), CCARBNS, Latin America, North America, PIIGS, Asia-Pacific and NORCS. Specifically, we investigate spillover and dependence across the energy sector around the world's regional markets. In particular, the connectedness of the regional energy sector will enable us to gain insight into the risk transmission and spillover channels, which are important in making optimal financial decisions. To the best of our knowledge, this is the first study to investigate the connectedness between the energy sector at the international level. A sound understanding of the connectedness of these markets may assist investors in designing better investment and risk management strategies.

This paper focuses on the energy sector because it is one of the most significant segments of the world economy. As a result, disruptions in the production of a particular energy commodity can lead to a shift in demand for another energy commodity, and the flow of the energy commodity may also change from one country or region to the other. For instance, the Middle East has the largest share (48.1%) of proved oil reserves globally, with Europe having the least share of 0.8% (BP. 2020). Again, while in North America, Commonwealth of Independent States (CIS), the Middle East and Africa, natural gas is the dominant fuel used to generate electricity, more than 50% of the power in South and Central America is hydroelectricity, with the Asian region having about 57% of power generation from coal (BP, 2021). The case for Europe, however, is different as the region uses more renewables for its power generation as of 2020, constituting about 24%, followed by nuclear energy with about 22%. BP (2021) also shows that on energy consumption, crude oil remains the dominant fuel in Africa, Europe, and the Americas, while natural gas dominates in CIS and the Middle East, accounting for more than half of the energy mix in both regions. While the share of coal in primary energy in North America and Europe saw its lowest levels in 2020, coal remains the dominant fuel in the Asia Pacific region. Addressing this issue of connectedness across regional energy stocks is pertinent because different energy commodities may also compete for funds or investment. Portfolio managers are always looking for profitable investments with acceptable levels of risk. Insurance companies also look out for safer and viable markets to provide underwriting services for investments in these energy markets in different destinations. These issues imply that one must be concerned whether shocks, such as the energy markets in the Americas, could spill over to the Asian markets.

Our papers differ from other studies in the literature in the following ways: First, we provide the first novel evidence about return transmission processes across 20 major international, regional energy markets. To achieve this task and understand the dynamics, we applied the variance decomposition framework of Diebold and Yilmaz (2014) to daily energy-sector prices to measure the total, directional and net-pairwise spillover indices. Then, we employed the network connectedness approach of Diebold and Yilmax (2014). The advantage of the network connectedness approach lies in its ability to overcome the shortcomings of traditional correlation-related measures, such as the pairwise correlation. Diebold and Yilmaz (2014) argue that their measure overcomes the limitation of earlier measures, such as conditional value-at-risk (Tobias and Brunnermeier 2016) and marginal expected shortfall (Acharya, Engle, and Richardson 2012), which detects correlations between individual–firm and overall market movements both unidirectionally and bidirectionally. However, Diebold and Yilmaz (2014) methodology give us connectedness estimates in the time domain only. Additionally, we used the TVP-VAR and LASSO-DY approaches to provide dynamic connectedness across global energy-sector stocks for robustness purposes. Secondly, we provide novel empirical evidence on the effects of geopolitical risk, economic policy uncertainty, CBEO equity market volatility, CBOE oil price volatility and NYSE Oil and Gas index, which explains volatility spillover across the 20 regional energy-sector stocks. This is a novel contribution to the energy finance literature since we note from the finance literature that financial disasters such as the Asian financial crisis of 1997–1998, the global financial crisis of 2008, and the sovereign debt of the Eurozone in 2010 affected most global financial markets. Thus, we examine how energy stock connectedness around the world could be affected by these factors.

We documented several findings. Our empirical results from the DY approach showed that more advanced regions, including the CCARBNS, G12 and G7, are the major net contributors of volatility, while the biggest receiver of volatility is the Southeast Asia region. This was largely confirmed by the TVP-VAR and LASSO-VAR results, which revealed that Scandinavia, the Far East, and the Americas regions are net receivers of energy shocks, with net transmitters being CCARBNS, G7, G12 and Emerging Europe regions. We further found the significant roles of crisis periods (2007–2008 financial crisis and recent COVID-19 outbreak) and uncertainties in contributing to unprecedented high levels of energy spillovers. The structure of the paper is as follows: Section 2 provides a brief review of the empirical literature. Section 3 outlines the empirical methodology. Section 4 describes the data, while Section 5 presents the main empirical findings. Section 6 concludes the paper.

II. Integration in international energy stock market

The existence of an integrated and connected commodity energy market is implied through the economic theory of the law of one price. Heckscher (1916) originally argued that trade-based transaction costs emanating from the spatial separation of counterparties could lead to deviations from the law of one price (i.e. price divergence). The investigation of price divergence is inspired by studies including Taylor, Peel, and Sarno (2001), Sarno, Taylor, and Chowdhury (2004) and Apergis and Lau (2015). The price differential creates an arbitrate opportunity for the same, to some extent substitutable, good (e.g. crude oil of various qualities). Thus, lower-priced goods will be transported to another region and sold for higher prices (inclusive of all transaction and transportation costs). In equilibrium, the prices of the same good at different locations around the world will converge to a single price (or at least to a similar price level). It is noteworthy to mention that within this framework, trade only takes place on the condition that price differentials, or profits, generated from arbitrage activities can cover the transaction cost (Taylor, Peel, and Sarno 2001). For instance, let us assume the case where Saudi Arabia ships oil to Europe and Australia. If the law of one price holds, the price differentials between Europe and Australia should equal the price difference in shipping costs between Saudi-Arabia-Europe and Saudi Arabia-Australia (Warell 2006).

