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Volatility spillovers amid crude oil, natural gas, coal, stock, and currency markets in the US and China based on time and frequency domain connectedness

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ABSTRACT

This paper inspects volatility connectedness across crude oil, natural gas, coal, stock, and currency markets in the US and China. To accomplish this objective, we deploy methodologies advocated by Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) through gathering daily data from 12/8/2008 to 12/18/2020. The evidence from this research suggests total connectedness among energy, stock, and currency markets is not high, and accordingly, contemporaneity of losses in these assets seems highly improbable. Other results reveal that the S&P500, WTI, natural gas, and the US dollar number are net receivers, while Shanghai stock, coal, and USD/CNY are net givers. Thus, we conclude that Shanghai stock, coal, and USD/CNY should not be used for portfolio diversification. Furthermore, total connectedness in the long run outperforms that of the short run, implying investors cannot follow the buy-and-hold approach on account of these assets' high long-term volatility. All in all, these outcomes are advantageous for authorities and investors to broaden their knowledge of how price volatility shocks in these energy markets translate to stock and currency markets.

1. Introduction

Crude oil is one of the most strategic materials in the production of goods and services, and as such, it has an irreplaceable role in global economy. Stock markets are mainly affected by changes in crude oil price via two channels. First, oscillations in crude oil price can have adverse effects on stocks enterprises, as they increase production costs. Accordingly, sales volume in certain other industries can decline as a result from the upward trend in crude oil price. Second, crude oil price is a key factor for companies' value, in that it influences expected cash flows, and consequently, it will affect level of prices in equity markets (Jiang and Yoon, 2020; Zolfaghari et al., 2020). Moreover, there are connections between crude oil price and exchange rates. To clarify, currency markets are contingent upon crude oil via the trade channel, and therefore, a climb in crude oil price has a considerable impact on exchange rates. Furthermore, an increased oil price might depreciate the value of local currencies against global ones, particularly in oil-importing economies. By contrast, if the price of crude oil increases, the ratio of domestic currencies to international ones will also increase in oil-exporting countries, (Khraief et al., 2021; Lin and Su, 2020). In addition to crude oil, natural gas is one of the pivotal energy commodities that fulfills industrial and household needs (Mensi et al., 2021; Lin et al., 2019; Acaravci et al., 2012; Villar and Joutz, 2006). According to a report by the International Energy Agency (IEA), less than a quarter of the global energy supply is comprised of natural gas,[1] and economic theory suggests that crude oil and natural gas markets are closely related from both demand and supply perspectives. The natural gas market tends to be influenced by oscillations in the crude oil market; conversely, natural gas market affects price trends in crude oil (Mensi et al., 2021; Jadidzadeh and Serletis, 2017; Karali and Ramirez, 2014). Further, increasing natural gas price is a cause of inflationary conditions in oil-importing economies, and thus, it might negatively affect financial assets such as equity markets (Geng et al., 2021; Kumar et al., 2019). Coal is also being increasingly consumed as a source of energy. For example,

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[1] https://www.iea.org/reports/key-world-energy-statistics-2021/supply

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coal makes up approximately more than 25% of the total energy supply,[2] and more than two-fifths of electricity produced in 2013 used coal (Batten et al., 2019). Coal and crude oil share an interesting relationship. More specifically, crude oil is a partial replacement for coal, and an increment in crude oil price increases coal usage; contrariwise, when coal price climbs, crude oil usage increases (Li et al., 2019). Moreover, price oscillations in commodities such as coal impact supply and production costs, and this connection is crucial for countries reliant on energy and mineral sources. Additionally, commodity prices might affect economic status via currency markets. To elucidate, variations in commodity prices are more liable to be transformed to other markets by exchange rates, but their impacts can differ across countries (Ma and Wang, 2019). These markets have witnessed sharp fluctuations in not only daily transactions but also hourly ones, during periods of high volatility. Price trends of financial assets might remain stable for days or weeks, or they can be affected by occurrences in alternative financial markets, key macroeconomics indexes, and supply and demand shocks. Other pertinent factors, including economic or political turmoil in energy-intensive countries are more inclined to affect financial assets. More importantly, financialization is a key factor, exacerbating volatility in energy commodities, and it strengthens interrelations among energy markets and alternative financial assets, becoming a threat to financial market stability (Jiang et al., 2021).

In the case of the US, fossil fuels, such as crude oil, natural gas, and even coal, are consequential. To specify, this country is one of the leading crude oil producers and the leading crude oil consumer in the world. Besides, a vast quantity of natural gas is generated to supply the US's power sector, where coal is also still used (Zolfaghari et al., 2020; Hailemariam and Smyth, 2019). In addition, the US dollar has a pivotal role in commodity price oscillations (Wu et al., 2012). For instance, it is essential to trade crude oil in the global market, and crude oil price and the USD have a significant relationship. To be more exact, devaluation of the USD causes oil prices to decrease for foreign buyers. This leads to increased investment in the crude oil market, and therefore, it is a contributory factor to growth in crude oil prices (de Truchis and Keddad, 2016). There is an almost similar scenario for China, in that this economy also relies heavily upon energy use for its economic development. To illustrate, coal fulfills three-fifths of China's energy needs, thus oscillations in coal price exert pressure on China's economy (Li et al., 2019). In addition, China is by far the largest buyer of crude oil in the world (Kong et al., 2020; Li et al., 2019). Furthermore, 7% of total natural gas is consumed by China; thus, this energy market occupies a prominent role in China's economy (Chai et al., 2019). Finally, the importance of RMB (CNY) has increased in financial transactions. To illustrate, China's share of cross-border trade settled in RMB was approximately 17% in 2013, as opposed to less than 1% in 2009 (Ho et al., 2017). Furthermore, fluctuations in RMB are crucial for China's economy, for if the ratio of RMB to the USD depreciates, crude oil price will be lower for this country (Huang et al., 2020).

A multitude of investigations have spotlighted volatility connectedness between crude oil and stock markets (such as Bouri et al., 2021a, 2021b, 2021c; Shahzad et al., 2021; Cui et al., 2021; Ashfaq et al., 2020; de Jesus et al., 2020; Yu et al., 2020; Tiwari et al., 2020a, 2020b; Wang et al., 2020; Siddiqui et al., 2020; Hamdi et al., 2019; Ji et al., 2018a, 2018b; Antonakakis et al., 2018; Cai et al., 2017; Maghyereh et al., 2016; Khalfaoui et al., 2015; Masih et al., 2011). Additionally, volatility spillovers between crude oil and currency markets have been an enthralling topic in academic and economic research (Khraief et al., 2021; Bouri et al., 2021a, 2021b, 2021c; Akram, 2020; Albulescu et al., 2019; Huang et al., 2020; Basher et al., 2016; Brahmasrene et al., 2014; Wu et al., 2012; Ghosh, 2011; Lizardo and Mollick, 2010). However, a handful of studies have analysed the nexus among crude oil, stock, and currency markets (Chkir et al., 2020; Malik and Umar, 2019; Kumar, 2019; Bai and Koong, 2018; Roubaud and Arouri, 2018; Huang et al., 2017).

Several studies examine the linkage between natural gas and financial assets (Bouri et al., 2021a, 2021b, 2021c; Gong et al., 2021; Chai et al., 2019; Hailemariam and Smyth, 2019; Kumar et al., 2019; Ji et al., 2018a, 2018b; Jadidzadeh and Serletis, 2017; Batten et al., 2017; Nick and Thoenes, 2014; Erdős, 2012; Wang and Wu, 2012). Only a few studies, such as Batten et al. (2019) and Papież and Śmiech (2015), have focused on the coal market. Finally, a few publications merely concentrate on examining volatility connectedness between coal and other classic assets (Albulescu et al., 2020; Ali et al., 2020; Rehman et al., 2019; Zolfaghari et al., 2020; Li et al., 2019; Ma and Wang, 2019; Sun et al., 2019; Bachmeier and Griffin, 2006).

Nevertheless, there are major obstacles to obtaining more information regarding volatility spillovers among crude oil, coal, natural gas, stock, and currency markets. For one, papers like Zolfaghari et al. (2020) and Bachmeier and Griffin (2006) analyze linkages among these energy sources and other financial assets within the US market; on the other hand, studies such as Li et al. (2019), Ma and Wang (2019), and Sun et al. (2019), examine these associations in the Chinese context. Accordingly, there is not an in-depth study providing an insightful analysis about the markets in both powerful economies. Strangely, results of former investigations contradict each other. For instance, Zolfaghari et al.'s (2020) outcomes show that there is positive and significant connectedness among coal, other energy, and financial markets, whereas Bachmeier and Griffin's (2006) study confirms fossil fuels, including coal, crude oil, and natural gas, have weak cointegrations with each other. Further, investigations such as Albulescu et al. (2020), Ali et al. (2020), and Rehman et al. (2019) either concentrate on relationships among crude oil, natural gas, agriculture, and metal markets or crude oil, natural gas, coal, agriculture, and metal markets. However, testing links among crude oil, natural gas, coal, stock, and currency markets simultaneously have been overlooked by the mentioned studies. Additionally, from a theoretical perspective, VAR, multivariate GARCH, VEC, and Copula models are predominately employed by previous studies, but they can hardly gauge quantification spillovers under scrutiny (Zeng et al., 2020; Tiwari et al., 2019).

To overcome these hurdles, this paper embraces Diebold and Yilmaz's (2012) framework, which uses forecast error variance decompositions (FEVD). This proposed model is not affected by the ordering of the variables, for the invariant FEVD is not dependent on the Cholesky factor identification of VAR. Moreover, it aids us in gauging returns and volatility spillovers of multiple asset classes over time. Additionally, the spillover index approach allows measurement of the net directional spillovers from one market to another. Moreover, this proposed approach provides a rolling window so that we can recognize time-varying dynamics of the spillover index and directional spillover among crude oil, natural gas, coal, stock, and currency markets. In addition, we intend to deploy Barunik and Křehlik's (2018) frequency domain spillover index, which provides decomposition contributions of each market to global volatility at distinctive frequencies. Consequently, conducting this study on volatility spillovers among crude oil, coal, natural gas, stock, and currency markets is noteworthy in order for market participants to effectively curtail risk management and choose optimum portfolio diversification. Further, this paper has great merits for authorities who desire to understand how price shocks in energy markets are transmitted to other key markets such as stock and currency markets.

All in all, the novelty of this research is three-fold. First, we plan to examine volatility spillover among crude oil, coal, natural gas, stock, and currency markets for the US and China simultaneously. Second, we aim to deploy Diebold and Yilmaz's (2012) approach because this suggested methodology can remove limitations of previous methodologies. Thirdly, we employ time-varying connectedness amid financial assets via gauging Baruník and Křehlík (2018).

[2] https://www.iea.org/reports/key-world-energy-statistics-2021/supply

2. Literature review

The nexuses among fossil fuels and other financial assets can be classified into five categories. The first category is connections among crude oil and stock markets (See Table 1). To exemplify, Bouri et al. (2021a, 2021b, 2021c) demonstrate volatility connectedness among crude oil, gold, and stock markets strengthens in the US economy as financial chaos occurs in global markets. In addition, Shahzad et al. (2021) identify the existence of multiple tail dependence regimes amid crude oil and equity markets in Brazil, Russia, India, China, and South

Table 1
Summary of literature on volatility spillovers among crude oil and stock markets.

