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Stéphane Goutte
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Financial Market Dynamics after COVID 19

The Contagion Effect of the Pandemic in Finance

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Contents

Market-Timing Skills in the Aftermath of COVID-19 Outbreak: Evidence from Islamic Funds

Sonia Arsi and Soumaya Ben Khelifa

Abstract The COVID-19 outburst triggered all activity sectors, altering even the financial markets dynamics. And, the Islamic finance segment has not been spared. This chapter has a special focus on the market-timing abilities of Islamic funds to time stock markets before and during the COVID-19 pandemic era through cross-regional investigations, *i.e.*, North America, Europe and Asia. The results reveal that only European Islamic funds' managers exhibit market timing skills for the two-time spans. Equally, the Islamic funds' excess of return appears to be associated with that of equity, but mixed results are displayed for each region.

Keywords Islamic funds · Market-timing · COVID-19 pandemic · Excess return

1 Introduction

The Islamic finance industry is experiencing steady growth. Considering the segment of Islamic funds, Puri-Mirza (2020) reported that "*the total value of Islamic funds outstanding worldwide amounted to 140 billion U.S. dollars*" in 2019. Indeed, several researchers and practitioners cast light on the strong potential of Islamic finance and its products, since they represent Sharia-compliant investment instruments (Islamic law) as stated by the International Sharia Standards. Within this framework, Alam & Ansari (2020a, p. 504) reported that "*the paramount principle of Islamic Shariah (law) is the prohibition of the receipt or payment of Riba (usury). In addition, the Islamic law forbids investment in activities that involve Gharar (uncertainty, chance or risk), Maysir (gambling, speculation), hoarding or trading in any prohibited commodities deemed haram, for example, alcohol, pork, arm and armaments and pornography*". Such features made that investment in Islamic assets is a good alternative to conventional ones during breakdown times (Al-Khazali et al., 2014).

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With the emergence of the Coronavirus (COVID-19 hereafter) pandemic, growing attention is attributed to Islamic finance. Faturohman et al. (2021) and Haji-Othman et al. (2020) underlined the role of Islamic finance in reviving economic activities in the wake of a pandemic crisis like the COVID-19. Furthermore, Hidayat (2020) stated that "*Islamic finance could relieve government's burden in facing COVID-19*" through offering alternative investment instruments with ethics- and faith-based screening.

Interestingly enough, a specific emphasis should be accredited to Islamic funds. Indeed, they represent a good investment opportunity during these recent times, due to the low systemic risk (Climent et al., 2020; Naveed et al., 2020) and their performance compared to conventional ones (Abdullah et al., 2007; Alam & Ansari, 2020a; Arif et al., 2019; Reddy et al., 2017). Accordingly, and in order to fill out the current empirical void, this chapter examines the ability of Islamic fund managers to time market return before and during the COVID-19 pandemic era.

The chapter is structured as follows. Section 2 provides an overview of the theoretical framework related to market-timing abilities and Islamic funds. Section 3 describes the related methodology, while Sect. 4 displays the data. Section 5 exposes the main outputs. Lastly, Sect. 6 concludes.

2 Theoretical Underpinnings

Several studies handled timing abilities across funds, especially hedge funds and mutual funds. Considering market-timing abilities, the results of Chen and Liang (2007) on U.S. hedge funds exposed their market-timing skills over the period 1994–2005, especially during downswings periods. They assimilated such skill to a *hedging instrument* against troubling market conditions. Cuthbertson et al. (2010) found that UK mutual fund managers are not skilled in timing the market based upon private information. Indeed, fund managers tend to consider the current level of volatility before adjusting their market exposure. And, their market exposure increases (decreases) in a downward (upward) market due to the impact of cash withdrawn (pumped). Besides, Tchamyou et al. (2018) and Tchamyou and Asongu (2017) examined the effect of asymmetric information on the market timing abilities of U.S. mutual fund managers over the period 2004–2013. The outputs exhibit a significant reaction towards asymmetric information and vary in coherence with the current level of market exposure. However, such behavior is still overtaken by their feedback following volatility. In this context, Sherman et al. (2017) found that poor market-timing skills across Chinese funds managers can be explained by the fact that they are devoted entirely to time the market volatility instead. And, public information enhances the market-timing performance of Chinese funds. Recently, Nikolaos et al. (2020) highlighted the lack of timing skills across Greek mutual funds before the 2010's debt crisis. Even more, the crisis conditions contributed to enhance their market-timing abilities. The innovative approach of Mascio et al. (2020) tried to investigate to which extent market timing can use predicting models based on sentiment indices. Their study showed that the model was performing especially during downward periods. Additional works to mention are those of Hassan (2013), Agarwal and Pradhan (2019), and Wattanatorn and Padungsaksawasdi (2020), among others. Another strand of timing abilities literature to indicate is liquidity and volatility timing. Wattanatorn et al. (2020) showed that Thai mutual funds are good market liquidity timers in a high co-moment context. The same results are obtained by Foran and O'Sullivan (2017) who found that UK mutual funds managers are skilled in timing market volatility and liquidity, compared to the market return. However, they noticed that it was a short-lived ability. The outcomes of Li et al. (2020) highlight that the timing behavior of hedge funds managers is time-varying, i.e., they adjust their risk exposure upon the state of the liquidity in the FX market. This behavior adds value to their investment. Alam and Ansari (2020b) considered that liquidity timing ability is protection from any liquidity risk exposure.

Considering Islamic fund managers' timing skills, the bulk of empirical evidence is trivial. Among the few seminal papers on market timing across Islamic funds, Ashraf (2013) showed that Islamic mutual funds have market-timing skills during economic slowdowns in Saudi Arabia compared to conventional ones. Then, the analysis of Elmessearya (2014) across Egyptian Islamic funds during and after the 2007–2008 financial meltdown exposed that they mistime the market and they are poor performers as their conventional peers. Zouaoui (2019) analyzed the market timing skills across Saudi Arabian funds managed by HSBC from April 2011 till December 2018. The results display poor market timing skills for Islamic funds compared to their conventional and internationally focused peers, which can be due to Sharia-compliant strategies. Recently, Nawraz Khan et al. (2020) applied the models of Jensen (1968) and Treynor and Mazuy (1966) to study the selectivity and market timing ability of Pakistani Islamic and conventional funds. The results highlight an absence of market timing skills. A similar result is found with Mansor et al. (2020) and Bani Atta and Marzuki (2020) during bearish market conditions. Interestingly, Yarovaya et al. (2020) examined the performance of Islamic funds during the stages of the COVID-19 (from January to June 2020) across the countries of Malaysia, Pakistan, Saudi Arabia, Qatar, Kuwait, and the UAE. The outputs highlighted the *resilience* of these funds compared to their non-Islamic peers during this turbulent period. They assimilated them to a "safe haven" investment to adjust their pandemic risk exposure.

Following this background, main researchers tend to deal with Islamic funds per one country or a sample of countries during a specific period of time. Accordingly, this chapter bridges the gap in the current literature at two levels. First, to the best of our knowledge, this is the first work dealing with a cross-regional study on the market-timing ability of Islamic funds. Additionally, the time span of our investigation considers before and during the COVID-19 pandemic period. This would give fund managers and market practitioners an outlook on the market-timing skills of Islamic funds for three different regions.

3 Methodology

Building on the approach of Treynor & Mazuy (1966), we propose a model to examine whether Islamic funds managers can time the stock market return. In general, a timing model is based mainly upon the classical Capital Asset Pricing Model (CAPM hereafter), which suggests that the excess return on any financial asset « a » is explained as follows:

$$R_{a,t+1} - R_{F,t+1} = \complement_{\mathsf{a}} + \beta_{a,t+1}(R_{M,t+1} - R_{F,t+1}) + \epsilon_{a,t+1} \tag{1}$$

And,

$$\beta_{a,t+1} = \beta_1 + \partial_a(R_{M,t+1} - R_{F,t+1}) \tag{2}$$

Where $R_{M,\ t\ +\ 1}$ is the return of the stock market index, and $R_{F,\ t\ +\ 1}$ is the return of the government bond index.

Hence, the market-timing model is estimated following this equation:

$$R_{a,t+1} - R_{F,t+1} = \complement_{\mathsf{a}} + \beta_1(R_{M,t+1} - R_{F,t+1}) + \partial_a(R_{M,t+1} - R_{F,t+1})^2 + \epsilon_{a,t+1} \tag{3}$$

In this study, we calculate the return of each index as shown:

$$R_i = \frac{(P_{t+1} - P_t)}{P_t}$$

where P_t is the value of the index i at time t.

4 Data

We use daily values of Islamic funds indices for the regions of Europe, North America, and Asia, extracted from Bloomberg. Equally, in order to approximate the risk-free rates, we employ daily values of government bond indices, which are obtained from the database S&P Global for our three regions. The data span of this analysis is from April 2019 to February 2021 and it is divided into two subperiods. Considering the first subperiod, it ranges from April 2nd, 2019 to March 10th, 2020. This time interval comes before the announcement of the World Health Organization stating the COVID-19 as a pandemic. The second subperiod is from March 11th, 2020, until February 17th, 2021, and it consists of the international propagation of the disease.

5 Empirical Results

5.1 *Descriptive Statistics*

Table 1 reports the summary statistics of the available data for each market. North America Islamic Funds index has the highest mean, followed by Asia Islamic Funds index and Europe Islamic Funds index, respectively. The same findings are found for the stock markets and bond markets.

5.2 *Results*

Tables 2 and 3 present the empirical results based upon the market-timing model in Eq. (3) before and during the spread of the COVID-19 pandemic, respectively. We find that the coefficient of market-timing is significantly positive only for the Europe Islamic Funds Index during the two sub-periods. This suggests that European

Table 1 Descriptive statistics

Country	Variables	N	Mean	Standard Deviation	Minimum	Maximum
Europe	Europe Islamic Funds	488	0.0002973	0.0087057	−0.0875005	0.0767005
	MSCI Europe	488	0.0002364	0.0136074	−0.115864	0.0852375
	Euro Government Bond Index	488	0.0000782	0.0018122	−0.0132561	0.0057796
North America	America Islamic Funds	470	0.0009008	0.0142241	−0.1405306	0.1600338
	MSCI America	470	0.0008538	0.0167129	−0.120241	0.0955611
	U.S. Government Bond Index	470	0.000207	0.0028371	−0.0165109	0.0175674
Asia	Asia Islamic Funds	490	0.0003574	0.0069134	−0.0859775	0.0738021
	MSCI Asia	490	0.0006898	0.0101752	−0.0559082	0.0558172
	Asia Government Bond Index	490	0.0002239	0.0024386	−0.0126947	0.0081772

Table 2 Test of market-timing ability during the first subperiod (before the spread of COVID-19 pandemic)

Islamic Fund	N	C_a	β_1	∂_a	R^2
Europe	244	−0.0000268 (−0.04)	0.1227083^{**} (2.45)	1.351984^{*} (1.67)	0.0124
North America	235	0.0000855 (0.14)	0.0903934 (0.79)	−1.515746 (−0.64)	0.0337
Asia	245	−0.0000401 (−0.16)	-0.0853639^{**} (−2.52)	-2.856351^{***} (−2.70)	0.0167

Table 3 Test of market-timing ability during the second subperiod (during the spread of COVID-19 pandemic)

Islamic Fund	N	$\complement_a$	β_1	∂_a	R^2
Europe	244	0.0002942 (0.55)	−0.0162869 (−0.40)	0.4682883** (2.02)	0.0045
North America	235	0.0016547 (1.24)	0.0691393** (2.16)	−0.3488354 (−1.27)	0.0089
Asia	245	0.0003019 (0.46)	−0.0744499 (−1.61)	1.436824 (1.47)	0.0107

Islamic funds managers are good market timers of the equity market during crisis and non-crisis periods. However, North American and Asian Islamic funds managers do not possess the skills to time the equity market return. Indeed, the majority of these managers demonstrate market-timing ability neither before nor during the spread of the COVID-19 pandemic. This may be explained by the fact that fund managers are focusing on timing market volatility rather than market return (Sherman et al., 2017).

Interestingly enough, we denote that the market-timing coefficient is two to three times higher before the propagation of COVID-19 for the three regions. Moreover, the outputs in Table 2 highlight that the coefficient related to the stock excess returns is positive and significant for European Islamic Funds, while it is negative and significant for Asia Islamic Funds. Nevertheless, during the health crisis, this coefficient becomes non-significant for the two regions. This suggests that Islamic funds returns are associated with stock market returns only during non-crisis periods. Our results are consistent with the comments of S&P Global (2020), which expects that the Islamic finance industry will achieve a low growth in 2020–2021 after a strong performance in 2019. Yet, we find that the coefficient related to the stock excess returns is positive and significant for North American Islamic funds only during the COVID-19 pandemic period. Such controversies in results underline the role played by the investor behavior in a panic set to define his decision-making process (Aziz et al., 2020; Jin et al., 2020).

6 Conclusion

This chapter examines the market-timing abilities of Islamic funds over the period spanning from April 2019 to February 2021, subdivided into two subperiods. The outputs display good market-timing abilities only across European Islamic funds managers before and during the pandemic crisis. Additionally, we show that there is a relationship between the excess return of Islamic funds and that of equity during the pandemic period only for North America, while it is the case for Asia and Europe before the COVID-19 pandemic. This provides implications for portfolio diversification and arbitrage strategies as the findings can give perspective upon the general dynamics of Islamic funds' managers in North America, Europe, and Asia.

Our investigation embraces shortcomings. The analysis focused only on three main regions. Besides, the study period handled the pre- and during COVID-19 outbreak. Finally, the standard version of CAPM following Treynor and Mazuy (1966)'s model was used. Additional studies may try to overcome these drawbacks. Primarily, cross-regional investigations can be held according to the available data. An extension of the regions' sample towards the Middle East and North Africa or even Latin America regions can bring further insights into the behavior of Islamic funds. Then, a focus on the post-COVID-19 pandemic period can give us the opportunity to state the market timing skills of Islamic funds through different periods, *i.e.*, pre-, during, and post-COVID-19. Equally, the results are obtained without consideration of liquidity timing should be taken with caution (Bazgour et al., 2017). Then, more sophisticated models of timing ability can be adopted. Thus, filling this gap can yield additional outputs.

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The Relationship Between US Stock, Commodity and Virtual Markets During COVID-19 Forced Crisis

Myriam Ben Osman and Kamel Naoui

Abstract This study is aiming on investigating the relationship between the US stock, commodity, and virtual markets. Using a vector autoregressive model, we study the impulse response signal over the period going from December 02, 2019, to May 28, 2021, catching the time of the first appearance of the coronavirus pandemic. Our results outcomes that the commodity and cryptocurrency markets behave the same way for the S & P 500 stock market during the pandemic while the response of the commodity market is respectively unbalanced and positive for the US stock and cryptocurrencies markets. The virtual market, on the other hand, is found to behave differently when there is shocks emanating from the remaining two markets. In terms of variance decomposition, we realize that the commodity market explains 21% of the forecast error variance in the U.S. stock market which is the highest share of forecast for the three markets during the sanitary crisis. Our finding clarifies the necessity for investors to take into account the dependence of the three markets understudy to make better investment policies during a crisis.

Keywords Financial market · Stock market · Cryptocurrency market · Virtual market · Commodity market · Bitcoin · VAR model · S&P 500 Index return shocks · S&P GSCI Index return shocks · Bitcoin price return shocks

1 Introduction

The subprime crisis has left its sequels on the financial market after limits of traditional finance have been exposed worldwide. Hence, when (Nakamoto, 2008) first presented Bitcoin as an alternative to cash payments as well as a medium of

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exchange, investors that lost faith in the traditional finance, has turned their trust toward this cryptocurrency that, according to (Baur et al., 2018), is characterized as something between gold and the US dollar. Its major mediatization and fast-growing popularity are majorly due to its blockchain technology as well as its peer-to-peer system that gets rid of the sovereign risk. As this new system doesn't need the contribution of a third part that would play the role of financial institutions, it replaced the traditional finance that is based on the trust in the third-party mechanism, which led investors to use it as a shelter against limits in the traditional financial system. This shelter can be observed as the Bitcoin price spiked during the European debt crisis and the Cypriot banking crisis that occurred respectively from 2010 to 2013 and 2012 to 2013. Even though the Bitcoin price is associated with high volatility, it's very used as an investment asset given that it's weakly connected to traditional assets that leads it to be used as a diversifier (Dyhrberg, 2016; Bouri et al., 2017). As legitimacy is provided to cryptocurrencies, it became difficult for individuals as well as institutional investors to neglect it as an alternative investment option (Bouri et al., 2020). The CBOE and the CME group even initiated futures contracts with Bitcoin as an underlying asset, in December 2017. This is what contributed to lead this cryptocurrency to be more stated in the commodity category; knowing that, according to (Bouri et al., 2020), in several developed and emerging economies, commodities are considered diversifiers against stock market returns. The authors explain that this cryptocurrency shares a lot of similarities to gold as it is non-political and independent from inflation (the total number will never exceed 21 million). Wang et al. (2020) explains that, currently, Bitcoin and traditional finance are coexisting even though the public believes that this cryptocurrency can potentially replace the antiquated finance paradigm.

To resume, if the stock market is being shaken by some stress emanating from a potential financial crisis, Bitcoin should be considered as a hedge. However, with the appearance of the novel Coronavirus, the financial world has been shaken and Bitcoin is facing for the first time a financial crisis after its creation in 2008. First appeared in Wuhan city (Hubei province of China) in December 2019, the coronavirus disease (COVID-19) has strained healthcare systems all around the world through the speed of transmission of the virus which led countries to shut down their doors by imposing a quarantine policy. Wątorek et al. (2020) stated that, during the COVID-19 crisis, cryptocurrencies moved from being a hedger and are currently facing a "phase transition" to becoming a segment of the global market that is associated with the traditional financial instrument.

Nonetheless, this major downturn isn't only proper to this cryptocurrency. Indeed, the US stock market registered a major fall in the prices, and commodities prices like the west Texas intermediate (WTI) crude oil price ended up turning negative for the first time in its lifetime while the price of the gold kept climbing. If Bitcoin is known for being a diversifier during periods of improbabilities, its price plunged by 37% in a day after the pandemic announcement on March 11, 2020 while the global commodity market registered a major fall leaded by the crude oil price downturn. When it comes to the S & P 500 index, better known as the US stock market, huge losses has been comptabilized with a dramatic recovery. Hence, market theories are being reformed with the appearance of this forced crisis which led us to investigate the dynamic connection between the US stock, commodity, and cryptocurrency markets proxied respectively by the S & P 500 index return, the S&P Goldman Sacks commodity Index return (GSCI) and the Bitcoin price return. We chose to work on the American stock market as the United States is the country with the most cases of coronavirus in the world according to worldometers.

The impulse response functions as well as the variance decomposition methods were presented through the vector autoregressive framework to be able to study the impact of those variables on each other during the crisis. We find that a shock in each of those three markets is more driven to impact the rest of the markets during the COVID-19 crisis. The response of the US stock market to one standard variation in the commodity and cryptocurrency markets is negative at the beginning before turning positive after a couple of days while the response of the commodity market to the US stock market is unbalanced despite being strictly positive for the cryptocurrency market. The virtual market, on the other hand, responds right away negatively to shocks emanating from both the US stock and commodity markets. However, the response takes another turn for both cases which highlights the fact that the cryptocurrency market reacts differently for the remaining two markets. The variance decomposition shows that, from the three markets, the commodity market is driven to forecast 21% of the error variance in the US stock market during the crisis, which is the highest share of forecasting that we found.

To our knowledge, our work is the first to study the dynamic relationship of those three markets during the sanitary crisis while focusing on the United States case.

The article is reported as follows: Section 2 holds a literature review, Sect. 3 explains the data as well as the VAR methodology that we are going to use while Sect. 4 describes the empirical results and Sect. 5 presents the conclusion.

2 Literature Review

With the spread of the COVID-19 pandemic, stock market volatility has been higher than in the past crisis of 2008 (Thakur, 2020). According to the author, various researches focused on the effect of different shocks on the stock market and its return. Yan et al. (2020) analyzed the impact of the COVID-19 on the stock market and found that, in the short run, markets will react adversely when facing shocks while, in the long run, they will eventually correct themselves and increase. According to (Gupta & Wohar, 2017), a large literature exists on the relationship between stock prices and economic activity as well as a large one that relates the short and long-run movements between oil and stock markets with economic activity. Derbali and Chebbi (2018) looked after the dependence between the S&P 500 and sixteen selected commodities from the S&P GSCI and found the existence of a high dependency between both markets. The authors explain that several types of research has been made on the nexus between stock markets and commodities indices as the commodity sector contributes to the world trade as well as speculation and employment. Indeed, as the commodity indices are based on supply and demand, developing countries such as India and China need massive investment in commodities such as oil to build their infrastructures which increases the demand and accentuates the volatility of the prices. This automatically attracted investors, that were in the first order only interested in the stock and bonds markets, and made them take benefit of the commodity market. Nordin et al. (2014) took the Malaysian stock market and investigated the impact of commodity prices on it. The author found a cointegrating relationship between the variables with palm oil being the most significant variable while he failed to detect a relationship between oil and gold price.

According to Liu et al. (2020), many studies have provided international confirmations that the oil price shocks affect economic activity. The authors studied the impact of oil price shocks on macroeconomic fluctuations in the Chinese market and found that a positive oil price shock has negative impacts on the money supply and economic growth, highlighting the strong effect on China's real economy since the 2008 financial crisis. Papapetrou (2001) used a VAR model to shed light on the dynamic relationship that exists between oil prices, stock prices, real economic, employment, and interest rates in Greece. The author found that oil price affects employment and real economic activity and that it is important in explaining stock price movements. Even though the financial markets seem to struggle when facing the sanitary crisis, cryptocurrencies like Bitcoin, which some take as a commodity, behave with ups and downs, faithful to its extremely volatile reputation. The impact of the oil price, the exchange rate, and the Dow Jones index on the Bitcoin price has been studied by Ciaian et al. (2016). The authors didn't find proof of the significant impact of the financial variables in the long-run; confirming the results of Van Wijk (2013). During the COVID-19 period (Yousaf & Ali, 2021) used a VAR–BEKK–AGARCH model to look after the unidirectional return transmission from S&P 500 to other cryptocurrencies. The author found that the volatility transmission between the S&P500 and the Bitcoin isn't significant while it is for Litecoin. The relationship between the Bitcoin price, the S&P 500, and the VIX as well as Bitcoin realized volatility, the SP 500, and the VIX was studied by Estrada (2017). The author found the existence of a bidirectional Granger-causality relationship affecting Bitcoin realized volatility and the VIX and that the rejection of the hypothesis that Bitcoin realized volatility do not Granger-causes S&P 500 cannot be done. Using a VAR model (Wang et al., 2020), examined the connection between the Bitcoin and stock market and found that the effect of the S & P 500 on the Bitcoin price is significant and that, generally, the Dow Jones and the S & P 500 have an advantageous impact on the Bitcoin price. Given the fact that the Bitcoin system is more driven to be the object of attacks or fraud behavior through online transactions, traditional finance seems to stand in a more advantageous position according to Wang et al. (2020). However, the many advantages that are presented by the system make the cryptocurrency, commodity, and stock markets complementary. For that reason (Corbet et al., 2018), focused on the connectedness between leading cryptocurrencies and other assets like the S&P 500 Index, US VIX, gold price, and GSCI commodity index. The authors concluded that Bitcoin and leading cryptocurrencies are isolated from financial assets, pointing out the diversification possibilities offered for investors. Ji et al. (2020) highlight that growing risks have been noticed in stock markets since the spread of the coronavirus while market interdependencies has changed.

To be able to control the fast growing contagion of the virus, countries all over the world had imposed lockdown policies and closed their borders which caused the suspension of the economy in various places. This led to an imposed crisis with well known repercussion. Hence, while stock markets were having trouble, we assist to a dramatic twist in the commodity market with the demand going downturn. Although the gold kept behaving as a safe haven, Bitcoin-the virtual gold-crushed down, faithful to its extremely volatile price fluctuation before climbing to more than $60.000 on April 2021. Hence, given that those three markets has been affected by the coronavirus propagation, this drove us to look after the response of the US stock, commodity and cryptocurrency markets to shocks emanating from each other during the sanitary crisis.

3 Data and Methodology

3.1 Data

To be able to measure the impact of the US stock, commodity, and virtual markets on each other, we gather daily data covering the period between December 02, 2019 to May 28, 2021, catching the period of the first coronavirus apparition in China. We proxy the US stock, commodity, and cryptocurrency markets respectively by the S & P 500 index return, the S&P Goldman Sacks Commodity Index (GSCI)[1] return and the Bitcoin price return that we extract respectively from Investing.com, Nasdaq.com, and Yahoo finance.

3.2 Methodology

To be able to catch the short-run dynamics between the variables, we employ an unrestricted vector autoregressive (VAR) analysis developed by Sims (1980). This model is significant in explaining the effect that produces a variable on another one. Hence, we employ it to look after the response of the S & P 500 index return, the S&P GSCI return, and the Bitcoin price return to each other. Ravnik and Žilić (2011) clarifies that starting from the eighties, macroeconomists used the VAR models for

[1] The Goldman Sachs Commodity Index (GSCI) is a commodity index that gather 24 traded futures on commodity exchanges. It was first calculated by Goldman Sachs before being taken over by Standard Poor's; hence, the notation S&P GSCI.

empirical analysis as they are easy to use and are efficient at predictions compared to the complex simultaneous models.

We then consider a VAR model on daily data for $Y_t = (S\&P\ 500, S\&PGSCI, BTC)$, where the S & P 500 is the US stock market index return reflecting 500 of the biggest companies listed on American stock exchanges, the S &P GSCI is the Goldman Sachs Commodity Index return and the BTC refers to Bitcoin price return. The model is stated as following:

$$Y_t = \sum_{i=1}^{n} \beta_i Y_{t-i} + e_t \tag{1}$$

Knowing that α represent the constant term matrix, e_t refers to the residual error of the model that will be used to study the impact of different vector interaction and the β_i is the coefficient matrix.

To be able to estimate this particular model (Sims, 1980), explains that the stationarity of the variables is required. We then firstly proceed by a unit root test.

4 Empirical Results

We start by implementing the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) stationarity tests test to look after unit roots in our variables. The results are presented in Table 1 and shows that all the variable are non-stationary on level but they all follow an I(1) process.

We then look into the correlation between our studied variables and the results are presented in Table 2. We observe that, during the sanitary crisis, the correlation between the variables is positive, implying that a positive variation of the prices of one of the variables under study results on a positive variation of the price of the remaining variables during our time span. We also realize that the strongest correlation is found between the S&P 500 and S&P GSCI (0.88) followed by the S & P 500 index and the Bitcoin price (0.84) and the S&P GSCI and the Bitcoin price (0.79); highlighting the highly dependency between the three markets.

Moving on to the VAR models, we look after the optimal lag order, which we found to be four.[2] We then proceed with the estimation of the Johanson co-integration test to inspect if there is a long-run relationship between the variables. Table 3 presents the results of our estimation highlighting the non-existence of a long-run relationship between the variables at 5% level. This result justifies the use of a VAR model while taking variables on the stationary form. As our variables follows a I(1) process, we then proceed to their differentiation to get a hold of the returns before re-estimating the model while eliminating a lag.

[2] The suitable lag length selection criteria was found via the AIC information criteria test and results show that four lags are relevant for our model.

Table 1 ADF and PP Unit Root test

	ADF (level)		ADF (first Diff)		PP(level)		PP (first diff)	
Variables	Coeff	Prob	Coeff	Prob	Coeff	Prob	Coeff	Prob
S & P 500	−2.660928	0.2537	−5.354660	0.0001*	−2.270224	0.4487	−25.11238	0.0000*
S & P GSCI	−1.493913	0.8303	−18.78634	0.0000*	1.562595	0.8059	−18.90853	0.0000*
BTC	−1.471636	0.8377	−20.36467	0.0000*	−1.567629	0.8040	−20.38152	0.0000*

Note: The S & P 500, S & P GSCI and BTC designate respectively the Standard and Poor's 500 index, the Standard and Poor's Goldman Sacks commodity Index and the Bitcoin price. The Dickey and Fuller (1979) and Phillips and Perron (1988) tests possess as a null hypothesis the presence of a unit root.
*Represent significance at 5% level

Table 2 Correlation matrix

BTC	S & P 500	S & P GSCI
BTC	1	
S & P 500	0.849	1
S & P GSCI 0.791	0.88	1

Note: The S & P 500, S & P GSCI and BTC designate respectively Standard and Poor's 500 index, the Standard and Poor's Goldman Sacks commodity Index and the Bitcoin price

Table 3 Johanson cointegration test

Hypothesized No. of CE(s) Eigenvalue Trace Statistic 0.05 Critical Value Prob.**				
None	0.042179	20.80833	29.79707	0.3697
At most 1	0.009002	4.820500	15.49471	0.8276
At most 2	0.003942	1.465495	3.841466	0.2261

Note: * designate the rejection of the null hypothesis at 5% level

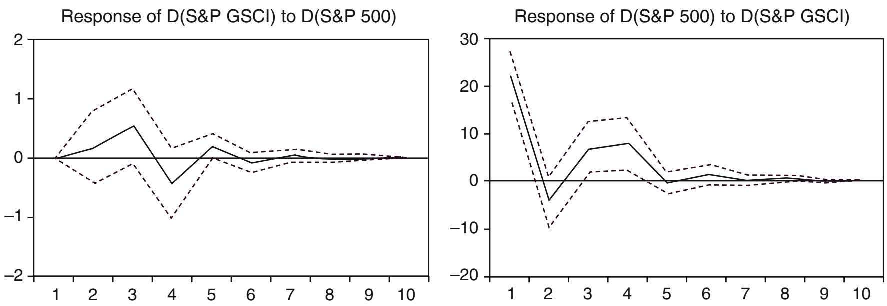

Fig. 1 Plots of impulse response functions to respectively S&P500 and S&P GSCI

We then proceed to the estimation of the impulse response function and variance decomposition to be able to investigate the consequence of shocks as well as variations generated by a specific variable on another one. We assess the dynamics of the S & P 500 index return as well as the S&P GSCI return and the Bitcoin prices return in response to a shock to one of the variables using impulse response functions (IRFs) generated through the VAR model estimation. We first check the response of the S & P 500 index return and S& P GSCI return to one standard deviation in each variable. The results are provided in Fig. 1; knowing that the dashed lines indicate the 95% confidence bound.