A number of empirical studies have applied the theoretical, non-linear version of the law of one price to allow differences in the degree of income and price convergence (e.g.; Lau et al. 2012;

Akhmedjonov and Lau, 2012; Suvankulov, Lau, and Ogucu 2012). Similarly, Akhmedjonov and Lau (2012) examined the pattern of price convergence in Russian energy markets, comprising diesel, gasoline, electricity and coal, from January 2003 to October 2010 over 83 Russian regions. Given the geographical scale of Russia and the variation in transport and infrastructure costs, it is not surprising that they find evidence of segmentation. Nonetheless, the unequal distribution of energy reserves and limited cross-border transmission capacity across different regions creates a complex set of pricing distortions, with the coal price correctly converging in only 37% of the Russian region. Another obstacle to regional convergence is local protectionism. For example, Young (2000) argues that there is increasing local protectionism in China as provinces attempt economic adjustment driven by national policy change (e.g. the decision not to use local coal that may be more polluting than imported ones). Market structure is another factor that affects the degree of market integration. Warell (2006) suggests that since the coal industry has experienced some mergers and acquisitions, this, in turn, may lead to larger and more monopolistic corporations being able to manipulate and control prices (Regibeau 2000). Mergers and acquisitions may result in barriers to entry, price discrimination, and collusion; therefore, price convergence across markets is invalid because the law of one price does not hold. However, one may also argue that mergers and acquisitions drive productivity improvement in the form of cost-cutting, and this potential increase in profit may encourage price convergence.

The existing empirical evidence concerning the scope of energy-sector stock market connectedness and integration is somewhat largely unexplored. Batten et al. (2019) examined the degree of integration of the global-steam coal market. Using a variety of measures, they showed that the Australian market remains the dominant force in setting world coal prices, followed by Mozambique and South Africa. Lin and Tamvakis (2001), for instance, studied the spillover effect between the London International Petroleum Exchange (IPE) and the New York Mercantile Exchange (NYMEX). Their results showed that spillover effects exist between both markets when they trade simultaneously and that IPE morning prices are affected by the close of the previous day on NYMEX. Their study is, however, only limited to two exchanges without considering the specific sector of our study's interest-energy. Mensi et al. (2013)considered energy markets and examined the dynamic return and volatility spillovers among some major international energy and cereal commodity markets, using the VAR-BEKK-GARCH and VAR-DCC-GARCH models. Their results showed strong linkages between the energy markets and the cereal markets. As seen, the authors do not consider connectedness among regional energy indices; rather, they examine the connectedness between energy markets and commodities markets. More recently, Mensi et al. (2021)examined the connectedness between commodities (crude oil and gold) and Chinese sector stocks. The authors found asymmetric spillovers, with the industrial sector being the largest contributor while the consumer sector is the largest receiver of spillover. These results showed the importance of considering sectors in spillover studies. Naeem et al. (2020)considered connectedness across energy markets. Their study focused on oil shocks, electricity and clean energy markets. The authors particularly found higher connectedness in the short run than in the long run as the global financial crisis and the shale oil revolution period increased this connectedness. In an earlier study, Zhang and Wang (2014)examined the return and volatility spillover but only between China and the world oil markets. The study found a bi-directional and asymmetric return and volatility spillover between China's oil market and the world oil market. Zhang et al. (2020) examined the return and volatility spillover among the natural gas, crude oil, and electricity utility stock indices in North America and Europe in a recent related study. They used the DY method for the time domain and the Baruník and Křehlík's method (2018)for the frequency domain. Their results showed that the return and volatility spillovers between the energy stock indices are stronger in both North America and Europe, as spillovers across the energy indices from 2009 to late 2013 remained stable in North America and Europe.

Our study differs from Zhang et al. (2020) in that we not only use the DY approach but also use additional measures of connectedness (TVP-VAR, LASSO-VAR). We also not only cover North America and Europe in our study but also use the energy indices of 20 regions, unlike Zhang et al. (2020), who focused on crude oil natural gas and electricity. We are, therefore, able to have a broader context for studying connectedness and directional spillovers in energy stock indices across the globe. A key novelty of this paper is that it is the first study to provide an empirical analysis of price connectedness and spillovers across international energy-sector stocks.

III. Methodology and data

Methodology

In this study, we used several estimation techniques to ensure the robustness of our results. We first used the DY (2014) model, followed by the TVP-VAR approach of Antonakakis and Gabauer (2017), which extends the originally proposed connectedness approach of Diebold and Yılmaz (2012). We, additionally, used the LASSO-VAR approach. The online supplementary file provides detailed explanations of the models used.

Data, summary statistics and time trends

In this paper, we studied connectedness and returns spillovers across 20 regional energy-sector markets indices for the period of 5 July 1994 to 21 April 2020, yielding a total of 6,731 observations. From Datastream, we obtained daily energy indices prices of 20 regional markets: Americas, Australasia, BRIC, Southeast Asia, Scandinavia, Southern Europe, Far East, Europe, European Union, Emerging Europe, Asia, G7, G12, Economic and Monetary Union (EMU), CCARBNS, Latin America, North America, PIIGS, Asia-Pacific and NORCS. In Table A1 in Appendix A, we define all the regional markets using codes for the purposes of the study. Daily returns of energy prices are in log form.

Table A2 in Appendix A presents summary statistics for the daily returns of regional markets energy prices. We found that the daily mean of energy prices for all 20 regional markets is positive, with Emerging Europe recording the highest mean return of 0.029, followed by Latin America with a mean return of 0.026. Asia-Pacific recorded the lowest average return of 0.015. From the standard deviation, Emerging Europe with a standard deviation of (2.391) is more volatile than Latin America (2.14). The lowest standard deviation was recorded by Asia-Pacific (1.26). Even though the extent of volatility is low for all the series, the results showed a considerable number of fluctuations in all the price indices. Furthermore, we observed significant negative skewness for all 20 regional markets indices. Negative (positive) skewness connotes the tendency of higher negative (positive) returns without matching the tendency of positive (negative) returns. In addition, as shown in Table A2, all the series record kurtosis exceeded Threshold 3, which surmises that the returns series of regional energy prices for the period have flatter tails compared to what would be anticipated from a normally distributed series.