Author	Period study	Data frequency	Variables used	Modeling approach	The main results
Bouri et al. (2021a, 2021b, 2021c)	Sept. 22, 2008 to May 28, 2020	Daily	Gold, Heating oil, Light crude oil, Natural gas, Copper, Platinum, Cocoa, Coffee, Corn, Cotton, Orange Juice, Soybean, Soybean meal, Sugar, and Wheat	Diebold and Yilmaz based on TVP-VAR	Volatility connectedness among crude oil, gold, and stock markets strengthens in the US economy as financial chaos occurs in global markets.
Shahzad et al. (2021)	January 1, 2002 to August 20, 2019	Daily	Crude oil and stock markets in BRICS counties	Time- varying optimal copula	Multiple tail dependence regimes amid crude oil and equity markets exist in the BRICS members. Further, Brazilian and Russian stock markets witness more positive lower tail dependence compared to those of markets in India and China.
Cui et al. (2021)	January 5, 2004 to October 23, 2020	Daily	Crude oil and stock markets in China, the US, India, Japan, South Korea, and the EU, Saudi Arabia, Russia, Canada, the UAE, Oman, and Qatar	Wavelet	There are long-term total risk spillovers among crude oil and equity markets, plus American, Russian, and Canadian stock markets transform huge risk to the global crude oil market.
Ashfaq et al. (2020)	Sept. 1, 2009 to August 31, 2018	Daily	Crude oil and stock markets in Saudi Arabia, the UAE, Iraq, China, Japan, India, and South Korea	VAR-DCC-GARCH	Pronounced nexuses among crude oil prices and equity markets exist in oil-producing Asian countries. But oil-importing ones have weak connections with the volatility of crude oil prices.
Yu et al. (2020)	May 2, 1991 to May 31, 2016	Daily	Crude oil and stock markets in the US and China	VAR-BEEK-GARCH	Nexuses among the WTI and stock markets in China are weaker than those in the US.
Tiwari et al. (2020a, 2020b)	January 1, 2003 to Nov. 30, 2017	Daily	Crude oil and stock markets in G7 members	Asymmetric Spline-GARCH and Markov-switching copula	Crude oil price dynamics are burdensome for stock markets in seven industrial countries, in particular Canada, as large shocks happen.
Wang et al. (2020)	Sept. 2, 1995 to Dec. 30, 2018	Daily	Crude oil and stock markets	Granger causality	High volatilities of crude oil price symmetrically affect stock index, making it extremely fluctuant.
Siddiqui et al. (2020)	July 14, 2008 to August 29, 2016	Weekly	Crude oil and stock market	NARDL	A decrease in the price of crude oil significantly affects stock markets in oil-exporting countries, but positive oil price innovations considerably impact oil-importing ones.
Hamdi et al. (2019)	January 1, 2006 to August 1, 2017	Daily	Crude oil and stock markets	Quantile Regression	Bank and insurance sectors are immune from crude oil price volatility in the GCC countries, and surprisingly, transport and telecommunication sectors do not react against oil price volatility.
Ji et al. (2018a, 2018b)	February 1994 to Dec. 2016	Monthly	Crude oil and stock markets	Amalgam of SVAR model and copula-GARCH	There are dependent relations as time-varying among stock returns and crude oil shocks in the BRICS countries. Further, a noticeable asymmetric effect between upside and downside risk spillover in Brazil, Russia, and India is identifiable
Antonakakis et al. (2018)	June 18, 2001 to February 1, 2016	Daily	Crude oil and stock markets	DCC and, Diebold and Yilmaz	There is a strong connectedness among crude oil and companies' stocks, that are active in oil and gas industries, and that relationship is not often directional.
Cai et al. (2017)	January 3, 1992 to October 22, 2015	Daily	Crude oil and stock markets	Wavelet coherence analysis	Fluctuations in Asian stock markets are affected by crude oil prices, particularly in the long horizon.
Maghyereh et al. (2016)	March 3, 2008 to 3 February 2015	Daily	Crude oil and stock markets	Diebold and Yilmaz	A bidirectional spillover between crude oil and the stock market is existent, and connections among the markets are significant other than from 2009 until mid-2012.
Khalfaoui et al. (2015)	June 2, 2003 to February 7, 2012	Daily	Crude oil and stock markets	Wavelet and GARCH-BEKK	There are significant volatility spillovers between crude oil and stock markets. Plus, there are inextricable time-varying relationships among different market pairs.
Masih et al. (2011)	May 1988 to January 2005	Daily	Crude oil and stock market in South Korea	VAR	The effects of crude oil price volatility dominate real stock returns, and they intensify. Further, they find that investment and firms are greatly affected by crude oil fluctuations in South Korea.

Africa (BRICS) members. Likewise, Ji et al. (2018a, 2018b) detect dependent relations as time-varying among stock returns and crude oil shocks in the BRICS countries. Further, they expound a noticeable asymmetric effect between upside and downside risk spillover in Brazil, Russia, and India. The outcomes of Cui et al. (2021) suggest there are long-term total risk spillovers among crude oil and equity markets, plus American, Russian, and Canadian stock markets transform huge risk to the global crude oil market. Tiwari et al. (2020a, 2020b) investigation reveals that crude oil price dynamics are burdensome for stock markets in seven industrial countries, in particular Canada, as large shocks happen. Interestingly, similar outcomes are also reported by Wang et al. (2020). Moreover, Yu et al. (2020) examine how West Texas Intermediate (WTI) oil affects stock markets in China and the US; then they discuss how nexuses among the WTI and stock markets in China are weaker than those in the US. In the case of Asian countries, Ashfaq et al.'s (2020) study demonstrates pronounced nexuses among crude oil prices and equity markets in oil-producing Asian countries; however, oil-importing ones have weak connections with the volatility of crude oil prices. On the other hand, Cai et al. (2017) confirm that fluctuations in Asian stock markets are affected by crude oil prices, particularly in the long horizon. In another study, Siddiqui et al. (2020) evaluate how a fall in crude oil price affects Arabian, Chinese, Japanese, Indian, and Korean stock markets. They conclude that a decrease in the price of black gold significantly affects stock markets in oil-exporting countries, but positive oil price innovations considerably impact oil-importing ones. This finding is also consistent with that of Masih et al. (2011) in the Korean context. By contrast, Hamdi et al. (2019) perceive that bank and insurance sectors are immune to crude oil price volatility in the Gulf Cooperation Council (GCC) countries, and surprisingly, transport and telecommunication sectors do not react against oil price volatility. Further, Antonakakis et al. (2018) observe that there is a strong connectedness among crude oil and companies' stocks that are active in oil and gas industries, and that relationship is not often directional. Similarly, Maghyereh et al. (2016) find a bidirectional spillover between crude oil and the stock market, and connections among the markets are significant other than from 2009 until mid-2012. The outcomes of Khalfaoui et al.'s (2015) research show consistency with those of Maghyereh et al. (2016). Additionally, Khalfaoui et al. state there are inextricable time-varying relationships among different market pairs.

The second category investigates the nexuses among crude oil and exchange rates (See Table 2). To begin with, Khraief et al. (2021) realize that there are long-run asymmetric impacts from crude oil prices to exchange rates in China and India, but this effect seems to be symmetric for Rupee as time passes. In stark contrast, Huang et al. (2020) observe that relations among crude oil price shocks and exchange rates are not only symmetric for Yuan but also for Euro, Yen, and the US dollar. Another pertinent study is Akram (2020), who analyses whether fluctuations of crude oil price can be a causative factor in changing Canadian dollar and Norwegian Krone. His evidence supports that an increment in crude oil price rooted in demand and supply sharpens these currencies to different extents. An academic investigation by Albulescu et al. (2019) uncovered documents showing how volatility spillovers of crude oil materially affect exchange rates in Australia, Canada, South Africa, New Zealand, Chile, and Brazil through the US Economic Policy Uncertainty (EPU) channel. Furthermore, Basher et al. (2016) state that fluctuating crude oil only puts a severe strain on appreciation of

Table 2
Summary of literature on volatility spillovers among crude oil and currency markets.

Author	Period study	Data frequency	Variables used	Modeling approach	The main results
Khraief et al. (2021)	1990 to 2019	Monthly	Crude oil and exchange rates in China and India	Wavelet, NARDL and causality test	There are long-run asymmetric impacts from crude oil prices to exchange rates in China and India, but this effect seems to be symmetric for Rupee as time passes.
Akram (2020)	January 15, 2010 and December 31, 2018	Weekly	Crude oil and exchange rates in Canada and Norway	Decomposition and Groen et al. (2013) version	An increment in crude oil price rooted in demand and supply sharpens Canadian dollar and Norwegian Krone to different extents.
Albulescu et al. (2019)	May 8, 1997 to June 1, 2017	Daily	Crude oil and exchange rates in Australia, Canada, South Africa, New Zealand, Chile, and Brazil	Diebold and Yilmaz, and Barunik and Křehlik	Volatility spillovers of crude oil materially affect exchange rates in Australia, Canada, South Africa, New Zealand, Chile, and Brazil through the EPU channel.
Huang et al. (2020)	January 2000 to September 2018	Daily	Crude oil and exchange rates in EUR, British Pound, Yen, and Yuan	VAR	Relations among crude oil price shocks and exchange rates are not only symmetric for Yuan but also for Euro, Yen, and the US dollar.
Basher et al. (2016)	Different data collection from 1976 to 2014	Monthly	Crude oil and exchange rates in Brazil, Canada, Mexico, Norway, India, Japan, South Korea, the UK, and Brazil, Canada, Mexico, Norway, and Russia	SVAR and Markov-Switching	Exporters of crude oil put a severe strain on appreciation of exchange rate following crude oil demand shocks. However, impacts of the supply shocks upon currency markets are not proven.
Ghosh (2011)	July 2, 2007 to November 28, 2008	Daily	Crude oil and exchange rates in India	GARCH and EGARCH	The ratio of Rupee to US dollar devalues during a climb in crude oil price.
Brahmasrene et al. (2014)	January 1996 and December 2009	Monthly	Crude oil and exchange rates in Canada, Mexico, Colombia and UK, Angola, Nigeria, Saudi Arabia, Venezuela, Kuwait, and Russia	Cointegration, variance decomposition and Granger causality	Currency markets are appreciably affected by variations in crude oil prices in the mid and long runs, and there is a negative shock effect from currency market to crude oil market pronouncedly. In addition, in the long term, there is Granger causality from crude oil prices to currency markets; and vice versa in the short term.
Ding and Vo (2012)	July 28, 2004 to September 28, 2009	Daily	Crude oil and exchange rates in Canada, Norway, the euro India, Japan, Singapore, Brazil, Mexico and the US	Multivariate stochastic volatility and MGARCH	Currency and crude oil markets reacted against shocks prior to 2008 GFC. But two-way volatility is recognizable among these markets in financial chaos.
Lizardo and Mollick (2010)	1973 to 2008	Monthly	Crude oil and exchange rates in the US	Cointegration test	A negative connection among crude oil prices and exchange rates in Russia, Canada, Chile (excluding Japan).

exchange rate in oil-exporting countries following crude oil demand shocks. Ghosh (2011) also supports this finding for India, implying the ratio of Rupee to US dollar devalues during a climb in crude oil price. This finding and that of Lizardo and Mollick (2010) show similarities. To be more exact, Lizardo and Mollick (2010) validate a negative connection among crude oil prices and exchange rates in Russia, Canada, and Chile (excluding Japan). Besides, Brahmasrene et al. (2014) state currency markets are appreciably affected by variations in crude oil prices in the mid and long runs, and there is a pronounced negative shock effect from currency market to crude oil market. In addition, they corroborate that in the long term, there is Granger causality from crude oil prices to currency markets, and vice versa in the short term. Finally, the results of Ding and Vo (2012) reveal that currency and crude oil markets reacted against shocks prior to Global Financial Crisis (GFC) in the 2008. But two-way volatility is recognizable among these markets in financial chaos.

The third strand of the literature focuses on the linkages among crude oil, stock, and currency markets (See Table 3). For illustrative purposes, Bouri et al. (2021a, 2021b, 2021c) argue that there is a steady but modest connection amid crude oil, stocks, and the US dollar index prior to the beginning of 2020. On the other hand, a swell in total connectedness and structural changes in network of connectedness are observable among the markets since the outbreak of COVID-19. In addition, Chkir et al. (2020) discover that apart from British and Japanese exchange rates, there are inextricable relations among crude oil and other currencies in oil-producing and oil-consuming countries. For example, Kumar (2019) asserts that there are nonlinear two-way connections between crude oil and the Indian currency market, plus a unidirectional, nonlinear Granger-causal relationship exists between crude oil and Indian stock. Additionally, Malik and Umar (2019) contend that demand and risk shocks in crude oil price are causative factors in fluctuating currency markets, but supply-side shocks do not affect currency markets. The research of Bai and Koong (2018) indicate that in China, a glut of crude oil has an appreciable, negative impact on the equity market; additionally, stocks in the US and China have positive correlations with currency markets. Similarly, Roubaud and Arouri (2018) conclude that there are pronounced nonlinear linkages among the US dollar, crude oil, and equity markets, meaning changes in crude oil price are likely to create shocks in currency and stock markets.

Relationships amid natural gas and other financial assets fall into the fourth category in the existing literature (See Table 4). Included in this grouping, Bouri et al. (2021a, 2021b, 2021c), findings exhibit pronounced but limited volatility spillovers across heating oil, light crude oil, natural gas, copper, and platinum. Gong et al. (2021) impart more information about connections among crude oil, gasoline, heating oil, and natural gas. They explain that volatility spillover has plunged in the natural gas market since the shale gas revolution. Additionally, they verify the existence of the pronounced pairwise volatility spillover between crude oil and natural gas in future markets. Another study, Chai et al. (2019), concludes that an appreciable, asymmetric connection between the global natural gas market and domestic market is not observable in China, but this link is only significant in the long run. Hailemariam and Smyth's (2019) study contends that the demand shocks are determinant factors in pricing of the natural gas market. On the other hand, shocks rooted in supply are contributory factors to natural gas price trends. Jadidzadeh and Serletis (2017) show that less than three-fifths of natural gas price fluctuations are associated with shocks in the crude oil market in the long run. Surprisingly, Batten et al. (2017) explain that although there were weak linkages among crude oil and natural gas prior to 2007, these types of energy's pricing is not contingent upon one another at the present. Conversely, Nick and Thoenes (2014) discern that developing this market is linked to crude oil and coal prices in the long run, but heat, storage, and paucity of supply impact natural gas prices in the short run. Moreover, Ji et al. (2018a, 2018b) assert the effects of oil price on natural gas have decreased since the 2008 GFC. Concerning linkages between natural gas and stock, Kumar et al. (2019) discover that cointegration between natural gas and Indian stock prices are not observable in the long run. However, unidirectional and nonlinear connections from currency markets to natural gas prices are shown prior to the GFC by Wang and Wu (2012); still, this causality does not exist after the GFC. Finally, Erdős (2012) finds no nexuses among prices of natural gas in the US and Europe after the year 2009, but before this period, co-movements exist in the short run and integrations in the long run.