Figure 1 presents the bidirectional response of S & P GSCI index return to a shock in the *S&P* 500 index return and vice versa. On the left, we find the response of the S & P GSCI index return to a 1% positive deviation in the S&P 500 Index return and observations concludes that a progressive increase during the first couple of days is listed and the response reaches a spike of 0.5% during the beginning of the third day before facing a downturn and becoming negative during the end of the same day. Thereafter, the response reaches −0.5% before taking an exponential progressive increase, becoming positive on the fifth day before fading away on the

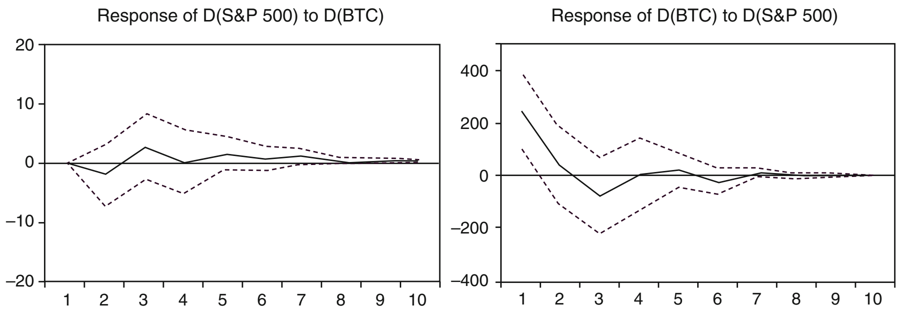

Fig. 2 Plots of impulse response functions to respectively S&P 500 and BTC

eighth day. The commodity and stock markets are known to be linked as trending and events in one market can affect the price movement on the other one. As stocks are the individual shares of ownership in corporate businesses, commodities consist of natural resources as well as materials that are used in those corporate businesses. If a positive shock in the S&P 500 is registered, it means that the profitability of the companies that it presents has improved which can be the consequence of a drop in the commodity prices. This eventually will lead to investors behaving with a bullish attitude on the commodity market which explains the positive response on the first couple of days. However, as prices always take back their original values, the confrontation between supply and demand will eventually make the price drop again, reaching −0.5%. On the other hand, when it comes to the response of the S&P 500 to one positive standard deviation in the S&P GSCI, we find that a sharp decrease is listed during the first couple of days going from 22% on the first day to −4% the day that follow. Afterward, the response becomes positive the couple of days that follows, stabilizing around 7.5% on average before fading and nullifying during the fifth day. On the sixth day, the response is positive and goes by 1% before totally disappearing on the ninth day. A change in the commodity index is then more susceptible to affecting stock markets during the sanitary crisis than a change in the stock market. Indeed, the negative and sharp decrease is because a change in the commodity prices generates a trickle-down effect that impacts directly and negatively the operational costs of corporations; which ends up reflecting on the stock market as corporations need the redefine the prices they charge consumers leading to reports that can bring investors to make a different decision that impacts individual stocks price at the beginning and the whole stock market later. Our findings are in line with (Derbali & Chebbi, 2018) which highlighted the highly dependency between the S & P 500 and the S & P GSCI commodities indexes.

Figure 2 portrays the response of the S & P 500 index return to shocks emanating from a 1% deviation in the Bitcoin price return and vice versa. We find that a positive shock in the Bitcoin price return generates no response at the beginning of the first day before ultimately decreasing to −2% during the day that follows. By the end of the second day, the response becomes positive all along the period going from the third day until its disappearance on the eighth day; reaching a spike of 3% during the

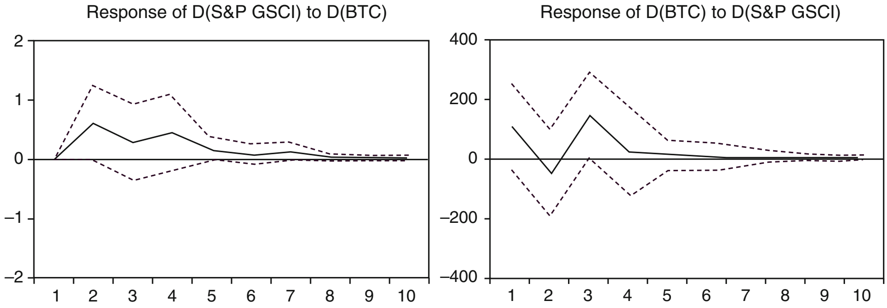

Fig. 3 Plots of impulse response functions to respectively BTC and S&P GSCI

third day. Bitcoin is known as a cryptocurrency that is independent of states which makes it a part of a market in perfect decorrelation with the stock market. As the Bitcoin price is volatile and pursued as a financial bubble, a 1% positive deviation in the price attracts speculators that are willing to make short-run profits based on the initial growth in the price. This price increase makes some investor withdraw their investment on the stock market to invest monumentally in the cryptocurrency market, making a momentary drop in the stock market prices. This drop will eventually attract other investors that see an opportunity in the under-evaluation of some assets in the stock market; which eventually will make the prices up again. On the other side, the response of the Bitcoin price return to a 1% positive deviation in the US stock market decreases on the first couple of days until becoming negative on the third day, reaching a negative spike of -81%. The response then goes up to 17% during the period going from the fourth to the fifth day before going down to -27% on the sixth day. Afterward, when the S&P 500 index return increases by 1%, the response of Bitcoin price return is by 5% on average until the tenth day. In this case, we can observe that a 1% variation in the S& P 500 impacts more significantly the Bitcoin price than the contrary. As the Bitcoin price is known to be volatile and is frequently taken as a hedge against stock market price fluctuation, it is meaningful to find that a positive movement in the S&P 500 index can lead the Bitcoin price return to respond negatively. Our results concord with (Wang et al., 2020) that proved the non-significance of shocks emanating from the Bitcoin on the S&P 500 Index, highlighting that the effect calms down rapidly. Our work also concord with the author since he also found a strong influence of the S&P 500 growth on the Bitcoin price, explaining that the impact is negative at lag 1 before slightly becoming positive at lag 4. Moreover, Goczek and Skliarov (2019) found that a shock in the stock market drives the Bitcoin price to a negative reaction which is in line with our findings.

Figure 3 represents the impulse response of the S&P GSCI index return to one standard deviation in the Bitcoin price return and vice versa. The response of the S&P GSCI index return is positive during the first week that follows a shock in the Bitcoin price return, reaching a variation of 0.6% during the second day before fading away and nullifying on the eighth day. As Bitcoin is having an identity crisis,

Table 4 Variance decomposition

Days	S.E.	S&P GSCI	S&P 500	BTC
S & P 500				
1	50.35979	19.66255	80.33745	0.000000
3	53.50707	19.87462	79.72260	0.402787
5	54.42073	21.32838	78.20263	0.468993
7	54.45993	21.35907	78.12588	0.515046
10	54.46401	21.36515	78.11481	0.520035
S&P GSCI				
1	6.104544	100.0000	0.000000	0.000000
3	6.170581	98.00370	0.810635	1.185667
5	6.217659	96.82077	1.425189	1.754037
7	6.220595	96.74908	1.447486	1.803437
10	6.220830	96.74407	1.448496	1.807433
BTC				
1	1406.744	0.569102	3.004069	96.42683
3	1426.025	1.689713	3.309189	95.00110
5	1438.747	1.678017	3.264734	95.05725
7	1439.905	1.675474	3.298343	95.02618
10	1439.954	1.676332	3.299836	95.02383

it is commonly seen as a commodity since it behaves a lot like gold and oil (it can be sold or bought in cash markets or as derivatives like futures). Hence, the positive response. Goczek and Skliarov (2019) estimate that a shock in the commodity market drives to a positive reaction in the Bitcoin price although, after the fifth period, it becomes non-significant which is halfway in line with our results as we find a positive reaction starting from the second day before fading away on the eighth day. Meanwhile, the response of the Bitcoin price return to a 1% positive variation in the S&P GSCI index return decreases on the first day until becoming negative on the second day, with a variation of −51%, before leveling up progressively reaching 143% on the third day. Starting from then, the response gradually decreases becoming 18% on the fourth day and nullifying on the sixth day. This result again highlights that, given the volatile property of the Bitcoin price, its response to shocks emanating from both the US stock market and commodity market during the sanitary crisis is highly significant. The forecast error variance decomposition is estimated up to tenth days for the studied variable and results are presented on Table 4.

We find that the commodity market and the cryptocurrency market explain respectively 19% and 0% of forecast error variance, during the first day, for the US stock market. The forecasting power increases respectively up to 21.36% and 0.52% during the tenth day. With regards to S & P GSCI index return, on the first day, the S & P 500 index return and the Bitcoin price return don't explain the error variance in the commodity market. The size of the share of error variance increases up to 1.44% for the S & P 500 index return and 1.8% for the Bitcoin price return during the tenth day. For the crypto-market, represented by Bitcoin price return, we find that both the US stock market and the commodity market explain the forecast error variance up to 3% and 0.56% during the first day. However, the forecast error variance goes up to 3.3% for the US stock market and 1.68% for the commodity market during the third day before going down respectively to 3.29% and 1.67% during the tenth day.

5 Conclusion

In this research paper, we inspected the dynamic impact existing between the US stock, commodity, and cryptocurrency markets, that are proxied respectively by the change in the S & P 500 index, S & P GSCI index, and the Bitcoin price, using a VAR model. The results of the response of the commodity market to shocks emanating from the US stock market present a positive relationship up to three days before becoming negative the day that follows and dying out starting from the eighth day. On the contrary, the response of the US financial market to a shock emanating from the commodity index is negative on the first couple of days before turning positive the day that follows and fading away starting from the ninth day. Hence, the bidirectional response of those two markets to each other is opposite during the coronavirus crisis. When it comes to the response of US stock market to one positive standard deviation in the cryptocurrency market, we find that, during the sanitary crisis, the response is negative on the first day before turning positive the days that follow. In contrast, the response of the cryptocurrency market declines during the first couple of days, when the shock is issued from the US stock market, until becoming negative on the third and sixth day and nullifying later. Meanwhile, when we study the response of the commodity market.

to a shock emerging from the cryptocurrency market, we get a hold of a positive response during the pandemic crisis while the response of the cryptocurrency market to one standard deviation in the commodity market is negative on the second day before becoming positive the couple of days that follow and nullifying later. Even though the ravage of the pandemic is still very high in some countries, including the US, more efforts are being deployed to get a hold of policies that can canalize the impact of the COVID-19 on the US stock market as well as the commodity market while the Bitcoin, faithful to its reputation, continue being a hedge against traditional assets as well as an attractive investment in perfect decorrelation with states. Investors then must take into consideration that the impact of those three markets on each other is real and that, even though the cryptocurrency market is facing its first real crisis since its creation, its effect on the real economy continues to persist during the pandemic.

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Towards a Better Comprehension of Tourism Crisis in the Era of Covid-19

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Abstract This chapter takes stock of the situation of the tourism sector at the time of the pandemic based on a literature review on the impacts and the management of crisis situations and a collection of testimonies from experts in the field. Moreover, expert interviews with hotel managers were conducted to provide a better understanding of the impact of the crisis on their business, their management of the crisis and their vision of potential solutions to their difficulties. All those interviewed confirm the idea that the Covid-19 pandemic has accelerated the tourism crisis already installed since 2018. Energy-related issues and ecological alternatives as possible solutions to the problems of the sector hardly figure in the concerns of professionals in the sector at the moment.

1 Introduction

For more than a year, the Covid 19 pandemic has placed the planet at war with a virus, which is becoming the global health emergency for the World Health Organization. This unprecedented and sudden health crisis required the implementation of measures, often drastic against a virus, poorly known and difficult to define. Governments are continually confronted with making quick and urgent decisions.

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The measures taken to fight this pandemic have serious consequences on the economic situation. Many sectors of activity have been paralyzed because of the health crisis. The physical distancing and the gauges imposed in work and commercial spaces, the establishment of a curfew, the closure of international borders, the multiple confinements, have led to a major disruption and some closures of several productions, commercial or service activities. The consequences have been heavy on the treasury and the economy of several countries, which have found themselves forced to implement policies of financial aid to the most precarious households and sectors in difficulty.

If from an ecological point of view, the planet may have had a moment of respite during this pandemic, economists foresee the onset of a major financial and economic crisis with very serious consequences. Among the sectors most affected by the health crisis, tourism is experiencing an unprecedented collapse, the cost of which would have tripled compared to the financial crisis of 2009.[1] This sector closely linked to transport, it is indeed very impacted by travel restrictions and the reduction of air, land and sea traffic. These same restrictions are also not without impact on the energy sector.

The objective of this chapter is to take stock of the situation of the tourism sector at the time of the pandemic based on a literature review on the impacts and the management of crisis situations and a collection of testimonies from experts in the field. Moreover, expert interviews with hotel managers were conducted to provide a better understanding of the impact of the crisis on their business, their management of the crisis and their vision of potential solutions to their difficulties.

2 The Economic Crisis Linked to the COVID-19 Pandemic

The global economic crisis linked to the pandemic Covid-19 is also known as the economic crisis of 2020 (Beck, 2020; Cecchetti & Schoenholtz, 2020). Considered to be unprecedented in its nature and violence, it is considered more serious than previous crises and it affects almost all sectors (Weder di Mauro, 2020; Boone et al., 2020; McKibbin & Fernando, 2020; Arezki & Nguyen, 2020; Baldwin & Tomiura, 2020; Mzoughi et al., 2020; Beck, 2020; Cecchetti & Schoenholtz, 2020).

Two main economic shocks characterize this crisis: a supply and a demand shock. In fact, the supply shock is characterized by a drop-in production due to supply constraints and the shutdown of factories. The demand shock mainly refers to a fall in external demand, implying a decrease in exports (Wren-Lewis, 2020; Wyplosz, 2020).

This situation has given rise to a macroeconomic imbalance which can result in inflation, unemployment, external imbalance, budget deficit, poverty, financial instability, etc. (Cochrane, 2020; Wren-Lewis, 2020; Wyplosz, 2020; Baker et al.,

[1] https://www.unwto.org/fr

2020; Mann, 2020; Meninno & Wolff, 2020; Voth, 2020; Tobias & Aditya, 2020; Albulescu, 2020a, 2020b, 2020c).

The economic crisis linked to COVID-19 has significantly influenced several sectors. The tourism sector is one of the sectors that continues to suffer from the adverse effects of Covid-19. Difficulties are particularly important in countries and cities where tourism is a vital sector in terms of employability and source of income.

2.1 The Tourism Crisis in the Era of Covid 19

The tourism sector is the third most important one in the world economy. Through tourism, millions of people can appreciate their own cultures and those of others (Tobias & Aditya, 2020; Albulescu, 2020a, 2020b, 2020c). In 2019, tourism generated 7% of world trade and employed about the tenth of people worldwide, according to the World Tourism Organization (UNWTO).[2] Tourism activity has registered a significant drop with 98% international tourists since May 2020, which represents about 300 million tourists and 320 billion USD in losses in terms of international tourism receipts.[3]

More than a third of humanity is confined. Air traffic has decreased by 90% (the World Tourism Organization "UNWTO", 2020). Touristic attractions are closed. It is a real disaster for a sector that handled more than 1.5 billion tourists per year, which represented more than 10% of global gross domestic product and which employed more than 300 million people.[4]

The World Tourism Organization also records that the number of international tourists fell from 56% to 78% throughout the year 2020. The amount of this fall would drop from 1.5 trillion dollars in 2019 to an amount between 310 and 570 billion dollars in 2020 (UNWTO, 2020). This has had a negative impact on more than 100 million direct jobs in the tourism sector.

In Brazil, for example, the tourism sector has suffered considerable losses. About 80% of hotel services and all parks and tourist attractions have closed. The industry lost approximately US $ 6.2 billion. Arrivals of international travelers to Brazil fell by 50% in 2020.[5]

In France, the containment measures imposed have led to the closure of 75,000 restaurants, 3000 nightclubs and 40,000 cafes. This created technical unemployment of a million of employees.[6] Indeed, technical unemployment is when an employer

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[2] https://www.un.org/sites/un2.un.org/files/policy_brief_covid-19_and_transforming_tourism_french

[3] https://www.unwto.org/fr

[4] https://www.unwto.org/fr

[5] Euromonitor "The Impact of Coronavirus in Brazil: Uneven Prospects Across Industries" 14 avril 2020

[6] La Chaîne Info, "Restaurants, cafés et bars fermés: un million de salariés dans l'inquiétude" 15 mars 2020

temporarily cuts back or creases an employee's employment with the understanding that the employee will be recalled within a certain period.

In the United States, since the beginning of the crisis, nearly 1.6 million hotel workers have been made redundant or placed on unpaid leave. Thus, 3.9 million jobs supported by the hotel industry were lost.[7]

In the UK, 80% of workers in the hotel and restaurant industries have been on unpaid leave and around a third of jobs have been threatened in the long term.[8] Kandoussi and Langot (2021) reinforce the idea that the drastic confinement plays a major role. Indeed, the hotels were forced to lay off some of their employees.

The constraints on the movement of people have an impact on tourist accommodation and restaurants, which have faced massive technical unemployment and waves of layoffs (Defraigne, 2020; Cortes & Forsythe, 2020; Dares, 2020). As the tourism sector is closely linked to the transport sector, the tourism crisis cannot be dissociated from an energy crisis.

2.2 A Tourism Crisis that Hides an Energy One

Travel restrictions, repeated confinements, decisions to close borders, the requirement of a negative PCR test and compulsory isolation for entry into many countries, are all factors that have been at the origin of a significant reduction in air traffic in particular, which kept the planes on the ground for several months. The energy sector, closely linked to the transport one, is thus strongly affected. The pandemic has particularly influenced fossil energy. Monday, March 9, 2020 is the date of the outbreak of the current oil crisis, which comes after that recorded between 2014 and 2016. This crisis was until then marked by the biggest fall in the price of a barrel of oil in modern history, falling by around 70% over two years (Heyer & Hubert, 2020). On that day, the price of oil precipitates the price of a barrel to 33.87 dollars, a level not seen since 2016.[9]

The unprecedented recession in the global economy following the development of Covid-19 caused oil prices to drop instantly (Heyer & Hubert, 2020; Urom et al., 2021; Khelifa et al., 2021). Indeed, the demand for petroleum products had collapsed. This drop can be especially explained since the country with the greatest demand for oil is China.

[7] American Hotel and Lodging Association (AHLA) "COVID-19's impact on the hotel industry" 22 avril 2020

[8] The Guardian "UK tourism hotspots could face worst of post-lockdown job losses", 27 avril 2020.

[9] https://www.nouvelobs.com/economie/20200309.OBS25786/effondrement-sans-precedent-du-baril-du-petrole-qui-perd-plus-de-30-en-asie.html

China consumes 14% of world consumption, or 14 million barrels per day.[10] Seen as the cradle of the epidemic that crippled the world economy, China is the world's second largest consumer of oil. These disturbances in the oil sector have been felt notably in the Gulf countries, whose economic success lies largely in the exploitation of their resources.

In addition, the Coronavirus crisis has not spared the renewable energy sector. Some producers are already anticipating delays on many wind and solar projects.

Indeed, they manufacture many solar panels, batteries, silicon components and raw materials related to these technologies. These manufacturers had to partially or totally stop their production for several weeks. After the sharp declines recorded in 2020, several studies forecast for 2021 a substantial drop in the prices of energy products, which also include natural gas and coal (Heyer & Hubert, 2020).

The connectivity offered by air, land and sea transport is also at the heart of tourism. Before the Covid-19 pandemic, around 58% of the 1.5 billion tourists crossed borders each year by air, compared to 39% of land.[11] Aviation was responsible for nearly 37 million jobs in the tourism sector, contributing approximately $ 897 billion annually to global GDP.[12] Based on these findings, the pandemic has resulted in unprecedented restrictions on the global movement of people, isolating many countries and regions. Today, the aviation industry has, presumably the most crisis in its history.

In 2020, airlines tracked losses amounting to $ 387 billion in gross revenue. The situation is considered more serious than during the SARS epidemic of 2003.[13] The health crisis has also influenced maritime passenger transport. Indeed, some countries have advised against boat travel and that the major cruise companies have suspended their activities. Based on these findings, the tourism sector, closely linked to the transport sector and therefore to the energy one, is severely affected by the delays caused by the closure of international borders and the lack of coordination and mutual assistance between countries.

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[10] https://www.lemonde.fr/economie/article/2020/03/09/fin-de-l-alliance-russie-arabie-saoudite-coronavirus-les-cours-du-petrole-s-effondrent-et-entrainent-avec-eux-les-bourses-asiatiques_6032284_3234.html

[11] Tourism Data Dashboard, OMT, Global and Regional Tourism Performance, consultable à l 'adresse https://www.unwto.org/ globaland-regional-tourism-performance

[12] Aviation Benefits Report 2019, consultable à l'adresse https://www.icao.int/sustainability/Documents/AVIATION-BENEFITS-2019- web.pdf

[13] Statistiques du transport aérien de l'Organisation de l'aviation civile internationale au mois de juillet 2020, https://www.icao.int/ sustainability/Pages/Economic-Impacts-of-COVID-19.aspx.

2.3 Case Study on Tunisian Context: The Tourism Sector Facing the COVID-19 Pandemic

The tourism sector in Tunisia is seen as an engine of growth for the national economy. Its contribution to the national GDP is around 15% and it employs more than 10% of the working population with nearly 400,000 direct and indirect jobs. The current health crisis has affected the Tunisian tourism sector as a whole: hotels, travel agencies, touristic restaurants, crafts and other activities related to this sector. All these activities are in fact closely linked to each other and represent the main sources of income in some touristic towns.

The interest of this investigation will be centered on the hotel sector in Tunisia, whose crisis has been at the origin of the paralysis of several other related activities. The number of border arrivals has fallen by around 75% during the first 9 months of 2020 (Tourmag, 2020). Receipts for accommodation have fallen by around 64% and overall overnight stays by around 80%.[14]

According to the latest statistics from the BCT, tourism receipts have fallen to 78% compared to 2019.[15] The closure of land borders with Algeria and Libya recorded a 56% drop in admissions for the first half of 2020 compared to the same period in 2019.[16]

Despite the measures taken by the government to lighten hotel charges, general confinement has forced the majority of professionals in the tourism sector to lay off a large part of the staff. Indeed, the unemployment rate in the tourism sector is estimated at 21.6% currently against 15% in 2019. The closure of land borders, sea and air have increased the indebtedness of the majority of hotels (Tourmag, 2020).

Otherwise, the Tunisian tourism sector and the hotel industry, in particular, were already in crisis before the pandemic. Characterized by a great dependence on tour operators, hoteliers were strongly impacted by the announcement of the bankruptcy of the tour operator Thomas Cook, which generated a significant drop in turnover in the period 2018–2019.

This decline continued until early 2020, because of a deficit winter season in the hotel sector. The hope of an end to the crisis in the spring of 2020 was dashed by the declaration of the pandemic.

A near-total closure of hotels during the next three months has further deteriorated the already vulnerable situation. In order to better understand the impact of the health crisis on the hotel sector, expert interviews were carried out by hotel professionals whose testimonies confirm the catastrophic situation of the sector at the time of the epidemic.

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[14] Central Bank of Tunisia BCT, (2020)

[15] https://www.veilleinfotourisme.fr/

[16] https://www.tourmag.com/

For owners and managers of hotels in Hammamet, Djerba and downtown Tunis were interviewed. The interviews were conducted in February 2021 and lasted between 60 and 90 min each.

The interviews were conducted according to a guide organized according to the following main themes:

- Impact of the health crisis on the tourism sector
- Impact of the health crisis on the hotel business
- Impact on the operational management of hotels
- Place of energy and ecological alternatives in the management of the crisis
- Strategic vision and outlook for the sector after Covid.

Regarding the impact of the health crisis on the tourism and hotel sector in particular, the owner of a hotel in the Hammamet region states:

> The pandemic has accelerated the tourism crisis already installed for almost two years. The month of March, which was to be the start of a recovery with the coming of spring, was the start of a collapse with a sharp decline of around 70% in activity.
>
> We had to close completely in April-May to restart gradually at a rate of 30% of our capacity in June. This period, which coincided with the start of deconfinement and the gradual reopening of borders. The summer season saw some recovery in activity of up to 60%, which remains very low for a seaside hotel usually operating at 100% in July–August. From September, we were hit by the second wave that we did not really foresee and whose repercussions of which were disastrous. While in the first wave we avoided layoffs, we couldn't afford seasonal recruitments as usual.
>
> Our clientele has been mostly local, and made up of our loyal customers; so, we were able to save a few jobs and to avoid closure. The closure avoids costs that are difficult to cover in these conditions.

The same situation is described by the manager of a hotel on the island of Djerba who explains how the crisis has impacted the whole city beyond the establishments.

> The health crisis has not only challenged the hotel, it has turned some towns into ghost ones. The island of Djerba, like other coastal towns, has become a dead city because of the crisis.
>
> The impact on employment is significant with fewer hires and more layoffs, sources of income are clearly diminished, purchasing power and demand are falling. All sectors are affected in a city whose survival depends mainly on tourism.
>
> To cope with this crisis, the manager of a hotel in the Hammamet region tells us: With the decline in activity, the cost of shutting down is certainly less than the cost of maintaining reduced activity. However, we had to reopen to maintain the activity of our employees but with restrictive conditions. Some parts of the hotel have been condemned, and only the rooms near the restaurant and the reception have been kept open for accommodation for groups of at least forty people particularly for the organization of professional events. The operational workforce is small and the staff work mainly on alternate terms. Supply management has necessarily been revised based on an unstable and very low occupancy rate compared to the average.

The situation turned out to be a little different at a hotel in Tunis downtown, whose owner and manager said:

> “The hotels in the capital are relatively less impacted than those at the seaside. We are now operating with an occupancy rate of only 10 rooms and a staff of 60. The forbidden buffet had to be replaced by table service. We continued to pay employee salaries throughout the

lockdown period. However, we had to remove half of the contract during a pandemic. For a downtown hotel, our customer is diverse. Our business is not seasonal like that of seaside hotels. However, we were not spared from the crisis. With the establishment of a curfew, bars and restaurants are closed at night, whose activity represented a source of additional income for employees thanks to tips.

In addition to the absence of any compensation from the state, we were also forced to choose between the options of becoming a hotel for confined people or maintaining an offer aimed at other regular customers. We could not combine the two options, despite the health protocol imposed by the Health Ministry. The establishment of such, a protocol has also been very costly in terms of investment, equipment and staff training. ".

Regarding the issue of energy and the resulting charges, the manager of the seaside hotel in Hammamet adds:

"The decline in activity has resulted in lower energy consumption. However, this does not really allow us to reduce our energy costs. Indeed, we are forced to subscribe to a maximum power level that we pay in all cases regardless of our energy."

The owner and manager of the hotel in the capital confirm these comments when asked about the issue of energy:

"It's incompressible! For heating, for example, it is a boiler that operates at full capacity for 5 or 100 rooms. We cannot afford to turn off parts of the hotel or turn down the heat when the number of customers is low. A customer must feel important, even if he is the only hotel guest.

Paying bills is inevitable regardless of the situation. We have continued to pay our bills, despite the crisis in accordance with the contract power. It is an obligation for the sector.

However, we were able to reduce the ceiling for this subscription, which allowed us to make small savings, certainly negligible but which are felt considerable in a crisis situation. We can no longer afford the least waste when we are in financial difficulty."

The issue of energy and ecological alternatives does not seem to figure at all in the priorities of professionals in the tourism and hotel sector in this context of crisis. Their main concern is paying their charges and avoiding bankruptcy.

"*Thinking about the environment and green alternatives is a luxury for companies in these conditions. There are other priorities*", confirm all the interviewed managers.