Concerning the diagnostic tests of the series,[1] we use the Jarque-Bera (JB) test for the normality assumption in the series. We reject the null hypothesis of normality for all series at the 10% level. We adopt the ADF test of Dickey and Fuller (1979), PP test and KPSS test to examine the stationarity of our study variables. Our results from the insignificant KPSS statistics show that our series is stationary, which is confirmed by the ADF and PP unit root test as well. The presence of autocorrelation is tested using the Ljung-Box test, with the results confirming the presence of autocorrelation for all series. We also tested for the presence of ARCH effects using the ARCH-LM test of Engle (1982), and the results suggested the presence of ARCH effects in all the series. The test of statistics for all the estimated non-linearity tests (Teraesvirta NN Test, White NN Test, Keenan Test, Tsay Test, Likelihood Ratio

[1]The results are available upon request.

Test and Bootstrap Symmetry Test) rejected the null hypothesis that the time series follows some AR process.

IV. Empirical results and interpretation

Connectedness and directional spillovers results

Connectedness using the DY model

Table 1 presents the DY spillover empirical results. The results reveal substantial differences in the magnitude of shocks transferred from one regional market to another. We observed that the lowest value of volatility transmission transmitted from one regional market to another is the Far East, followed by South-East Asia. The highest spillovers are from the returns of the G12 index to the return's series of North America and Americas' indices with the component of transmission from the returns of the G12 price series to North America and Americas, which has been 11.6 and 11%, respectively.

Moreover, the figures in the diagonal, which represent the magnitude of own shock spillover, are much less than the value of the total connectedness index (TCI). This suggests that external shocks impact energy price indices at the regional level more than shocks internal to each regional market. With regard to contribution to others, about 122% of the variation in the return series of the G12 energy index is spilt to return indices of other markets. Moreover, more than 120% of the realized variance in the return's series of the G7 energy index and about 109% of the variation in the return series of the European Union energy price index were transmitted to other markets. The emergence of the European Union energy-sector returns as major transmitters of shocks over North America differs from the findings of Zhang et al. (2020). We found that South-East Asia contributed the least to other markets, followed by the Far East and Emerging Europe.

In addition, we observed from Table 1 that the range of directional volatility transferred from all the regional markets to a specific regional market is relatively wide, from 73.9% to 90.2% for Southeast Asia and Europe, respectively. Therefore, we conjecture that the volatility in all observed regional markets at minimum starts from 72%. Likewise, we noted that Europe is the most affected by shocks from other regional markets, which is in consonance with the conclusion of Zhang et al. (2020). Overall, from the DY spillover analysis, shocks related to volatility from other regional markets account for 1723.6% of the volatility forecast error variance in our sample.

Furthermore, Table 1 reports the net directional connectedness, which measures the net spillover indices for each specific regional market.[2] We found that the Americas, Scandinavia, Southern Europe, Europe, European Union, G7, G12, CCARBNS, North America, PIIGS and NORCS have positive net spillover value, which implies that these regional markets are net contributors of volatility, while Australasia, BRIC, Southeast Asia, Far East, Emerging Europe, Asia, Latin America and Asia-Pacific are net receivers. The biggest net contributor of volatility is CCARBNS, followed by G12 and G7, in that order, while the biggest receiver is Southeast Asia, followed by Far East regional markets. The dominance of the G12 and G7 energy sectors is not surprising since the countries constituting these blocs are major players in the world economy and financial system. Overall, the G12 energy sector maintains its leadership position as the benchmark for ascertaining energy prices across all market conditions.

Static connectedness

Table A3 in Appendix A reports a static analysis of volatility spillover between all 20 regional energy markets in the world. This approach allows detecting to what extent expectations in the markets change in reaction to events in other markets and how the connectedness between different markets evolves. For the purposes of static volatility spillovers analysis, we focus on examining net volatility.[3] The last row of Table A3 contains the net volatility spillover effects for each regional energy market, quantifying the input by each of them to the global energy market volatility. It is

[2] A positive net spillover value indicates that the regional energy index is a spillover contributor while a negative spillover suggests that a specific regional market is net receiver. Thus, it receives spillover from other regional markets.

[3] This choice is because Net volatility allows us to establish a global figure and gain understanding on how each regional energy market is related to the entire market.

Table 1. DY Spillover Results.