In the fifth category, few papers have examined linkages among crude oil, natural gas, coal, and other financial assets, and surprisingly, the findings of some studies agree with one another (See Table 5). To illustrate, Albulescu et al. (2020) assert energy commodities only

Table 3
Summary of literature on volatility spillovers among crude oil, stock and currency markets.

Author	Period study	Data frequency	Variables used	Modeling approach	The main results
Bouri et al. (2021a, 2021b, 2021c)	May 12, 2011, May 12, 2020	Daily	Gold, crude oil, world equities, currencies, and bonds	TVP-VAR connectedness approach	There is a steady, modest connection amid crude oil, stocks, and the US dollar index prior to the beginning of 2020. On the other hand, a swell in total connectedness and structural changes in network of connectedness are observable among the markets since the outbreak of COVID-19.
Chkir et al. (2020)	January 1990 to March 2017	Daily	Crude oil, stock, and exchange rates in France, Australia, the UK, the US, Canada, Mexico, Norway, and Japan	Vine copulas	Apart from Britain and Japanese exchange rates, there are inextricable relations among crude oil and other currencies in oil-producing and oil-consuming countries.
Kumar (2019)	January 1994 to December 2015	Monthly	Crude oil, stock, and exchange rates in India	The Hiemstra and Jones nonlinear Granger causality and NARDL	There are nonlinear two-way connections between crude oil and Indian currency market, and a unidirectional as well as nonlinear Granger-causal relationship exists between crude oil and Indian stock.
Malik and Umar (2019)	March 1996 to February 2019	Daily	Crude oil and exchange rates in Brazil, Canada, China, India, Japan, Mexico, and Russia	Diebold and Yilmaz	Demand and risk shocks in crude oil price are causative factors in fluctuating currency markets, but supply-side shocks do not affect currency markets.
Bai and Koong (2018)	January 1991 to December 2015	Monthly	Crude oil, stock and exchange rates in the US and China	SVAR and Diagonal BEKK	In China, a glut of crude oil negatively and appreciably impacts the equity market, and stocks in the US and China have positive correlations with currency markets.
Roubaud and Arouri (2018)	1979 to 2015	Monthly	Crude oil, stock and exchange rates in the US	VAR and MS-VAR models	There are pronounced nonlinear linkages among the US dollar, crude oil, and equity markets, meaning change in crude oil price are likely to create shocks in currency as well as stock markets.

Table 4
Summary of literature on volatility spillovers among natural gas, stock and currency markets.

Author	Period study	Data frequency	Variables used	Modeling approach	The main results
Bouri et al. (2021a, 2021b, 2021c)	April 11, 2006 to April 29, 2019	5-min data	Crude oil, natural gas, stock, and gold markets in the US	Diebold and Yilmaz based on TVP-VAR	There are pronounced as well as limited volatility spillovers across heating oil, light crude oil, natural gas, copper, and platinum.
Gong et al. (2021)	October 3, 2005 to April 12, 2019.	Daily	Crude oil, gasoline, heating oil, and natural gas	Time-varying spillover mixed methods of TVP-VAR-SV and Diebold and Yilmaz	Volatility spillover has plunged in natural gas market from the shale gas revolution onwards. Plus, the pronounced pairwise volatility spillover between crude oil and natural gas exist in future market.
Chai et al. (2019)	April 24, 2014 to March 5, 2018	Monthly	Natural gas market in China	DCC-GARCH-NARDL-ARDL-ECM	An appreciable, asymmetric connection between global natural gas market and domestic market is not observable in China. But this link is only significant in the long run.
Hailemariam and Smyth (2019)	January 1978 and July 2018.	Monthly	Natural gas in the US	SHVAR	Demand shocks are determinant factors in pricing of the natural gas market. On the other hand, shocks rooted in supply are contributory factors to natural gas price trends.
Kumar et al. (2019)	July 10, 2006 to November 30, 2015	Daily	Crude oil, Natural gas, and stock markets in India	MGARCH family	Cointegration between natural gas and Indian stock prices is not existent in the long run.
Ji et al. (2018a, 2018b)	1999 to 2017	Daily	Crude oil, Natural gas and various factors in the US	Cointegration and causal relationship	Effects of oil price on natural gas have decreased since the 2008 GFC.
Jadidzadeh and Serletis (2017)	January 1976 to December 2012	Monthly	Crude oil and Natural gas in the US	SVAR	Less than three-fifths of natural gas price fluctuations are associated with shocks in the crude oil market in the long run.
Batten et al. (2017)	January 13, 1994 and December 9, 2014	Daily	Crude oil and Natural gas	Granger causality tests	Although there were weak linkages between crude oil and natural gas prior to 2007, these energy prices are not contingent upon one another at the present.
Nick and Thoenes (2014)	January 2008 to June 2012	Weekly	Crude oil, Natural gas, coal in Germany	SVAR	The developing natural gas market is linked to crude oil and coal prices in the long run, but heat, storage, and paucity of supply impact natural gas prices in the short run.
Wang and Wu (2012)	January 2, 2003 to June 3, 2011	Daily	crude oil, gasoline, heating oil and natural gas, and nominal trade-weighted US exchange	SVAR	Unidirectional and nonlinear connections from currency markets to natural gas price are indicated prior to the GFC. Still, this causality does not exist after the GFC between currency markets and natural gas prices.
Erdős (2012)	January 1994 to December 2011	Weekly	Crude oil and Natural gas	SVAR	There are no nexuses among natural gas prices in the US and Europe after the year 2009. But before this period, co-movements exist in the short run and integrations in the long run.

provide diversification in portfolio management as the markets experience bullish trends; Ali et al.'s (2020) investigation reports the same results. Likewise, Rehman et al. (2019) realize price fluctuations of crude oil negatively and profoundly impact price oscillations in gold and silver markets, proving crude oil has merits as a suitable diversifier in a portfolio of gold and silver, but the mixture of crude oil with platinum reduces diversification. Further, natural gas also increases diversification in copper, platinum, or palladium portfolios, and combing coal with gold and silver has a beneficial effect on portfolio diversification. Still, Zolfaghari et al. (2020) reveal there are positive and pronounced connectedness among coal, other energy sources, and the US dollar, especially between energy and the US equity market, although the results of Ma and Wang (2019) and Bachmeier and Griffin (2006) indicate that there are not robust connections among prices of coal and RMB, and coal, crude oil, and natural gas in turn. In the same way, Sun et al. (2019) verify that crude oil, natural gas, and coal have negligible effects on one another, yet Li et al. (2019) exhibit similar trends among crude oil and coal markets in China's local market.

Although several investigations have provided valuable insight into nexuses among crude oil, natural gas, coal, and other financial assets (Albulescu et al., 2020; Ali et al., 2020; Zolfaghari et al., 2020; Li et al., 2019; Rehman et al., 2019; Ma and Wang, 2019; Sun et al., 2019; Bachmeier and Griffin, 2006), our paper stands out among those existing studies. To elucidate, investigations such as Albulescu et al. (2020), Ali et al. (2020), and Rehman et al. (2019) either concentrate on relationships among crude oil, natural gas, agriculture, and metal markets or crude oil, natural gas, coal, agriculture, and metal markets; however, scrutinizing linkages among crude oil, natural gas, coal, stock, and currency markets simultaneously are neglectful. Additionally, other studies, seeking to investigate nexuses among crude oil, natural gas, coal, stock, and currency markets are imperfect. To be more precise, those studies deployed models such as Copula, VAR, Error Correction, MGARCH, including a sign of weakness (Zeng et al., 2020; Tiwari et al., 2019). Moreover, there is not an in-depth study providing an insightful analysis about relations among crude oil, natural gas, coal, stock, and currency markets simultaneously in the US and China. To bridge that gap, this study on volatility spillovers among crude oil, coal, natural gas, stock, and currency markets fosters awareness among market participants for minimizing risk management and selecting optimum portfolio diversification. Finally, this study offers policy makers more information regarding integrations among pivotal markets, including energy, stock, and currency markets.

3. Data

This paper employs data daily derived from Investing.com between 12/08/2008 and 12/18/2020. Our data collection encompasses crude oil, natural gas, coal, stock, and currency markets in the cases of US and China. Simultaneously considering these variables is noteworthy on account of some convincing arguments. To begin with, fluctuations in crude oil affect stock and currency markets through increased production costs and decreased expected cash flows, and the trade channel, in

Table 5
Summary of literature on volatility spillovers among coal and financial assets.

Author	Period study	Data frequency	Variables used	Modeling approach	The main results
Zolfaghari et al. (2020)	April 1, 2011 to January 31, 2020.	Daily	Crude oil, natural gas, coal, stock, and currency markets in India	Diagonal BEKK	There is positive and pronounced connectedness among coal, other energy sources, and the US dollar, especially between energy and the US equity market.
Bachmeier and Griffin (2006)	1999 to 2017	Daily	Crude oil, natural gas, and coal	Error Correction	Pricing coal is more reliant on the domestic market in the US, and fossil fuels, including coal, crude oil and natural gas do not completely cointegrate with each other.
Albulescu et al. (2020)	January 3, 2005 to August 1, 2018	Daily	Energy, agriculture and metal commodities markets	Copula based on local Kendall's tau	The extreme upper-tail dependencies amid energy markets and metal commodities are neither symmetric nor positive for high returns. Energy commodities only provide diversifications in portfolio management as the markets experience bullish trends; however, in financial chaos, they are not appropriate diversifiers.
Ali et al. (2020)	January 1, 2001 to December 18, 2018,	Daily	Commodities and stock markets	Baur and McDermott (2010), the cross-quantilogram, and Christoffersen et al. (2018)	Mixing equity with energy, metals, and agricultural commodities can pave the way for gaining maximum benefits in portfolio management.
Rehman et al. (2019)	January 2, 2012 and February 3, 2017	Weekly	Energy and non-energy commodities	NARDL and Causality in Quantile	Price fluctuations of crude oil negatively and profoundly impact price oscillations in gold and silver markets, proving crude oil has merits as a suitable diversifier in a portfolio of gold and silver, but a mixture of crude oil with platinum reduces diversification. Plus, natural gas also increases diversification in copper, platinum or palladium portfolios, and combing coal with gold and silver has a beneficial effect on portfolio diversification.
Li et al. (2019)	February 28, 2003 to Jun 5, 2019	Weekly	Crude oil, Natural gas, and stock markets in Egypt	MGARCH and Diebold and Yilmaz	There are similar trends among these energy markets in China's local market; on the other hand, from an international perspective, the coal market relies on coal trade.
Sun et al. (2019)	June 30, 2010	Monthly	Crude oil, Natural gas, coal, stock markets in China	VAR	Non-renewable energies have negligible impacts.
Ma and Wang (2019)	June 19, 2010, to February 25, 2019	Daily	Crude oil, Natural gas, coal, iron ore, and exchange rates in China and Australia	Copula	There are not robust connections between prices of coal and RMB in China.

turn (Khraief et al., 2021; Jiang and Yoon, 2020; Zolfaghari et al., 2020; Lin and Su, 2020). In addition, crude oil is a replacement for natural gas, and oscillations of crude oil price are more liable to impact natural gas prices (Karali and Ramirez, 2014). Besides, the stock market tends to be influenced by economic changes in natural gas (Geng et al., 2021). Also, crude oil is a partial substitute for coal, and vice versa (Li et al., 2019). Besides, fluctuating commodities prices, including those of natural gas and coal, affect supply and production costs, influencing economic status through currency markets (Ma and Wang, 2019). More importantly, financializing fossil energy markets strengthens interrelations with alternative assets and threatens financial market stability (Jiang et al., 2021). Further, our data collection provides an insightful analysis, for it encompasses several political and economic events between 12/8/2008 and 12/18/2020, including the US shale revolution; OPEC supply-side policies; oil price plunges; political events such as Brexit, the European Debt Crisis (EDC), the US withdrawal from the Iran nuclear deal, conflicts between Russia and Ukraine, and mounting unrest and political tensions in the MENA region; and the Coronavirus outbreak. To that end, we gauge returns series (r_t) for the whole variables via deploying the first difference of the level series with natural logarithms.

$$r_t = 100^*[\Delta log(P_t)]$$

Table 6
Descriptive statistics.