The manager of the downtown hotel adds, "*The cost of purchasing electricity is increasing significantly and finding cheaper alternatives is imperative. In our hotel, we are sensitive to environmental causes and we are environmentally labeled thanks to our waste recovery policy and the agreements signed with our partners for recycling. In terms of energy, we see solar power as a solution. We are engaged in projects to produce part of our electricity, but the investment is very heavy with profitability of beyond 15 years. This can be more achievable in seaside hotels built on very large sites unlike town hotels. But this is the last worry for a company in financial difficulty at the moment.*"

The analysis of interviews with professionals in the hotel sector provided a better understanding of the crisis situation experienced by companies in the sector during the time of the pandemic. While the financial and economic health of the sector had been already vulnerable before the Covid, it has deteriorated further. The health crisis exposed the problems of a precarious sector and accelerated its collapse. The priorities were mainly oriented towards operational management in the absence of support from the State, whose decisions and measures were deemed very insufficient, unsuitable, or even absent. It is clear that faced with these priorities, energy issues can no longer figure in the concerns of managers in the sector, whose main concern becomes controlling energy consumption and paying electricity bills. In the final part of the interview, the experts were asked about their post-covid outlook and the prospects that could help revive the sector.

"*The crisis has exposed deeper sector flaws to date. It's time to change radically the strategies and the vision. It is no longer a question of reviving the sector, but rather the need for a complete overhaul and a deep reform* ", an idea supported by all the interviewees.

The explanations refer to the synergies between the tourism sector and the air transport one in particular. *"There is a real imbalance between the supply of accommodation in terms of the number of beds and the number of seats available on the planes that serve the country. If this imbalance already existed before the health crisis in a context of a ban on Open Sky and the limited offers of companies serving Tunisian airports, it has grown with the pandemic.* ".

Border closures and travel restrictions have dramatically reduced, air traffic. This has resulted in very low hotel occupancy rates, with all the repercussions on other related sectors.

"*We are in a situation marked by a lack of visibility and by a total blur. The hope of returning to work in the short term is linked to vaccination. But access to vaccination remains very limited in some countries to this day, and not yet possible in several countries, including Tunisia to date.* ".

3 Conclusion

The recent COVID-19 crisis has had an unprecedented impact on the tourism sector with all the drastic measures imposed. These measures have paralyzed international transport, which is closely linked to that of tourism in general and the hotel industry in particular. As part of this work, we tried to understand the situation of the Tunisian tourism sector at the time of the pandemic. To this end, expert interviews with hotel professionals were carried out. The results revealed a catastrophic situation for a sector already in difficulty and which the crisis has exacerbated. All those interviewed confirm the idea that the Covid-19 pandemic has accelerated the tourism crisis already installed since 2018. Energy-related issues and ecological alternatives as possible solutions to the problems of the sector hardly figure in the concerns of professionals in the sector at the moment.

The relaunch of tourism in the post Covid-19 crisis requires deep and sweeping reforms and strong measures that ensure business development and support employment. This is not at all a resumption of activity and a short-term bailout, but a complete and a necessary overhaul of the entire industry. The recommendations are in particular oriented towards a global sanitation of the sector and a revision the labels given to establishments. Moreover, strategic reflection on the development of the autonomy of the sector, which is until there very dependent on tour operators, is also recommended.

In addition, the close dependence of the tourism sector and the transport sector requires government decisions in favor of the open sky and the increase in airplane seats, which could contribute to a better filling rate of the beds. Finally, if the question of ecology seems the last concern of professionals for the moment, it is obvious that measures in favor of the environment can only be very beneficial for the sector. Indeed, customers are more sensitive to the ecological cause and establishments engaged in this direction are generally well received and appreciated.

In fact, the customer experience is at the heart of the priorities of tourism service providers. Hotel accommodation and dining are not the only attractions for a guest. He seeks to have a satisfying experience within the hotel but also in its environment. The cleanliness and maintenance of the public space surrounding and exterior of the hotel with authorities is just as important as the interior space for a guest. Actions to protect the environment, upkeep of waste, cleanliness of the city, are all details to which the customer is now very sensitive.

However, in order to respond immediately to the crisis and build the confidence of travelers, it will be crucial to put in place adequate health and safety protocols at all stages of travel. Solutions and responses will have to be implemented gradually and in a coordinated manner between several sectors in a global and coherent vision.

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The Asymmetric Response of Equity Markets to Sentiment Risk: A New Asset Pricing Model

Abderrazak Dhaoui and Saad Bourouis

Abstract While much research uses linear models to examine the equity market dynamics and investor sentiment, one particular type of association consisting in the asymmetric response of stock returns to positive and negative changes in investor emotions and beliefs has been non examined. This paper uses an Non Linear Autoregressive (NARDL) approach to model the asymmetric association between the US&500 stock returns and a set of independent variables including the investor sentiment, ADS, GOLD, VIX, and Spot. The main results suggest that investor sentiment play a pivotal role in stock market. The results suggest particularly that investor sentiment acts as a systematic risk that may be priced by the equity market. The results suggest also that low and high emotions are with asymmetric impact on the stock returns. Investor with low emotions (pessimism) are in general more and are much more likely to succeed than those with high emotions (optimism, overconfidence) as these latter fall into the trap of sheep-like behavior and refuse to admit their mistakes. After a series of gains they become euphoric and believe themselves invincible. Consequently, they react probably aggressively and take important risks and will completely ignore their trading plan, ignoring the present alternatives as well as the possible risk to which they are exposed.

Keywords Sentiment risk · Stock market returns · Systematic risk · NARDL model

JEL Classification G02 · G11 · G12 · G14 · G17

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1 Introduction

Traditional asset pricing models such as the CAPM of Sharpe (1964), Lintner (1965) and Mossin (1966), the APT initially developed by Ross (1976, 1977), the Fama and French three factor model of (1993), the Fama and French Five factor model of (2015), among others suggest that financial market is efficient and the investor act fully rational. However, many authors supporting the behavioral finance document that financial market are not efficitient and the investors are not fully rational. The reject of the hypohesis of rational decision find his history since early 1936 when Keynes suggests that investors do not act rationally and that most probably of our decisions are not the consequence of a weighted average of quantitative benefits produced by quantitative probability. However an unexplained dynamic that he calls an *animal spirit* dynamic drives our decision. Keynes (1936) defines this dynamic as "*a spontaneous urge to action rather than inaction*".

A large body of studies converges to confirm the rejection of the efficient market hypothesis and the rational reaction of investors and attribute to psychological factors higher ability to explain the dysfunction and the disequilibrium of financial markets. Notice that the presence of abnormal returns and anomalies (calendar, meteorological anomalies) constitutes strong arguments against the efficient market hypothesis. The authors explain these anomalies in terms a consequence of investor emotions and believes such as overconfidence (Daniel et al., 2001), optimism (Otten, 1989; Haruvy et al., 1999; Dhaoui, 2015), Pessimism (De Bondt and Thaler, 1985; Dhaoui, 2015).

Akerlof and Shiller (2009) reassert the pivotal role of psychological factors in economic policymaking and attribute to human psychology the ability to influence the economic activity. In this line, they propose, explicitly, to incorporate additional factors relating to the behavioral aspect in the macroeconomic standard models to better understand how the economy does really work.

The traditional financial theory raised by Fama (1970) assumes that most investors behave in line with the Efficient Market Hypothesis (EMH). This hypothesis reveals that the market is efficient, stock prices rapidly and correctly react to all market information, and stock price change is due to new information, immediately and completely analyzed by investors. Because the generation of new information is random and unpredictable, a random walk characterized the stock prices. In addition, the traditional theory assumes that investors are rational, and each investor's analysis is independent and without contagion by the others. Even if irrational investors cause the stock price to deviate from its fundamental value, rational investors will use arbitrage to lead the stock price to return to his equilibrium state. According to the aforementioned analyses, investors' trading behavior is rarely affected by their sentiment, so the market exhibits a weak reaction to investor emotions and the irrational behavior will be considered as a noise component of the asset valuation.

Empirical studies converge to support the presence of abnormal returns and anomalies, indicating that the stock market is not as perfect as the traditional financial theory assumes. These anomalies challenge the existence of EMH; for instance, most investors, especially noise traders and retail investors, are not rational and have herding behavior. This means that an investor will be influenced by other investors' behavior or market sentiment, and ignores his own information, instead of following the market trend (Nofsinger & Sias, 1999; Banerjee, 1992). Furthermore, Cote and Sanders (1997) note that herding leads retail investors to change their mind, and attempt to achieve close to market expectations. Bikhchandani et al. (1992) introduce information cascades, which argue that herding is an irrational behavior where investors disregard personal information and follow others, leading to mispricing in the stock market. Taken together the analyses above discussed allows us to document that stock prices are not only influenced by fundamental factors, but also investors' psychology, thus the appearance of behavioral finance completes the gap between traditional theory and the real world, and attempts to explain the market anomalies.

Behavioral finance experts believe that investors' psychology, including confidence, emotions, personal ability and their degree of risk aversion, and the ability to obtain and analyze new information, affected their decision-making. Kahneman and Tversky (1979) firstly propose the Prospect Theory, which points out the view from a psychological angle that people make different decisions under different circumstances; that is, investors have different risk attitudes on profit and loss, and they sell a stock when they can make a profit because they worry that their profit may decrease in the future. Conversely, they continue to hold the stock when at a loss because they do not want to face the loss position and believe that the stock price will eventually rise. The result is that such reactions do not match the assumptions about EMH. Grossman and Stiglitz (1980) believe that the market cannot achieve perfect efficiency as if the price adequately reflects all available information, traders will not have any incentive to acquire costly information. Olsen (1998) indicates that investors' decisions affect the price change, and their decisions are influenced by their mentality. In other words, investors' sentiment and price change will affect each other.

The main aim of this study is to examine whether investor sentiment acts as a systematic risk that must be priced or as a specific risk that lead investors to select an optimal diversified portfolio to lower their exposition to it. This study contributes to the existing literature in three points. Firstly, this study is the first to use an explicit model capturing the asymmetry in the impact of investor sentiment on the equity market returns. Our model captures specifically the asymmetry in the short and the long-run dynamics of the stock market returns. We included in the estimate models factors capturing the implied investor sentiment and together additional factors expected to have significant influence on investor perceptions and expectation about the future evolution of equity market which determine in a large part their emotions. Third, this paper is the first to decompose risk sentiment to specific and systematic risk and suggest empirically selecting a full risk sentiment diversified portfolio to reduce the specific risk sentiment and to reward the investor exposition to the systematic risk sentiment that cannot be diversified.

The remainder of this paper proceeds as follows. The Sect. 2 overviews the main literature review on the popular pricing model and the contribution of behavioral factors such as believes and emotions to the explanation of asset pricing. In the third section, we describe the sampled variables composing our estimate model and we present the main methodology. The Sect. 4 provides the main results and the discussion. Finally, the last section concludes.

2 Literature Review

Predicting the main factors explaining the variability of stock returns is attracting the considerable attention of investors, academics and policy makers. Supply and demand are theoretically considered the essential elements of price setting. The optimal price, the price resulting from the equilibrium state is a function of the supply-demand law. A large number of studies link the excess returns to the investor exposition to risk. In this line, the well known Capita Assets Pricing Model (CAPM), as developed by Sharpe (1964), Lintner (1965) and Mossin (1966), associates the returns in excess to the systematic risk of an asset. The two components are, in fact, associated following the Eq. (1).

$$E(R_i) - r_f = \big(E(R_M) - r_f\big)\beta_i \tag{1}$$

In Eq. (1), $(E(R_i) - r_f)$ is the return in excess of the asset i computed as the excess of the expected return of the asset i $(E(R_i))$ on the risk free interest rate (r_f), $(E(R_M) - r_f)$ is the risk premium computed as the excess of the expected stock market return $(E(R_M))$ reduced by the risk free interest rate, and β_i is the systematic risk of the asset i measuring the contribution of the asset i to the global risk of the portfolio.

Many extensions have been developed as a response to the weaknesses of the standard CAMP model. For instance, the Arbitrage Pricing Theory (Ross, 1976, 1977), proposed a multi-factor asset pricing model as a first extension of the CAMP model. The new specifications of an asset's return in excess as proposed in the APT specification can be illustrated as:

$$E(R_i) - r_f = F_1\beta_1 + F_2\beta_2 + \cdots + F_n\beta_n \tag{2}$$

Where, $(E(i) - r_f)$ is the return in excess of the asset i, $\beta = (\beta_1, \beta_2, \cdots, \beta_n)$ is a $(1 \times n)$ matrix of systematic risk associated to the different factors expected to impact the return in excess of the asset i, and $F = (F_1, F_2, \cdots, F_n)$ is $(1 \times n)$ matrix of Risk premium associated with the respected variables. Notice that under this specification, the return in excess of the asset i can be predicted using a linear setting between the asset's expected return and a number of macroeconomic factors supposed to capture systematic risk. Unexpected changes in inflation, gross national product, corporate bond spreads, yield curve, gross domestic product, commodity prices, and exchange rates are largely considered as main predictors of the expected asset returns.

In their seminal study, Fama and French (1993) proposed the well-known three factor model. In this model, the three factors to which the excess in returns is associated capture the market risk, size risk, and value risk. This model is presented as:

$$R_{it} - r_{ft} = \alpha_i + \beta_{1i}\left(R_{Mt} - r_{ft}\right) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \varepsilon_{it} \tag{3}$$

In Eq. (3), R_{it} is the return on an asset or a portfolio i for the period t, r_{ft} is the risk free rate, R_{Mt} is the return on the value-weighted market portfolio, SMB_t is the size factor computed as the difference between the return on a diversified portfolio of small stocks reduced by the return on a diversified portfolio of big stocks, and HML is the value factor capturing the return on a diversified portfolio of high book-to-market stocks minus the return on a diversified portfolio of low book-to-market stocks and finally, ε_{it} is a zero-mean residual term.

In 2015, Fama and French proposed an expanded version of the first three factor model by introducing two additional factors capturing profitability and investment patterns. The five-factor Fama French model is specified as:

$$\begin{aligned} R_{it} - r_{ft} = \alpha_i + \beta_{1i}\left(R_{Mt} - r_{ft}\right) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}RMW_t + \beta_{5i}CMA_t \\ + \varepsilon_{it} \end{aligned} \tag{4}$$

In Eq. (4), all parameters are denoted as aforementioned, while RMW_t and CMA_t capture the profitability and the investment and are computed respectively as the return of a diversified portfolio with robust profitability, reduced by the return of a diversified portfolio with weak profitability and the return of a diversified portfolio of conservative investment stocks reduced by the return of a diversified portfolio of aggressive investment stocks.

Many extensions of these standard models have been proposed over the recent years. Momentum effect, Value at Risk factor, VIX index, CDS spreads, among others, are largely included in different specifications of asset pricing. For instance, Urom et al. (2020) introduced the conditional regime-switching CAPM with time-varying betas. Also, Changsheng and Yongfeng (2012) and Dhaoui and Bensalah (2017) proposed new extension of the Fama-French three factors and five factors, respectively, by adding new factor capturing investor sentiment effect. Their empirical findings converge to suggest the superiority of the model with investor sentiment in predicting the return in excess of an asset or a portfolio compared to the standard Fama-French three factors and five factors models.

Over the two decades, investor sentiment as a main factor affecting asset pricing has attracted the attention of investors, academics, analysts and policy makers. Investor sentiment constitutes particularly as systematic risk that may be priced by the capital market. In this line, Ciccone (2003) documents that investor sentiment plays a pivotal role in the stock market. Given this important role the sentiment may play in predicting the stock market returns, numerous authors such as Baker and Wurgler (2006, 2007), Schmeling (2009), Chung et al. (2012), Stambaugh et al.

(2012), Huang et al. (2015), Dhaoui (2015), You et al. (2017), among others, conducted many studies on the predictive power of investor sentiments. These studies are not the first ones focusing on the role the investor sentiment may play. In his well known General Theory of Employment, Interest and Money, Keynes (1936) attributed to behavioral component a strong importance in determining the way the investors may act. He suggests in fact that most of the decision an agent may make are not a result of a rational analysis, but are rather attributed to the influence of animal spirits as a natural dynamism that can be defined as a spontaneous urge to action rather than inaction. In the same perspective, Akerlof and Shiller (2009) proposed to incorporate factors relating to human psychology into macroeconomic model in order to better understanding how the economy do really work.

Different sentiment proxies are suggested by previous studies. Local consumer confidence indices are commonly used as a reliable proxy for domestic investor sentiment (Lemmon & Portniaguina, 2006; Qiu & Welch, 2006). Other investor sentiment proxies are also used in previous studies. To capture the investor expectation of future market (Bullish-Bearish) trends Dhaoui and Bacha (2017) used the AAII indicator as a proxy for investor sentiment. Another indicator of market trend previously used by Dhaoui and Khraief (2014) consists in the oscillator stochastic. The Put-call ratio have also been previously used by many authors such as Bandopadhyaya and Jones (2008), Finter et al. (2012) and Bathia and Bredin (2013) as an indicator allowing assess whether the stock market is buying or selling.

Many other empirical studies document also that the media may affect investors. Cutler et al. (1989) find that news reports can't fully explain the impact of major economic events on the stock market. Klibanoff et al. (1998) and Huberman and Regev (2001) analyze the influence of the front page of the *New York Times*. With the Internet's development changing the reading pattern of investors, the 'web' is becoming a major source for investors to access information. Da et al. (2011) use Google's Search Volume Index (SVI) as an investor attention proxy. They conclude that search volume has an impact on the stock market. Similarly, Bollen et al. (2011) and Karabulut (2013) established an investor sentiment indicator from social networks such as Twitter and Facebook and found that sentiment on social networks can not only predict stock market distresses but also stock returns.

The hypothesis of a nonlinear link between investor sentiment and stock returns is empirically supported by many researches such as Dergiades (2012), Li et al. (2017). For instance, Dergiades (2012) and Li et al. (2017) employed, respectively, a nonlinear Granger causality model and a quantile Granger non-causality test model and found strong evidence of a non-linear causality running from sentiment to stock returns.

The asymmetric impact of investor sentiment may be due to the heterogeneity in the investor reaction because of the disparity in their beliefs and emotions. For instance, the more prudent investors (such as the less informed or those with lower emotions) are much more likely to succeed than the more informed, overconfident or more optimistic investors. Indeed, some investors lose control without even understanding why. Furthermore, the more informed and particularly, the more overconfident and more optimistic investors fall into the trap of sheep-like behavior and refuse to admit their mistakes.

Notice, in the same perspective, that investor sentiment as a psychological bias is often dynamic in the sense that one bias may more likely engender another. For example, a low emotion, as a reaction to a series of losses can make the investor doubt his skills and plunge him into a state of exaggerated pessimism. Consequently, it may push him to make wrong decisions, due to a depressed state, and worsen his situation. In the same line, a series of gains can move an investor from a serene emotional state to a euphoric. After a series of winnings, an investor will be euphoric and believe himself invincible. He reacts probably aggressively and takes important risks and will completely ignore his trading plan, ignoring the present alternatives as well as the possible risk to which he is exposed. In other words, investors become extremely confident and impulsive after a series of gains. Consequently, they take bigger risks because they believe playing with money easily earned.

3 Data and Methodology

3.1 Data Descriptions

In this paper, we used weakly data for stock return, investor sentiment, gold, VIX and CDS for the S&P500 stock market. The analysis covers the sample period from first January 2000 to 30 November 2018. The stock market returns, denoted R_t, are computed using the first difference in the natural logarithm of the stock market prices following the specification $R_t = [ln(P_t) - ln(P_{t-1})] \times 100$, where P_t corresponds to the stock market index at time t. Data for the stock market prices are available in the Federal Reserve Bank of St. Louis data base. The Auroba-Diebold-Scotti (ADS) business condition index is commonly used as a good proxy for the general business conditions. This indicator is previously used in Chan and Marsden (2014) and Guesmi et al. (2018). We can extract data on the Auroba-Diebold-Scotti business condition index from the Federal Reserve Bank of Philadelphia. The volatility index, denoted VIX, measures the implied volatility over the next 30 days and represents the option-implied volatility based on the S&P500 index option. VIX index is previously used in Galil et al. (2014) and Guesmi et al. (2018). Data on the VIX index are available from the yahoo-Finance. Gold prices are measured by the Chicago Mercantile Exchange continuous futures contract on gold. Data for gold are available from the Quandl website. The five-year Treasury Constant Maturity Rate is used as a proxy for the spot interest rate (SPOT). Data on the spot interest rate can be extracted from the database of the Federal Reserve Bank of St. Louis. The American Association of Individual Investors (AAII) publishes weekly results of the sentiment survey. We used the results of the survey published on the website of the AAII association to compute the sentiment indicator. This indicator allows us to get a better idea on the bullish-bearish market trends. Optimistic investors expect higher probability of bullish trends while pessimistic investors attribute higher probability to bearish trends. The AAII sentiment indicator (denoted AAII-sent) is computed based on the following relation: $AAII - sent = Bullish - Bearish$. This indicator is previously used by Dhaoui and Bacha (2017). The Put-Call ratio (denoted CP) is a derivative indicator designed to help investor gauge the overall sentiment of the stock market. It assesses whether the market is buying or selling. The Put-Call ratio is computed as the number of put options traded divided by the number of call options traded in a given period. This indicator is previously used in Finter et al. (2012) and Bathia and Bredin (2013).

3.2 Estimated Model Specification

The aim of this study was to examine the asymmetry in the dynamics of the equity market impact of investor sentiments in the specific case of the US. Therefore, we perform a Nonlinear AutoRegressive Distributed Lag (NARDL) model initially developed by Shin et al. (2014) as an extension of the classical ARDL model. The long run relation can be specified as:

$$\begin{aligned} R_t = {} & \alpha_0 + \alpha_1 AAIIsent_t^+ + \alpha_2 AAIIsent_t^- + \alpha_3 VIX_t^+ + \alpha_4 VIX_t^- + \alpha_5 ADS_t^+ \\ & + \alpha_6 ADS_t^- + \alpha_7 GOLD_t^+ + \alpha_8 GOLD_t^- + \alpha_9 SPOT_t^+ + \alpha_{10} SPOT_t^- \\ & + \alpha_{11} CP_t^+ + \alpha_{12} CP_t^- + \varepsilon_t \end{aligned} \tag{5}$$

In Eq. (5), R_t is the stock market return at the time t, and for each independent variable denoted iv (with $iv = (AAII, VIX, ADS, GOLD, SPOT, CP)$, the positive and negative changes at the time t are captured by iv_t^+ and iv_t^-, respectively. The partial sum of positive and negative changes in each independent variable can be computed as:

$$iv_{it}^+ = \sum_{i=1}^{t} \Delta\, iv_i^+ = \sum_{i=1}^{t} max\,(\Delta iv_i, 0) \tag{6}$$

and

$$iv_{it}^- = \sum_{i=1}^{t} \Delta\, iv_i^- = \sum_{i=1}^{t} min\,(\Delta iv_i, 0) \tag{7}$$

The ARDL specification of the Eq. (5) can be written as follows:

$$\begin{aligned} R_t = {} & \alpha_0 + \beta_1 AAII_t^+ + \beta_2 AAII_t^- + \beta_3 VIX_t^+ + \beta_4 VIX_t^- + \beta_5 ADS_t^+ + \beta_6 ADS_t^- \\ & + \beta_7 GOLD_t^+ + \beta_8 GOLD_t^- + \beta_9 SPOT_t^+ + \beta_{10} SPOT_t^- + \beta_{11} CP_t^+ \\ & + \beta_{12} CP_t^- + \sum_{i=1}^{k} \phi_i \Delta R_{t-i} + \sum_{i=0}^{m} \left(\theta_i^+ \Delta AAII_{t-i}^+ + \theta_i^- \Delta AAII_{t-i}^- \right) + \sum_{i=0}^{n} \\ & \times \left(\gamma_i^+ \Delta VIX_{t-i}^+ + \gamma_i^- \Delta VIX_{t-i}^- \right) + \sum_{i=0}^{p} \left(\delta_i^+ \Delta ADS_{t-i}^+ + \delta_i^- \Delta ADS_{t-i}^- \right) + \sum_{i=0}^{q} \\ & \times \left(\tau_i^+ \Delta GOLD_{t-i}^+ + \tau_i^- \Delta GOLD_{t-i}^- \right) + \sum_{i=0}^{r} \\ & \times \left(\omega_i^+ \Delta SPOT_{t-i}^+ + \omega_i^- \Delta SPOT_{t-i}^- \right) + \sum_{i=0}^{s} \left(\lambda_i^+ \Delta CP_{t-i}^+ + \lambda_i^- \Delta CP_{t-i}^- \right) + u_t \end{aligned} \tag{8}$$

In Eq. (8), k, m, n, p, q, r and s are the lag orders and $\alpha_i = -\beta_i/\beta_0$ and $\alpha_j = -\beta_j/\beta_0$ (j = i + 1) capture, respectively, the long-run impact of the positive and negative change in each independent variable *iv*. Similarly, the short-run impact of positive and negative changes in each independent variable are captured, respectively, by $\sum \pi_i^+$ and $\sum \pi_i^-$, where $\pi = (\varnothing, \theta, \gamma, \delta, \tau, \omega, \lambda)$.

The procedure to estimate the NARDL model consists of four steps. In the first step, we proceed with the unit root testing using the conventional unit root tests ADF, PP, and KPSS. The estimation of the NARDL model requires in fact that all time series are integrated or cointegrated in an order less than 2. In the second step, we estimate the Eq. (8) using the MCO. We apply the "general to specific" procedure previously used by Katrakilidis and Trachanas (2012) to obtain the final specification of our NARDL model. The third step consists in performing the F-bound testing of countegration. The null hypothesis of long run cointegration between the dependent and independent variable can be specified as: $\beta_0 = \beta_1 \cdots = \beta_{11} = 0$. The result is a F-Wald statistic that can be compared to a theoretical critical value as illustrated in Pesaran et al. (2001). In the last step we test for the asymmetry in the short-run dynamics. The dynamic cumulative multipliers are thus computed, for the 1% positive and negative changes in each independent variable iv_i, as follows:

$$m_n^+ = \sum_{i=0}^{n} \frac{\partial y_{t+i}}{\partial iv_{it-1}^+} \; et \; m_n^- = \sum_{i=0}^{n} \frac{\partial y_{t+i}}{\partial iv_{it-1}^-} \tag{9}$$

as: $n \to \infty, m_n^+ \to \alpha_i \; and \; m_n^- \to \alpha_j$; with $j = i + 1$.

4 Empirical Estimates and Discussions

4.1 Preliminary Statistical Analysis

The first step by which we start our analysis consists to examine the stationarity of the sampled time series. Therefore, we perform three conventional unit root tests, namely, the Augmented Dickey-Fuller (ADF), the Phillips-Perron (PP), and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. The results reported in Table 1 show that all sample time series are either stationary at level or at the first difference. Consequently, all the sampled time series are stationary at an order lower than 2, a condition which is necessary to continue our analysis based on the NARDL model.

4.2 Empirical Results

Preliminary statistics indicated that all sampled time series are either I(0) or I(1). This to say that all time series are stationary in order less than 2, a condition required for the estimation of the NARDL equation. We can then proceed in the estimation of our Eq. (8) using the MCO method. We start, our analysis by performing the F-bound test of cointegration. The results reported in Table 2 show a statistically significant

Table 1 Conventional unit root tests

	ADF		PP		KPSS	
	At level	1st difference	At level	1st difference	At level	1st difference
R	−1.8560	−7.4905***	−1.7194	−7.6865***	0.2308	0.2779
AAII	−5.0403***	−7.0233***	−4.2531***	−12.7773***	0.1819	0.2629
VIX	−1.6949	−7.0431***	−1.6289	−7.0717***	0.2772	0.3154
ADS	−1.5261	−2.5959**	−1.5394	−2.4455**	0.3476*	0.2516
GOLD	−1.7471	−8.3736***	−1.9105	−8.2466***	0.5599**	0.4530*
SPOT	−1.9116	−4.9283***	−2.0150	−5.2512***	0.4896**	0.1684
PC	−5.6680***	−6.0980***	−6.6706***	−23.9616***	0.1238	0.0500

Notes: ADF denotes Augmented Dickey-Fuller unit root tests, PP refers to Phillips-Perron unit root tests, KPSS denotes Kwiatkowski–Phillips–Schmidt–Shin tests. *, **, and *** denote rejection of the null hypothesis at the 10%, 5%, and 1% levels of significance, respectively. The lag length in all the tests has been selected according to the Akaike Information Criteria (AIC)

Table 2 F-bound test

F_{pss}	t_{BDM}	Decision
10.2405***	−6.4007***	Cointegration

Note: ***Denotes significance levels at 1%. Asymptotic critical value bounds for the F-statistic, the upper and lower bounds at 5% significance level are 4.43 and 3.15, respectively. As for asymptotic critical value bounds of the t-statistic, the upper and lower bounds at 5% significance level are −4.99 and −3.43, respectively

F-wald statistic at the 1% significance level, suggesting a long-run cointegration between the equity market returns and the different regressors.

Before testing for the long and short-run asymmetry and the estimation of the long-run equation, we start by analyzing the adequacy of the dynamic specification of the estimate model. We refer to different diagnostic statistics including the LM statistics for the order 12 (denoted $\chi^2_{\mathrm{SC}}(12)$) allowing us to test for the serial correlation, the Heteroskadasticity tests (denoted χ^2_{HET}) et the Ramesey RESET test of stability (χ^2_{FF}). The results of these diagnostic tests are reported at the lower of the Table 5 (see Appendix). Based on these results we can easily show that our model surpasses the serial correlation and the Heterosedasticity problems at the significance level of 1% and 5%. The hypothesis of stability of parameters is also confirmed at the 1% and 5% significance level as the results of the RESET test suggest that we cannot reject the null hypothesis that our model has no omitted variables. Finally, we show that the coefficient associated with the lagged stock market returns (see Table 5) is negative and statistically significant at the 1% significance level. Overall, these results can be considered as quite satisfactory to conclude that our estimated NARDL model is stable and correctly specified and we can, consequently, pursue our analysis based on the estimation results of the long-run equation and the long-run and short-run asymmetry testing.