	ENE GYAM	ENE GYAZ	ENE GYBC	ENE GYSE	ENE GYSC	ENE GYSS	ENE GYFE	ENE GYER	ENE GYEU	ENE GYUE	ENE GYAS	ENE GYG7	ENE GY12	ENE GYEM	ENE GYCC	ENE GYLA	ENE GYNA	ENE GYPI	ENE GYAP	ENE GYNC	FROM
ENEGYAM	**12**	1.6	2.7	0.8	3.7	3.5	0.7	5.1	5.1	1.2	1.2	11.2	11.1	4.5	7.2	4.9	11.9	3.5	1.4	6.6	88
ENEGYAZ	**5.5**	15.8	3.2	2	4.9	3.6	3.1	5.3	4.9	1.8	3.4	5.9	6.1	4.4	6.6	3.6	5.3	3.7	5.1	5.9	84.2
ENEGYBC	**4.1**	2.1	15.1	1.6	4.2	3.1	1.4	5.8	3.9	9.2	3.8	4.1	4.2	3.7	9	6.6	3.4	3.2	4.2	7.5	84.9
ENEGYSE	3.6	3.4	3.7	26.1	3.6	2.5	3.7	3.7	3.2	2.1	8.2	3.8	3.9	2.9	4.8	3.2	3.3	2.5	7.7	4.3	73.9
ENEGYSC	4.9	2.8	3.5	1.3	12.5	5.6	1.3	7.5	6.7	2.5	2	5.8	6	6.5	7.5	3.4	4.6	5.6	2.4	7.7	87.5
ENEGYSS	4	1.8	2.5	0.8	5.5	12.3	0.8	8.3	8.9	1.6	1.3	5.7	5.9	10.2	5.1	2.8	3.7	12.3	1.6	5.1	87.7
ENEGYFE	4.1	3.5	2.8	2.5	3.6	2.9	16.9	4	3.7	1.3	11.5	4.5	4.6	3.4	4.9	3.1	3.9	2.9	11.3	4.4	83.1
ENEGYER	5	2.1	3.7	0.9	5.8	6.6	1	9.8	9.1	2.7	1.6	6.8	6.9	8.4	6.6	3.1	4.8	6.6	1.9	6.6	90.2
ENEGYEU	5.1	1.9	2.6	0.8	5.5	7.5	0.9	9.7	10.5	1.6	1.4	7.3	7.4	9.5	5.6	3	4.9	7.5	1.7	5.5	89.5
ENEGYUE	3	2	13.7	1.4	4.5	3	1	6.4	3.7	22	1.7	3.4	3.4	3.5	8.1	3	2.7	3.1	2	8.5	78
ENEGYAS	3.5	3.3	4.8	4.7	3.4	2.7	10.1	3.9	3.4	1.6	15.2	3.9	4	3.2	4.7	2.9	3.2	2.7	14.6	4.2	84.8
ENEGYG7	9.8	1.7	2.4	0.8	4.2	4.6	0.8	6.6	6.8	1.3	1.3	10.5	10.5	6	6.5	3.7	9.8	4.7	1.5	6.3	89.5
ENEGY12	9.6	1.8	2.5	0.8	4.3	4.7	0.9	6.6	6.9	1.3	1.3	10.4	10.4	6.1	6.5	3.7	9.6	4.8	1.6	6.3	89.6
ENEGYEM	4.7	1.8	2.5	0.8	5.5	8.9	0.9	9.3	9.9	1.6	1.3	6.7	6.8	10.8	5.4	2.9	4.5	8.9	1.6	5.3	89.2
ENEGYCC	6.5	2.6	5.7	1.2	5.8	4.1	1.2	6.5	5.2	3.5	1.9	6.7	6.7	4.9	10.2	5.6	6	4.1	2.3	9.5	89.8
ENEGYLA	7.1	1.9	7	1.2	4.2	3.7	1.1	5	4.6	2	1.7	6.2	6.3	4.3	9.4	17.1	5.6	3.7	2	5.8	82.9
ENEGYNA	12.5	1.5	2.3	0.8	3.6	3.4	0.7	5.1	5.1	1.1	1.1	11.7	11.6	4.5	6.9	4	12.6	3.4	1.4	6.6	87.4
ENEGYPI	4	1.8	2.5	0.8	5.5	12.2	0.9	8.3	8.8	1.6	1.3	5.7	5.9	10.1	5.1	2.8	3.8	12.2	1.6	5.1	87.8
ENEGYAP	3.9	4.5	4.7	3.9	3.7	2.8	8.9	4.1	3.7	1.7	13	4.3	4.4	3.4	5.1	3.1	3.6	2.9	13.6	4.6	86.4
ENEGYNC	6.2	2.4	5	1.1	6.3	4.3	1.2	7	5.5	3.8	1.8	6.7	6.8	5.1	10	3.7	6	4.3	2.2	10.6	89.4
TO others	107.1	44.4	77.8	28.2	87.8	89.6	40.6	118.3	108.9	43.5	60.7	120.8	122.6	104.4	124.8	69.3	100.6	90.4	67.8	115.9	1723.6
NET	19.1	−39.8	−7	−45.7	0.2	1.9	−42.5	28.1	19.4	−34.5	−24.1	31.3	33	15.2	35	−13.6	13.2	2.7	−18.6	26.6	**TCI =**
NPDC t	14	3	7	0	8	9	1	16	13	2	4	18	19	11	17	6	12	10	5	15	**86.2**

worth mentioning that the CCARBNS regional market has the highest spillover value (35.46), followed by the G12 (33.84) and G7 (32.28) markets. This implies that these regional markets are the biggest contributors to the world energy market. Like the results obtained in Table 1, we found that the biggest receivers are Southeast Asia and the Far East. We estimated the net pairwise static volatility spillovers to obtain more detailed information about the direction and magnitude of the volatility spillovers. We used return data and reported the net pairwise static spillovers with results in Table A4 in Appendix A.

Dynamic connectedness

In this section, we move from the static analysis towards a dynamic one to analyse volatility spillovers over time. This dynamic framework permits us to examine how shocks spread across regional energy markets and underline existing indirect linkages between them. Table A5 in Appendix A presents the results. The lowest value of volatility transmission from one regional market to another is from the Fast East and Southeast Asia, while the highest spillovers are from the returns of G12, G7, and CCARBNS. Concerning contribution to others, we find that about 124% of the variation in the return series of the G12 energy price index is spilt to return indices of other markets. Moreover, more than 123% of the realized variance in the return's series of the G7 energy price index is about 118% of the variation in the return series of the CCARBNS energy price index, which is transmitted to other markets. South-East Asia contributes the least to other markets, followed by Australasia.