Statistics	Coal	Natural gas	WTI	S&P500	The US dollar	Shanghai stock	USD/CNY
Mean	−0.006	0.027	−0.026	−0.052	−0.002	−0.017	0.002
Std. Dev.	1.244	3.231	2.909	1.211	0.506	1.446	0.191
Skewness	0.472 *	−0.664 *	−0.267 *	0.554 *	0.166 *	0.728 *	−0.534 *
Kurtosis	11.345 *	8.251 *	25.714 *	15.480 *	6.967 *	8.022 *	13.311 *
JB	8226.1 *	3421.5 *	60,201.7 *	18,306.7 *	1848.4 *	3188.7 *	12,533.5 *
ADF	−13.1999	−14.5502	−12.2259	−14.386	−14.0106	−13.4044	−11.8083
PP	−2507.35	−2905.25	−2787.65	−3305.31	−2750.15	−2804.49	−3083.08
KPSS	0.142189	0.031441	0.09255	0.020349	0.10445	0.053299	0.264354
LB	38.4 *	38.2 *	67.9 *	178.5 *	10.69986	20.51721	20.98519
LB (2)	232.8 *	255.1 *	1805.9 *	3004.7 *	251.5 *	704.2 *	269.3 *
ARCH-LM (10)	139.6 *	151.2 *	653.5 *	894.2 *	167.6 *	305.8 *	185.3 *
Observation	2799	2799	2799	2799	2799	2799	2799

Note: *** denotes the statistical significance of the estimates at the 1% level. The Std. Dev. represents the standard deviation; Obs. is the number of observations.

As shown in Table 6, the mean statistic represents negative amounts for coal, WTI, the S&P500, and the US dollar, namely −0.006, −0.026, −0.052, and − 0.002, respectively. Natural gas and the USD/CNY have positive amounts, which are 0.027 and 0.002, respectively. Generally, the highest amount belongs to natural gas, but the lowest pertains to the S&P500. From the standard deviation, natural gas is the most volatile variable; however, the lowest volatility is reported by the USD/CNY. Another statistic is skewness, which depicts coal, the S&P500, the US dollar, and Shanghai stock, which are positive; on the other hand, natural gas, WTI, and the USD/CNY show negative values. This means that the frequency of positive returns is greater in comparison with negative ones in reverse. According to kurtosis, results of the whole variables confirm that they have a fat tail, and they follow leptokurtic distribution. From the Jarque-Bera (JB) statistic, it is verified that the null hypothesis is rejected, which signifies returns do not follow normal distribution. Besides, outcomes of other unit root tests (augmented Dickey Fuller (ADF), Philips Perron (PP), Kwiatkowski, Phillips, Schmidt, and Shin (KPSS)) prove that all variables are stationary. The Ljung-Box (LB) test suggests that returns of variables are strongly autocorrelated. Finally, results from the autoregressive conditional heteroscedasticity (ARCH) model reveal the ARCH effects are not observable in return variables.

Fig. 1 depicts a network analysis of pairwise correlations among the whole markets in the chosen period. In this figure, negative correlations are recognizable by red lines, and green lines indicate positive correlations among markets. The clusters of variables are modelled on correlation magnitude, which deploys the absolute values of the correlations as the proximity or distance metric. To identify proximity of one asset to another, the total magnitude of the correlation between two assets is used. At first sight, some assets, including WTI, natural gas, and Shanghai stock are clustered; additionally, coal, the US dollar, USD/CNY, and the S&P500 are clustered.

Fig. 2 represents estimations of two network structures such as partial contemporaneous correlations and partial directed correlations. The partial contemporaneous correlations report the same results, also observable in Fig. 1. Yet, findings for partial directed correlations denote that the S&P500 has a negative Granger-causal relationship with WTI, and there are no connections from the S&P500 to the US dollar, or from natural gas to WTI, respectively.

4. Econometrics model

4.1. Diebold and Yilmaz time domain spillover index

The primary objective of this study is to impart more information on oscillations in fossil fuels, including how crude oil, natural gas, and coal, affect stock and currency markets in the US and China. To accomplish this, we deploy the Diebold and Yilmaz's (2012) methodology. This approach is modelled on the VAR system and generalized variance decomposition (GVD); plus, this version is an easy and direct way to quantify the amount of volatility connectedness in the system. The role of GVD is to segregate forecast error variance of one asset from sections that are affected by other assets during the estimation process. Consequently, the GVD version helps to overcome any disturbance induced, which is attributed to ordering other variables. In the middle of the GVD version, the past distribution of errors is utilized, and it creates the correlated shocks (Diebold and Yilmaz, 2012). Additionally, the GVD is efficacious to curb the degree of connectedness among financial assets.

To follow kth order, the VAR version is formed by M variable:

$$L_t = \sum_{k=1}^{j} \sigma_k \, L_{t-k} + \mu_t \tag{1}$$

L_t is a vector of random terms of the form (l_{1t}, l_{2t}, l_{3t}, l_{4t}, l_{5t}, l_{6t}, l_{7t}), and independent distributions of error terms are determined by μ_t, which is a vector. Moreover, σ_k is a matrix of the coefficient of the form (7×7).

It is assumed that the VAR system is not a non-stationary covariance; after that, the moving average representation is expounded as:

$$L_t = \sum_{j=o}^{\infty} B_j \, \mu_{t-k}, \text{ where } B_j = \sum \sigma_j \, B_{k-j} \tag{2}$$

In the above equation, B_0 is N×N identity matrix, and B_j is equivalent to zero.

More importantly, the moving average is deployed in order to gauge total spillover, pairwise spillover, and directional spillover among crude oil, natural gas, coal, the S&P500, the US dollar, USD/CNY, and it is modelled on the GVD. The h-step-ahead forecast error, the GVD matrix, is derived by:

$$P_{ij}(\mathrm{h}) = \frac{\mathrm{v}_{\mathrm{ii}}^{-1} \sum_{\mathrm{h}=0}^{\mathrm{h}-1} \left(\mathrm{e}_{\mathrm{i}}' \, \mathrm{b}_{\mathrm{h}} \sum \mathrm{e}_{\mathrm{j}}\right) 2}{\sum_{\mathrm{h}=0}^{\mathrm{h}-1} \mathrm{e}_{\mathrm{i}}' \, \mathrm{b}_{\mathrm{h}} \sum \mathrm{b}_{\mathrm{h}}' \mathrm{e}_{\mathrm{j}}} \tag{3}$$

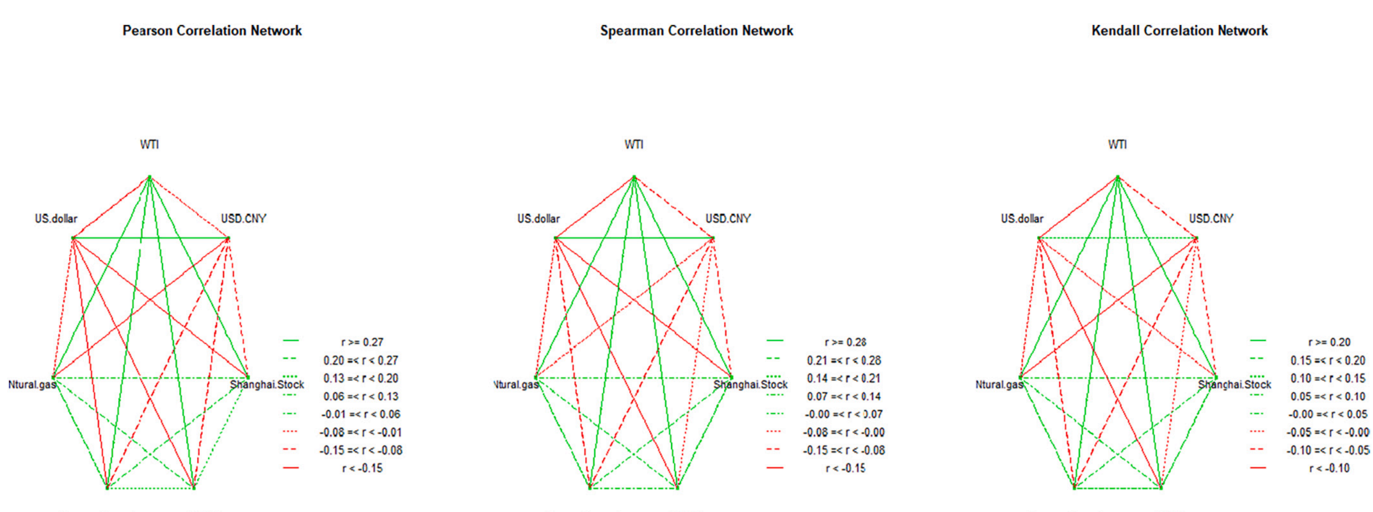

Fig. 1. A network analysis of pairwise correlations among crude oil, natural gas, coal, the S&P500, the US dollar, Shanghai stock, and USD/CNY.

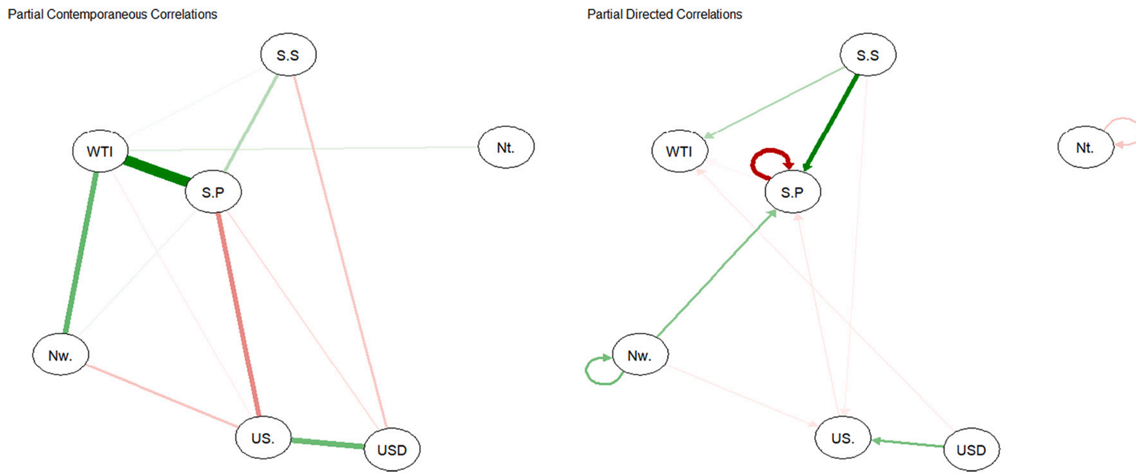

Fig. 2. Figures for partial contemporaneous and partial directed correlations.

From Eq. (3), $e_i$is selected as vector that its i^{th} element is equivalent to one and zeros; on the other hand, b_h denotes the coefficient matrix times the h-lagged shock vector. Besides, Σ is the variance matrix of the error vector ϵ; and v_{ii} represents i^{th} diagonal element of Σ. Furthermore, in the P(h) matrix, input amounts are transformed into normalized ones through the row sum so that we can make sure that the sum of forecast error variance contributions is one. After this stage is completed, some steps should be taken in order to test volatility spillovers among crude oil, natural gas, coal, the S&P500, Shanghai stock, the US dollar, and USD/CNY.

4.1.1. Total directional volatility spillover

To gauge all information spillover “from and to” every financial asset, we use total spillover index. The below equations indicate total volatility connectedness “from and to” in turn.

$$M_{i\leftarrow 0} = \sum_{j=1}^{N} P_{ij}, \text{based on assumption of j is not equal to i} \tag{4}$$

$$M_{0\leftarrow j} = \sum_{i=1}^{N} P_{ij}, \text{based on assumption of i is not equal to j} \tag{5}$$

4.1.2. Net volatility spillover

This index represents which variables are transmitters and which are receivers in the system. This spillover is derived by subtracting other variables from volatility spillovers and this can be expounded as:

$$\text{M'} = M_{i\leftarrow 0} - M_{0\leftarrow j} \tag{6}$$

4.1.3. Total net volatility spillover

To work out how much crude oil, natural gas, coal, the S&P500, Shanghai stock, the US dollar, and USD/CNY are integrated with each other and how risks are systemically transmitted to variables, we need to analyze total net volatility spillover. This index is defined as below:

$$\text{TSI} = \frac{1}{N} \sum_{i,j=1}^{N} P_{ij}, \text{i is not equivalent to j} \tag{7}$$

4.1.4. Net pairwise spillover

To obtain more information regarding net volatility i and volatility j, we refer to net pairwise spillover. This index is extracted by contrasts among spillover impacts running from j to i and, vice versa based on Eq. (3). In this spillover, P_{ij} is not equal to P_{ji} based on description of the GVD.

4.2. Baruník and Křehlík (2018) frequency domain spillover method

To gauge spillovers' frequency domain, we deploy Baruník and Křehlík (2018), which enables us to conduct an in-depth analysis, and therefore, this study can provide a deep understanding of chosen assets. To impart more information about which assets should be opted for in long-term and short-term investments, we plan to test which frequency spillover is higher than other frequencies. This method was launched by Barunik and Křehlik (BK) in the year 2018, and it decomposes the original Diebold and Yilmaz spillover at some frequencies. To specify, the BK is deployed as a formulation modelled on a spectral formulation of decomposing variance usage. We employ a frequency response function that is defined as:

$$\alpha(\pi^{-xy}) = \sum_{z} \pi^{-xyr}\, \alpha_r \tag{8}$$

The above equation is derived by the Fourier information of the coefficient α, with $x = \sqrt{-1}$.