The next step consists in testing the hypotheses of asymmetry in the equity returns impacts of positive and negative changes in each of the regressors. The results of the long-run asymmetry are reported in Table 3. The results of the long-run asymmetry testing suggest the rejection of the null hypothesis of symmetry in the long-run dynamic between equity market and either of the investor sentiment indicators (AAII and Put-call ratio), the volatility index (VIX), and the ADS business condition index. GOLD and SPOT appear to have symmetric impacts on the equity market returns.

Table 3 Long and short-run asymmetry testing

Long run asymmetry			Short run asymmetry		
	Coefficient	p-value		Coefficient	p-value
W_{LR} (AAIIsent)	−0.2238**	0.0177	W_{SR} (AAII)	−0.2571**	0.0177
W_{LR} (VIX)	0.0260***	0.0013	W_{SR} (VIX)	0.0299**	0.0013
W_{LR} (ADS)	0.3342**	0.0133	W_{SR} (ADS)	0.3840**	0.0133
W_{LR} (GOLD)	0.0005	0.2758	W_{SR} (GOLD)	0.0006*	0.0761
W_{LR} (SPOT)	0.0746	0.7376	W_{SR} (SPOT)	0.0857*	0.0737
W_{LR} (CP)	−0.3794***	0.0018	W_{SR} (CP)	−0.4359***	0.0019

Notes: This table reports the results of the long- and short-run symmetry tests for the effect of each explanatory variable (AAIIsent, VIX, ADS, GOLD, SPOT, and CP) on stock market returns spreads. $\mathrm{W_{LR}}$ denotes the Wald statistic for the long-run symmetry, which tests the null hypothesis of $\theta^{+} = \theta^{-}$ for each explanatory variable in Eq. (4). $\mathrm{W_{SR}}$ corresponds to the Wald statistic for the short-run asymmetry, which tests the null hypothesis that $\pi_i^{+} = \pi_i^{-}$ for each explanatory variable in Eq. (4). The numbers in brackets are the associated p-values. *, **, and *** indicate rejection of the null hypothesis of symmetry at the10%, 5%, and 1% levels, respectively

Table 4 Long-run coefficients

	Coefficient	p-value
$L^+_{AAIIsent}$	0.3288**	0.0477
$L^-_{AAIIsent}$	0.1050*	0.0819
L^+_{VIX}	−0.0198**	0.0143
L^-_{VIX}	−0.0061*	0.0628
L^+_{ADS}	0.2616**	0.0120
L^-_{ADS}	0.0726*	0.0646
L^+_{GOLD}	0.0061**	0.0355
L^-_{GOLD}	0.0091*	0.0872
L^+_{SPOT}	−0.0902*	0.0612
L^-_{SPOT}	−0.08156*	0.0934
L^+_{CP}	0.1750*	0.0658
L^-_{CP}	0.2044*	0.0656

Notes: ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% levels of significance, respectively

The results of the long-run equation estimation are reported in Table 4. Based on these results we show statistical significant positive coefficient associated with the variables AAIIsent and Put-call Ratio capturing the investor sentiment. The volatility index (VIX) has a negative and statistically significant coefficient. As for the variables GOLD and ADS business condition, the coefficient associated with positive and negative changes in each of them is positive and statistically significant. The Sport rate has a negative and a statistically significant coefficient. Notice that for the different sampled variables, positive and negative changes have coefficient of the same sign.

The negative coefficient associated with positive and negative changes in the implied volatility index (L^+_{VIX} and L^-_{VIX}), used as a proxy for investor sentiment, implies that investors are able to lower their exposition to specific risks, associated to the sentiments, by selecting optimal diversified portfolios. Particularly, the negative links between the stock market returns and the VIX index suggest strong evidence of economic benefit of diversification.

The positive coefficients associated two other variables (AAIIsent and Put-Call Ratio) capturing the investor sentiment may be explained in terms of impact of investor reaction as a response to their expectation about the future evolution of the stock market's fundamentals (price and trading volume: supply and demand, market trends). Good news are followed by an increase in stock returns while bad news are followed by a decrease in stock returns. Notice, however, that an investor is at any time exposed to the risk that the other investors may make irrational decisions either due to their emotions (overconfidence, unrealistic state of optimism, pessimism), or due to an under or overweight of risk to which they are exposed, which lead to a disequilibrium on the stock market. The positive signs associated with positive and negative changes in both AAII ($L^+_{AAIIsent}$ and $L^-_{AAIIsent}$) and Put-call ratio (L^+_{PC} and L^-_{PC}) imply that this component of risk, associate to investor sentiment, cannot be diversified and may act as a systematic risk. Accordingly, investors exposed to this risk will have to charge a risk premium to offset the additional risk to which they are exposed. In other words, the component of risk sentiment, which acts systematic risk and cannot be smoothen or eliminated by an optimal diversification, should be remunerated by the market.

The positive coefficient associated with ADS business conditions implies that stock market returns tend to increase in the period of good economic perspective. In periods of crisis, investors lower or postpone their investments which results in lower returns. In fact, in a period of crisis, investors express low emotions and they made irrational decisions leading to a higher probability of losses.

As for the positive and negative changes in gold (L^{+}_{GOLD} and L^{-}_{GOLD}), positive and statistically significant coefficients are found. Investors consider Gold as a safe haven asset that may offer a better hedge strategy, especially in a period of high uncertainty. This implies that including GOLD as a safe haven asset in the portfolio of an investor offer to him a guarantee of lower risk of losses in a period of crisis. Investors consider also that even in a period of stability GOLD remains an asset that allows them higher opportunity of gains.

As for positive and negative changes in the SPOT interest rate (L^{+}_{SPOT} and L^{-}_{SPOT}), we found negative and statistically significant coefficients. This implies that all increases or decreases in the SPOT rate are followed by a reaction of the stock market returns in an opposite direction. The increase in SPOT rate lowers the stock returns because it reduces the net present value of the expected future cash-flows as it is used approximately as a discount rate.

We analyze the null hypothesis of symmetry in the short-run against the alternative hypothesis of short-run asymmetry using the dynamic multipliers graphs. The null hypothesis relating to each independent variable denoted iv is tested using the Wald statistics supposing the following hypothesis: $H_{SR,iv} : \sum_{i=1}^{k} \pi_i^{+} = \sum_{i=1}^{k} \pi_i^{-}$, with π_i^{+} and π_i^{-} are the coefficients associated with the lagged positive and negative changes in the independent variable iv, and $iv = (AAIIsent, VIX, ADS, GOLD, SPOT, PC)$. The short-run dynamics are presented in Figs. 1a to f. The results show strong evidences of asymmetry in the short-run impacts of negative and positive changes in each of the independent variables on the stock market returns. An important result may be easily observed that is the short run impact cannot be persistent over time. It is rapidly smoothed and the adjustment to a new equilibrium can take place after about 2 to 3 months for ADS, GOLD and SPOT. The short-run impact can be smoothed and a new equilibrium state is reached after about 9 months for the sentiment indicators and for VIX index suggesting an average persistence of the stock returns dependence on investor sentiment and on the volatility acting as two different risk measures. The short-run dynamics show also positive association between investor sentiments and stock returns and negative associations between VIX and stock returns. This result confirms again the results of the long-run estimators.

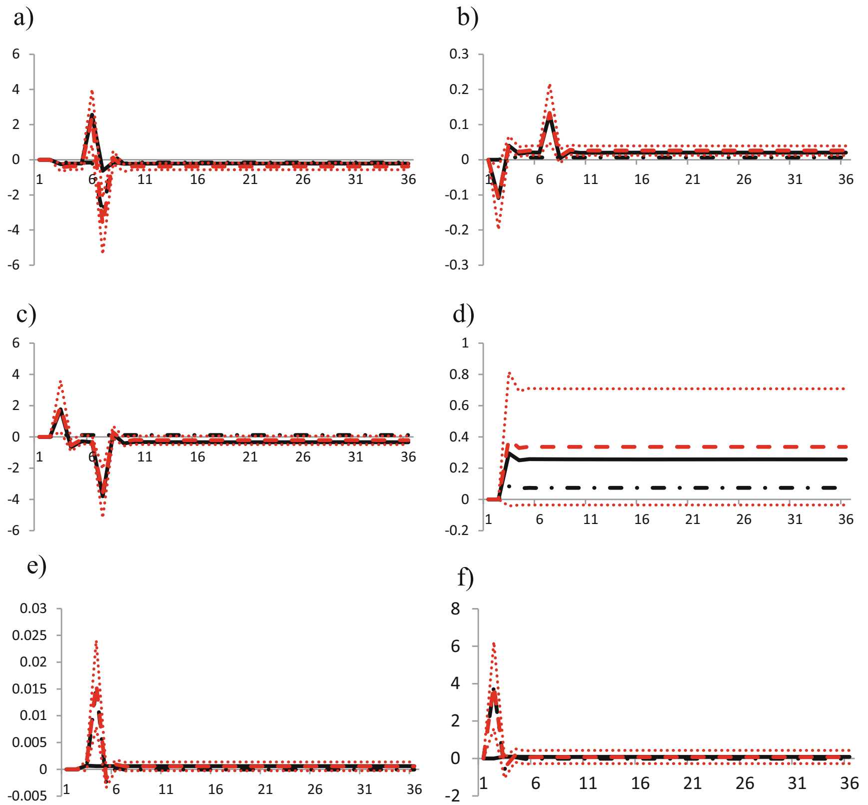

Fig. 1 Dynamic cumulative multipliers for the stock market returns. (**a**) Dynamic multipliers for the S&P500 stock market returns and AAIIsent. (**b**) Dynamic multipliers for the S&P500 stock market returns and VIX. (**c**) Dynamic multipliers for the S&P500 stock market returns and GOLD. (**d**) Dynamic multipliers for the S&P500 stock market returns and Put-call Ratio. (**e**) Dynamic multipliers for the S&P500 stock market returns and ADS. (**f**) Dynamic multipliers for the S&P500 stock market returns and SPOT. (Note) Solid black line shows the positive impact of the independent variable on the dependent variable (*R*) while the dashed black line shows the negative impact. The double dash red line shows the asymmetry in short term. And finally, the dotted red lines show the upper and the lower bounds of the asymmetry

Overall, taken together, the signs of the coefficient associated to the three variable VIX, AAII and Put-Call Ratio under the hypothesis that many researchers and investors consider the volatility index as a proxy for investor sentiment can provides us strong economic implications. In fact, the total risk associated with investor sentiment can be decomposed into two types. The first, which is captured by the VIX index, constitutes a specific risk and can be reduced by an optimal diversification. Under this condition, the stock market does not reward this risk. The second component is a systematic risk that cannot be diversified and that must be rewarded by the financial market. These results are in strong conformity to those in a large empirical studies suggesting that investor sentiment plays a pivotal role in stock markets such as Changsheng and Yongfeng (2012) and Dhaoui and Bensalah (2017) Ciccone (2003) and especially those suggesting a strong predictive power of investor sentiments to the stock returns such particularly Baker and Wurgler (2006, 2007), Schmeling (2009), Chung et al. (2012), Stambaugh et al. (2012), Huang et al. (2015), Dhaoui (2015), You et al. (2017) among others. Our results confirm also previous theoretical predictions about the significant contribution of human psychology (emotions and beliefs) to the financial markets such as suggested by Akerlof and Shiller (2009).

5 Conclusion

Investor sentiment was being one of the most factors impacting the investors' investing strategies and the gain-losses they realize. Theoretical recommendation in the financial field proposed to incorporate investor sentiment as expressed in terms of their emotions and believes into macroeconomic models to better understand how economies does really work. In this perspective, we proposed a new model in which we examined the impact of a set of factors capturing specific and systematic risk relating to investor sentiment in addition to the main factors and assets sensitively determining the investor expectation about the future evolution of asset prices and market trend.

We used weekly data for the US stock market over the period from first January 2000 to 30 November 2018. We performed a nonlinear autoregressive distributed lag (NARDL) model to examine the possible asymmetries in the impact of investor sentiment on the return in excess observed in the S&P500 stock market. Our results provide strong evidence of a negative and statistical association between equity market and volatility suggesting economic benefits of diversification. The second important results we found positive and statistically significant association between equity market returns and investor sentiment indicator suggesting that investor sentiment acts as a systematic risk that must be rewarded by the financial market.

Particularly, our results provide three important implications that investors may take into consideration. First, investor may select an optimal diversified portfolio to take part of the economic benefits of diversification. Secondly, investors are invited to require substantial premium to recompense their exposition to sentiment risk as financial markets incorporate together investors with heterogeneous expectation, emotions, and trading intensities. Third, investors may include Gold in their portfolio, specially, in a period of crisis as Gold acts as a safe haven asset that provides them a better hedge strategy toward the risk.

Annexes

Table 5 NARDL estimation

	Coefficient	t-statistic
Cons.	−0.5321	−1.0695
R_{t-1}	−1.1488***	−36.4007
$AAIIsent^{+}_{t-1}$	0.3778	0.71043
$AAIIsent^{-}_{t-1}$	0.1206	0.2284
VIX^{+}_{t-1}	−0.0227***	4.6331
VIX^{-}_{t-1}	−0.0071***	4.8375
ADS^{+}_{t-1}	0.3006***	5.299
ADS^{-}_{t-1}	0.0834***	4.5839
$GOLD^{+}_{t-1}$	0.0007	0.9241
$GOLD^{-}_{t-1}$	0.0001	0.1607
$SPOT^{+}_{t-1}$	−0.1037***	5.0735
$SPOT^{-}_{t-1}$	0.0179	0.8279
PC^{+}_{t-1}	0.2010***	4.4178
PC^{-}_{t-1}	0.2348***	4.4552
$\Delta AAIIsent^{+}_{t-1}$	2.2007**	2.2306
$\Delta AAIIsent^{+}_{t-5}$	−3.4437***	−3.7604
ΔVIX^{+}_{t}	−0.1078**	−2.0282
ΔVIX^{+}_{t-5}	0.1094**	2.1395
$\Delta GOLD^{-}_{t-2}$	−0.0153***	−2.9786
$\Delta SPOT^{-}_{t}$	−3.8625***	−2.7238
ΔPC^{+}_{t-5}	−2.9805***	−3.2714
ΔP^{-}_{t-4}	−2.8625***	−2.9588
Diagnostic tests		
R^2	0.5962	
Adj. R^2	0.5872	
DW-stats[a]	1.9862	
$\chi^2_{SC}(12)$[b]	0.9749	0.4805
χ^2_{HET}[c]	0.0946	0.7590
χ^2_{FF}[d]	0.3263	0.5694

Note: This table reports the results of the estimation of the best-fitted NARDL model for the adjustment of the industry Stock markets returns to positive and negative unit changes in AAIIsent, VIX, ADS, GOLD, SPOT, and CP. The superscripts + and – denote positive and negative partial sums, respectively. For each independent variable (denoted IV), L^{+}_{IV} and L^{-}_{IV} are the estimated long-run coefficients associated with positive and negative changes respectively, defined by $\widehat{L} = -\widehat{\theta}/\widehat{\rho}$. Adj. R^2 represents the value of the adjusted R^2 coefficient of the estimated model. DW, χ^2_{SC}, $\chi^2_{HET,}$ and χ^2_{FF} denote the Durbin-Watson test, LM tests for serial correlation, heteroskedasticity, and functional form, respectively. The superscripts *, **, and *** indicate the 10%, 5%, and 1% levels of significance, respectively

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The Transmission of Oil Shocks to the Developed and Emerging Stock Markets: COVID-19 from First to the Second Wave

Yosra Ghabri and Donia Aloui

Abstract Stock markets around the world have plummeted to their lowest levels during the 2008 global financial crisis. However, the impact of COVID-19 on stock markets is more severe than any previous crisis. In this context, the aim of this chapter is to investigate the reaction of developed and emerging stock markets to the adverse shocks of oil prices. To this purpose, we use a BVAR model with time-varying coefficients and stochastic volatility (TVP-BVAR-SV) between first, January 2019 through 31st December 2020, while distinguishing between the COVID-19 two waves. The results show that in comparison to the first wave, the responses of the developed and emerging MSCI indices to the oil prices shocks are moderate during the second wave. In particular, the second wave of the pandemic was anticipated by the financial analysts, making investors and policymakers able to overcome the big disruption witnessed in the first wave. Interestingly, our results show that the negative impact of oil prices shocks on emerging stock markets was transmitted slowly, contrary to that for the developed stock markets. Our findings are useful for portfolio managers, regulators, and investors and suggest that policymakers need to take into account the economic and financial characteristics of emerging countries when assessing the effect of COVID-19 on their stock markets. However, the implications of oil prices shocks on global stock markets are expected to persist during the ongoing pandemic.

Keywords Oil shocks · Stock markets · COVID-19 · TVP-BVAR-SV model · Stochastic volatility

JEL Classification C11 · G01 · G15 · Q02 · Q4

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1 Introduction

Numerous studies have examined the interaction between oil price fluctuations and stock markets volatility especially when financial crises occurred (Wen et al., 2012; Creti et al., 2013; Kang et al., 2015; Bouri & Demirer, 2016; Degiannakis et al., 2018; Basher et al., 2018; Smyth & Narayan, 2018). Oil-stocks relationship is attributed to the “financialization” of commodities, considered as a substitute to common financial assets (Umar & Spierdijk, 2013; Zaremba et al., 2020). Globally, previous literature supports that oil-stock interaction is an inverse one, however other studies document that stock prices are positively associated with oil price dynamics for emerging markets. For instance, Raza et al. (2016) find that emerging stock market indexes are positively affected by oil price shocks. Further, Kayalar et al. (2017) use a sample of data for oil importers and exporters and emerging and developed markets. They show that oil and stock prices relationship is stronger in oil exporters and emerging market countries. Using a multi-factor Markov switching approach, Basher et al. (2018) examine the causal relationship between oil and stocks for major oil exporting countries and show that stock markets are negatively related to oil supply shocks for all countries. However, stock returns are positively associated to demand shocks for most countries.

Other studies examine the relationship between oil and stock markets focusing on financial contagion. Using a time-varying approach, Wen et al. (2012) show that crude oil and stock prices interdependence increases significantly during the 2008 global crisis. Based on regime switching method, Guo et al. (2011) find similar results and document an increased interdependence between oil prices and stock markets in the financial global crisis of 2008. Recently, Zhang and Liu (2018) analyze the financial contagion from oil price shocks to a sample of emerging and developed stock markets and find that the financial contagion occurred in the form of contemporaneous shocks from both oil and stock markets of developed countries to the Brazilian stock market. Using a time-varying model, Fang and Egan (2018) investigate the relationship between oil and stock market excess returns in China and show evidence of financial contagion between oil and stock market in times of turmoil.

Another strand of the literature focuses on the dependence structure and the volatility spillover between oil and stock markets, however the findings are mixed. Using multivariate VAR-GARCH models, Arouri et al. (2011) analyze the volatility spillover effect between oil prices dynamics and various stock markets based on weekly data from 1998 to 2009. They find that both US and European stock markets are affected by oil prices shocks. Similarly, using the same approach for both oil importing and exporting countries, Filis et al. (2011) investigate the time-varying correlations between oil prices and stock market indexes and show no significant evidence of volatility spillovers between oil and stock prices. In the same vein, Creti et al. (2013) examine the time-varying correlations between commodities and stock market volatility. They conclude that commodity price correlations increase considerably after the global financial crisis of 2008. Based on DCC-GARCH methodology, Sadorsky (2014) studies the dynamics of conditional correlations between oil, cooper and wheat prices and emerging stock market returns. He finds that asset correlations increased significantly after financial crises. Reboredo et al. (2014) investigate the co-movement between oil and both European and US stock markets. Using Wavelet framework, they show that oil price fluctuations have no significant effect on financial market returns before the financial crisis.

Using the Diebold and Yilmaz (2014) method, Zhang (2017) examines the connectedness between oil price shocks and six stock markets and find that oil price dynamics have a limited impact on financial markets. In the same line, using a frequency approach to study the co-movement between oil markets, Huang et al. (2018) show different interactions between oil stocks (Brent, Minas, Dubai, shanghai composite index, and OPE) in the short run. As for the dependence structure, Christoffersen and Pan (2014) investigate the oil-stocks relationship in the BRICS markets based on copula method, during the period 2000–2012 and find a high dependence between oil and stock markets during economic turbulences. Applying a quantile regression framework, Zhu et al. (2016) reveal an asymmetric dependence between oil and BRICS stock markets. In addition to that, Ding et al. (2016) document a causal relationship between Dubai oil prices and some Asian stock markets; however, no causality was shown between Chinese stock markets and Dubai oil prices. Mensi et al. (2017) find that oil and major stock markets show tail dependence. Using wavelet coherence approach, Cai et al. (2017) show high interdependence between oil and East Asian stock markets in the long term. Similar results are also shown by Mensi et al. (2018) especially during periods of financial turmoil. Using the same approach, Huang et al. (2018) examine the co-movement between oil and stock markets and show a low correlation between OPEC stock and Brent stock in the long run, however the findings are different in the short run.

Given the widespread of the novel COVID-19 pandemic, a new strand of literature have been emerged to investigate the impact of COVID-19 pandemic on energy and stock market returns (e.g. Bakas & Triantafyllou, 2020; Ashraf, 2020; Zhang et al., 2020; Zaremba et al., 2020). The recent studies reveal that the global pandemic has a severe effect on the worldwide financial markets. For instance, Zaremba et al. (2020) examine the stock market response to the global pandemic focusing on the impact of governmental interventions. Bakas and Triantafyllou (2020) study the effect of COVID-19 outbreak on the volatility of commodity prices. Baret et al. (2020) document that the global pandemic has significant effects on financial markets worldwide including stocks, bonds, and crude oil prices that have fallen sharply.

The studies dealing with the effect of COVID-19 pandemic on financial markets are relatively scant. Our study joins this recent strand of literature and attempts to investigate the effect of oil prices shocks on developed and emerging stock markets during the COVID-19 crisis. More precisely, this chapter contributes to the previous literature and examines how developed and emerging stock market returns respond to the severe oil prices shocks during the ongoing pandemic. For this purpose, we apply the TVP-BVAR-SV model to study the oil-stocks interaction during the current COVID-19 crisis. The outcomes will be useful for investors, portfolio managers, regulators and policymakers whose policy and investment decisions are widely affected by the uncertainty surrounding crude oil markets.

Using a Bayesian VAR approach with time-varying coefficients and stochastic volatility (TVP-BVAR-SV), our findings reveal that in comparison to the first wave, the response of the MSCI indices to the oil prices shocks is moderate during the second wave. In particular, the second wave of the pandemic was anticipated by the financial analysts, making investors and policymakers able to overcome the big disruption witnessed in the first wave. Interestingly, our results show that the negative impact of oil prices shocks on emerging stock markets was transmitted slowly, contrary to that for the developed stock markets.

The remainder of the chapter is organized as follows: Section 2 outlines the econometric methodology. Section 3 describes the data. Section 4 discusses the empirical results. Section 5 concludes and gives possible policy implications.

2 Methodology

We opt for BVAR model with time-varying coefficients and stochastic volatility (TVP-BVAR-SV model) proposed by primiceri (2005) and Del Negro and Primiceri (2015). The TVP-BVAR model allows us to measure the responses of stock market indices to oil prices shocks and identify possible modification of their evolution over time. The model is presented as follows:

$$Y_t = c_t + b_{1,t}Y_{t-1} + \ldots . + b_{p,t}Y_{t-p} + u_t \tag{1}$$

Where Y_t is a vector of three variables, namely: WTI-oil prices, MSCI developed market and MSCI emerging market index. p is the number of lags, c_t is $n \times 1$ vector of constants, $b_{p,t}$ is $n \times n$ matrix of coefficients, and u_t is $n \times 1$ vector of residuals which are normally distributed. We follow Primiceri (2005) and Del Negro and Primiceri (2015) to estimate the model.

3 Data

In order to evaluate the responses of the financial market to oil price shocks, we use daily data of WTI-crude oil prices, MSCI developed market index and MSCI Emerging market index. Our framework covers the time span between first, January 2019 through 31st December 2020. We take the logarithm of MSCI indices. The first 42 days constitute the pre-sample from which we draw the prior probabilities. We analyze the responses of MSCI indices to WTI-Oil prices shocks on two different dates, namely: on April, 20th, 2020, which is featured by the first wave, and on September, 10th, 2020, which is characterized by the second wave of the pandemic.

4 Results

4.1 *Stochastic Volatility*

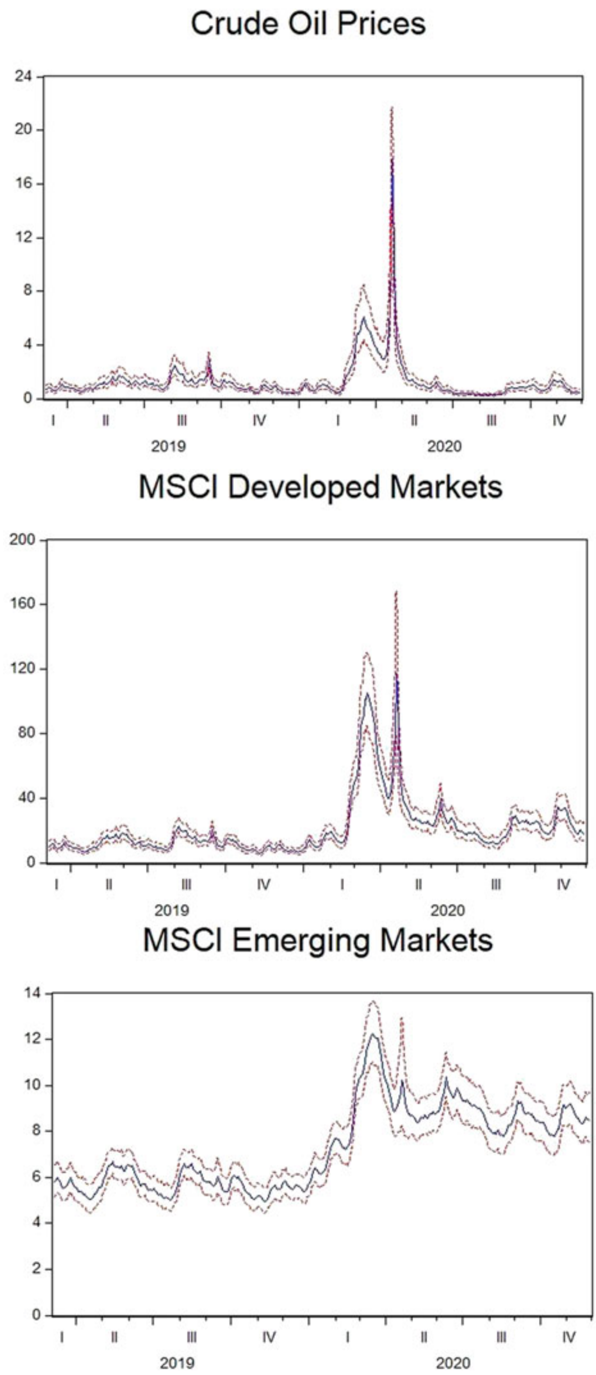
Figure 1 plots the stochastic volatility of the WTI-Oil, the MSCI Developed Markets and the MSCI Emerging Markets indices. We observe a strong instability of the studied variables over the entire period from March to the end of 2020. In particular, the figure reveals two successive peaks of the WTI-Oil index. The first peak is related to the announcement of a global pandemic on March 11th, 2020 by the WHO (World Health Organization), and the stock market crash of March 12th. Then, the WTI-Oil index recorded its historical spike on April, 20th, when oil prices fell to their lowest level, hitting negative prices for the first time in history. These events generate a great disturbance in the entire financial market. Indeed, the stochastic volatility curves of the two MSCI indices show a high instability during the same period. This substantial spike in financial market volatility can be explained by several factors: a serious economic re-cession, the stock market crash occurred in March 2020, an unforeseen situation, ambiguity and extreme uncertainty. The volatility of the MSCI emerging market index remains moderate compared to the MSCI developed market index. Subsequently, we observe a drop in volatility that began from June 2020. Indeed, thanks to the hot weather, the death rate recorded a significant drop in summer. The decrease of the number of COVID-19 confirmed cases has encouraged countries to resume economic activity and air traffic, resulting in a gradual recovery in oil consumption.

With the start of the second wave in September 2020, there is a slight increase in the volatility of the two MSCI indices. However, the volatility reached in the second wave is lower compared to that of the first wave. During the second wave, scientific studies predicted the return of the pandemic in the fall of 2020. Consequently, the surprise effect of the first wave is not present this time. Thus, this second wave was introduced in the forecasts of the investors. As a result, financial market participants have taken precautions to avoid the scenario of a second collapse similar to the one that occurred in March and April 2020.