We find slight differences in the results reported earlier regarding contribution to others. We note further from Table A5 that the range of directional volatility transferred from all the regional markets to a specific regional market is relatively wide, from 66% to 90% for Southeast Asia and Europe, respectively. We conjectured that the volatility in all observed regional markets at minimum starts from 66%. Europe is the most affected by shocks from other regional markets. Overall, from the dynamic spillover analysis, shocks related to volatility from other regional markets account for 166% of the volatility forecast error variance in our sample. Finally, Table A6 in Appendix A reports the dynamic net directional connectedness, which measures the net spillover indices for each specific regional market. Compared with the results reported in Table 1, we find from Table 1 that the Americas, Scandinavia, Southern Europe, Europe, European Union, G7, G12, CCARBNS, North America, PIIGS and NORCS have positive net spillovers values, which implies that these regional markets are net contributors of volatility. However, from the dynamic analysis, we find that Scandinavia regional markets joining Australasia, BRIC, Southeast Asia, Far East, Emerging Europe, Asia, Latin America and Asia-Pacific are net receivers. Again, the dominance of CCARBNS as the biggest net contributor, followed by G7 and G12, is confirmed with the dynamic analysis, while the biggest receiver is Southeast Asia, followed by Far East regional markets. The comparison of TCI for DY spillovers, static volatility spillovers, and dynamic volatility spillovers – as presented in Table 1, Table A3 and Table A5, respectively – shows that the TCI is 86.2% in Tables 1, 86.33% in Tables A3 and 83.28% in Table A5. This is the manifestation of the fact that regional energy sector indices are highly connected.

Total connectedness plots

Our period study from 5 July 1994 to 21 April 2020 covers some key global events, such as the Asian financial crisis in 1997, the 11th September terrorist attack on the US, the 2007–2008 financial crisis, the dramatic fall in oil prices from mid-2014 to early 2016, and the outbreak of COVID-19 in early 2020. Assessing the changes in the degree of integration between the regional energy markets during these major global events is essential. While the previous static and dynamic analyses provide a useful overview of the average volatility spillover over the period, we further check the sensitivity of the results to the choice of the order of VAR. We calculate the sensitivity of the spillover index and plot the minimum, maximum, and median values obtained in Figure 1. From this figure, we note a decreasing trend of spillovers from the return series of world energy markets during the 2001 terrorist attack on the USA. We also find an increasing trend during the Asian financial crisis in 1997 and the US mortgage crisis in 2007–2008. For 2015, we

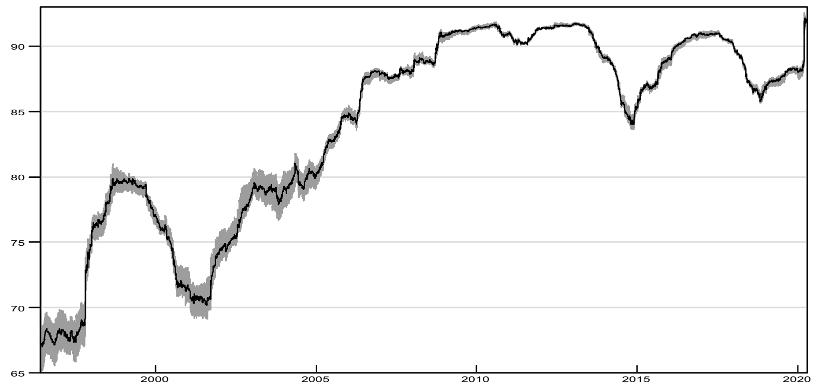


Figure 1. DY Spillover sensitivity analysis (lag-mini-max). The grey line is min and max while the black line is the median.

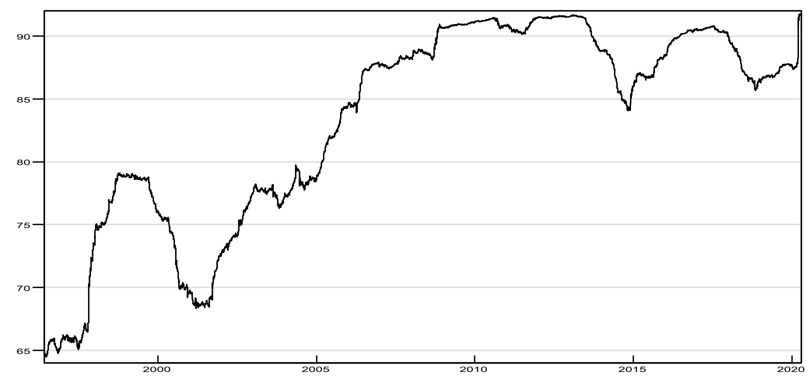


Figure 2. DY Spillover sensitivity analysis (forecast horizon).

observed that the price indices dropped from about 98% level to 84%. The results seen in 2015 are not surprising following the drop in oil prices that started in the second half of 2014. After the crisis, the price indices increased again to about 93% level after 2015. Figure 2 presents the spillover index for forecast horizons. The results from both Figure 1 and Figure 2 do not differ substantially from each other.

Additional Results

Net pairwise total connectedness using TVP-VAR & LASSO-VAR

In this section, we investigate connectedness across regional energy markets and spillovers using TVP-VAR and LASSO-VAR spillover approaches in a time-varying framework. The time-varying net-pairwise spillovers are presented in Table 2, while net pairwise spillovers using LASSO-VAR are reported in Table 3.

We find from Table 2 that the price index of the NORCS regional bloc comprises the following countries USA, Russia, Finland, Sweden, Norway, Greenland and Canada as a net pairwise contributor of volatility to Europe, European Union, G7 and G12 price returns. The PIIGS price index made of Portugal, Italy, Ireland, Greece, and Spain, which were the weakest economies in the Eurozone during the European debt crisis, serves as the net contributor of volatility with reference to G7 and G12. The Australian price index acts as a net contributor of volatility with reference to the Americas. We further note that Australasia is the largest net receiver of volatility from Asia and the Asia Pacific, while Scandinavia is the largest net receiver of volatility from G7 and G12. South-East

Table 2. NET pairwise Spillover TVP-VAR.