The generalized causation spectrum over frequencies, with $\alpha \in (-k, k)$ is definable below as:

$$(f(\alpha))_{j,k} = \frac{\omega_{kk}^{-1}\, |(\alpha(\pi^{-xy}) \sum j\, , k|^2)}{\alpha(\pi^{-xy}) \sum \alpha' \, (e^{+xy}) j, j} \tag{9}$$

where $\alpha(\pi^{-xy}) = \sum_{m} e^{-ixy}\, \alpha_m$ signifies the Fourier transformation in the impulse response α. It should not be forgotten that $(f(\alpha))_{j,\, k}$ exhibits segment of the spectrum of the j-th variable at frequency α on account of shocks in the k-th variable. We can derive Eq. (9) in order to quantize within frequency causation based on spectrum of the j-th variable under frequency α. For the purpose of derogating a natural generalized decomposition of variance, $(f(\alpha))_{j,\, k}$ is weighted via frequency share of variance of j variable. We can define the weighting function as below:

$$\varnothing_j = \frac{(\pi^{-xy}) \sum \alpha' \, (e^{+xy}) i,j}{\frac{1}{2\beta} \int_{-\beta}^{\beta} e^{-i\partial} \sum \alpha' \, (e^{+i\partial}) j,j \; d\partial} \text{ (10).}$$

From Eq. (10), the power of the jth variable at a given frequency is observable, and it performs under frequency α, plus the sum of frequencies is a constant value of 2β. Notably, although the Fourier transform of the impulse response consists of a complex number, the generalized spectrum is the squared coefficient of a weighted complex number, and thus, it is a real number. To formalize, we incorporate frequency band v = (p, s): p,s $\in (-\beta, \beta)$, s > p, and generalized FEVD on frequency band v can be expressed as below;

$$(\gamma_v)_{j,k} = \frac{1}{2\beta} \int_{v} \varnothing_j (f(\alpha))_{j,k}\, d\alpha \tag{11}$$

It is not challenging to denote a connectedness calculation on a given frequency band through spectra representation of GFEVD usage. We delineate scaled GFEVD on the frequency band v = (p, s): p,s ∈ $(-\beta, \beta)$, s > p as can be seen:

$$(\approx \gamma_v)_{j,k} = \left(\gamma_{vj,k} \Big/ \sum_k (\gamma_\infty)_{j,k}\right) \tag{12}$$

The frequency spillovers on the frequency band v are then definable as:

$$\mathrm{N}_{\mathrm{v}}^{\mathrm{f}} = 100\left(\frac{\sum_{j\neq k} \approx (\gamma_{\mathrm{v}})_{\mathrm{j,k}}}{\sum_{k}(\gamma_\infty)_{\mathrm{j,k}}} - \frac{\mathrm{Tr}\,\{\gamma_{\mathrm{v}}\}}{\sum \approx (\gamma_{\mathrm{v}})_{\mathrm{j,k}}}\right) \tag{13}$$

The formulation of spillovers is identifiable via the frequency band v as below:

$$\mathrm{N}_{\mathrm{v}}^{\mathrm{f}} = 100\left(1 - \frac{\mathrm{Tr}\,\{\gamma_{\mathrm{v}}\}}{\sum \approx (\gamma_{\mathrm{v}})_{\mathrm{j,k}}}\right) \tag{14}$$

5. Empirical results

According to Table 7, overall, Shanghai stock is the most influential variable as a net giver; on the other hand, natural gas is the massive net receiver in this system. WTI is a net giver of spillovers, and it can be rooted in the crude oil market financialization. Furthermore, results exhibit that WTI has the highest effect on the S&P500, and vice versa, with having 8.7% and 8.19%. These results are suggestive of the fact that just over 8% of shocks to the S&P500 and WTI are explainable by fluctuations in these markets. These findings are consistent with empirical evidence that the volatile crude oil market is more inclined to affect equity market via strengthening uncertainty. Further, these results verify the studies of Bouri et al. (2021a, 2021b, 2021c) and Ahmed and Huo (2021), revealing pronounced nexuses among crude oil and stock markets. Notably, there is a significant bidirectional connectedness between USD/CNY and the US dollar, indicating effects of these variables on each other are 4.25% and 4.95% in turn. In the case of China, findings reveal that Shanghai stock is considerably affected by the S&P500 index and USD/CNY, whereas, neither coal nor natural gas spillovers have an impact on the Chinese stock market. Further, our evidence supports that Shanghai stock is considerably influenced by WTI, implying China fulfills energy needs via importing crude oil. Moreover, volatility connectedness for Shanghai stock and USD/CNY markets is slightly affected by natural gas and coal because these energy commodities are dominated by Chinese authorities. Consequently, a price freeze prevents significant transfer of volatility spillovers from these energy sources to USD/CNY and Shanghai stock markets. This outcome agrees with Lin and Su (2020) and Gatfaoui (2016), concluding there is not a pronounced linkage between the natural gas and stock market. The results for other fossil fuels confirm that WTI and coal have inextricable volatility with each other, as crude oil shows an upward trend resulting in increased coal usage. Natural gas has a negligible volatility effect on coal, only 0.36%, indicating there are dependencies among volatility spillovers of coal and natural gas. To explain this connection, it can be said that this weak spillover might be rooted in technological advancement, which creates a negative trend for coal consumption. However, 1.01% is a share of WTI volatility to natural gas, which shows consistency with the Gong et al. (2021) and other economic studies, showing volatility effects between natural gas and crude oil couple with each other. To clarify, crude oil is more prevalent in production than other energy products, which is a key factor in market prices of other energy commodities. Further, expanding crude oil production capacity results in growth of natural gas production, and thus, it positively affects crude oil supply. Generally, policies concerning the crude oil market significantly affect the natural gas market.

Table 8 gives more information about pairwise spillover among the financial assets. There is a two-way spillover between Shanghai stock and the S&P500, which is by far the most powerful pairwise linkage among the variables. Further, the second pronounced pairwise connectedness pertains to the relationship between the S&P500 and WTI, at −0.073. On the other hand, a trivial linkage, which is −0.007%, is identifiable between USD/CNY and Shanghai stock, and a weak connection is recognizable between USD/CNY and coal. Surprisingly, pairwise spillovers between USD/CNY and natural gas and WTI are negative and significant as well. The US dollar has a bilateral connectedness with USD/CNY, −0.099%. According to another row in Table 8, pairs of Shanghai stock, natural gas, and coal do not have a strong link with each other, for these values are −0.006% and − 0.005%, in turn. However, the couples of Shanghai stock, the US dollar, and WTI are interrelated significantly, and these spillovers are −0.038% and − 0.066%. For the S&P500, results indicate that positive pairwise relations are observable between the S&P500 and coal. However, these outcomes are negative among S&P500, natural gas, and the US dollar.

Concerning pairwise spillovers among coal and other assets, it is found that there is not a powerful nexus between coal and natural gas, but other pair nexuses are −0.030 and 0.041 for the US dollar and WTI. This finding is partly in line with the study of Zolfaghari et al. (2020), despite the existence of weak net spillovers among couples of the S&P500, natural gas, the US dollar, and WTI, but our results confirm that there is only a positive pair between coal and WTI. Also, our results are consistent with Bachmeier and Griffin's (2006) research, which expounds that these energy markets only have weak nexuses with each other in the US. Regarding China, our results are consistent with those of Ma and Wang (2019) and Sun et al. (2019), which suggest these nonrenewable energy sources do not have pronounced connections with the equity market. Additionally, this result for the US dollar confirms that there is not a strong linkage between the US dollar and WTI.

Furthermore, findings of the BK test reveal that (See Table 9) the share of frequency of 1 day to 6 days as a contributing factor in total connectedness is 9.14%; however, the frequency of 6 days to 12 days makes a small contribution in total spillover, approximately 1.04%. Finally, the last frequency, 12 days to infinity, contributes toward total connectedness, which is 1.21%. Moreover, the S&P500 is the most contributory factor in this system. To clarify, contributions from the S&P500 in the total spillover are 2.78%, 2.37%, and 2.36%, respectively. Further, WTI is ranked second as another significant contributor in this system. Next, the US dollar is the third contributor to total connectedness, and its amounts are 1.66%, 2.17%, and 2.19%,

Table 7
Results of Diebold and Yilmaz's (2012) test for volatility connectedness amid crude oil, natural gas, coal, stock and currency markets in the US and China.

Variables	Coal	Natural gas	WTI	The US dollar	S&P500	Shanghai stock	USD/CNY	From	Net
USD/CNY	0.62	0.01	0.58	4.25	1.66	1.75	91.13	1.27	0.124396
Shanghai stock	0.80	0.03	1.19	0.15	2.27	93.76	1.8	0.89	0.402174
S&P500	2.29	0.47	8.19	3.59	79.62	4.31	1.53	2.91	−0.20018
Coal	90.05	0.32	4.32	1.96	1.89	0.84	0.61	1.42	0.046551
Natural gas	0.36	97.19	1.16	0.57	0.56	0.07	0.09	0.40	−0.05916
The US dollar	2.17	0.56	1.72	86.28	3.89	0.42	4.95	1.96	−0.20987
WTI	4.03	1.01	82.11	1.72	8.7	1.66	0.76	2.56	−0.10391
To	1.47	0.34	2.45	1.75	2.71	1.29	1.39	TCI = 11.41	

Table 8
Results of pairwise net spillover.

	USD/CNY	Shanghai Stock	S&P500	Coal	Natural gas	The US dollar	WTI
USD/CNY	0	−0.00752	0.018313	0.001841	−0.01134	−0.09964	−0.02605
Shanghai Stock		0	−0.29186	−0.00644	−0.00592	−0.03876	−0.06672
S&P500			0	0.05636	−0.01239	−0.04353	−0.0738
Coal				0	−0.0062	−0.0302	0.041605
Natural gas					0	0.002471	0.020852
The US dollar						0	0.0002
WTI							0

Table 9
Results of Baruník and Křehlík (BK) test.

	USD/CNY	Shanghai Stock	S&P500	Coal	Natural gas	The US dollar	WTI	FROM_ABS	FROM_WTH	NET
The spillover table for band: 3.14 to 0.52, which roughly corresponds to 1 day to 6 days.										
USD/CNY	76.12	1.4	1.41	0.52	0.01	3.39	0.44	1.02	1.23	0.025066
Shanghai Stock	1.55	77.37	1.96	0.69	0.02	0.11	1.01	0.76	0.92	0.180633
S&P500	1.16	3.08	69.55	1.6	0.41	2.81	6.98	2.29	2.76	0.018118
Coal	0.5	0.63	1.66	71.54	0.22	1.58	3.59	1.17	1.41	−0.04839
Natural gas	0.07	0.05	0.47	0.25	82.72	0.46	0.92	0.32	0.38	−0.03673
The US dollar	3.53	0.29	3.17	1.55	0.41	71.64	1.47	1.49	1.79	−0.10798
WTI	0.52	1.15	7.51	3.24	0.9	1.31	68.39	2.09	2.51	−0.03071
TO_ABS	1.05	0.94	2.31	1.12	0.28	1.38	2.06	**TCI = 9.14**		
TO_WTH	1.26	1.14	2.78	1.35	0.34	1.66	2.48		TCI = 11.01	
The spillover table for band: 0.52 to 0.26, which roughly corresponds to 6 days to 12 days.										
USD/CNY	7.06	0.16	0.12	0.05	0	0.4	0.07	0.11	1.43	0.045658
Shanghai Stock	0.12	7.71	0.15	0.05	0	0.02	0.09	0.06	0.77	0.102071
S&P500	0.17	0.57	4.78	0.32	0.03	0.36	0.57	0.29	3.63	−0.10022
Coal	0.05	0.1	0.11	8.63	0.05	0.18	0.34	0.12	1.49	0.043168
Natural gas	0.01	0.01	0.04	0.05	6.83	0.05	0.11	0.04	0.49	−0.01051
The US dollar	0.66	0.06	0.34	0.29	0.07	6.89	0.12	0.22	2.75	−0.04676
WTI	0.11	0.24	0.57	0.37	0.05	0.19	6.46	0.22	2.75	−0.03341
TO_ABS	0.16	0.16	0.19	0.16	0.03	0.17	0.19	**TCI = 1.06**		
TO_WTH	2.01	2.05	2.37	2.03	0.36	2.17	2.33		TCI = 13.32	
The spillover table for band: 0.26 to 0.00, which roughly corresponds to 12 days to infinity.										
USD/CNY	7.94	0.19	0.13	0.06	0	0.46	0.08	0.13	1.45	0.053672
Shanghai Stock	0.13	8.69	0.16	0.06	0	0.02	0.1	0.07	0.76	0.119471
S&P500	0.2	0.66	5.3	0.37	0.03	0.42	0.64	0.33	3.67	−0.11808
Coal	0.06	0.11	0.12	9.88	0.05	0.2	0.39	0.13	1.49	0.051774
Natural gas	0.01	0.01	0.05	0.06	7.63	0.06	0.12	0.04	0.5	−0.01192
The US dollar	0.76	0.07	0.39	0.34	0.08	7.76	0.14	0.25	2.81	−0.05513
WTI	0.13	0.27	0.63	0.42	0.06	0.22	7.26	0.25	2.77	−0.03979
TO_ABS	0.18	0.19	0.21	0.19	0.03	0.2	0.21	**TCI = 1.21**		
TO_WTH	2.04	2.09	2.36	2.07	0.36	2.19	2.32		TCI = 13.44	

respectively. Moreover, it is self-evident that natural gas has the most trivial contribution, and having 0.34% and 0.36% in total spillover. In summary, it can be deduced that total connectedness shows higher performance in the long horizon than compared to the short horizon.