4.2 *Impulse Responses*

In order to compare the behavior of the MSCI indices against the two COVID-19 waves, we investigate their responses to two shocks in two different periods. The first shock of oil prices realized on April, 20th, 2020, is related to the first wave. The second shock linked to the second wave is taken on September, 10th, 2020. Figure 2 reveals that during the first wave, the negative effect on the MSCI developed market index gradually appears after 15 days from the WTI-oil price shock. While, during the second wave the index drops after 20 days from the shock with a less pronounced magnitude. On the other hand, the MSCI emerging market index reveals a very slight

Fig. 1 The stochastic volatility



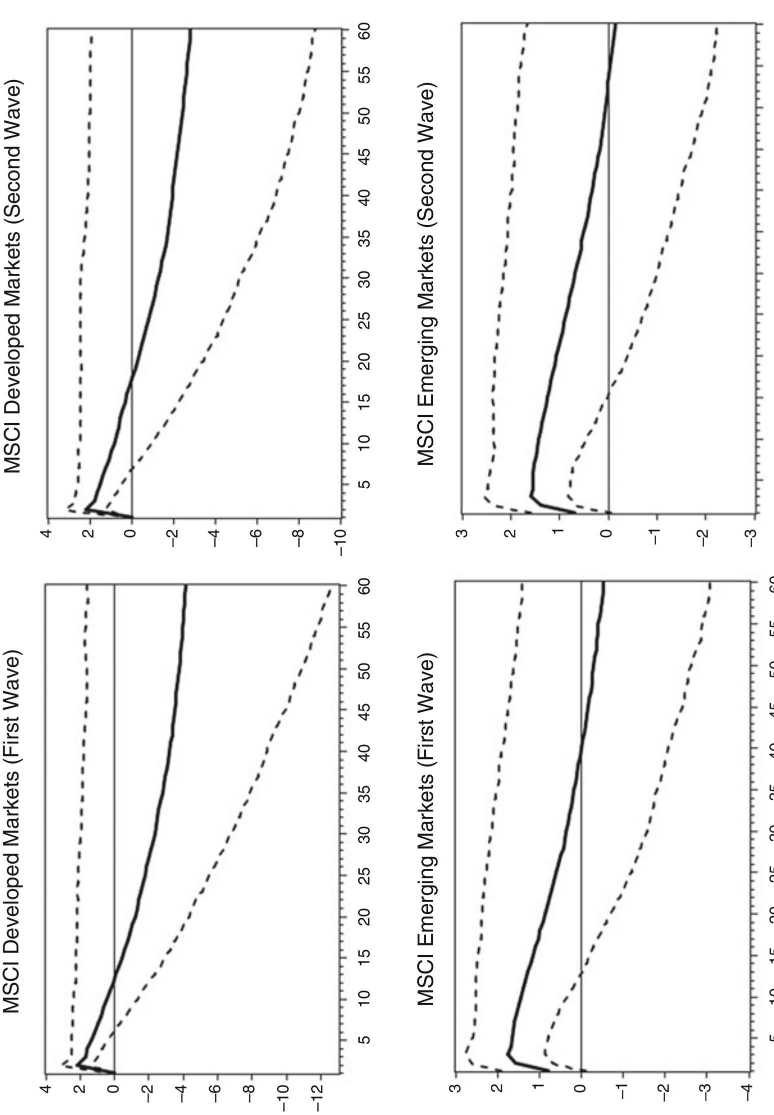


Fig. 2 Impulse responses of the developed and emerging markets to oil price shocks

negative effect after 45 days. However, we do not notice a drop in the MSCI emerging index over the first 60 days following the shock. Our findings are consistent with the results of Topcu and Gulal (2020) who show that the negative effect of COVID-19 on Emerging Market has gradually weakened after April, 15th and disappeared in May 2020. Our result is probably owed to two main reasons: The first reason is related to the fact that the COVID-19 pandemic has dramatically damaged the developed countries such as Italy, the US and France whereas the negative impact is modest in Emerging countries. The second reason may be related to the fact that emerging financial markets are in a transitional phase of financial integration from closed market systems to open market systems. However, the emerging market is still relatively considered as an isolated market compared to the developed financial market. This characteristic makes the financial spillover to emerging markets less pronounced and may slow down the transmission of the negative effect from the commodity market to the stock market (Fig. 2).

5 Conclusion

We use a Bayesian VAR with time varying coefficients and stochastic volatility to study the effect of oil prices shocks on MSCI indices. We show that the MSCI indices volatility reached in the second wave is moderate compared to that of the first wave. Moreover, our findings reveal that the global stock market was less reactive and less harmed by oil prices shocks during the second wave. In fact, the rapid and unprecedented spread of the COVID-19 outbreak in the first wave was unforeseen. Whereas, the second wave was anticipated, making financial market participants able to avoid the big disruption that happened in the first quarter of 2020. We also found that the negative effect of the oil prices shocks is transmitted slowly to the emerging stock markets. Our results suggest that policymakers need to increasingly take into account the financial and economic specificity of emerging countries and the characteristics of their financial systems in assessing the consequences of COVID-19 on the global financial market.

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The Volatility Connectedness Between Oil and Stocks: Evidence from the G7 Markets

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Abstract This paper examines the asymmetric volatility spillovers between oil and G7 stock markets based on the forecast error variance decomposition from a standard vector autoregresssions framework (VAR) and a Bayesian VAR with stochastic volatility. Our database encompasses daily returns on the G7 Stocks and the WTI index for the period that spans from June-2006 to May-2019. Using the Diebold and Yilmaz (International Journal of Forecasting 28:57–66, 2012) and Baruník et al. (Journal of Financial Markets 27:55–78, 2016), the results show that the oil market is rather a volatility receiver. Moreover, our results support the evidence of an asymmetric volatility connectedness with either standard or Bayesian VAR. In fact, in both Models, bad total volatility spillovers dominate good volatility spillovers, proving the pessimistic mood of the whole system. Moreover, oil is more sensitive to negative markets shocks since it receives more bad volatility than good. Furthermore, spillover asymmetry is enhanced in all turbulence periods. Our findings suggest that, in crisis periods, the uninformed traders dominate the markets and increase volatility, which enhances the negative spillovers.

Keywords Asymmetric volatility spillovers · Bayesian VAR · Stochastic volatility · Forecast error variance decomposition · Good volatility · Bad volatility

1 Introduction

The mechanism of risk transmission between markets has been the objective of many studies (see for example: Engle et al., 1990; Lin et al., 1994; Choi et al., 2009; Diebold & Yilmaz, 2009; Zhou et al., 2012; among others). Studying spillover effects and contagion mechanism is crucial to risk managers and investors because of the globalization and market integration.

Most of the papers in the literature define the volatility spillover effects as a situation in which variations in volatility in a market disturb the volatility of other

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markets. Engle et al. (1990) developed a test for volatility spillover including two hypotheses: the first is "heat waves" which means that volatile day or period in one market will be followed by another volatile period in that same market but not necessary in other markets. The second is "meteor shower" meaning that a volatile period on one market can be followed by a volatile period on other markets. A later work by Lin et al. (1994) which employed a univariate GARCH model to analyze return and volatility spillover between New York and Tokyo showed evidence of bidirectional spillovers. Consequently, a large literature dealing with volatility spillovers has been developed since and found evidence of volatility shocks transmission between markets (see for example: Hsin, 2004; Choi et al., 2009; Zhou et al., 2012; Diebold & Yilmaz, 2012; Balli et al., 2015; among others).

Like the growing literature on volatility spillovers, various studies have explored the asymmetric volatility spillovers. In fact, it is well documented in the literature that *good news* and *bad news* have different impacts on volatility (see for example: Chen & Ghysels, 2011; Bekaert et al., 2015; Patton & Sheppard, 2015; Segal et al., 2015; among others). For example, Allen et al. (2017) studied the volatility spillovers between the New York and the London stock markets. They found that the impact of negative shocks is larger, but shorter in duration. Baruník et al. (2016) found that Spillovers of bad and good volatility are transmitted at different degrees that change with sectors and time. They showed that the volatility spillover of US stocks had increased substantially during the financial crisis. Baruník et al. (2017) studied the asymmetric volatility on foreign exchange futures contracts of six currencies. They found that bad volatility dominates good one during sovereign debt crisis in Europe, while positive spillovers are correlated with the subprime crisis. BenSaida (2019) analyzed the asymmetric volatility spillovers across G7 financial markets and found that good and bad volatilities are transmitted with different time-varying intensities.

Due to the higly interaction between the oil market and stock markets (see: Jones & Kaul, 1996; Huang et al., 1996; Sadorsky, 1999; Papapetrou, 2001; Park & Ratti, 2008; Yurtsever & Zahor, 2007; Sadorsky, 2001; Lin et al., 2014; among others), another bulk of studies has investigated the volatility spillover between the two markets. For instance, Malik and Hammoudeh (2007) used the BEKK-GARCH technique to measure shocks interactions between oil price and GCC stock Markets. They observed a significant volatility spillover from equity markets to oil price.

Arouri et al. (2011) used a VAR-GARCH method to study the volatility spillover between oil and US Stock returns. They found evidence of bidirectional volatility spillover between oil and stocks.

Jouini (2013) investigated volatility spillovers between oil price and stock market of Saudi Arabia while using the VAR-GARCH technique. The results showed that spillovers effect from oil to sectors returns are unidirectional and bidirectional for sectors to oil. He attributed the results to the fact that the Saudi Arabia is among the leading oil-exporter countries of the world.

Gomes and Chaibi (2014) studied volatility spillovers between oil and MSCI Frontier Markets and MSCI World indices using a multivariate BEKK-GARCH model. They found that the spillover effect is bidirectional in several markets.

However, there is unidirectional transmission of volatility spillovers in developed stock markets. They concluded that volatility is transferred more frequently from oil to stocks. Bouri and Demirer (2016) studied the volatility spillovers between oil and emerging oil importing and exporting nations utilizing univariate GARCH technique and causality-in-variance test. The results showed a volatility spillover effect in the pre-crisis period for the net oil exporter nations. Whereas in the post-crisis period frequent volatility interaction seen for oil importer and exporter nations except Lebanon. A recent paper by Sarwar et al. (2020) investigated the volatility spillovers between oil and three Asian stock markets (namely Karachi, Shanghai and Bombay) while using a bivariate BEKK-GARCH model. Their findings have confirmed a significant volatility spillovers between oil and stock returns.

Despite the growing literature on the study of the volatility spillovers between oil and stocks, the study of the asymmetric volatility spillovers between oil and stock markets is still in its early phase. Wang and Wu (2018) examined the asymmetric volatility spillovers between oil and international stock markets in a vector auto regression framework using a directed acyclic graph (DAG) technique. They found that Positive spillovers of oil markets dominated from 2006 to mid-2009, but inverted after mid-2009. Besides, the spillovers from good volatilities in oil markets to bad volatilities in global stock markets were significantly positive during the economic recovery period.

Xu et al. (2019) investigated the Asymmetric volatility spillovers between oil and the US and Chinese stock markets. They found that Bad volatility spillovers dominate good volatility spillovers for most of the sampling period.

However, in recent years, an important advance in time series analysis is the development of autoregressive models with a time-varying dimension (see for example: Kitagawa & Gersch, 1985; Lundbergh et al., 2003; Moulines et al., 2005; Prado and Huerta, 2002; Primiceri, 2005, among others). The stochastic volatility models have gained a considerable popularity in modelling time variation in time series. In fact, since the seminal paper of Cogley and Sargent (2001, 2005) and Primiceri (2005) the time varying VAR with stochastic volatility has become an important tool in studying the inter-dependence between various macroeconomic variables (see for instance: Benati., 2008; Koop et al., 2009; Koop and Korobilis, 2013; Liu and Morley, 2014). Moreover, Bayesian VAR models with stochastic volatility are often found to forecast better than the other VAR versions as demonstrated by Clark (2011) and Clark and Ravazzolo (2015).

In addition, Bayesian vector autoregressions have gained much interest in modelling time series fluctuations (see: Litterman (1979), Doan et al. (1984), and Doan's RATS Manual (1990). Bayesian VARs with Stochastic volatility provide an alternative approach to model time variation in the size of fluctuations.

Motivated by the shortage of studies on the asymmetric time varying volatility spillovers between oil and stocks, we fill this gap in the literature by separating the good and bad innovations. Moreover, we use both a standard VAR and Bayesian VAR with a stochastic volatility to account for time series variation. In addition, contrary to previous studies (e.g. Diebold & Yilmaz, 2012; Baruník et al., 2016;

Finta et al., 2017, among others), we extract the good and bad innovations from a conditional heteroskedastic model.

The rest of this paper is organized as follows. Section 2 introduces the data and the methodological approach. Section 3 reports our main empirical results. Section 4 concludes the paper.

2 Data and Methodology

Our data encompasses the daily prices of G7 (Canada, UK, US, Japan, Italy, France, Germany) for the period that spans from June-2006 to May-2019. For the crude oil market, we choose the West Texas Intermediate (WTI) that serves as a reference price for buyers and sellers of crude oil.

We first introduce the conditional heteroskedastic model used to extract the volatility. Then, we present the methodology of Diebold and Yilmaz (2012, 2014) based on the variance decomposition from a VAR to calculate the volatility spillovers index. We afterwards, calculate the asymmetric volatility spillovers using the approach of Baruník et al. (2016). Finally, we present some robustness checks.

2.1 The Volatility Process

Dozens of empirical literature have reported asymmetry in volatility (see for example: Bekaert & Wu, 2000; Wu, 2001; Andersen et al., 2006). To account for the asymmetric volatility, we use three competing Models, which are: The Exponential GARCH of Nelson (1991), the GJR-GARCH of Glosten et al. (1993) and the APARCH of Ding et al. (1993).

Nelson (1991) introduce the EGARCH model with a conditional variance formulation that captured the asymmetric effect of the variation in stock market returns and explored the conditional moments. The E-GARCH allows modelling the asymmetric reaction of volatility to good and bad innovations. Formally, the E-GARCH Model is presented as follows:

$$\ln\left(h_{i,t}\right) = \omega_i + \gamma_i \ln\left(h_{i,t-1)} + \eta_i \frac{\varepsilon_{i,t-1}}{h_{i,t-1}} + \theta_i \left[\frac{\mid \varepsilon_{i,t-1} \mid}{h_{i,t-1}} - E\left(\frac{\mid \varepsilon_{i,t-1} \mid}{h_{i,t-1}}\right)\right]\right. \tag{1}$$

The parameter η_i permits to model an asymmetrical effect related to the sign of the innovation Z_t. If $\eta_i > 0$ (respectively if $\eta_i < 0$), a positive shock on the conditional variance at the date t will be translated at the date t + 1 by an increase (respectively a decrease) in the conditional variance, i.e. of volatility, process y_t. The parameter θ_i allows considering an asymmetry related to the amplitude of the innovation Z_t measured by the variation $\left[\frac{|\varepsilon_{t-1}|}{h_{t-1}} - E\left(\frac{|\varepsilon_{t-1}|}{h_{t-1}}\right)\right]$. If $\theta_i = 0$, then a positive innovation will have the same effect (in absolute value) on the conditional variance that a negative innovation. On the other hand, if $\theta_i > 0$ then a shock of strong amplitude will have a relatively more effect (in absolute value) on the conditional variance than a shock of weak amplitude.

Moreover, we suppose that the errors ε_t follow a standard Student's t distribution to account for stylized facts observed on financial markets, such as non-normality, sharp peaks, and heavy tails.

Glosten et al. (1993) introduced the GJR GARCH model to captures volatility assymetry allowing for negative shocks to have a stronger impact in the variance than positive shocks. This asymmetry is called the leverage effect indicating that an increase in risk comes from the increased leverage induced by a negative shock. The GJR-GARCH is presented as follows:

$$\sigma_t^2 = \omega + \left(\alpha + \gamma I_{[\varepsilon_{t-1<0}]}\right)\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{2}$$

α, γ and β are restricted to be positive. The indicator function $[(I_{t-1})\varepsilon_{t-1}]$ equals 1 if $\varepsilon_{t-j} < 0$, and 0 otherwise. Thus, the leverage coefficients are applied to negative innovations, giving negative changes more weight. The leverage effect is captured by the coefficient γ. Likewise, we suppose that the errors ε_t follow a standard Student's t distribution.

Finally, Ding et al. (1993) introduced the asymmetric Power Arch (APARCH) model that captures the Fat tails, Excess kurtosis and Leverage Effects. The general structure of the APARCH mode is as follows:

$$\sigma_t^2 = \omega + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^\delta + \beta\sigma_{\varepsilon_{t-1}}^\delta \tag{3}$$

γ, captures the leverage effect. A positive γ indicates that negative information has stronger impact than the positive information on the volatility. The model that minimizes the AIC and BIC criteria is retained for the Data.

2.2 *The Vector Auto-regression Model (VAR)*

The vector auto regression (VAR) model is one of the most successful, flexible, and easy to use models for the analysis of multivariate time series. It is the most applied models in the empirical economics to capture the linear interdependencies among multiple time series.

Introduced by sims (1980), the VAR process is a generalization of autoregressive models (AR). In the VAR model, each variable is modeled as a linear combination of past values of itself and the past values of other variables in the system. Since you have multiple time series that influence each other, it is modeled as a system of equations with one equation per variable (time series).

For any order of lags p, Var(p) with N variables is written in matrix form as:

$$X_t = \Phi_0 + \Phi_1 X_{t-1} + \ldots + \Phi_2 X_{t-p} + \varepsilon_t \tag{4}$$

Where: where Φ_i are (n × n) coefficient matrices and ε_t is an (n × 1) unobservable zero mean white noise vector process (serially uncorrelated or independent) with time invariant covariance matrix $\Sigma\varepsilon$.

$X_t = (X_{1t}, \ldots, X_{Nt})$ an (n × 1) Vector of variables.

$\Phi p = \begin{pmatrix} a_{1p}^1 & \cdots & a_{1p}^N \\ \vdots & \ddots & \vdots \\ a_{Np}^1 & \cdots & a_{Np}^N \end{pmatrix}$ is a (N x N) matrix of lag coefficients to be estimated.

Thus, X ~ VAR(p) if and only if there exists a white noise ε_t (ε_t ~ white Noise $(0,\Sigma\varepsilon)$), $\Phi_0 \in R^N$ and p matrices $\Phi_1, \ldots, \Phi_p$ such that:

$$X_t - \sum_{i=1}^{p} \Phi_i X_{t-i} = \Phi_0 + \varepsilon_t$$

To determine the p-order of the VAR process, we estimate VAR models for order p ranging from 0 to h where h is the maximum number of lags. We retain lags number p which minimizes the criteria AIC and BIC.

2.3 The Bayesian VAR Model with Stochastic Volatility

The Bayesian VARs approach was originally developed by Litterman (1980) to overcome the over fitting problem that may appear in a standard VAR. The Bayesain approach allows specifying some regularities in time series by imposing a probability distribution to the parameters. In this way, the mean coefficient assigned to all lags superior to one are equal to zero, the variance of coefficient depends inversely on the number of lags and, finally, the coefficients of variable j in equation g are assigned lower prior variance than those of variable g.

The Bayesian VAR is presented as follows:

$$Y_t = X_t B + \varepsilon_t \tag{5}$$

Where $X_t = I_n \times W_{t-1}$ *is* $n \times nk$, $W_{t-1} = y'_{t-1}, \ldots, y'_{t-p} + z'_t$ which is a $k \times 1$ matrix. $B = vec(B_1, B_2, \ldots, B_p, D)$ is $nk \times 1$ matrix. The unknown parameters to be estimated in the model are B and the variance covariance matrix.

ε_t , is the error precision matrix and it follows a random walk (Stochastic Volatility) to account for time variation in the volatility spillover presented in the following section.

The Bayesian estimation is simple and works as follows. First, given the probability density functions (pdf) of the data conditional on the model's parameters, and a joint prior distribution on the parameters, the joint posterior distribution of the parameters conditional on the data is obtained via the Bayes rule as follows:

$$p(B, \Sigma/y) = \frac{p(B, \Sigma)L(Y/B, \Sigma)}{p(Y)}$$

We use Litterman and Mimenosa priors and a time varying error precision matrix with stochastic volatility deriving in closed form the Bayesian posterior.

2.4 The Spillover Index

Diebold and Yilmaz (2009) introduced a measure to calculate a spillover index (hereafter the DY index) based on the forecast error variance decomposition from a vector autoregression model.

The variance decomposition indicates how much of the H-step-ahead forecast error variance of some variable i is due to innovations in another variable j, and therefore provide a simple, intuitive way of estimating volatility spillovers. However, the DY spillover index (2009) have some handicaps. First, it relies on Cholesky-factor identification of VARs, and thus the resulting variance decomposition can be dependent on variable ordering. In addition, the DY index (2009) allows measuring total spillovers but not directional ones.

Thus, Diebold and Yilmaz (2012) extended their spillover measure of (2009) to make it invariant to variable ordering. DY index (2012) measure both total and directional volatility spillovers.

Consider a covariance stationary N-variable VAR(p):

$$V_t = \sum_{i=1}^{p} \varphi_i V_{t-i} + \varepsilon_t \tag{6}$$

Where,

V_i is an N-dimensional vector of assets volatility, $V_t = (V_{1t}, \ldots, V_{nt})$.
φ_i: a parameters matrix for $i = 1, \ldots, p$, and.
$\varepsilon_t \sim N(0, \Sigma\varepsilon)$: a vector of independently and identically distributed disturbances in case of a standard VAR. and ε_t is randomly distributed in case of the Bayesian VAR.

To calculate the variance decomposition, we consider the moving average representation of the VAR as follows:

$$V_t = \sum_{i=0}^{\infty} \Psi_i \varepsilon_{t-i} \tag{7}$$

With: Ψ_i, is an NxN matrix: $\Psi_i = \varphi_1 \Psi_{i-1} + \ldots + \varphi_p \Psi_{i-p;} \Psi_0 = I_N$ and $\Psi_i = 0$ for $i < 0$.

The KPSS H-step-ahead forecast error variance decompositions for H = 1, 2. . ., +∞ denoted by $\theta_{ij}^{g}(H)$ is formulated as follows:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Psi_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Psi_h \sum \Psi_h' e_i\right)} \tag{8}$$

Where,

σ_{jj}: the standard deviation of the error term for the j^{th} equation
e_i: the selection vector, with one as the i^{th} element and zero otherwise
Σ: is the variance matrix for the error vector ε_t
Ψ_h: are moving average coefficients from the forecast at time t

The sum of the elements in each row of the variance decomposition is not equal to one: $\sum_{j=1}^{N} \theta_{ij}^{g}$ (H) $\neq 1$.

As the shocks to each variable are not orthogonalized, each element should be normalized by row sum as:

$$\widetilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{9}$$

Noting that: $\sum_{j=1}^{N} \widetilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}^{g}(H) = N$.

Diebold and Yilmaz (2012) construct the total volatility spillover index using the volatility contributions from the KPPS variance decomposition as:

$$S^g(\mathrm{H}) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \widetilde{\theta}_{ij}^{g}(H)}{N} .100 \tag{10}$$

The total spillover index measures the contribution of spillovers of volatility shocks across all markets to the total forecast error variance.

The generalized VAR approach allows calculating the directional volatility spillovers across the studied markets. In fact, since the generalized impulse responses and variance decompositions are invariant to the ordering of variables, we can extract the direction of volatility spillovers using the normalized elements of the variance decomposition matrix.

The directional volatility spillovers received by market i from other markets j is calculated as follows:

$$S_i^g(\mathrm{H}) = \frac{\sum\limits_{\substack{j=1 \\ j \neq i}}^{N} \widetilde{\theta}_{ij}(H)}{\sum\limits_{i,j=1}^{N} \widetilde{\theta}_{ij}(H)} * 100 = \frac{\sum\limits_{\substack{j=1 \\ j \neq i}}^{N} \widetilde{\theta}_{ij}(H)}{N} * 100 \tag{11}$$

The directional volatility spillovers transmitted by market i to all other markets j is calculated as follows:

$$S_i^g(\mathrm{H}) = \frac{\sum\limits_{\substack{j=1 \\ j \neq i}}^{N} \widetilde{\theta}_{ji}(H)}{\sum\limits_{j,i=1}^{N} \widetilde{\theta}_{ij}(H)} * 100 = \frac{\sum\limits_{\substack{j=1 \\ j \neq i}}^{N} \widetilde{\theta}_{ij}(H)}{N} * 100 \tag{12}$$

Then, we can obtain the net volatility spillover by the difference between the gross volatility shocks transmitted to and those received from all other markets as follows:

$$S_i^g(H) = S_{.i}^g - S_{i.}^g \tag{13}$$

2.5 Asymmetric Volatility Spillovers Index

The phenomenon of asymmetric volatility on financial markets supposes that market volatility is higher in declining markets than in rising markets. Hence, past returns are negatively associated with present volatility (Bekaert & Wu, 2000). Since volatility is transmitted across markets through spillovers, it is expected that volatility spillovers show asymmetries due to good and bad innovations. To inspect the spillovers asymmetry, we use the measure (SAM) introduced by Baruník et al. (2016).

SAM is simply the difference between positive and negative spillovers:

$$SAM = S^{+}\text{-}S^{-} \tag{14}$$

Where,

S^{-}: the spillovers from volatility due to negative returns
S^{+}: the spillovers from volatility due to positive returns

In order to calculate the SAM, we need to replace the vector of volatilities: $V_t = (V_{1t}, \ldots, V_{nt})$' with the vector of positive spillovers $SVt^{+} = (SV_{1t}{}^{+},\ldots,SV_{nt}{}^{+})$', Or the vector of negative spillovers $SV_t{}^{-} = (SV_{1t}{}^{-},\ldots,SV_{nt}{}^{-})$'

$$\begin{cases} H_0 : S^{-} = S^{+} \\ H_1 : S^{-} \neq S^{+} \end{cases}$$

Accepting the null hypothesis means that we have symmetric spillovers. However, by rejecting the null hypothesis we can conclude that there are asymmetric spillovers. In fact, SAM can be an indicator of whether the market is in an optimistic or pessimistic mood. Thus, SAM shows how the agents on markets are sensitive to bad or good news. If SAM >0, we conclude that positive spillovers dominate negative ones. However, when SAM < 0 means that negative spillovers dominate positive spillovers.

3 Results

In this section, we employ the methodology illustrated previously to analyze the asymmetric volatility spillovers between oil and the G7 Markets. We first present the descriptive statistics of the synchronous returns of the WTI index and Stock Market indices. Then, we extract the volatility from a univariate conditional heteroscedastic Model namely the E-GARCH. Basing on these volatilities, we present the bidirectional volatility spillovers index of DY (2012). Next, to measure the asymmetric volatility spillovers, we use the spillover asymmetry measure (SAM) introduced by Baruník et al. (2016). Finally, we present some robustness checks.

Table 1 reports the descriptive statistics of the synchronous returns of the G7 indices and the oil index. The results show that all means are different from zero. U.S shows the highest mean (0.000112) and Italy exhibits the lowest one (−0.00007). Italy exhibits the highest standard deviation (0.00688) and Canada the lowest one (0.0047). All series display a kurtosis higher than 3; meaning that all distributions are leptokurtic and heavy tailed. The skewness coefficient is negative for almost all series (except for Japan and Oil) meaning that the distributions are skewed left. The Jarque-Bera and the Cramer-Von Mises tests obviously reject normality for all series, which justify the use of the student's t distribution in Eqs. (1), (2) and (3). Finally, the Augmented Dickey Fuller test (ADF) rejects the null hypothesis of unit root, which means that all our series are stationary.

Table 1 Descriptive statistics of the synchronous results of G7 markets and oil index

Returns	Germany	U.S.	France	U.K	Italy	Japan	Canada	Oil
Mean	0.000103	0.000112	0.0000162	0.0000338	−0.00007	0.0000119	0.000045	0.0000138
Median	0.000235	0.000150	0.0000426	0.0000179	0	0.0000	0.000305	0.000247
Maximum	0.046893	0.045635	0.046012	0.040756	0.047238	0.053315	0.040694	0.071287
Minimum	−0.032283	−0.035614	−0.041134	−0.040240	−0.057898	−0.045264	−0.042508	−0.055706
Std.dev	0.005820	0.004829	0.006002	0.004976	0.006884	0.007482	0.004723	0.009932
Skewness	−0.021928	−0.151366	−0.024251	−0.137930	−0.219827	0.234201	−0.698946	0.094354
Kurtosis	9.496153	14.03921	9.839882	11.49462	8.372504	8.469071	14.78875	7.727128
J-B Test	5934.6***	17150***	6579.3***	10158***	4086.1***	4237***	19824***	3060***
ADF Test	−21.3462***	−21.9610***	−21.4216***	−21.4923***	−26.7855***	−23.3595***	−18.7380***	−24.5611***
Cramer-Von Mises Test	8.602029***	17.08803***	8.227449***	9.84230***	6.65348***	20.51313***	13.13878***	6.116618***

[a]Indicate significance level at 1%

To model the volatility of our series, we use three competing Models, which are the APARCH, the EGARCH and the GJR-GARCH. We use the AIC and BIC criteria to choose the model that best fits the data. The estimation results are presented in the following table.