	ENE GYAM	ENE GYAZ	ENE GYBC	ENE GYSE	ENE GYSC	ENE GYSS	ENE GYFE	ENE GYER	ENE GYEU	ENE GYUE	ENE GYAS	ENE GYG7	ENE GY12	ENE GYEM	ENE GYCC	ENE GYLA	ENE GYNA	ENE GYPI	ENE GYAP	ENE GYNC
ENEGYAM	0	0.009	−0.577	−0.140	−0.101	−0.120	−0.342	−0.396	−0.387	−0.355	−0.389	−0.443	−0.457	−0.336	−0.241	−0.267	−0.279	−0.127	−0.435	−0.017
ENEGYAZ		0	−0.730	−0.249	−0.164	−0.328	−0.555	−0.478	−0.489	−0.423	−0.649	−0.619	−0.619	−0.464	−0.377	−0.308	−0.495	−0.317	−0.683	−0.257
ENEGYBC			0	−0.146	−0.150	−0.301	−0.607	−0.229	−0.247	−0.435	−0.652	−0.343	−0.352	−0.294	−0.312	−0.030	−0.281	−0.272	−0.659	−0.152
ENEGYSE				0	−0.260	−0.260	−0.364	−0.461	−0.455	−0.369	−0.514	−0.538	−0.568	−0.389	−0.675	−0.650	−0.444	−0.274	−0.493	−0.358
ENEGYSC					0	−0.215	−0.319	−0.594	−0.555	−0.462	−0.362	−0.617	−0.618	−0.466	−0.245	−0.419	−0.567	−0.223	−0.399	−0.328
ENEGYSS						0.0	−0.515	−0.401	−0.426	−0.545	−0.478	−0.592	−0.585	−0.457	−0.330	−0.399	−0.444	−0.028	−0.485	−0.153
ENEGYFE							0	−0.433	−0.448	−0.459	−0.258	−0.581	−0.580	−0.435	−0.206	−0.265	−0.486	−0.226	−0.271	−0.167
ENEGYER								0	−0.082	−0.454	−0.285	−0.274	−0.291	−0.085	−0.275	−0.394	−0.254	−0.024	−0.329	0.008
ENEGYEU									0	−0.448	−0.270	−0.251	−0.278	−0.040	−0.290	−0.387	−0.202	−0.023	−0.315	0.015
ENEGYUE										0	−0.357	−0.364	−0.364	−0.229	−0.215	−0.221	−0.275	−0.194	−0.398	−0.146
ENEGYAS											0	−0.592	−0.590	−0.435	−0.176	−0.262	−0.489	−0.195	−0.075	−0.165
ENEGYG7												0	−0.068	−0.047	−0.253	−0.376	−0.038	0.020	−0.330	0.042
ENEGY12													0	−0.052	−0.259	−0.380	−0.017	0.035	−0.338	0.046
ENEGYEM														0	−0.273	−0.412	−0.301	0.075	−0.237	0.004
ENEGYCC															0	−0.303	−0.464	−0.265	−0.520	−0.237
ENEGYLA																0	−0.266	−0.222	−0.484	−0.212
ENEGYNA																	0	−0.043	−0.396	−0.027
ENEGYPI																		0	−0.477	−0.153
ENEGYAP																			0	−0.159
ENEGYNC																				0

Table 3. NET pairwise static average spillover dynamics between regional energy markets estimated using LASSO-VAR.

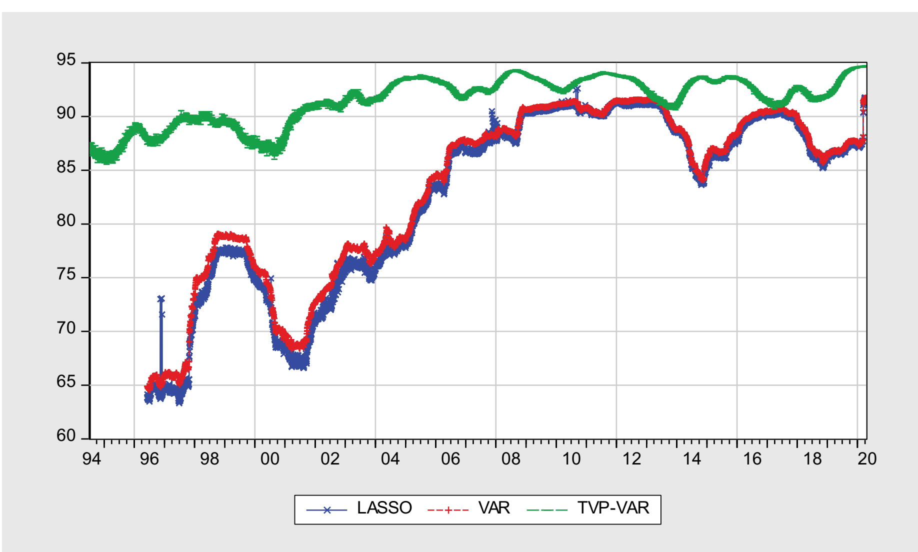
	ENE GYAM	ENE GYAZ	ENE GYBC	ENE GYSE	ENE GYSC	ENE GYSS	ENE GYFE	ENE GYER	ENE GYEU	ENE GYUE	ENE GYAS	ENE GYG7	ENE GY12	ENE GYEM	ENE GYCC	ENE GYLA	ENE GYNA	ENE GYPI	ENE GYAP	ENE GYNC
ENEGYAM	0	−4.3	−1.3	−2.8	−1.2	−0.6	−3.5	0	−0.1	−1.8	−2.4	1.4	1.5	−0.3	0.7	−2.2	−0.6	−0.6	−2.6	0.3
ENEGYAZ		0	1.1	−1.5	2	1.8	−0.5	3.2	2.9	−0.2	0.1	4.3	4.4	2.6	4	1.8	4	1.8	0.5	3.5
ENEGYBC			0	−2.1	0.8	0.6	−1.4	2.1	1.4	−4.4	−1	1.7	1.8	1.2	3.2	−0.4	1.1	0.7	−0.5	2.4
ENEGYSE				0	2.3	1.5	1.3	2.6	2.3	0.7	3.7	2.9	3	2	3.5	2	2.5	1.6	3.9	3.1
ENEGYSC					0	0.2	−2.3	1.7	1.2	−2	−1.4	1.6	1.7	1	1.7	−0.8	1	0.2	−1.3	1.4
ENEGYSS						0	−2.1	1.7	1.3	−1.4	−1.3	1.2	1.3	1.2	1	−0.9	0.4	0.1	−1.2	0.7
ENEGYFE							0	3	2.7	0.3	1.2	3.8	3.8	2.5	3.8	2.2	3.3	2.1	2.2	3.3
ENEGYER								0	−0.6	−3.7	−2.2	0.2	0.3	−0.8	0	−1.9	−0.2	−1.7	−2.2	−0.4
ENEGYEU									0	−2.1	−1.9	0.5	0.5	−0.3	0.4	−1.6	−0.1	−1.3	−1.9	0
ENEGYUE										0	0.1	2.1	2.2	1.9	4.7	1.1	1.6	1.5	0.3	4.6
ENEGYAS											0	2.6	2.7	1.8	2.8	1.4	2.2	1.4	1.5	2.5
ENEGYG7												0	0.1	−0.7	−0.2	−2.5	−1.9	−1.1	−2.8	−0.5
ENEGY12													0	−0.7	−0.3	−2.6	−2	−1.2	−2.8	−0.6
ENEGYEM														0	0.4	−1.4	0.1	−1.2	−1.7	0.2
ENEGYCC															0	−3.8	−0.9	−1	−2.8	−0.5
ENEGYLA																0	1.6	0.9	−1.2	2.1
ENEGYNA																	0	−0.5	−2.3	0.6
ENEGYPI																		0	−1.2	0.8
ENEGYAP																			0	2.4
ENEGYNC																				0