To provide an in-depth analysis regarding volatility spillover among crude oil, natural gas, coal, stock, and currency markets in the US and China, results of pairwise connectedness are also reported based on Table 10. From the short term (1 day to 6 days), there are positive spillovers among USD/CNY the S&P500, and coal; on the other hand, negative volatility relationships exist among USD/CNY and Shanghai stock, natural gas, and WTI. The outcomes for Shanghai stock represent that a positive spillover is only recognizable between Shanghai stock and coal, while this variable has negative spillovers with other markets. Additionally, findings for the S&P500 indicate that this stock market has negative connectedness to other variables, but these spillover effects are most positive for coal, except for natural gas. Finally, spillover connections from the US dollar to WTI are positive, at 0.022%.

According to the frequency of 6 days to 12 days, volatility of USD/CNY to Shanghai stock is positive; however, other spillovers are negative. For Shanghai stock, whole of pairs connectedness are negative, but these pairwise spillovers are positive for the S&P500 and other markets besides natural gas. Remarkably, coal has negative spillovers to natural gas, the US dollar, and WTI; plus, the results of natural gas volatilities reveal that it has negative and positive connectedness with the US dollar and WTI, in turn. In addition, the same pairwise spillover is observable from the US dollar to WTI. In the over 12 days category, there is positive volatility from USD/CNY to Shanghai stock, while other couple spillovers are negative among USD/CNY and other markets. Further, negative signs are identifiable from Shanghai stock to variables, but pairwise spillovers are positive from the S&P500 to other markets, save natural gas. Moreover, pairs of coal with natural gas, the US dollar, and WTI are negative; plus, these pairwise spillovers for natural gas and the US dollar and WTI are negative and positive. The last pairwise spillover belongs to the US dollar, and it has negative connectedness with WTI, −0.012%.

6. Rolling-window analysis

To account for time-varying total spillover and net pairwise spillovers among crude oil, natural gas, coal, stock, and currency markets in the US and China in this segment, we deploy rolling-window analysis with 250 days as the rolling window size. This index is extracted by the DY (2012) approach, and it greatly fluctuates because it includes several important events like the GFC between 2007 and 2008, the EDC between 2010 and 2012, and the COVID-19 pandemic. The most fascinating point

Table 10
Results of BK net pairwise spillover.

	USD/CNY	Shanghai Stock	S&P500	Coal	Natural gas	The US dollar	WTI
The spillover table for band: 3.14 to 0.52, which roughly corresponds to 1 days to 6 days.							
USD/CNY	0	−0.02255	0.035591	0.00225	−0.00854	−0.01967	−0.01215
Shanghai Stock		0	−0.16092	0.008182	−0.00372	−0.02656	−0.02015
S&P500			0	−0.0088	−0.00874	−0.05066	−0.07525
Coal				0	−0.0046	0.004169	0.050446
Natural gas					0	0.007391	0.003746
The US dollar						0	0.022645
WTI							0
The spillover table for band: 0.52 to 0.26, which roughly corresponds to 6 days to 12 days.							
USD/CNY	0	0.006814	−0.00791	−0.0002	−0.0013	−0.0367	−0.00637
Shanghai Stock		0	−0.06062	−0.00665	−0.00101	−0.00563	−0.02133
S&P500			0	0.029762	−0.00177	0.00307	0.000625
S							
Coal				0	−0.00077	−0.01547	−0.00402
Natural gas					0	−0.00222	0.007874
The US dollar						0	−0.0102
WTI							0
The spillover table for band: 0.26 to 0.00, which roughly corresponds to 12 days to infinity							
USD/CNY	0	0.008211	−0.00937	−0.00021	−0.00149	−0.04327	−0.00753
Shanghai Stock		0	−0.07031	−0.00797	−0.00118	−0.00657	−0.02523
S&P500			0	0.035403	−0.00188	0.00406	0.000819
Coal				0	−0.00083	−0.0189	−0.00483
Natural gas					0	−0.0027	0.009233
The US dollar						0	−0.01225
WTI							0

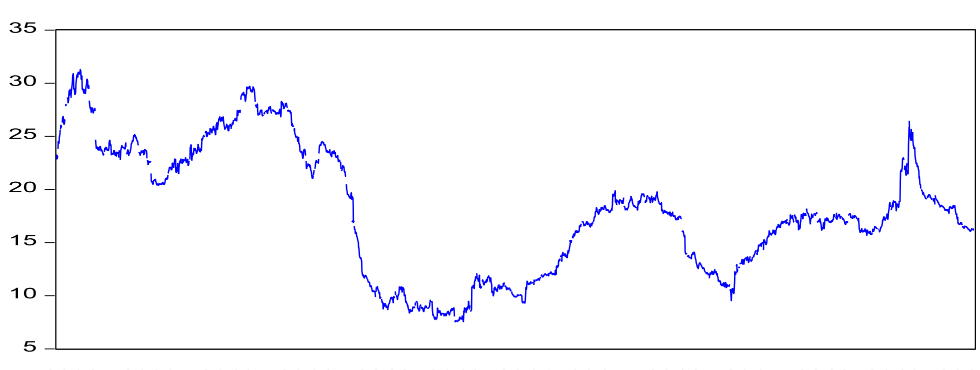

Fig. 3. Overall spillover based on the DY (2012) model from 12/8/2008 to 12/18/2020.

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is that overall spillover is at the apex of volatility, which is concurrent with the GFC, EDC, and corona virus pandemic. Those times which seem tranquil, show steady trends in the volatility index, which concurs with Bouri et al. (2021a, 2021b, 2021c) and Zhang and Broadstock (2020). This derivative index imparts more useful information as to whenever uncertain conditions become dominant in the markets, integrations among the markets intensify. Hence, increasing spillover interrelationships amid financial assets like stock, currency, and commodities creates a contagious impact when crises occur. As shown in Fig. 3, the total spillover trend rose sharply to over 30% in mid-2008 due to a glut of energy markets in the GFC. However, this index declined to approximately 20% until 2009 due to changes in the demand and supply conditions of commodities. The percentage of total spillover swelled to almost 20% in 2010, which pales in comparison to the significant effects of the GFC, but this was followed by a Japanese earthquake and a decrease in the US credit ranking in the year 2011. Notably, it fell dramatically in 2012 due to the alleviation of EDC effects, but it experienced a modest increase due to slow growth rate in China, and increasing worries about shadow financial institutions between 2012 and 2013. After that, it rebounded around 12% on account of downward trends of energy commodities, tension between Ukraine and Russia, the bond market flash crash in the US and concerns regarding stagnation in the global economy. From 2014 onward, it showed an upward trend until the year 2015 due to Asia Middle East respiratory syndrome and high volatility in global energy markets, too. One year later, this index rose due to the Brexit; however, it declined due to an increased interest rate by the US central bank. This downward trend continued by a steep nosedive to nearly 10% in 2017. For the rest of the period, total spillover saw an upsurge, and it reached around 25% because of commercial tension between China and the US, bringing about a reduction trade volume of energy commodities and exacerbation of market sentiment. Yet, it plunged to 15% in the year 2020 on account of lockdowns, decline in economic activities, and the feeling of uncertainty as to economic performance at the onset of corona virus. Further, to present more detailed information concerning volatilities among the markets, we separately plot net volatility spillover, which is observable in Fig. 4. According to this chart, the S&P500 trend indicates lower volatility in comparison with other charts, and this figure experienced a sharp fall in the year 2017, implying a stable trend, whereas other indexes are highly volatile during the corresponding period. In Fig. 5, we provide an insightful analysis regarding net pairwise connectedness among markets. For the US, results reveal that couples of coal, USD/CNY, and natural gas have mainly negative spillovers with the US dollar; however, there is a positive spillover between the US dollar and the S&P500. Also, pairwise between the US dollar and WTI is first positive, but this spillover is negative from 2017 onward. Findings for the S&P500 confirm that it has negative spillover with coal, but this connectedness becomes positive in the year 2010. This was followed by a sharp decline, which remains negative for the rest of the period. Moreover, the S&P500 paired with natural gas is almost zero, except for the years 2009, 2014, and 2017. Besides, the relationship between the S&P500 and the US dollar is mostly negative, but it shows an upward trend after 2018. Also, the pairwise connection between the S&P500 and WTI is highly volatile when positive or negative. To clarify, there is a positive connectedness between these markets; however, this linkage becomes a negative one until 2010. Then, it ranged 1% and − 4% for the rest of the period. In the case of Shanghai stock, at first glance, nexuses among Shanghai stock, coal, and S&P500 are analogous with each other, and these relations are

Fig. 4. Net volatility spillover based on the DY (2012) model from 12/8/2008 to 12/18/2020.

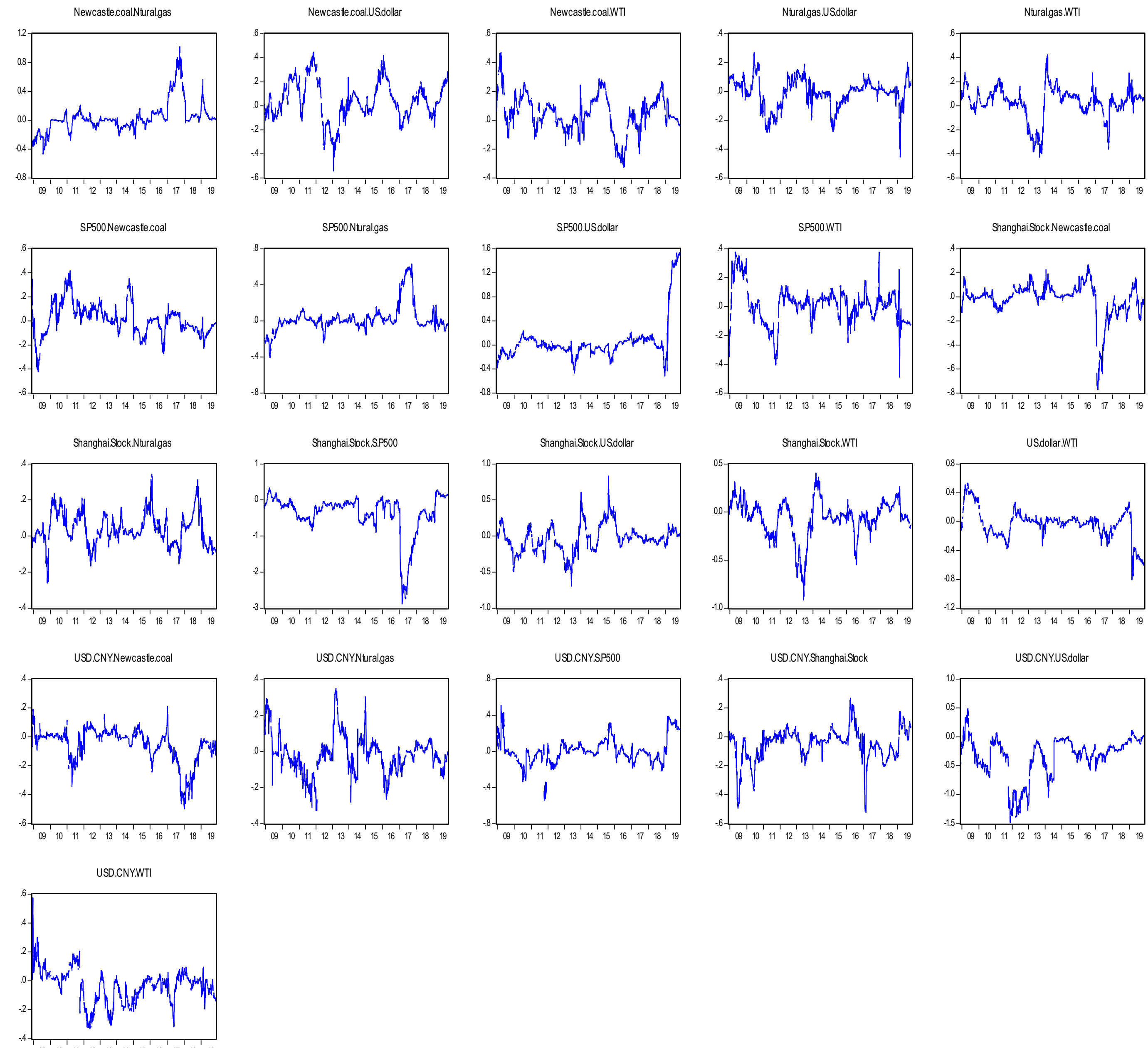

Fig. 5. Net pairwise spillovers based on the DY (2012) model from 12/8/2008 to 12/18/2020.

mainly positive. The figures for Shanghai stock, natural gas, and WTI fluctuated between 2.5% and − 2%, and 0.4% and − 0.9%, in turn. Further, the couple of Shanghai stock and the US dollar has a mostly positive connection. Finally, according to CNY/USD, the roughly pairwise connection between CNY/USD and other assets are negative, but the couples of CNY/USD natural gas and WTI show positive linkage in

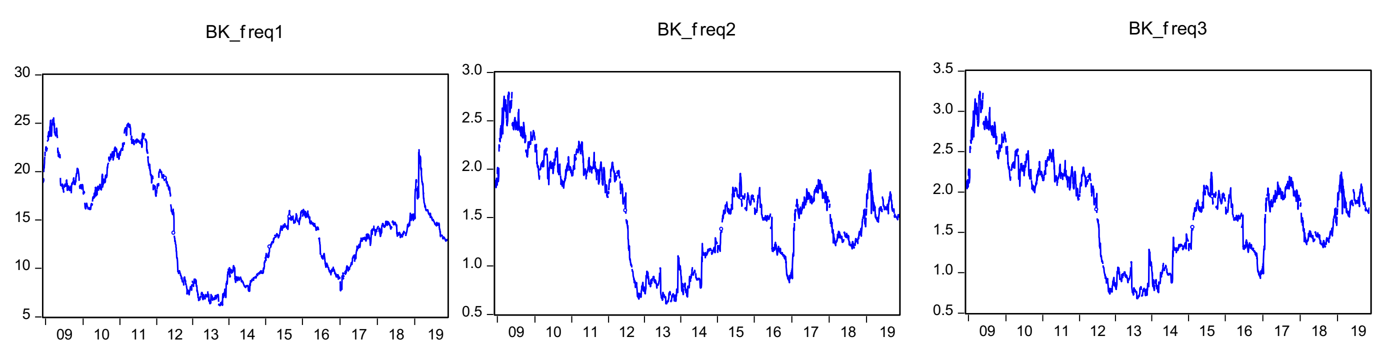

Fig. 6. Total spillover based on the BK model at three frequencies.

short periods.