Table 2 presents the estimation results of 3 competing volatility models; the E-GARCH, the APARCH and the GJR-GARCH. The results from the three models

Table 2 Estimation results of the volatility models

EGARCH $\ln(h_{i,t}) = \omega_i + \gamma_i \ln\left(h_{i,t-1}\right) + \eta_i \frac{\varepsilon_{i,t-1}}{h_{i,t-1}} + \theta_i\left[\frac{\lvert\varepsilon_{i,t-1}\rvert}{h_{i,t-1}} - E\left(\frac{\lvert\varepsilon_{i,t-1}\rvert}{h_{i,t-1}}\right)\right]$						
	Coefficients				Information Criterion	
	ω_i	γ_i	η_i	θ_i	AIC	BIC
Oil	−0,139,275***	0,992,597***	−0,058905***	0,103,698***	**−5,09**	**−5,07**
France	−0,308,021***	0,976,222***	−0,181,581***	0,118,911***	**−6,17**	**−6,16**
Italy	−0,238,051***	0,982,821***	−0,120,025***	0,114,212***	**−5,82**	**−5,81**
Germany	−0,314,135***	0,976,587***	−0,152,251***	0,134,832***	**−6,18**	**−6,17**
UK	−0,266,692***	0,982,135***	−0,138,615***	0,126,741***	**−6,58**	**−6,57**
US	−0,207,362***	0,977,808***	−4190188***	390621***	−6,75	−6,74
Canada	−0,192,751***	0,989,723***	−0,108,882***	0,115,743***	**−6,83**	**−6,82**
Japan	−0,479,511***	0,919,634***	−0,902,767***	4756202***	**−5,63**	**−5,62**
APARCH $\sigma_t^2 = \omega + \alpha(\lvert\varepsilon_{t-1}\rvert - \gamma\varepsilon_{t-1})^{\delta} + \beta\sigma^{\delta}_{\varepsilon_{t-1}}$						
	Coefficients				Information Criterion	
	ω	α	γ	β	AIC	BIC
Oil	0,000249***	0,053585***	0,637,697***	0,950,834***	−5,09	−5,08
France	0,000191	0,150,000**	0,05***	0,600,000	−5,42	−5,41
Italy	0,000242***	0,065541***	0,999,896***	0,932,785***	**−5,82**	**−5,80**
Germany	0,00018***	0,077761***	0,999,993***	0,914,966***	**−6,18**	**−6,17**
UK	0,000176***	0,078596***	0,999,989***	0,917,312***	**−6,58**	**−6,57**
US	0,000139*	0,099131***	0,999,987***	0,895,708***	**−6,80**	**−6,79**
Canada	0,000101***	0,064568***	0,93,974***	0,937,897***	**−6,83**	**−6,82**
Japan	0,0000151***	0,494,086**	0,113,023**	0,751,659***	**−5,64**	**−5,62**
GJR-GARCH $\sigma_t^2 = \omega + \left(\alpha + \gamma I_{[\varepsilon_{t-1}<0]}\right)\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$						
	Coefficients				Information Criterion	
	ω	α	γ	β	AIC	BIC
Oil	0,00000277***	0,028838***	0,059392***	0,935,533***	−5,08	−5,07
France	0,0000027***	−0,023903***	0,231,425***	0,895,102***	−6,15	−6,15
Italy	0,00000257***	−0,001487	0,14,398***	0,916,854***	−5,81	−5,80
Germany	0,0000023***	−0,018516**	0,18,436***	0,91,235***	**−6,18**	**−6,17**
UK	0,00000193***	−0,013395	0,195,425***	0,897,562***	−6,58	−6,56
US	0,00000169***	−0,020852	0,238,967***	0,884,734***	**−6,80**	**−6,79**
Canada	7,05E-07***	0,004560	0,122,477***	0,920,056***	−6,82	−6,81
Japan	0,0000409***	0,299,618**	0,207,778***	0,767,245*	**−5,64**	**−5,63**

[a]Indicate respectively the significance level at 1%, 5% and 10%

indicate the presence of the leverage effect which motivates us to use the asymmetric volatility models. In fact, the E-GARCH produces a negative and statistically significant coefficient η_i, meaning that negative shocks have relatively more impact on the conditional variance than positive shocks. In addition, the results from the APARCH model show positive and statistically significant coefficients γ indicating that negative information has stronger impact than positive information on the volatility. The Leverage effect is also confirmed by the GJR-GARCH since the γ coefficients are all positive and statistically significant.

To select the volatility model that best fits the data, we use the AIC and BIC criteria. The results from Table 2 indicate that EGARCH and APARCH produce similar results. In fact, in both models the AIC and BIC are minimized. However, the EGARCH model presents the minimum values for roughly all the series (except the US). Hence, so as to keep the same information contained in the volatility model, we retain the EGARCH.

From the synchronous returns, we extract the conditional volatilities using Eq. (1). The figures in Appendix 1 plot the volatility of the oil index and the G7 indices, respectively.

The figures show clearly similarities in the volatility patterns, which supports a spillover effect across markets and oil. The most volatile period for all stock price indices is between the end of 2007 and 2010, which is the subprime crisis period. Some other periods of high volatility are conspicuous: for example, the period between 2009 and 2012 representing the European sovereign debt crisis, and the Brexit vote in mid-2016. The graphical inspection supports the evidence of volatility spillovers across oil and markets.

We adopt the Diebold and Yilmaz (2012) framework based on the forecast error variance decomposition from a VAR. To use Diebold and Yilmaz index we first estimate the VAR for the volatility indices as in Eq. (4). Then, using the variance decomposition from the VAR, we compute the spillover index as in Eq. (10). The net volatility spillovers are finally calculated as in Eq. (13).

The total spillover index in all markets including the Oil is 49.70%. The most contributing market to the forecast error of other markets is Germany by transmitting a high level of 87.6% followed by France 87.2% and the US 78.9%. Moreover, the most receiver countries of spillovers are France 76.4%, followed by UK 74.6% and Germany 74%. We can conclude that France is the most sensitive to external shocks.

Japan and Canada seem to be the less sensitive to external shocks. Their contribution to others is weak; 0.4% for Canada and 2.1% for Japan. Regarding the oil market, it receives volatility from others more than it transmits with a negative net spillover of −10.8%. WTI transmits volatility the most to Canada, France and UK and receives the most from US and France (Table 3).

Figure 1 suggest that volatility spillovers showed significant variation over time. The spillover index is relatively high (65.3%) in the period of the subprime crisis that began in the mid of 2007 to the end of 2009. There is also a significant peak at the end of 2011 (66.3%) which corresponds to the terrorist attack events in the U.-S. Finally, a sharp peak is observed (70%) between the period of mid-2016 which corresponds to the brexit vote and the recent price oil crash by the end of 2018. Thus,

Table 3 Directional spillovers between oil and G7 markets

	France	Germany	Italy	UK	US	Japan	Canada	Oil	From Others
France	23,6	21,9	17,7	18,8	17,4	0,5	0	0,2	76,4
Germany	21,2	26	16,2	18,3	17,8	0,3	0,1	0,1	74
Italy	21,9	21,2	28,1	15,5	12,7	0,5	0	0,1	71,9
UK	20,2	20,1	12,2	25,4	21,4	0,4	0,1	0,2	74,6
US	15,7	17,2	9,2	17,5	40,1	0,1	0,1	0,1	59,9
Japan	5,9	5,5	5,8	5,7	5,5	71,5	0,1	0	28,5
Canada	0,1	0	0,1	0,2	0	0	99,2	0,3	0,8
Oil	2,2	1,7	1,6	1,9	4,1	0,3	0,1	88,2	11,8
Contribution to others	87,2	87,6	62,9	77,9	78,9	2,1	0,4	1	397,9
Contribution including own	110,8	113,6	90,9	103,3	119	73,6	99,6	89,2	**49,70%**
Net Spillover	10,8	13,6	−9	3,3	19	−26,4	−0,4	−10,8	

Note: This table reports the volatility directional spillovers in %, Spillovers are computed using Diebold and Yilmaz's (2012) framework. The results are based on generalized variance decompositions of 5-day ahead volatility forecast errors with rolling sample analysis. The entry on the *ith* line and *jth* column is the spillovers from market *i* to the forecast error variance of market *j*. the net spillovers is the difference between the columns "contribution to others" and "contributions from others". The number in bold represents the total volatility spillover index

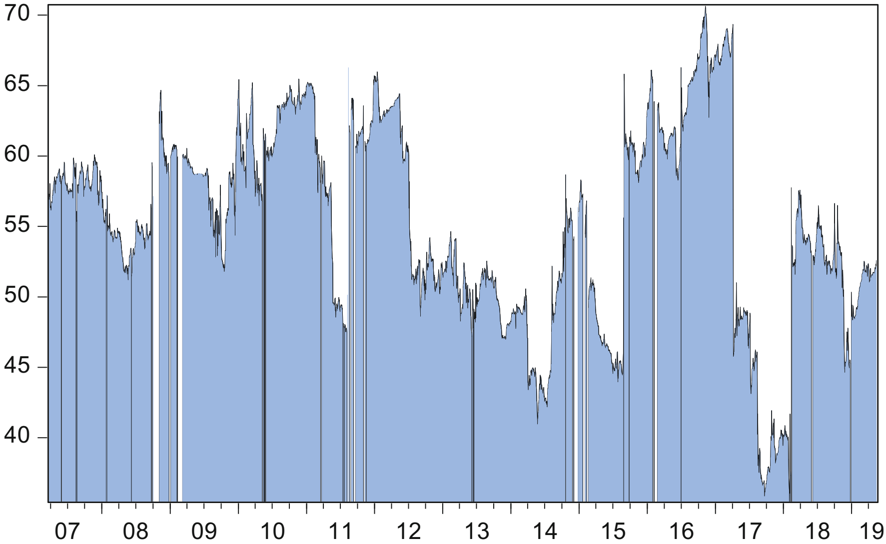


Fig. 1 Total spillover index across G7 and oil

when markets are under distress, volatility spillovers tend to be higher and investors become less confident about future flows, which results in an increase in risk and in volatility spillovers. According to Fig. 1, the volatility spillovers show dynamic patterns over time, which motivates us to study the asymmetric volatility spillovers.

To model the Time Varying aspect of time series, we use a Bayesian VAR with stochastic volatility. In fact, Bayesian VARs allow for the parameters to be as random variables, with prior probabilities, rather than fixed values. Most of the gain, in this paper, comes from allowing for stochastic volatility rather than time variation in the VAR coefficients. In fact, since our objective is to extract the forecast error variance decomposition, the time variation in the variance is empirically more important than changes in the coefficients of the VAR. We use Litterman and Mimenosa priors and allow for the variance of the posteriors to follow a stochastic volatility in the estimation of the Bayesian VAR model.

The directional spillover derived from the Bayesian VAR with stochastic volatility is presented in the following table:

Table 4 shows the results of the error variance decomposition from a Bayesian VAR. when, considering the time variation in the variance of the VAR, the spillover between the system reaches 63.98% compared to 49.70% for a constant variance. We can see that France still has the highest contribution to others and it's a net volatility Transmitter (positive net spillover). UK has the highest contribution from others (85.29%) and it's the most sensitice country to external shocks. The biggest difference is that Germany falls from the first to the fifth place in contribution to others and to the sixth place in total contribution. However, as results from spillovers

Table 4 The directional spillover between oil and G7 derived from Bayesian VAR

	France	Germany	Italy	UK	US	Japan	Canada	Oil	From Others
France	92,72	0,91	0,03	0,02	5,96	0,08	0,09	0,2	7,29
Germany	80	15,18	0,099	0,04	4,51	0,07	0,17	0,11	84,999
Italy	76,83	0,88	19,48	0	2,6	0,03	0,02	0,12	80,48
UK	71,2	2,64	2,7	14,7	8,18	0,08	0,25	0,24	85,29
US	38,56	3,73	2	1,67	53,29	0,3	0,21	0,26	46,73
Japan	6,27	0,34	0,53	0,4	1,66	90,53	0,07	0,18	9,45
Canada	0,056	0,004	0,013	0,04	0,01	0	99,83	0,3	0,423
Oil	7,18	0,09	0	0,9	3,8	0,04	0,26	87,71	12,27
Contribution to others	280,096	8594	62,9	77,9	78,9	2,1	0,4	1	511,89
Contribution including own	372,816	23,774	24,852	17,77	80,01	91,13	100,9	89,12	**63,98%**
Net Spillover	272,806	−76,405	−17,58	−2,58	32,17	−7,35	−0,023	−11,27	

Note: This table reports the volatility directional spillovers in %, Spillovers are computed using Diebold and Yilmaz's (2012) framework. The results are based on generalized variance decompositions from a Bayesian VAR of 5-day ahead volatility forecast errors with rolling sample analysis. The entry on the *ith* line and *jth* column is the spillovers from market *i* to the forecast error variance of market *j*. the net spillovers is the difference between the columns "contribution to others" and "contributions from others". The number in bold represents the total volatility spillover index we remark that Oil, Canada and Japan are still net receiver and are slightly integrated with other markets. Finally, it's worth noting that even when considering time variation in the variance decomposition, oil still a net volatility receiver.

The variance decomposition from the Bayesian VAR with stochastic volatility is depicted in Fig. 2.

We can see that the high value of stochastic volatility causes the variance residuals to jump to a high level and then move around such level during the whole period. The high value of residuals is noted for crisis periods such as; the Global Financial crisis of 2007–2008, the terrorist attack of the US in 2011, the Brexit Vote of 2016. However, in all cases, Oil market is smoothly integrated with other markets supporting its hedging characteristic.

3.1 Asymmetric Volatility Spillovers

This section reports the asymmetric volatility spillovers between the oil and stock markets. Baruník et al. (2016) defined asymmetry as the difference between positive and negative spillovers. Using the realized semi variance framework of Barndorff-Nielsen et al. (2010) and the volatility spillover index of Diebold and Yilmaz (2009, 2012), Baruník et al. (2016) introduce the spillover asymmetry measure (SAM). We study the asymmetric volatility transmission while separating between good and bad Volatility as in Eqs. (8) and (9) for both the standard VAR and the Bayesian VAR with stochastic volatility. Then, we calculate the spillover asymmetry measure (SAM), defined in Eq. (11).

Table 5 reports the Asymmetric volatility spillovers across G7 stocks and Oil.

Table 5 reports the asymmetric volatility spillovers across G7 and Oil. The results indicate that the total spillover is higher in bear markets (44.5%) than in bullish (29%). Hence, we can asset that the impact of good and bad innovations on volatility spillovers is asymmetric. Moreover, the volatility spillovers across countries show different patterns with reference to the type of innovations. For instance, while France was a leading country in the transmission of volatility shocks from the traditional spillover measure in Table 2, its contribution is lowered to reach only 3.3% in good innovations. However, in bearish markets France kept its leading role for volatility transmission with the highest contribution to other markets (90%) followed by Germany (86.7%) UK (74.1%) and Italy (66.4%). All markets (except for U.S and Canada), are shifting more bad volatility than good. Consequently, we can assert that the Global mood of the financial markets is pessimistic.

Regarding the Oil market, it is a net volatility receiver in both good and bad volatility. However, some specific patterns must be explained. First, in upturns it shifts volatility only to Canada and Japan. Then, in downturns, it transmits volatility to all markets (with the exception of Japan) with the same percentage 0.1%. Hence, we can conclude that all Markets (except for Japan) are more sensitive to negative oil

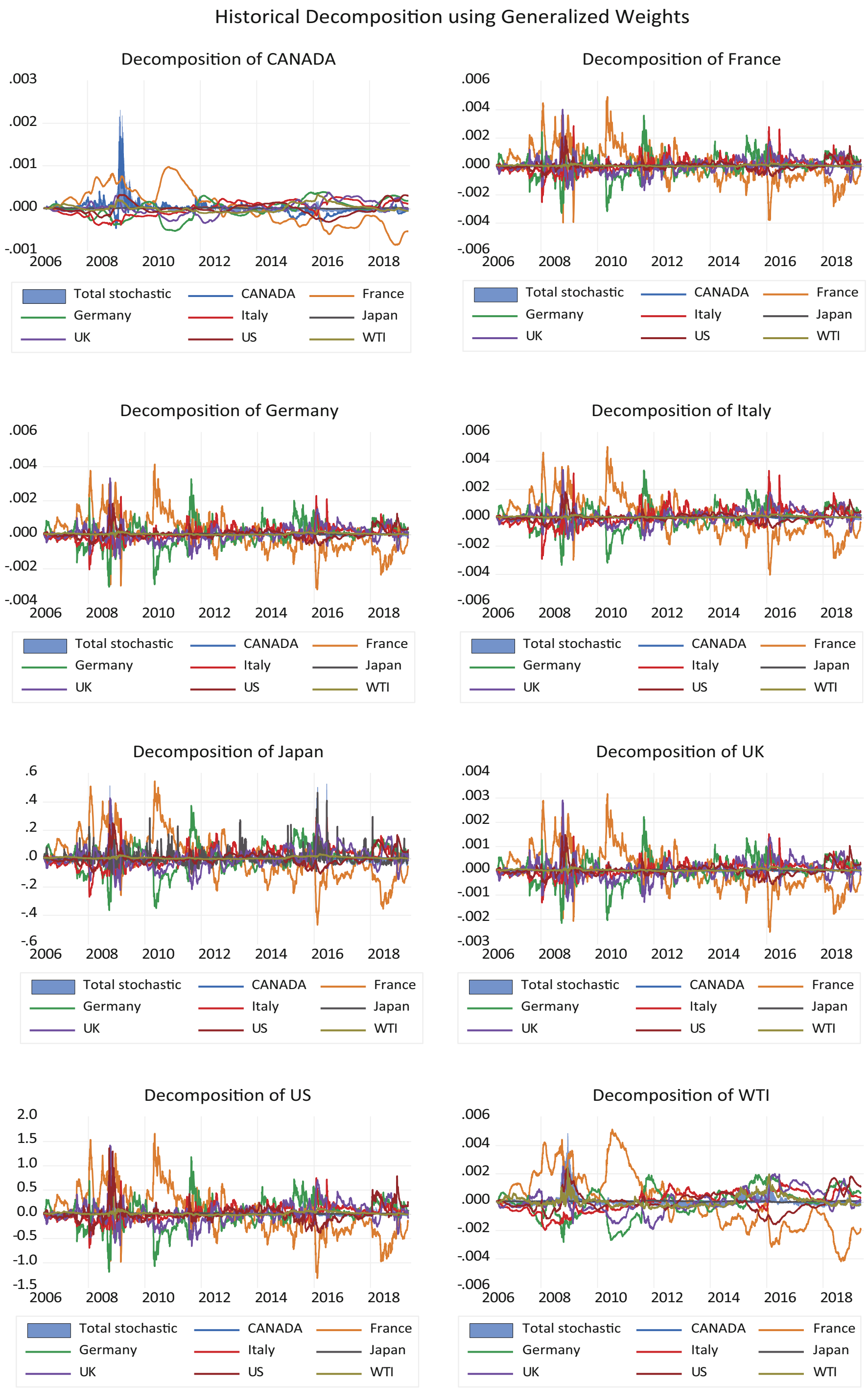


Fig. 2 Histrorical decomposition of the error variance derived from a stochastic volatility

Table 5 Asymmetric volatility spillovers across G7 stocks and Oil (Standard VAR)

	France	Germany	Italy	UK	US	Canada	Japan	Oil	From Others
Good									
France	96,6	0,1	0,6	2,1	0	0,2	0,3	0	3,4
Germany	0,4	43,5	18,9	24	12,8	0,1	0,3	0	56,5
Italy	0,2	25,9	46,1	20,2	7,4	0	0,2	0	53,9
UK	1,3	25,4	15,2	46,2	11,5	0	0,3	0	53,8
US	0,5	18,1	8,6	15,7	56,8	0	0,2	0	43,2
Canada	0,2	0	0,1	0,1	0	99,5	0	0,1 s	0,5
Japan	0,1	4,7	2,7	4,9	5,6	0	81,9	0,1	18,1
Oil	0,6	0,2	0,1	0,1	0,3	0,1	0,8	97,7	2,3
Contribution to others	3,4	74,4	46,2	67,1	37,7	0,4	2,1	0,3	**29,00%**
Contribution including own	100,1	117,8	92,3	113,2	94,5	100	84	98	
Net Spillover	0	17,9	13,2	13,3	−5,5	−0,1	−16	−2	
Bad									
France	27	23,7	20,6	19,8	7,9	0	0,9	0,1	73
Germany	24,2	28	19,4	18,7	8,9	0	0,6	0,1	72
Italy	24,1	22,6	30,7	15,6	6	0	0,9	0,1	69,3
UK	23,5	21,5	14,6	29,6	9,6	0	0,9	0,1	70,4
US	13,8	15,2	8,7	15	46,9	0	0,2	0,1	53,1
Canada	0	0	0,1	0,2	0	99,6	0	0,1	0,4
Japan	3,3	2,8	2,5	3,3	0,7	0	87,3	0	12,7
Oil	1	0,8	0,5	1,4	0,6	0,1	1	94,4	5,6
Contribution to others	90	86,7	66,4	74,1	33,7	0,2	4,4	0,7	**44,50%**
Contribution including own	117,1	114,7	97,2	103,8	80,6	99,8	91,8	95,1	
Net Spillover	17	14,7	−2,9	3,7	−19,4	−0,2	−8,3	−4,9	

Note: This table reports the good and bad volatility directional spillovers in %. The results are based on generalized variance decompositions of 5-day ahead volatility forecast errors with rolling sample analysis. The entry on the *ith* line and *jth* column is the spillovers from market to the forecast error variance of market *j*. Numbers in bold represent the total volatility spillover indices

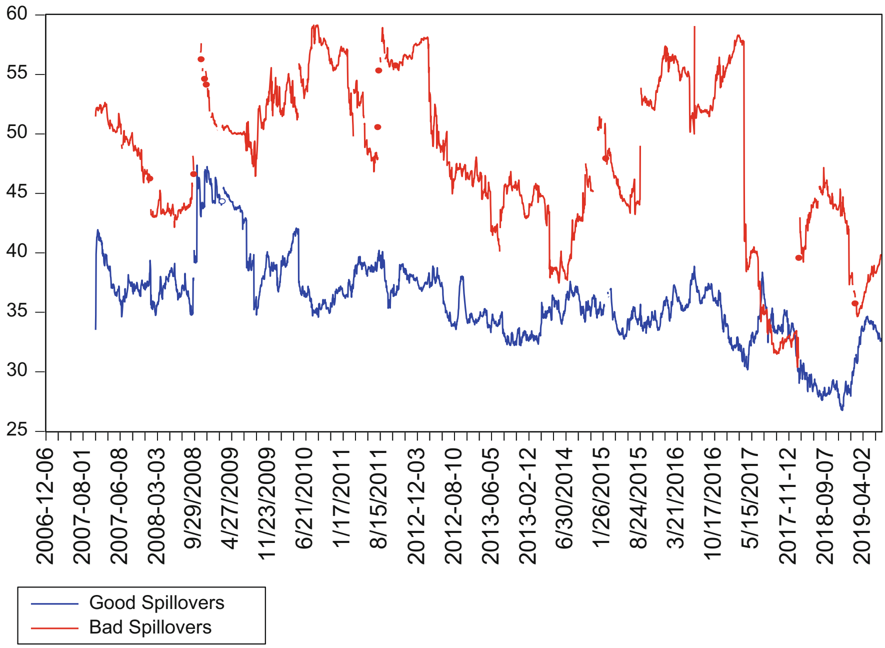


Fig. 3 Good and bad volatility spillovers

shocks. Finally, the oil market is more sensitive to negative markets shocks since it receives more bad volatility (5.6%) than good (2.3%) (Fig. 3).

Figure 3 clearly shows that negative spillovers dominate positive ones. Avramov et al. (2006) asserted that a positive return is followed by a bulk of sell activity that is ruled by informed traders, which reduces volatility. However, a negative return is followed by a bulk of sell activity that is dominated by uniformed traders, which increases the volatility. Therefore, since the asymmetry index is negative, we conclude that the uninformed traders dominate the whole system, and negative spillovers tend to be higher than positive spillovers.

Figure 4 plots the Spillover asymmetry (SAM) which measures the sensitivity of markets to good and bad news. The figure shows clearly that negative spillovers dominates positive ones. The peaks observed for negative spillovers are depicted in all turbulence periods such as the Global Financial crisis (mid-2007 to end-2009), the European sovereign debt crisis (2010), the terrorist attack in the US (2011), the Brexit vote (mid-2016) and the price oil crash by the end of 2018. The asymmetry index allows concluding that, generally, the whole mood of markets is rather pessimistic which is in line with the findings of Wang and Wu (2018).

In Order to account for time variation in the forecast error variance decomposition, we calculate the asymmetric volatility spillover derived from a Bayesian VAR with stochastic volatility. The results are presented in Table 6:

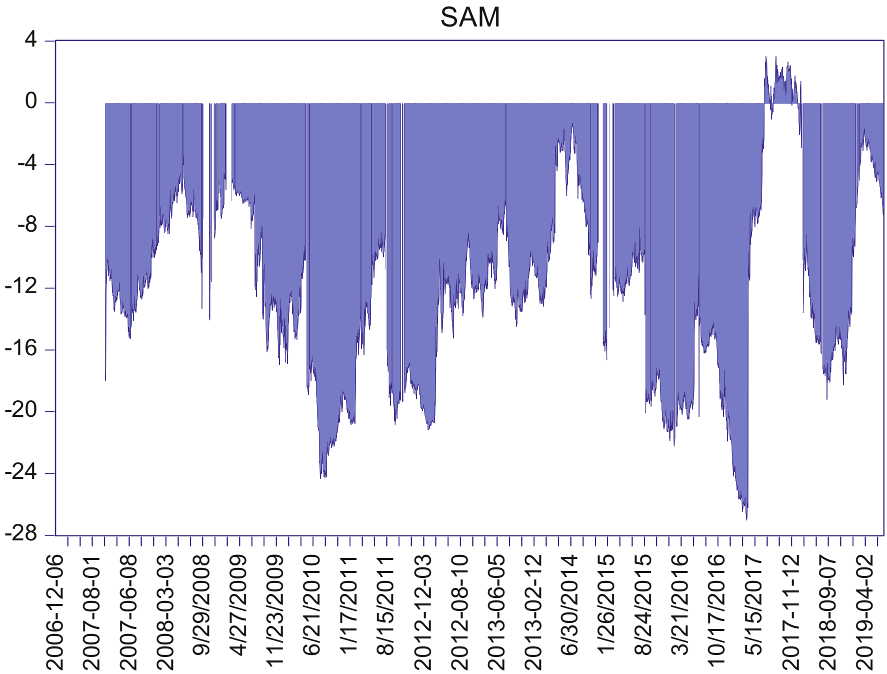


Fig. 4 Spillover asymmetry (SAM)

The Results of the spillover asymmetry from the Time varying VAR model show that bad total spillovers dominate good ones which confirm our results presented in Table 5. Moreover, In good volatility, Germany dominates the whole system with the highest contribution to others (112.09). However, in Bad volatility it's rather the US that governs the system with the highest contribution to others (158.03) and net spillover (155.928) followed by the UK. An interesting result must be mentioned concerning the net spillover. In fact, in bad volatility, all of the markets are volatility receivers except for the US and UK that manipulate the other markets. In addition, in both scenarios, oil still a net volatility receiver. Since our results differ from those in Table 4, we can conclude that as the residuals change in time, the mechanism of shock transmission changes which is an interesting result. Figures 5 and 6 plots the historical decomposition of the stochastic in both good and bad scenarios.