Asia is the net receiver of volatility from the CCARBNS, while the Americas is the net receiver of volatility from BRIC.

In the variance decomposition framework, we further construct a volatility connectedness network linking the 20 regional energy price indices using the LASSO-VAR for estimating high-dimensional VARs. In the analysis of high-dimensional data (in our sample, including 20 regional energy markets), we exploit the least absolute shrinkage and selection operator (LASSO) method to reduce dimensionality and shrink the sample when estimating VAR parameters, where the LASSO is a regression analysis method to increase the prediction accuracy and interpretability of the statistical model through variable selection and regularization. From Table 3, we note similar findings as in Table 2: the dominance of G7, G12 and CCARBNS regional markets is again revealed as these markets emerged as the biggest contributors to the volatility of other regional markets. G7, G12 and CCARBNS are the largest receivers of volatility from the Asia-Pacific price return. Americas is the largest receiver of volatility from the Australasia price return and the Far East. Comparing the magnitude of connectedness using TVP-VAR as discussed in Table 2 and LASSO-VAR as reported in Table 3, we conjectured that, overall, G12 is the largest contributor of volatility in respect to the other 19 regional markets, while Americas is the largest receiver of volatility from the other 19 regional markets.

Directional spillovers

We now turn our attention to the interpretation of the spillover plots based on the time-varying estimates of the various spillover indices according to the models used in this study. Figure 3 displays the time-varying total connectedness index. This figure shows a large variation in the spillover index of specific regional markets and the total connectedness index. We see that global energy markets turn out very responsive to global economic events such as the Asian financial crisis, which occurred in 1997, the mortgage crisis in 2007–2008 and the recent outbreak of COVID 19. During the 2007–2008 crisis and the recent COVID-19 outbreak, energy spillovers reached an unprecedented level (95%). These periods are characterized by intense unconventional fluctuations in world crude oil.



X axis: study period (1994-2020 Y-axis: Total Connectedness Index

Figure 3. Total Spillover Index from LASSO VAR, TVP-VAR Spillover.

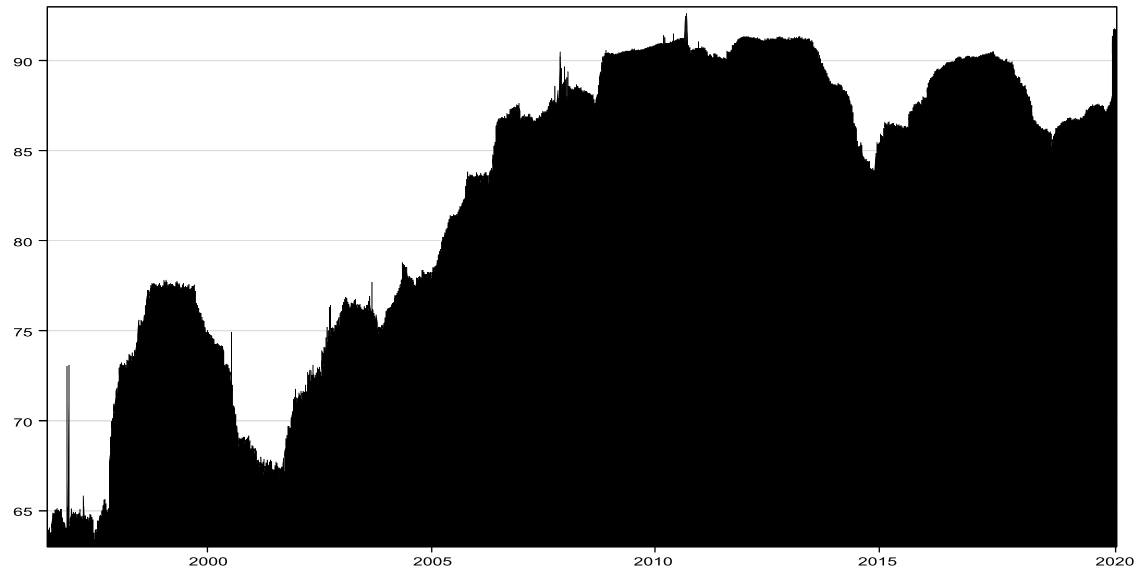


Figure 4. LASSO DY Spillover.