Fig. 6 illustrates overall connectedness among markets, which is modelled on the BK approach at three frequencies. Frequency 1 shows the short period; this chart stood at 25%, but it experienced a steep decline to around 16% in 2010. After that, it showed an upward trend before dramatically decreasing to less than 10% in mid-2013. This was followed by an upsurge; however, it dropped again just to under 10% in 2016. 2017 onward saw a constant increment in this index, and it reached slightly above 20%, but a 10% reduction happened in total spillover in 2020. Next is Frequency 2; despite its rise to more than 2.5% in 2009, it plunged to approximately 0.7% in mid-2012. Subsequently, it witnessed a hike to around 1.7%, then it declined sharply to 0.8% again in 2016. Furthermore, in the rest of the period, it oscillated between 2% and 1.2%. For a long period that is identifiable by Frequency 3, this chart was also highly volatile. To specify, it was 2% at the beginning of 2008, increasing to just over 3.2%, then it nosedived to almost 0.75% in 2012. Finally, it increased by 1.5% less than 3 years in 2015, and it stood at 1.7% in 2019. Overall, it is self-evident that trends for medium and long periods are similar.

Fig. 7 gives more information concerning net spillovers based on the BK test at three frequencies. At the first frequency, the plot reveals that spillovers for coal ranged between 0.6% and − 1.3% during the sample period. Natural gas also has large volatility spillovers, fluctuating between −0.6% and 1.3%., while the chart for the S&P500 was roughly constant, except for mid-2016 and early 2017. Further, Shanghai stock saw high volatility during the corresponding period. To clarify, movement of total spillovers for this market is larger than other markets, especially in 2017. Notably, the US dollar and the ratio of the US dollar to CNY, WTI were the only markets that experienced stability in 2017. Additionally, coal and USD/CNY had similarity in their movements, whereas spillovers for WTI are different. In the next frequency, coal showed approximately the same oscillations in comparison to the short term. Likewise, total connectedness for natural gas is nearly stable, save the last 2 years of the sample; yet the extracted figure from the S&P500 is different from the medium period. In addition, overall spillovers for Shanghai stock showed low volatility compared to the short term, and

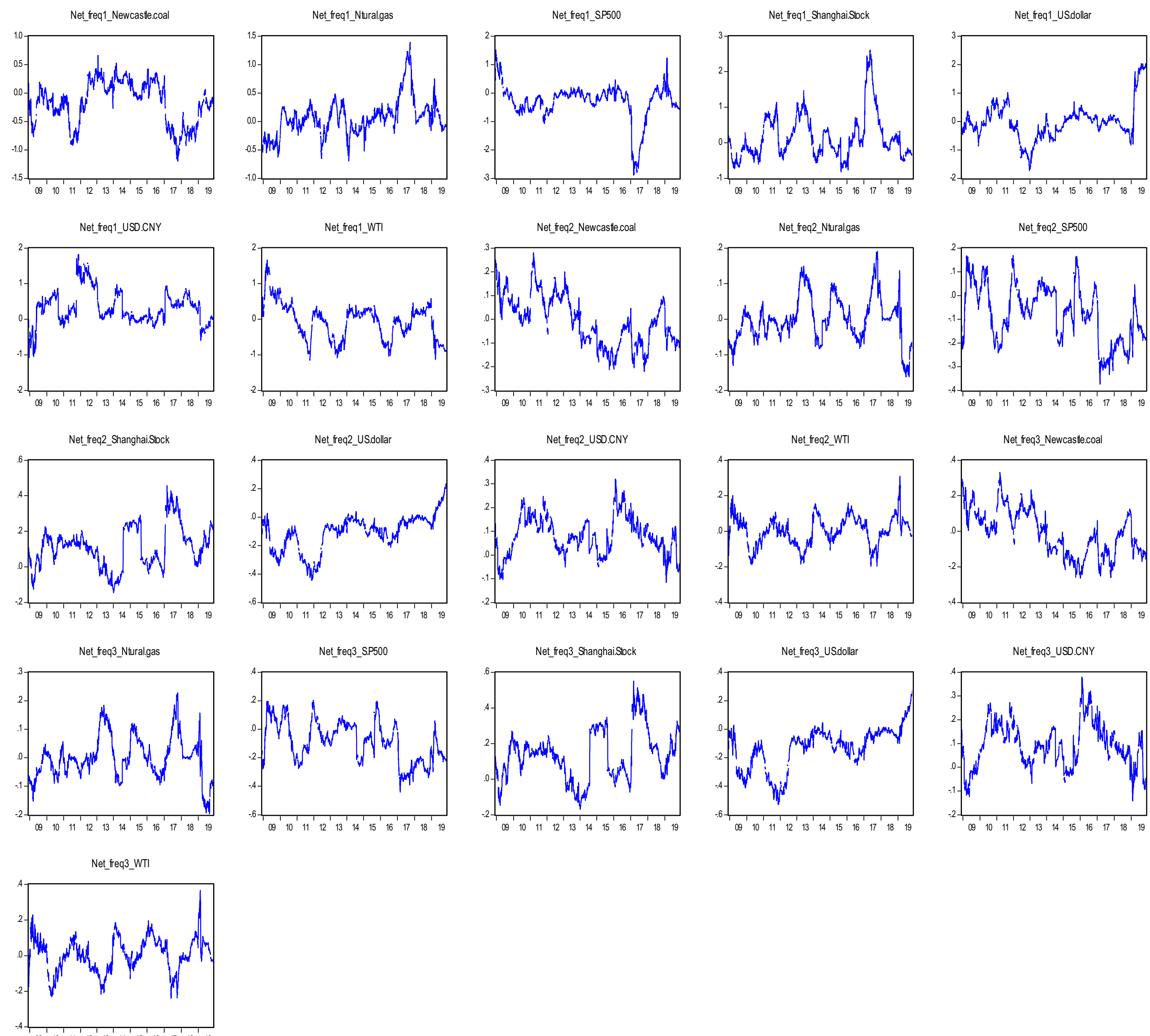

Fig. 7. Net spillovers based on the BK model at three frequencies.

interestingly, the US dollar spillovers had also the same movements in the medium term. By contrast, the chart belonging to USD/CNY represents high volatility in mid-term. Further, there was similarity between the short and medium terms for figures that belong to WTI; however, in Frequency 2, this chart had a sharp rise in 2018.

Regarding pairwise net spillovers among markets, we deploy the BK test at three frequencies, which is observable in Fig. 8. The first pairwise connection is coal and natural gas, which had positive linkage during the sample period; on the other hand, negative spillovers between coal and the US dollar were found in mid-2013 and 2014. In addition, coal and WTI had a mostly positive connectedness, but it showed a negative one in 2015 and in 2017. Moreover, natural gas and the US dollar show negative connectedness in most periods. Also, these spillovers are positive for natural gas and WTI until 2013, yet these markets show negative spillovers one year later. From 2015 onward, nexuses between natural gas and WTI become mostly positive, except in 2018. The S&P500 and other markets share mostly negative spillovers with financial assets. Further, plots for Shanghai stock reveal that there is a positive pairwise connectedness between Shanghai stock and coal as well as natural gas; however, the same results are not confirmed for other pairwise spillovers. Also, the US dollar and WTI have positive spillovers with each other before 2010, but this connectedness becomes negative for the rest of period. USD/CNY has positive and negative spillovers with coal, but in the year 2018, USD/CNY and coal have negative spillovers. For other plots, couples of USD/CNY and the US dollar, USD/CNY, and Shanghai stock are mainly negative, while pairwise connectedness among USD/CNY and the S&P500 and natural gas show positive spillovers. In the next frequency, there is high volatility

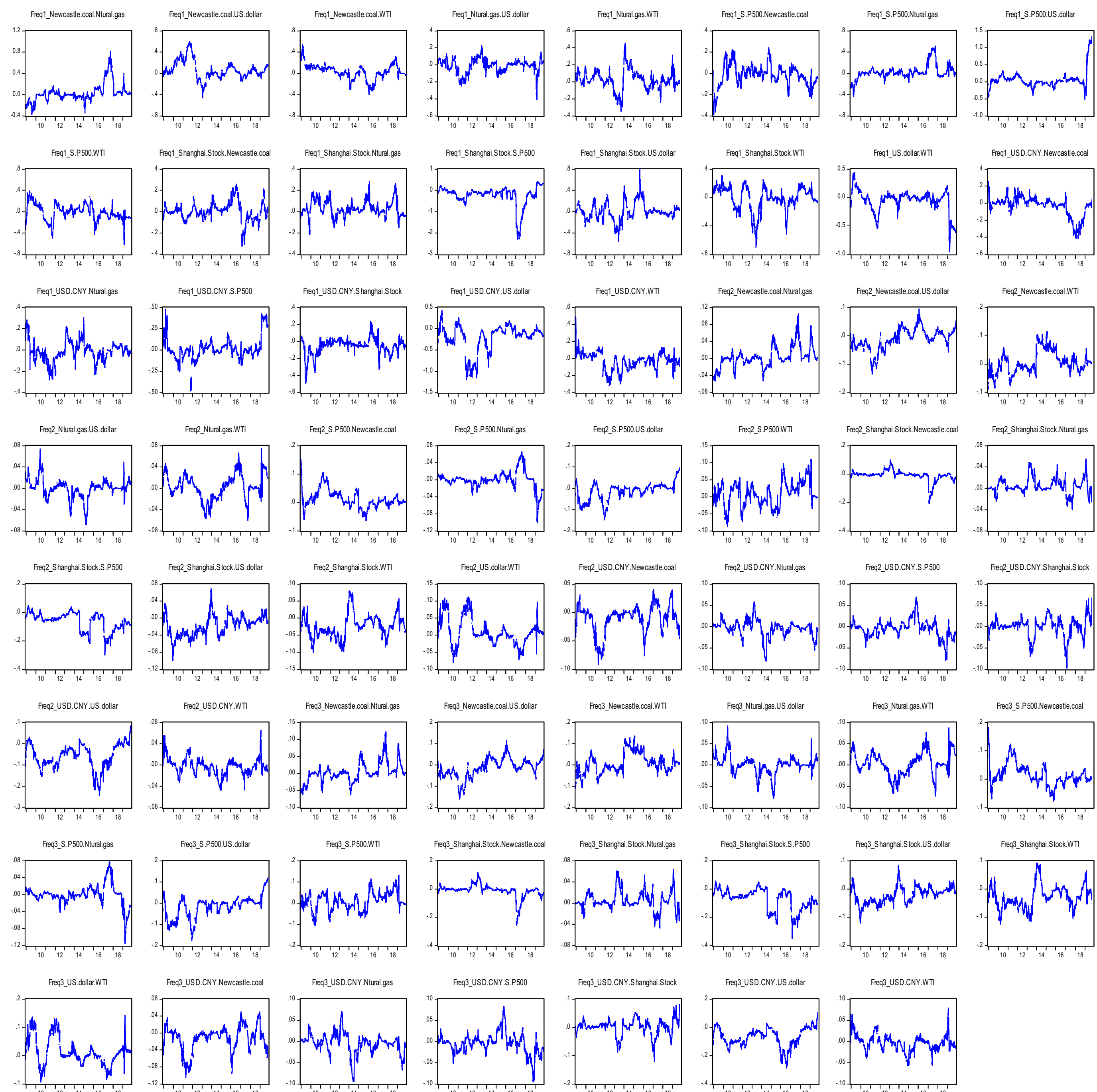

Fig. 8. Pairwise net spill overs based on the BK model at three frequencies.