3.2 *Robustness Checks*

In Order to evaluate the stability of our findings, we use an approach similar to Diebold and Yilmaz (2012), Narayan et al. (2014) and BenSaïda (2019). First, we use alternative H-step-ahead forecast error variance decompositions and alternative

Table 6 Asymmetric volatility spillover from Bayesian VAR with stochastic volatility

	France	Germany	Italy	UK	US	Japan	Canada	Oil	From Others
Good									
France	99,43	0,06	0,14	0,11	0	0,05	0,17	0,01	0,54
Germany	0,9	97,05	0,02	0,04	1,83	0,02	0,13	0	2,94
Italy	0,46	49,99	46,61	1,5	1,38	0,02	0,02	0	53,37
UK	2,68	52,72	1,62	37,72	5,08	0,08	0,07	0,01	62,26
US	38,56	3,73	2	1,67	53,29	0,3	0,21	0,26	46,73
Japan	0,16	5,24	0,1	0,74	1,9	91,81	0,02	0,02	8,18
Canada	0,11	0,14	0	0,01	0	0	99,7	0,12	0,38
Oil	0,65	0,21	0,04	0,12	0,13	0,92	0,12	97,8	2,19
Contribution to others	43,52	112,09	3,92	4,19	10,32	1,39	0,74	0,42	176,59
Contribution including own	142,95	209,14	50,53	41,91	63,61	93,2	100,44	98,22	**22,07%**
Net Spillover	42,98	109,15	−49,45	−49,18	−36,41	−6,79	0,36	−1,77	
Bad									
France	6,73	2,68	13,67	36,29	40,1	0,36	0,02	0,14	93,26
Germany	0,03	17,03	11,29	32	40	0,12	0	0,2	83,64
Italy	0,05	0	47,07	25,94	26,24	0,6	0,02	0,08	52,93
UK	0,25	0,03	0,04	53,94	45,44	0,1	0,13	0,08	46,07
US	0	0,1	0,07	1,19	97,88	0,04	0,022	0,68	2102
Japan	0,03	0,16	0,03	2,06	4,91	92,53	0,03	0,25	7,47
Canada	0,09	0,54	0,05	0,22	0,06	0,06	98,84	0,14	1,16
Oil	0,01	0,02	0,09	1,95	1,28	0,57	0	96,07	3,92
Contribution to others	0,46	3,53	25,24	99,65	158,03	1,85	0,222	1,57	290,552
Contribution including own	7,19	20,56	72,31	153,59	255,91	94,38	99,062	97,64	**36,32%**
Net Spillover	−92,8	−80,11	−27,69	46,72	155,928	−5,62	−0,938	−2,35	

Note: This table reports the good and bad volatility directional spillovers in %. The results are based on generalized variance decompositions of 5-day ahead volatility forecast errors with rolling sample analysis derived from a Bayesian VAR. The entry on the *ith* line and *jth* column is the spillovers from market to the forecast error variance of market *j*. Numbers in bold represent the total volatility spillover indices

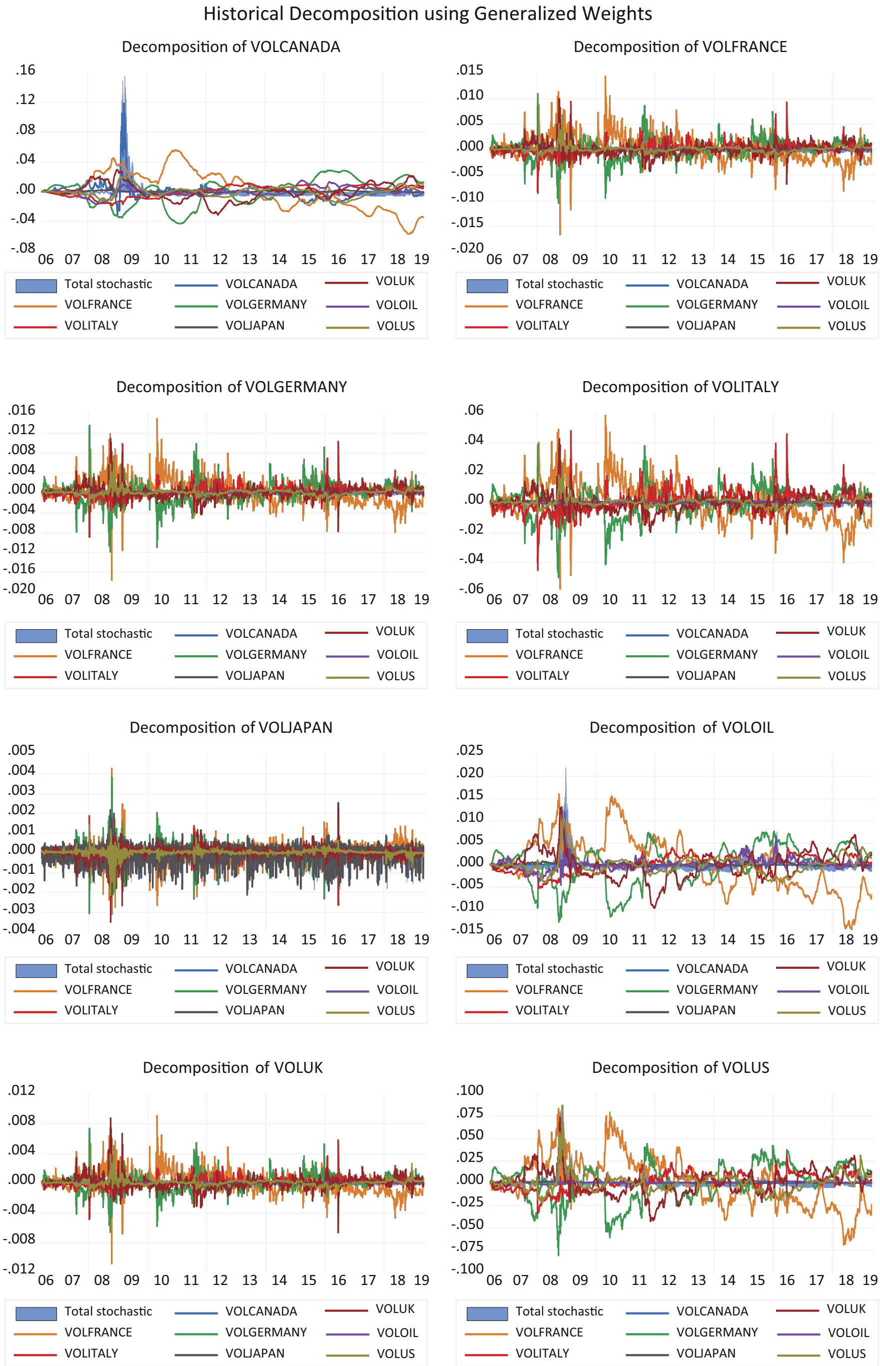


Fig. 5 Historical decomposition of bad total volatility (Bayesian VAR with stochastic Volatility

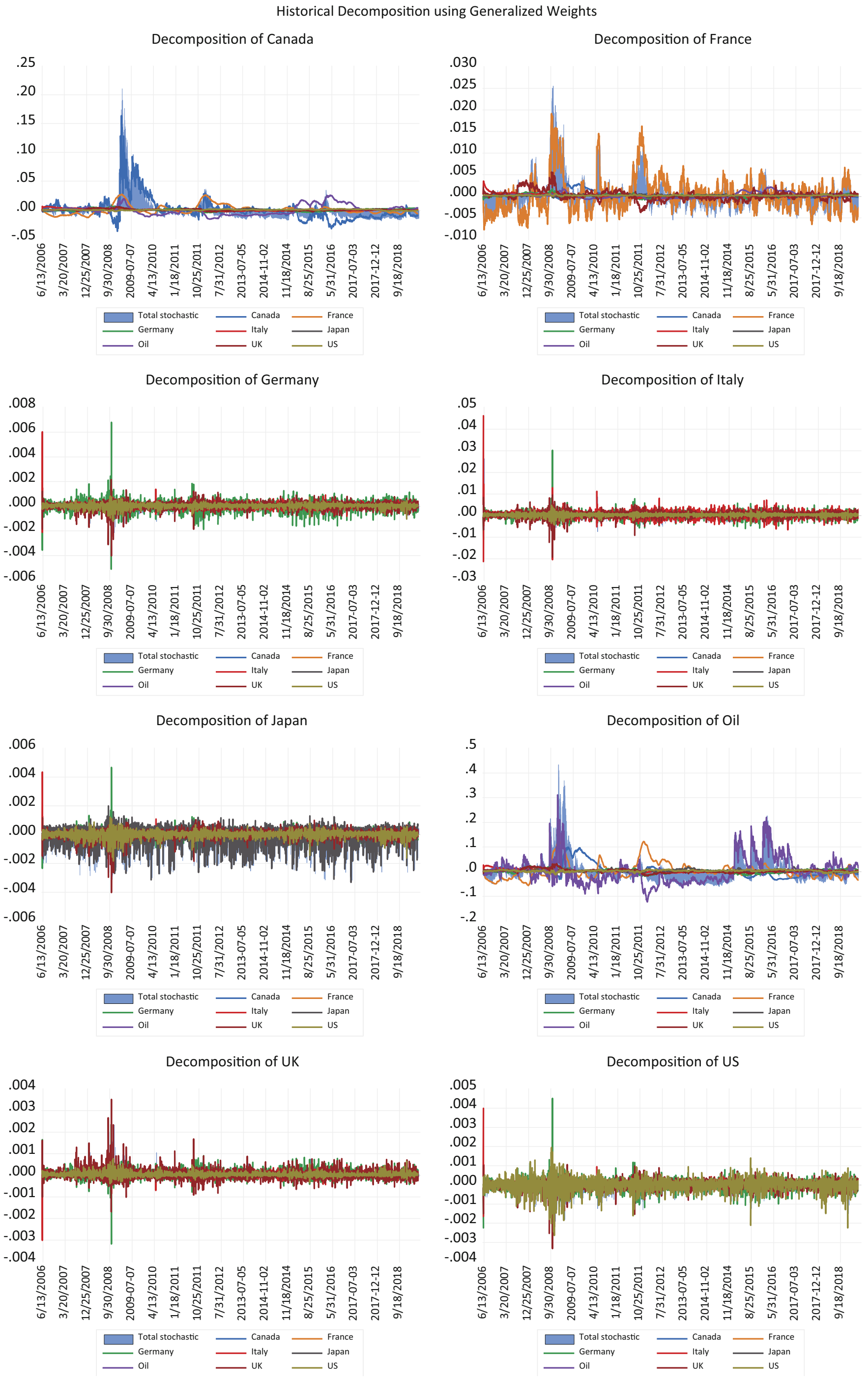


Fig. 6 Historical decomposition of the good total volatility (Bayesian VAR with Stochastic volatility)

Table 7 Robustness of total asymmetric spillovers

Model Configuration			Volatility spillover	
Volatility Model	Forecast horizons	VAR Lags	Good	Bad
E-GARCH	2	p = 1, p′ = 1	28,70%	43,00%
		p = 2, p′ = 2	30,30%	45,60%
		p = 4, p′ = 4	30,50%	45%
		p = 12, p′ = 12	30,60%	44,80%
	5	p = 1, p′ = 1	**29,00%**	**44,50%**
		p = 2, p′ = 2	31,10%	46,70%
		p = 4, p′ = 4	32,20%	48%
		p = 12, p′ = 12	32,50%	48,40%
	12	p = 1, p′ = 1	29,50%	47,80%
		p = 2, p′ = 2	31,70%	50,80%
		p = 4, p′ = 4	33,40%	51%
		p = 12, p′ = 12	34,30%	52,20%
GARCH	2	p = 1, p′ = 1	41,20%	44,10%
		p = 2, p′ = 2	46,70%	46,70%
		p = 4, p′ = 4	46,50%	46%
		p = 12, p′ = 12	47,20%	46,10%
	5	p = 1, p′ = 1	43,20%	46,80%
		p = 2, p′ = 2	43,30%	48,40%
		p = 4, p′ = 4	50,30%	51%
		p = 12, p′ = 12	50,60%	51,20%
	12	p = 1, p′ = 1	46,80%	50,60%
		p = 2, p′ = 2	51,60%	52,30%
		p = 4, p′ = 4	53,20%	54%
		p = 12, p′ = 12	52,50%	55,30%

Note: Table 4 reports the Good and Bad volatility spillovers in % for different model specifications. The volatility is estimated using an E-GARCH and a GARCH model under the Student's *t* distributions. The lags of the VAR model are denoted p and p' for good and bad spillovers, respectively, VAR orders vary from 1 to 12. The results are obtained from on generalized variance decompositions of m-day ahead volatility forecast errors ($m = 2, 5, 12$), as in Eq. (11). Numbers in bold correspond to the reference spillover indices as reported in Table 3

m-day rolling windows that ranges from 2 to 12 days. Second, we use VAR lag orders that range from 1 to 12. Finally, in determining volatilities, we use two volatility Models namely the E-GARCH and GARCH Models. Table 7 summarizes the robustness check results.

The results displayed in Table 7 do not contradict our earlier findings in Table 5 and our results remain qualitatively similar. In fact, negative spillovers dominate positive spillovers and the results are robust as they hold across various model specifications (Table 7).

4 Conclusion and Policy Implication

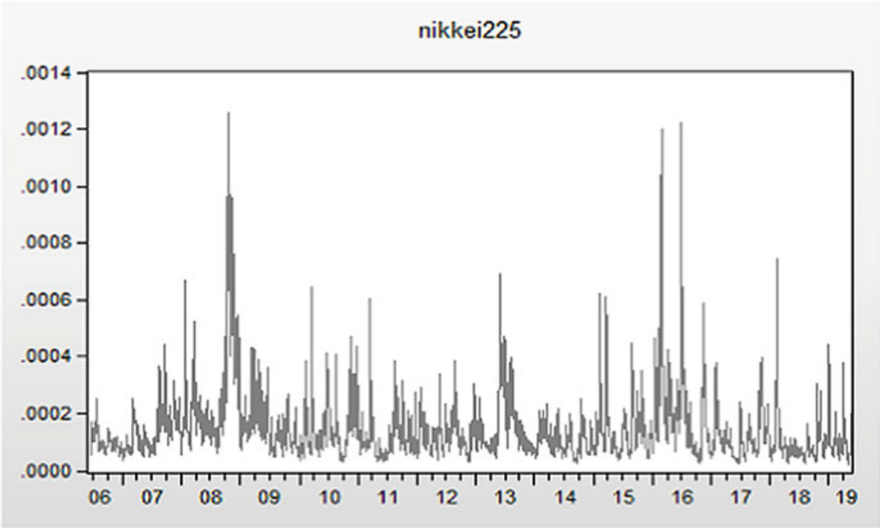
Our study investigates the asymmetric volatility spillovers between oil and stock markets using the approach of Diebold and Yilmaz (2012) coupled to that of Barùnik et al. (2016). Our analysis is conducted on daily returns of the G7 indices and the WTI oil index for the period that ranges from June-2006 to May-2019. The Volatility is estimated using the Heteroskedastik volatility Model E-GARCH. We first study the directional spillovers between oil and stocks based on the forecast error variance decomposition in a Standard VAR framework. Our results reveal a slight spillover between oil and stocks. Moreover, the bidirectional spillovers indicate that the oil market remains a net volatility receiver. Then, in order to account for the time variation in our variables, we study the spillover based on the error variance decomposition from a Bayesian VAR and allowing the variance to follow a stochastic process. Our results reveal that volatility spillovers is enhanced and the transmission mechanism reveals changing patterns. However, in both cases oil is considered as a volatility receiver.

We further investigate the asymmetric spillovers using the measure of Barûnik et al. (2016). Our results reveal the following interesting and important points. First, in either Static VAR or a time varying VAR, bad volatility spillovers dominate positive spillovers. Then, in both bad and good volatility, the oil market remains a volatility receiver. However, there are asymmetries in the transmission mechanism of spillovers in the system. In fact, within a standard VAR France and Germany are the leading countries in volatility transmission. However, when allowing for time variation in the Bayesian VAR, Germany loses its leading role in favor of the UK.

Finally, our results show that bad spillovers is enhanced in all turbulence periods, though it is reversed at mid-2017. Our findings suggest that uninformed traders dominate the system and increase volatility, which enhances negative spillovers.

Appendix 1

Volatility graphs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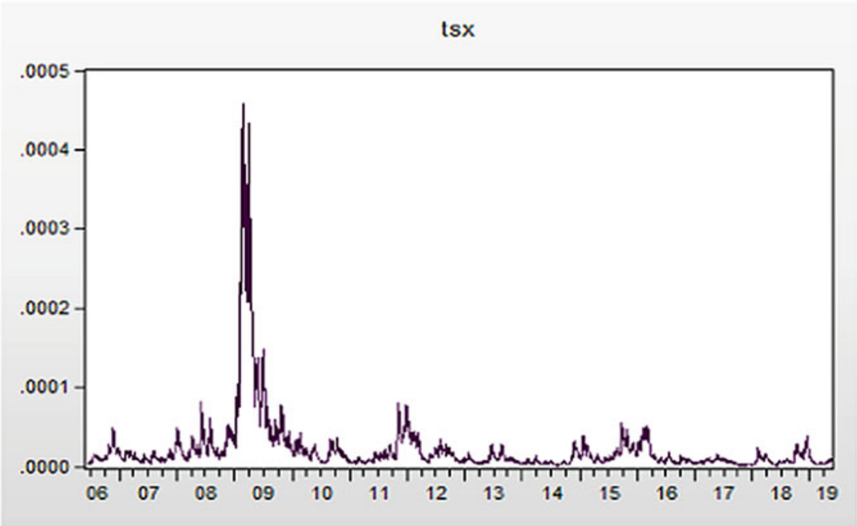
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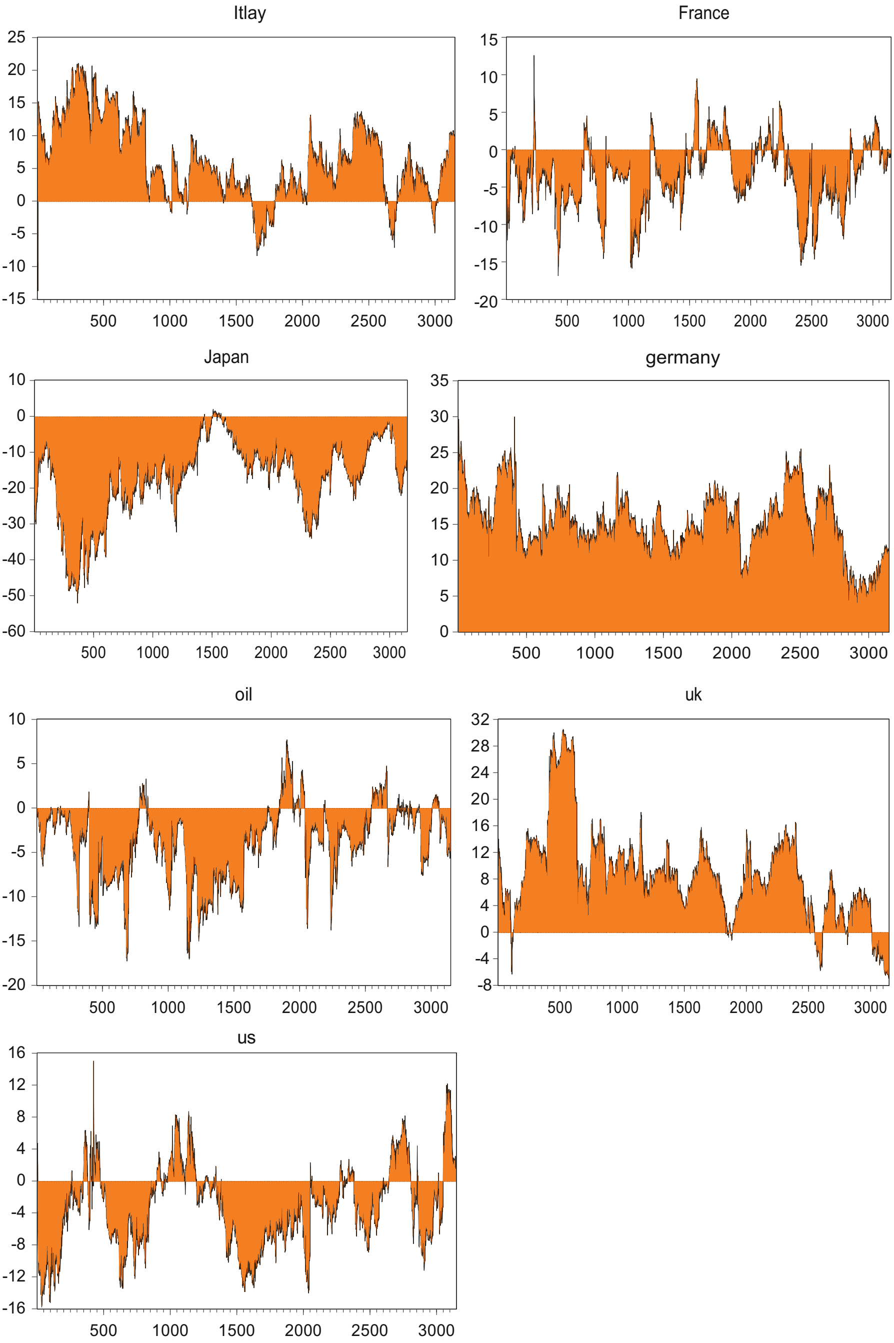
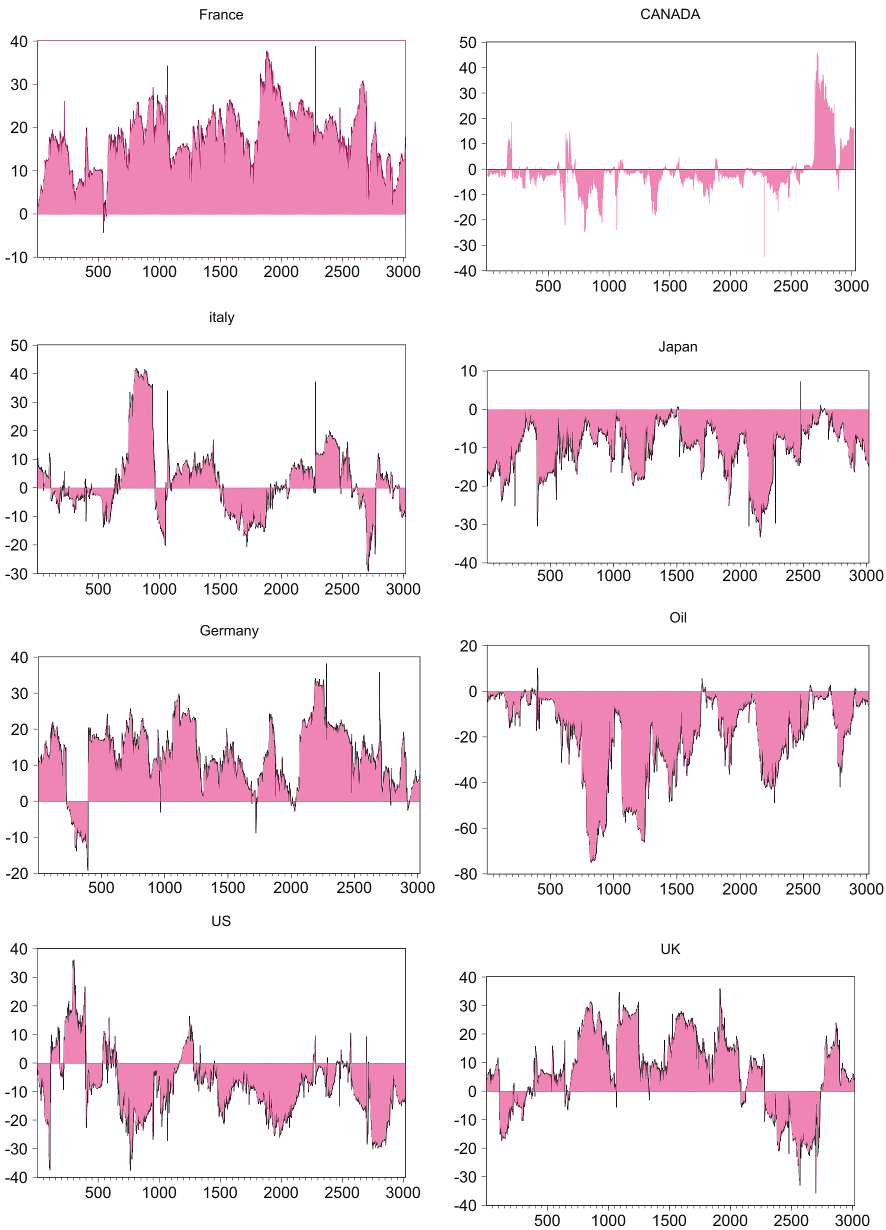
Appendix 2



Net good volatility spillover

Appendix 3



Net bad volatility spillover

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Economic Sentiment and Climate Transition During the COVID-19 Pandemic

Gideon Ndubuisi, Denis Yuni, and Ernest Ngeh Tingum

Abstract This paper analyzes the dependence between a newspaper-based economic sentiment index of the United States and four climate-themed financial indices since the outbreak of the COVID-19 pandemic. We use the quantile cross-spectral technique of Barunik and Kley (The Econometrics Journal 22:131–152, 2019), which allows dependence to vary across different time horizons and market conditions. Results show that when market conditions were very poor, dependence is strongest between economic sentiment and green bonds index in the intermediate time. However, under normal market returns, results show a similar pattern of increased dependence across the weekly, monthly and yearly cycles for all the climate-themed indices except green bonds. Besides, at the peak of the COVID-19 pandemic, normal returns dependence with economic sentiment was mostly positive and stronger than the lower and higher quantiles. Lastly, the strongest dependence under the 0.05|0.95 quantiles during the peak of COVID-19 pandemic occurred with green bonds in the short-term.

Keywords Quantile cross-spectral dependence · Economic sentiment · Climate transition · COVID-19 pandemic · Dependence · Climate-change · Newspaper

JEL Classification C32 · G15 · G41 · Q54

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1 Introduction

Climate change and climate-related risks have become one of the key issues of global concern in recent times. Bessec and Fouquau (2020) argue that the terms 'climate change' and 'global warming' have become frequently mentioned in the worldwide media, with the number of articles in the top five US newspapers mentioning these words reaching a milestone in September 2019, with about 800 articles per month compared to 100 in the early nineties. The increasing focus on environmental issues has given both political and economic actors a strong incentive to engage in more climate-friendly practices. The height of this incentive was demonstrated in the adoption of the 2030 Agenda for Sustainable Development Goals (SDGs) by all United Nations Member States in 2015, which provides a shared blueprint for peace and prosperity for people and the planet, now and into the future. At the core of the 17 SDGs are SDGs 7 and 13, which emphasized the need for affordable and clean energy and the commitments required to urgently reverse the already ravaging climate crisis and to abate climate change and its impacts, respectively.

The Paris Agreement on climate change and the SDGs aim to consolidate the global response to the impacts of climate change, in the context of sustainable development by limiting the increase in the global average temperature below 2 °C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5 °C above pre-industrial levels, believing that this would considerably reduce climate-related risks. Doubtless, as noted in Caldecott (2020), to deliver these objectives, the provision of finance and financial services that support, enable, and encourage companies and countries to transition towards cleaner activities and climate mitigation is a necessary condition. In this regard, climate transition requires financing for polluting companies to fund the transition to cleaner activities including energy production; governments to fund climate mitigation activities; and financing companies' sustainability performance. As argued in Weber and Saravade (2019), to deal with climate-related risks, both governments and private sector actors around the world have slowly mobilized efforts towards addressing the plight of temporal mindsets by offering economic and social spur. Recently, this has been increasingly demonstrated in the change of narrative towards investing in the future, with investments in fossil fuel corporations becoming frowned upon due to their impacts on the environment as well as the rising pressures of public awareness about long-term consequences of burning fossil fuels.

Given the urgency of climate change and its associated risks, it is crucial our society makes a transition toward a green and low-carbon economy. However, Weber and Saravade (2019) argue that about US$200 billion to US$1 trillion per year is needed to address climate-related risks. While the public sector has a lot to do in financing climate transition, these funds cannot exclusively come from government resources. Additional investments have to come from private investors, mainly through the financial markets. One way to do so is through finance markets that are tailored to fund low-carbon and climate-friendly projects. It is widely believed that climate-screened financial instruments can be an important factor in facilitating our society to make the transition. Since its market inception in 2007, the green bond has served as a crucial tool that allows various issuers including countries and organizations to mobilise traditional debt investments to fund projects that have positive environmental and/or climate benefits. Green bonds have been issued to finance climate-friendly infrastructure as well as to finance other sectors such as renewable energy, low-carbon transport, water and green buildings etc.

As noted in Weber and Saravade (2019), while green bonds have become the mainstream climate finance instrument used to raise long-term debt capital from various investors to finance or refinance climate-friendly assets and projects, it also allows investors to fulfill their environmental, social and governance (ESG) concerns and mandates by allowing for climate-aligned investments. The global push towards sustainable investing has led to increasing pressure to measure ESG criteria in several financial indices, which act as a catalyst for sustainable investment. These innovative financial indices track the performance of eligible equity securities, which are selected and weighted to be collectively compatible with several climate-scenario alignment. For instance, the S&P Dow Jones index-linked products contain the Climate Transition index tracks the performance of equity securities that is compatible with climate transition while the Paris-Aligned Climate index tracks the performance of equity securities that are compatible with a 1.5 °C global warming climate scenario, plus several other climate-themed objectives. Lastly, the Paris-Aligned Climate Sustainability Screened index measures the performance of equity securities that are compatible with the Paris Agreement, and addresses the risk of greenwashing. Taken together, these indices are designed to measure the performance of eligible equity securities from constituent firms, selected and weighted to be collectively compatible the factors that seek to manage transition risk and climate change opportunities in ways that aligns them with the Intergovernmental Panel on Climate Change's (IPCC) most ambitious 1.5 °C scenario, which equates to at least 7% GHG intensity reduction on average per year, without overshoot.

Green financial instruments are believed to have performed greatly in mobilizing both national or transnational financing to support climate transition in recent years. For instance, Climate Policy Change (2019) posits that Climate finance flows reached a record high of USD 612 billion in 2017, doubling the amount in 2013. However, this trend may have been retarded or even reversed in the face of the economic collapse ushered in by the coronavirus outbreak. Taghizadeh-Hesary et al. (2021) argue that in 2020–2021 due to the COVID-19 pandemic and the global economic recession, the increasing investment in renewable power, energy efficiency, and other green projects has fallen considerably. The pandemic-related systemic risk, which destabilized capital markets, leading to significant negative consequences for financial institutions and the broader economy has been convincingly documented in past studies (see e.g., Mzoughi et al., 2020; Boroumand et al., 2021; Khelifa et al., 2021; Chien et al., 2021; Urom et al., 2021; He et al., 2020). CERES (2020, p. 6) notes that investors may have been forced to rethink in terms of risks and solutions, reconsidering their consumption of modern financial instruments such as climate finance and that to hedge against systemic risk, investors' strategies basically involves the diversification of their investment portfolios.