Figure 4 presents the evolution of the total spillover and connectedness using the LASSO-VAR model, hence the co-movement of the regional energy markets. We note that world energy market connectedness decreased from the beginning of the study period until the Asian crisis in 1997, when it increased to about 78%. After this, we see a drop in the interconnectedness in world energy markets around 2000–2002. This drop lasted for a short time until it increased continually to about 98% from 2010 to 2011. Thus, we find extreme responses of world energy stock markets to world events such as the recent COVID-19 pandemic and the 2007–2008 financial crisis.

Analysis of hedging and portfolio weights

Table A7 in the appendix reveals the hedge ratio between the regional markets. The table reports that the $1 long position in the first asset, such as the energy-sector stocks of Australasia (ENEGYAZ), can be hedged with the average value of hedge ratio percentage of a short position in the second asset, such as the energy-sector stock of Americas (ENEGYAM). The result of the hedge ratios revealed that the cheapest average hedge is between Latin America and Asia energy sectors (0.16), and the most expensive hedge is between G17 and Americas (1.06) (see Table A8 in the appendix). From the results, the highest average optimal weight revealed for the G12 and the North America portfolios are .94, which means that for the $1 portfolio, 94 cents will be invested in G12 energy stocks, and the remaining 6 cents will be invested in North America energy stocks. On the other hand, the lowest average optimal weight is manifested for the G7 and G12 portfolios, which is 0.05. Thus, the hedge ratios and optimal weight results show that portfolio investors can minimize risk in their future energy portfolios by diversifying their assets to include regional energy stocks.

Extended analysis of the spillover index

Factors contributing to volatility spillover across regional energy markets

In this section, we analyse how factors such as geopolitical risk, economic policy uncertainty, CBEO equity market volatility, CBOE oil price volatility and NYSE oil and gas index explain volatility spillover across the 20 regional energy markets. We obtained monthly data for the above variables from multiple sources. First, World Economic Policy Uncertainty (EPU) and Geopolitical Risk Index (GPR) data were compiled from the website (www.policyuncertainty.com), CBEO equity market volatility (VIX), and CBOE oil price volatility (OVX) were obtained from the website of the CBOE website. Finally, we obtained the NYSE Oil and Gas index ($NYSEOilGas_t$) from

Thomson Reuters Eikon. All the above indices are found to be stationary in their raw level form. We used Quantile Regression (QR) to examine the impact of the five series on the total spillover index, with results presented in Table A9 in Appendix A. According to Ferrando, Ferrer, and Francisco (2017), QR analyses the impact of the explanatory variables on the tail ends and not only on the centre of the distribution. We find a significant negative relationship between the explanatory variables and the total spillover index, except for EPU. This suggests that high policy uncertainty increases the magnitude of volatility spillovers in world energy markets.

V. Conclusion and policy implications

In this paper, we shed light on how the energy price indices of 20 regional blocs in the world are integrated using daily returns from 5 July 1994 to 21 April 2020. We used the DY approach, TVP-VAR and LASSO-VAR and investigated the spillover across regional energy markets. The main results can be summarized as follows: From the DY spillover analysis, we found gross directional volatility transmission to other regional markets from each of the 20 regional markets. About 122% of the variation in the return series of the G12 energy price index is spilt to return indices of other markets. Moreover, more than 120% of the realized variance in the return series of the G7 energy price index and about 109% of the variation in the return series of the European Union energy price index were transmitted to other markets. South-East Asia contributed the least to other markets, followed by the Far East and Emerging Europe.

We estimated the net pairwise static volatility spillover to obtain more detailed information about the direction and magnitude of the volatility spillovers. We concluded that the price index of America is a net pairwise contributor of volatility with regard to North America, G7 and G12 price returns. On the magnitude of volatility shocks transmitted across the regional markets, we found that the lowest value of volatility transmission from one regional market to another in our sample is for Fast East and Southeast Asia, while the highest spillovers are seen to be from the returns of G12, G7, and CCARBNS. Using TVP-VAR and LASSO-VAR, once again, we highlighted the dominance of G7, G12 and CCARBNS regional markets as the biggest contributors to volatility to other regional markets, from the net static pairwise spillover dynamics. Comparing the magnitude of connectedness using TVP-VAR and LASSO-VAR, we found that overall, G12 is the largest contributor of volatility with respect to the other 19 regional markets, while Americas is the largest receiver of volatility from the other 19 regional markets. Finally, we inferred that global energy markets are very responsive to global economic events, such as the Asian financial crisis that occurred in 1997, the mortgage crisis in 2007–2008 and the recent outbreak of COVID-19. During the 2007–2008 crisis, dramatic fall in oil prices from mid-2014 to early 2016 and the recent COVID-19 outbreak, these periods were characterized by intense unconventional fluctuations in world crude oil and energy spillovers reached an unprecedented level (98%).

These findings have important implications for the portfolio diversification and hedging decisions of energy-concerned investors. In fact, investors should consider the presence of dependence between regional energy stock markets as an important factor in making more informed and rational choices in their portfolio formulation strategies. From a managerial perspective, our results offer more knowledge about the factors that influence the performance of energy companies. Thus, managers can make better business decisions regarding investments and enhance the performance of the company. This study also supports policymakers in articulating policies that seek to avoid the contagion risk stemming from volatile asset classes such as the energy-sector stocks. They should remain observant of the impact of extreme downside movements in equity and energy markets and intervene when necessary to ensure financial stability.

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