compared to previous frequency between coal and natural gas; however, these spillovers become negative. Similarly, coal and the US dollar have negative pairwise spillovers with each other until 2011, when spillovers become positive. As seen with coal and WTI, there is negative connectedness between these assets, but the majority of pairwise spillovers are positive from 2014 to 2020. The figure for natural gas and the US dollar is highly volatile; this means that pairwise spillovers between natural gas and the US dollar is negative in the mid-sample period; on the other hand, it shows positive spillovers in the early and late sample period. Results for natural gas and WTI indicate that spillovers are mainly positive during most sample periods, and similar outcomes are also confirmed for connectedness between the S&P500 and coal. Contrary to Frequency 1, pairwise spillovers between the S&P500 and natural gas are negative in most periods based on Frequency 2, whereas pairwise spillovers for the S&P500 and natural gas show less volatility in the short run, in comparison to the last frequency. In the case of the S&P500 and WTI, it is evident that spillover trends are analogous to Frequency 1, but they are accelerating in Frequency 2. Notably, there are constant spillovers between Shanghai stock and coal in the whole sample period, save 2018; plus, lower pairwise spillovers are recognizable between Shanghai stock and natural gas in the short run. Further, values of pairwise spillovers for Shanghai stock and the S&P500 are negative in most selected periods, which is not much different from the last frequency. Additionally, the resemblances among Shanghai stock, the US dollar, and WTI are marked in the medium horizon. However, the US dollar and WTI reveal strong spillovers with each other in Frequency 2. USD/CNY shows higher connectedness with coal in the medium term. To be more precise, these net spillovers are negative in 2011 and 2016, indicating there are negative transfers from USD/CNY to coal. Interestingly, USD/CNY and natural gas experience less volatility than the former frequency, and similar trends are also found between USD/CNY and the S&P500. However, USD/CNY and Shanghai stock represent high volatility in Frequency 2, demonstrating negative values in the short term. Furthermore, USD/CNY and the US dollar display signs of large spillovers, while evidence for USD/CNY and WTI confirm there is lower connectedness compared to Frequency 1. In Frequency 3, spillovers for coal and natural gas show movements like Frequency 2, but pairwise spillovers that belong to coal and natural gas exhibit more positive values than negative ones in most periods. Additionally, there are similarities among trends of spillovers for coal and the US dollar between the medium and long terms (Frequencies 1 and 2). Another plot displays that pairwise spillovers from coal to WTI remain mostly positive except for 2010, 2012, and 2018. In addition, findings for other figures do not reveal profound differences, and they are followed by minor alternations.

7. Robustness analysis

In this segment, we re-examine volatility connectedness among crude oil, natural gas, coal, stock, and currency markets based on different rolling windows. This instrument deployed the dynamics of restricted spillovers, causing the choice of rolling size to become arbitrary. Overreactions in the window size show negligibility or smoothen out the potential effect of different outcomes in which the window size is immense (Shah and Dar, 2021). Accordingly, to provide compelling evidence, evaluating the robustness test based on different rolling windows is important. To that end, we deploy various rolling windows based on 200 days and 500 days, observable in Fig. 9. According to the Fig. 9, there is no sensitivity toward alternation rolling windows sizes, which corroborates our evidence.

Moreover, we gauge time-varying spillovers by various lag length for the VAR model and alternative H-step-ahead forecast error variance decompositions. The first plot provides the minimum, maximum, and range of the dynamic total spillover indexes related to the aforesaid model. Our findings confirm selection of other lag lengths as well as forecast horizon in the VAR system.

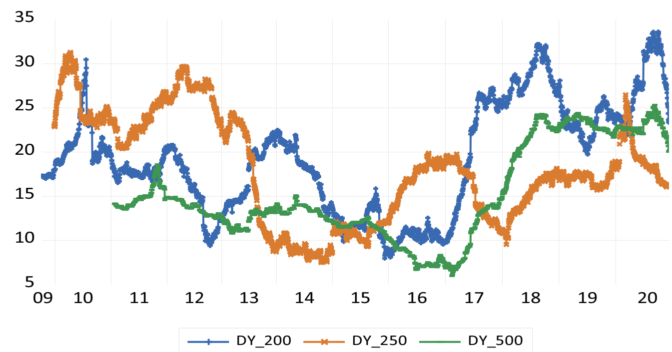

Fig. 9. Overall spillover based on the DY (2012) model via constructing various rolling windows.

The sensitivity of total spillover index to the VAR lag structure and Forecast Horizon has been presented in Fig. 10 in two panels. The upper panel of Fig. 10 presents the sensitivity analysis of the total spillover index to the VAR lag structure (max, min, and median values of the spillover index for the VAR).

And the lower panel of Fig. 10 presents a sensitivity analysis of the total spillover index to the H-step forecast error variance horizon (min, max, and median values). Overall sensitivity results indicate that results are robust to both namely, the VAR lag structure and the forecat horizon.

8. Conclusion and policy implications

This study delves deeply into an analysis of how volatilities in crude oil, natural gas, and coal affect stock and currency markets. To remedy shortcomings of previous academic research, we deploy frameworks by Diebold and Yilmaz (2012) as well as Baruník and Křehlík (2018). Furthermore, this paper is the first investigation gauging volatility spillover among crude oil, natural gas, coal, stock, and currency markets for the US and China simultaneously. To that end, we employ daily data from 12/8/2008 to 12/18/2020, which encompasses some important events such as the US shale revolution, OPEC supply-side policies; oil price plunges; political events such as Brexit, the EDC, the US withdrawal from the Iran nuclear deal, conflicts between Russia and Ukraine, and mounting unrest and political tensions in the MENA region; the crude oil surplus, and the outbreak of COVID-19.

The most remarkable results of this paper are that first, we find that volatility spillovers of WTI significantly affect those of the S&P500, and the reverse is true. Chinese stock volatility is not profoundly influenced by the WTI. Secondly, among fossil fuels, coal, WTI, and natural gas have substantial impacts on the US dollar, in turn, indicating coal is still an important energy market for the US, whereas evidence for USD/CNY reveals that crude oil has a greater influence on the Chinese exchange rate than other energy markets. Additionally, this research suggests that volatility spillover from crude oil to coal is pronounced; conversely, the effect of coal on volatility of crude oil is also noticeable. Although natural gas has a negligible effect on coal market spillover, this impact is significant from natural gas to crude oil. Next, even though USD/CNY weakly connects with coal and Shanghai equity markets, this ratio of US dollar to CNY has a pairwise relationship with WTI and natural gas. As for Shanghai stock and fossil fuels, there are weak pairwise links among these markets, save the Shanghai and WTI markets. For couples of the S&P500 and other assets, negative pairwise spillovers are found between this index and natural gas, although it has a positive pairwise spillover with coal. Lastly, the coal market portrays that it does not strongly connect with natural gas, but this result is not confirmed for coal and WTI. Results for the BK test show that, overall, total connectedness in the long horizon outperforms that in the short horizon, suggesting that to curtail risk, these assets should be bought by investors in the short term due to being volatile. Further, the formation of total

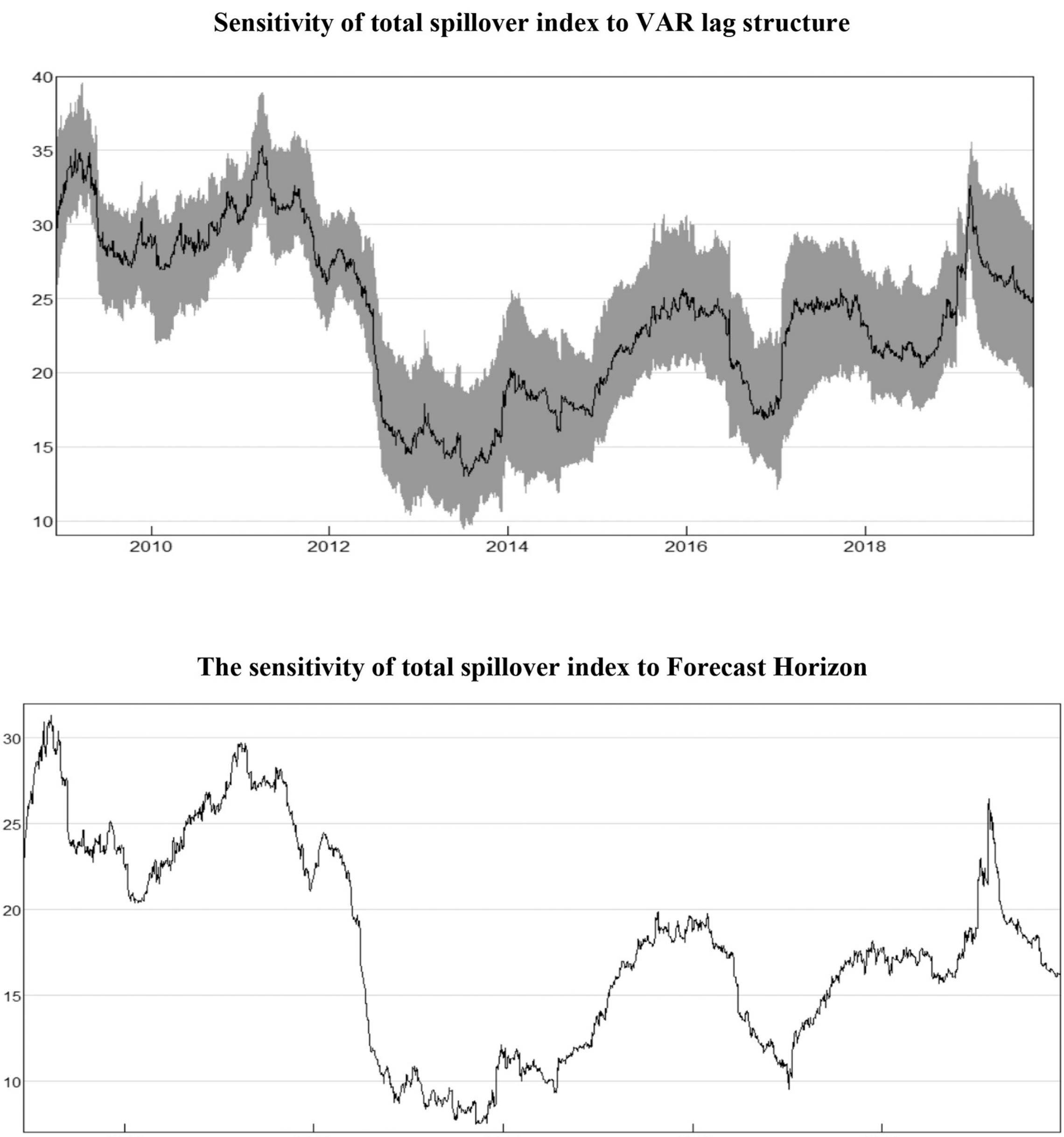

Fig. 10. Sensitivity of total spillover index to VAR lag structure.

connectedness is more dependent on the S&P500 index than other markets, whereas natural gas makes little contribution to this system. This implication explains that investors cannot follow the buy-and-hold approach due to the high volatility of assets in the long period. Overall, our evidence reveals that to limit risk management and to opt for optimum portfolio diversification, investors can use hedging opportunities via employing commodities like WTI in their portfolios due to weak connection with Shanghai stock. But in the US, WTI should be utilized as a diversifier. These implications are also applicable to connections between coal and the US market; however, nexuses between coal and Chinese markets emphasize on role of coal in hedging opportunities.

Further, our paper offers some recommendations for policy makers. First, since energy markets show high volatility, they require careful monitoring, or else unsatisfactory outcomes affect economic environment. For instance, controlling inventory of strategic fossil fuels is an effective implementation to preclude transformation shock prices into the markets. Further, authorities should adapt their economic policies to respond to financialization and the effects of the COVID-19 pandemic, as energy commodities markets have been more volatile and can impact other financial assets. To stress the importance of this topic, we can refer to the World Bank report,[3] which shows the impacts of COVID-19 on commodities are vague despite the importance of energy commodities for powerful economies. Also, our findings put forward a helpful suggestion concerning energy transition from coal to natural gas for Chinese authorities because this investigation reveals that the relationship between the Chinese market and coal is not strong. This paper provides authorities with a broadened knowledge of how volatility in price shocks in these energy markets are transmitted to other key markets, such as stock and currency markets.

Credit author statement

Mehrad Asadi: Data curation, Writing- Original draft preparation; Conceptualization, Visualization, Investigation. David Roubaud: Methodology, Software, Visualization, Investigation, Supervision, Writing-

[3] https://www.worldbank.org/en/research/commodity-markets

Reviewing and Editing. Aviral Kumar Tiwari: Visualization, Investigation, Supervision, Software, Validation, Writing- Reviewing and Editing,

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.105961.

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