Although the COVID-19 pandemic has proven to be one of the most economically costly pandemics in recent history, discerning and measuring the true effects of the COVID-19 on both the general economy and the global financial market has become the basic goal for economists and policy-makers. With particular reference to the first wave of the pandemic, the existence of many co-creating factors that occurred synchronously, including changes in expectations, policy interventions, and sudden increases in uncertainty, has made isolating the true effects of the pandemic very problematic because the overall effects appear not to be readily conformable to standard macroeconomic fundamentals. As the coronavirus disease rapidly spread across the world, people became more sensitive to the news and sentiments were built largely due to information from both the media, national and international periodicals. Lee (2020) note that it is largely recognized that stock market investors need high-quality data to make informed decisions, especially, in times of market crisis. Besides, empirical studies of financial markets describe many anomalies and puzzles, where asset prices are driven by factors that basic finance theories fail to predict sufficiently. Hudson and Green (2015) posit that to explain these anomalies, finance research has been extended to integrate psychological insights with neo-classical economic theories, which is concerned with the formation, development and effects of investor sentiment on asset returns.

In the context of climate transition during the COVID-19 pandemic, we address these issues and make three key contributions. First, we explore the co-movement between Economic Sentiment and the performance of climate financial instruments since the beginning of the pandemic. Second, we adopt an econometric technique, namely the Quantile-spectral (coherency), which enables us to examine the evolution of comovement across different investment horizons such as weekly, monthly and yearly. Lastly, we estimate a sub-sample that focuses on the first wave of the pandemic, during which the level of sentiment and uncertainty was considerably high. The Economic Sentiment (ES) Index is a high frequency measure of economic sentiment based on lexical analysis of economics-related news articles by Shapiro et al. (2020). The rest of this paper unfolds as follows: the next section presents the review of related literature. Section 3 presents the description of data and empirical methodology while Sect. 4 presents and discusses the results. Section 5 presents the conclusion.

2 Related Studies

Ye and Xue (2021) posit that earlier empirical analysis of financial market behaviour document that financial market investors' decision may be significantly influenced by noise (see e.g. Black, 1986; De Long et al., 1990; Mendel & Shleifer, 2012) as well as cognition bias (see e.g. Barberis et al., 1998; Daniel et al., 1998). Further, Mittal and Goel (2012, p. 15) argue that sentiment associated with opinion, evaluation, sentiments, attitudes and emotions expressed through different media outlets has been proven to affect investors' opinions. Hence, Baker and Wurgler (2006) characterized investor sentiment as the optimism or the pessimism expressed by an investor concerning stock market performance in the future. Following this, an increasing empirical studies that focused on the interactions between media content and stock market performance (see e.g. Tetlock, 2007; Bollen et al., 2011; Garcia, 2013; Nguyen et al., 2015; Lehrer et al., 2021). Specifically, Tetlock (2007) examined the association between media content and equity market activity based on daily content from *The Wall Street Journal* column from 1984 to 1999 and documented that news media content predicts changes in both equity prices and trading volume. Besides, Garcia (2013) demonstrate that the predictability of equity prices using news' content strengthens during recessions.

As noted in Piñeiro-Chousa et al. (2021), investor sentiment may also be measured using linguistic analysis tools which extract the sentiment directly from texts. This particular technique has been widely used by several past studies to capture sentiments from popularly used social networks including Twitter (see e.g., Ranco et al., 2015; Zhang et al., 2016) or StockTwits (López-Cabarcos et al., 2019) or from websites including Yahoo! Finance (Kim & Kim, 2014), or even from the news (Broadstock & Cheng, 2019). In particular, using the S&P 500 Index, Gan et al. (2020) confirmed that in contrast to the traditional news outlet, social media has become the dominant media source in recent years. Following this, increasing empirical evidence has emerged demonstrating the existence of clear evidence that sentiment from social media predicts the performance of equity markets (see e.g., Brown & Cliff, 2005; Asur & Huberman, 2010; Oh & Sheng, 2011; Liu, 2015). Particularly, these studies generally conclude that social network sentiment has the potential to considerably influence the level of stock market activity. In this respect, past studies including Zhang et al. (2011) and Piñeiro-Chousa et al. (2018) focus on the interactions between social network sentiment and the S&P 500 Index, describing the index as a reference for the equity market.

Moreover, You and Wu (2012) argue that sentiment expressed by news articles also exhibits the potential to influence investors, culminating in changes in opinion that may alter standard investors' behaviour which may affect the performance of equity markets. Basically, empirical studies in this category depend on news media contents from popularly read newspaper and periodicals to capture sentiment. Shiller (2000) argued that news media has the potential to influence readers' beliefs about the state of the economy by choosing the tone to draw attention to particular positive or negative events such as global financial crisis or the outbreak of global health crisis such as the COVID-19 pandemic. In particular, Shapiro et al. (2020) and Aguilar et al. (2021) developed newspaper-based economic sentiment indicators for the United States and Spain, respectively. This indices allows monitoring of the interactions between sentiment about future economic activity, providing significant information that has the potential to influence investors' opinions.

Following this, an increasing number of studies have emerged with focus on the predictive accuracy of economic news sentiment for equity prices (see e.g. Calomiris & Mamaysky, 2019; Lee, 2020; Balcilar et al., 2020) and the EU carbon prices such as in Ye and Xue (2021). Given that climate financial instruments are relatively new asset class, few past studies have focused on the effects of investor sentiment on their performance. For instance, Broadstock and Cheng (2019) show empirically that the interactions between green and other conventional bonds is sensitive to changes on news-based sentiment about green bonds. Also, Piñeiro-Chousa et al. (2021) focused on the impact of investor sentiment through social media on the performance of green bonds. However, to the best of our knowledge, this is the first empirical analysis of the connections between economic sentiment during the COVID-19 pandemic and climate transition through the lens of the performance of green bonds and other climate-themed indices.

3 Data and Empirical Methods

3.1 Data

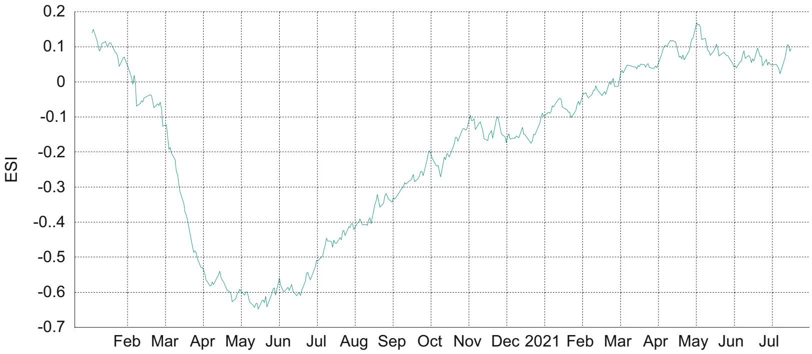
In this paper, we rely on high frequency daily data on Economic Sentiment (ES) Index and four measures of the performance of firms whose business model are compatible with climate transition for the period from January 02, 2020 to July 18, 2021. All the climate transition indexes are converted into daily returns as the natural logarithm of the price changes, i.e., $log(P_t/P_{t-1})$. The daily News Sentiment Index (NS) used in this study measures economic sentiment based on a lexical analysis of economics-related news articles as discussed in Buckman et al. (2020) and Shapiro et al. (2020). As described in Shapiro et al. (2020), sentiment scores are constructed from economics-related news articles from 24 major U.S. newspapers that cover all major regions of the country, including some with extensive national coverage such as the New York Times and the Washington Post. Articles used are those with not less than 200 words with topic as "economics" and the country subject as "United States".

Regarding our measure of climate transition, we use four S&P Dow Jones indexes including S&P 500 Climate Transition Index (SPCTI); S&P 500 Green Bond Select Index (SPGB); S&P 500 Paris-Aligned Climate Index (SPPACI); and S&P 500 Paris-Aligned Climate Sustainability Screened Index (SPPACSSI). Specifically, SPCTI is designed to track the performance of constituent firms in the S&P 500 whose business model is build around the climate transition; SPPACI series covers all the elements of the SPCTI series, but are differentiated by their additional restrictiveness and ambition, shown through their additional constraints and eligibility requirements. The indices apply exclusions based on companies' involvement in specific business activities, performance against the principles of the United Nations' Global Compact (UNGC), and involvement in relevant ESG controversies. Lastly, the SPPACSSI is designed to measure the performance of eligible constituent equity securities, selected and weighted to be collectively compatible with a 1.5 °C global warming climate scenario at the index level while SPGB is a market value-weighted subset of the S&P Green Bond Index that measures the performance of green-labeled bonds issued globally, subject to stringent financial and extra-financial eligibility criteria.

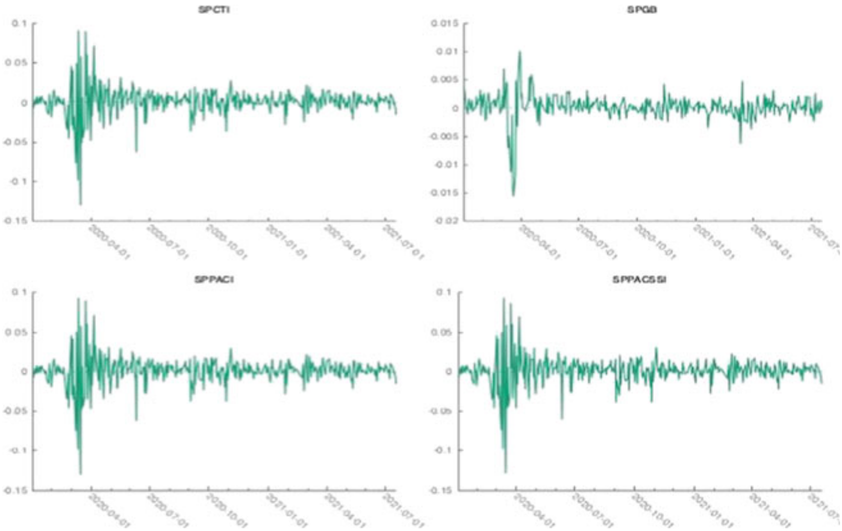
Figures 1, panel a–b and 2 display the evolution of the time series for this study and the contemporaneous correlation matrix. In both panel a and b in Fig. 1, the effects of COVID-19 pandemic is very visible, especially during the first wave of the crisis in 2020. This resulted in a notable drop in sentiment and an increase in return volatility due to fear and uncertainty in the global macroeconomy and financial markets. However, beginning from early July 2020, there appear to have been a sustained improvement in economic sentiment as the sentiment index rose steadily from this period. This coincides also with reduction in the level of return volatility in the financial market as climate transition indexes witnessed sustained increase in their stock prices. As shown by the heatmap in Fig. 2, as expected, correlations are positive and strong among the selected indexes of climate transition. However, correlations are negative between economic news sentiment and all the climate transition indexes. This confirms that the severe disruptions to daily life as well as economic activity caused by the COVID-19 pandemic which led to negative economic sentiment exhibit negative correlation with the performance of firms whose business model is concerned with climate transition. The strength of correlation is least with SPGB suggesting that the effects of the temporary disruption in sentiment was least for green bonds due to its long term investment horizon.

Furthermore, we show the descriptive statistics and results of the ADF unit roots test in Table 1. As shown in the table, the mean news sentiment index for the period under study is about -0.185. For the climate indexes, the highest mean return of about 0.0009 is associated with SPPACSSI while SPCTI and SPPACI share an equal mean of about 0.0008. As expected, the SPGB index has the least mean of about 0.0002. Among all the indexes, news sentiment appear to be the most volatile as shown by the standard deviation. This is expected given the swing in economic conditions during the sample period, mainly due to the COVID-19 pandemic. Also, all the transition indexes exhibit positive excess kurtosis, suggesting the existence of fat tails. All the indexes are negatively skewed. Given that the econometric technique employed in this study assumes that all the series are strictly stationary, we conduct the unit roots tests using the ADF test. The results show that all the series are stationary after the first difference.

Lastly, another crucial assumption of our econometric framework is that the time series are non-linear. Therefore, to further validate the use of the cross-spectral technique, we applied the BDS test, developed by Broock et al. (1996) on the time series of residuals retrieved from a Vector Autoregressive (VAR) model. Table 2 shows the BDS test results using the VAR model's filtered residuals for all the indexes across five dimensions ($m = 2, 3, \ldots 6$). For all the indexes and across all dimensions, the null hypothesis of linearity is rejected, offering evidence of non-linearity in all the indexed across different dimension. This justifies the use of a nonlinear econometric technique of analysis, that enable us to explore the heterogeneous interactions between economic news sentiment and the chosen climate transition indexes.



(a) Plot of Economic Sentiment Index



(b) Plot of Climate transition indicators

Fig. 1 Plots of News sentiment index and climate transition indexes. (**a**) Plot of economic sentiment index. (**b**) Plot of climate transition indicators

3.2 Empirical Methods

This paper is primarily concerned with the effects between economic sentiment and climate transition since the COVID-19 pandemic. To do this, we examine the comovement between changes in sentiment index and the performance of corporations whose business models are compatible with the climate transition as well as green bonds. We employ a recent novel econometric technique including the quantile cross-spectral (coherency) approach of Baruník and Kley (2019). This permits us to examine the dependence structure of the quantile in the tails of the

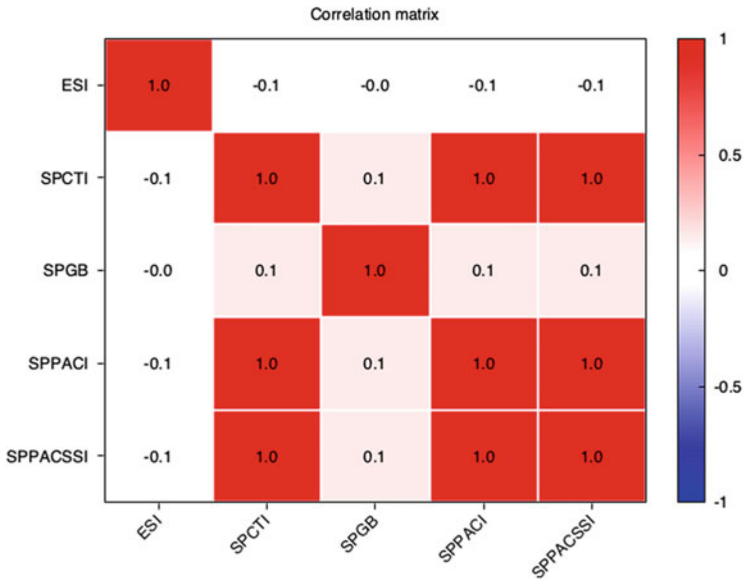


Fig. 2 Plots of correlation matrix

joint distribution and across frequencies. As noted in Maghyereh and Abdoh (2021), this methodology accounts for the presence of dependence at different market conditions (e.g., lower quantiles, intermediate quantiles and upper quantiles) and across various investment periods including the short-, intermediate- and long-term.

Following Baruník and Kley (2019), assume that $(R_t)_{t \in Z}$ represents a set, comprising two strictly stationary process, with components $R_t = (R_{t,j1}, R_{t,j2})$. The quantile coherency between these two processes denoted as $(R^{j1\ j2})$ may be written as:

$$\mathfrak{R}^{j_1 j_2}(\omega;\tau_1;\tau_2) = \frac{f^{j_1 j_2}(\omega;\tau_1;\tau_2)}{\left(f^{j_1 j_2}(\omega;\tau_1;\tau_2) f^{j_1 j_2}(\omega;\tau_1;\tau_2)\right)^{½}} \tag{1}$$

where ω denotes the time-frequency corresponding to $\omega \xi 2\pi 1/5$; $1/22$; $1/250$ respectively. Basically, the coherency (co-dependence) across these three frequencies is associated with the short-term (one week), the intermediate-term (one month) and the long-term (one year). Also, π corresponds to the periodic intervals of $\omega\xi$(-$-\pi < \omega < \pi$); τ_1 and τ_2 denotes the τth quantiles of $R_{t,j1}$ and $R_{t,j2}$ (i.e. 0.5, 0.05 or 0.95), consecutively, while $(\tau_1;\tau_2) \in [0,1], f^{\,j_1 j_2} f^{\,j_1 j_2}$ and $f^{j2\ j2}$ denotes the quantile cross-spectral density and the quantile spectral densities of processes $R_{t,j1}$ and $R_{t,j2}$, generated respectively from the Fourier transform of the matrix of quantile cross-covariance kernels represented by $\Gamma(\tau_1, \tau_2){:} = (f\omega;\ \tau_1\tau_2)_{j1\ j2}$, where:

Table 1 Descriptive statistics and ADF unit roots test

Variable	Mean	Med.	Min.	Max.	Std. Dev.	Skew.	Ex. Kurt.	ADF
ESI	−0.1852	−0.1358	−0.6473	0.1679	0.2454	−0.4747	−1.1321	−19.22*** (0.000)
SPCTI	0.0008	0.0015	−0.1304	0.0914	0.0186	−0.9207	11.935	−27.43*** (0.000)
SPGB	0.0002	0.0002	−0.0156	0.0102	0.0023	−2.0185	14.864	−21.17*** (0.000)
SPPACI	0.0008	0.0016	−0.1306	0.0934	0.0186	−0.8928	11.961	−27.58*** (0.000)
SPPACSSI	0.0009	0.0017	−0.1284	0.0935	0.0185	−0.8764	11.651	−27.68*** (0.000)

Table 2 BDS test for non-linearity from VAR model filtered residuals

Variable			Dimension		
	$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$
ESI	0.1991***	0.3384***	0.4351***	0.5020***	0.5478***
	(74.248)	(79.677)	(86.393)	(96.022)	(109.13)
SPCTI	0.0512***	0.1112***	0.1489***	0.1691***	0.1772***
	(8.9016)	(12.083)	(13.508)	(14.638)	(15.804)
SPGB	0.0419***	0.0734***	0.0900***	0.0971***	0.0937***
	(8.1607)	(8.9738)	(9.2213)	(9.5051)	(9.5051)
SPPACI	0.0505***	0.1094***	0.1458***	0.1654***	0.1732***
	(8.8053)	(11.931)	(13.281)	(14.362)	(15.496)
SPPACSSI	0.0478***	0.1034***	0.1377***	0.1559***	0.1631***
	(8.4514)	(11.436)	(12.728)	(13.756)	(14.828)

$$\gamma^{j_1 j_2} := Cov\left(I\left\{X_{t+k,j_1} \leq q_{j_1(r_1)}\right\}, I\left\{X_{t+k,j_2} \leq q_{j_2(r_2)}\right\}\right) \tag{2}$$

Furthermore, for j_1, j_2 1, d, k Z, τ_1, τ_2 [0, 1] an I $\{A\}$ represent the indicator function of event A. To generate details for serial and cross-sectional dependence, K is varied while $j_1 j_2$ is restricted. The matrix of quantile cross-spectral density kernels $f(\omega; \tau_1, \tau_2) := (f(\omega; \tau_1, \tau_2))_{j1\ j2}$, is generated from the frequency domain where:

$$f^{j_1 j_2}(\omega; \tau_1; \tau_2) := (2\pi)^{-1} \sum_{k=-\infty}^{\infty} \gamma_k^{j_1 j_2}(\tau_1; \tau_2) e^{-tk\omega} \tag{3}$$

Quantile coherency is estimated by the smoothed quantile cross-periodogram as defined below:

$$\widehat{G}_{n,R}^{j_1 j_2}(\omega; \tau_1; \tau_2) := \frac{2\pi}{n} \sum_{s=1}^{n-1} W_n\left\{w - \frac{2\pi s}{n}\right\} I_{n,R}^{j_1 j_2}\left\{\frac{2\pi s}{n}, \tau_1; \tau_2\right\} \tag{4}$$

where $I^{j1,j2}$ denotes the matrix of rank-based copula cross periodograms (CCR-periodograms) while W_n corresponds to a sequence of weight functions. Thus, the estimator for the quantile coherency may be written as:

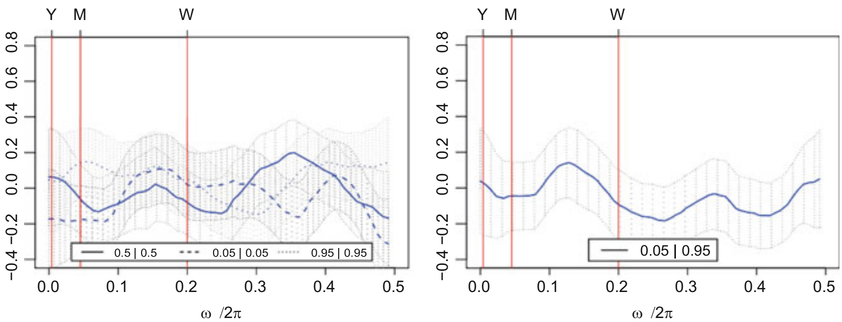
$$\mathfrak{R}_{n,R}^{j_1 j_2}(\omega; \tau_1; \tau_2) := \frac{\widehat{G}_{n,R}^{j_1 j_2}(\omega; \tau_1; \tau_2)}{\left\{\widehat{G}_{n,R}^{j_1 j_2}(\omega; \tau_1; \tau_1) \widehat{G}_{n,R}^{j_1 j_2}(\omega; \tau_2; \tau_2)\right\}^{½}} \tag{5}$$

Lastly, as in previous studies such as Maghyereh and Abdoh (2021), we explore the coherency matrices for three quantiles such as 0.05, 0.5 and 0.95, which is associated with the lower, mid and upper quantiles, respectively as well as the combinations of quantile levels including 0.05|0.05, 0.5|0.5, 0.95|0.95. This permits me to examine dependence under the left, intermediate and right tails of the distributions. Also, as in Baruník and Kley (2019), the quantile cross-spectral density kernels $f^{j1\,j2}$ (ω; τ_1, τ_2) in Eq. (1) may be decomposed into real and imaginary parts. However, following Maghyereh and Abdoh (2020), the real part represents the co-spectrum of the following processes: $\left(\mathrm{I}\left\{R_{t,j_1} \leq q_{j_1}(\tau_1)\right\}\right) t \in z$ and $\left(\mathrm{I}\left\{R_{t,j_2} \leq q_{j_2}(\tau_2)\right\}\right) t \in z$ while the imaginary part corresponds to the quadrature spectrum that circumvents several sources of noise coherence. To improve readability and clarity in presentation, I follow previous studies such as Maghyereh and Abdoh (2020) and Maghyereh and Abdoh (2021) by presenting only the real part of the quantile coherency estimates.

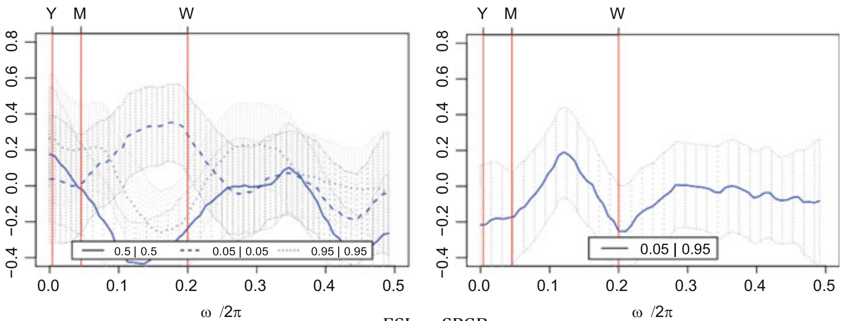
4 Results and Discussion

In this section, we present and discuss results of quantile coherency between economic sentiment and the chosen four indicators of climate transition. The realized results from the quantile cross-spectral analysis are presented in Figs. 3 and 4 for the full sample and the COVID-19 peak period sample, respectively. In both cases, we follow past studies such as Maghyereh and Abdoh (2020) where all presented plots represent the real part of the quantile coherency estimates for the lower, middle, and upper quantiles (0.05|0.05, 0.5|0.5, and 0.95|0.95) of the joint distribution across the different frequencies. Across the interval [0, 0.5], the daily cycles are denoted on the horizontal axis while the co-dependence between each pair of two time series are presented in the vertical axis. The frequencies cycles labeled on the upper horizontal axis show how weekly (W), monthly (M) and yearly (Y) frequencies are connected across quantiles of the joint distribution. As an instance, if the sample frequency corresponds to 0.2, it implies that there is 0.2 cycles per day, translating to a period of 5 days.

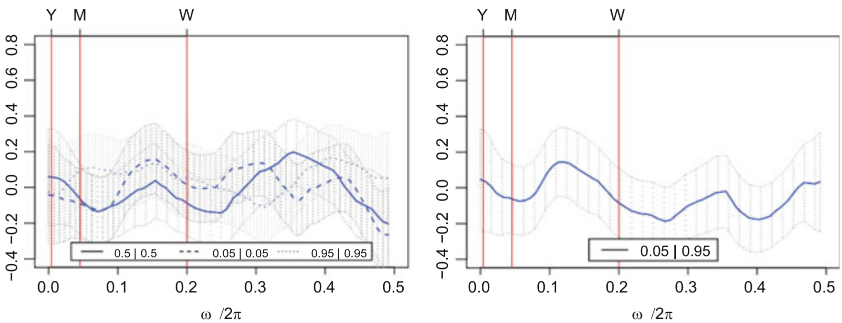
Generally, results for the full sample as shown in Fig. 3 suggest that the dependence between economic sentiment and each climate transition index varies across both return distribution and time scales, indicating that dependence changes based on market conditions and investment horizons. Specifically, for the normal market return (0.5 quantile), results show that dependence between economic sentiment and the four climate transition indices is stronger during the weekly frequency cycles. This implies that across the coherency between economic sentiment with the chosen indices is higher in the short-term during normal market condition. In addition, dependence appear to be mostly positive in the yearly frequency cycles but mainly negative in both the weekly and monthly cycles, especially with green bonds. Also, dependence is strongest and mostly negative in the weekly cycle between economic sentiment and green bonds (SPGB). The strongest positive dependence is exhibited with the climate transition index (CTI) in the weekly frequency cycle and with green bond (SPGB) in the yearly frequency cycle while strongest negative dependence



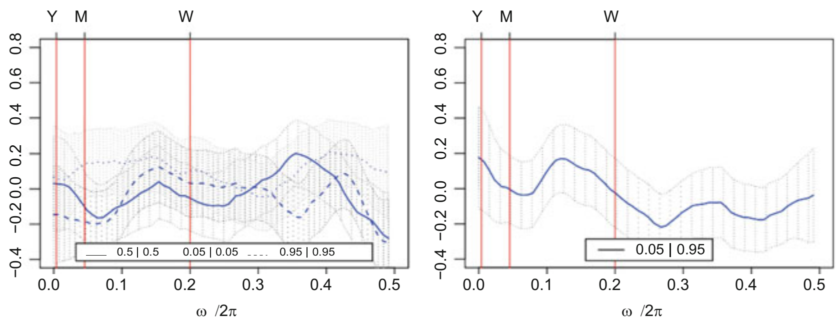
(a) ESI vs CTI



(b) ESI vs SPGB



(c) ESI vs SPPACI



(d) ESI vs SPPACSSI

Fig. 3 Quantile coherency estimates for the 0.05|0.05, 0.5|0.5, and 0.95|0.95 of the joint distribution across different frequencies for the full sample. Note: Plots of the real part of the quantile occurs with the green bond (SPGB) in both the weekly and monthly cycles. Taken together, these results suggest that as market conditions normalized during the study period, negative dependence occurred between economic sentiment and the performance of climate-themed financial instruments mostly in the weekly and monthly cycles, especially with green bonds. However, when the time horizon is increased to the yearly, dependence becomes mainly positive.

Regarding the bearish market condition as shown by the lower quantile (0.05), results suggest that in the weekly cycle, the dependence between economic sentiment and the climate transition index (CTI) and Paris-aligned climate sustainability screened index (SPPACSSI) are either zero or negative while there are periods of positive dependence with the Paris-aligned climate index (SPPACI) and green bonds (SPGB). However, as the time scale increasing to monthly, dependence is positive with green bonds but for the other three indices, dependence switches from negative to positive before the end of the time scale. As the time scale increases further to yearly, dependence is mainly negative, especially with CTI while the dependence with green bond is positive but low. In sum, the strongest dependence occurs in the monthly cycle and between economic sentiment and green bonds. With particular reference to climate-aligned financial instruments, the key take-away from these results is that when market conditions are very poor, dependence (coherency) is strongest between economic sentiment and the performance of green bonds in the intermediate time horizon. This suggests that when changes in economic sentiment persists into the monthly cycle, its effects on green bonds gets stronger than in the short and long-term.

Concerning the level of dependence with the four climate transition indices under the bullish market condition (0.95 quantile), results show that for the weekly time scale, dependence (coherency) is initially positive but switches to negative towards the end of this time horizon. The dependence between economic sentiment and CTI, SPPACI and SPPACSSI remains positive when the time horizon is increased to both monthly and yearly cycles. However, the dependence with green bonds (SPGB) switches from negative to positive at the end of the monthly cycle but becomes positive throughout the yearly cycle. Generally, the strongest dependence under this market condition occurs with green bonds (SPGB) under the yearly cycle. The implication of these findings is that at the higher quantiles of the distribution, dependence between economic sentiment and the chosen climate transition indices is mostly negative in the short-term and the beginning of the intermediate term especially for CTI, SPPACI and SPPACSSI. However, in the long-term, dependence becomes positive and strongest with green bonds. This suggests that when the market condition is good, increase in economic sentiment may have positive effects

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Fig. 3 (continued) coherency estimates of Baruník and Kley (2019) for 0.05, 0.5, and 0.95 quantiles together with 95% confidence intervals. W, M, and Y denote weekly, monthly, and yearly periods, respectively. The ____, ------ and ___ line corresponds to the 0.5, 0.05 and 0.95 quantiles, respectively

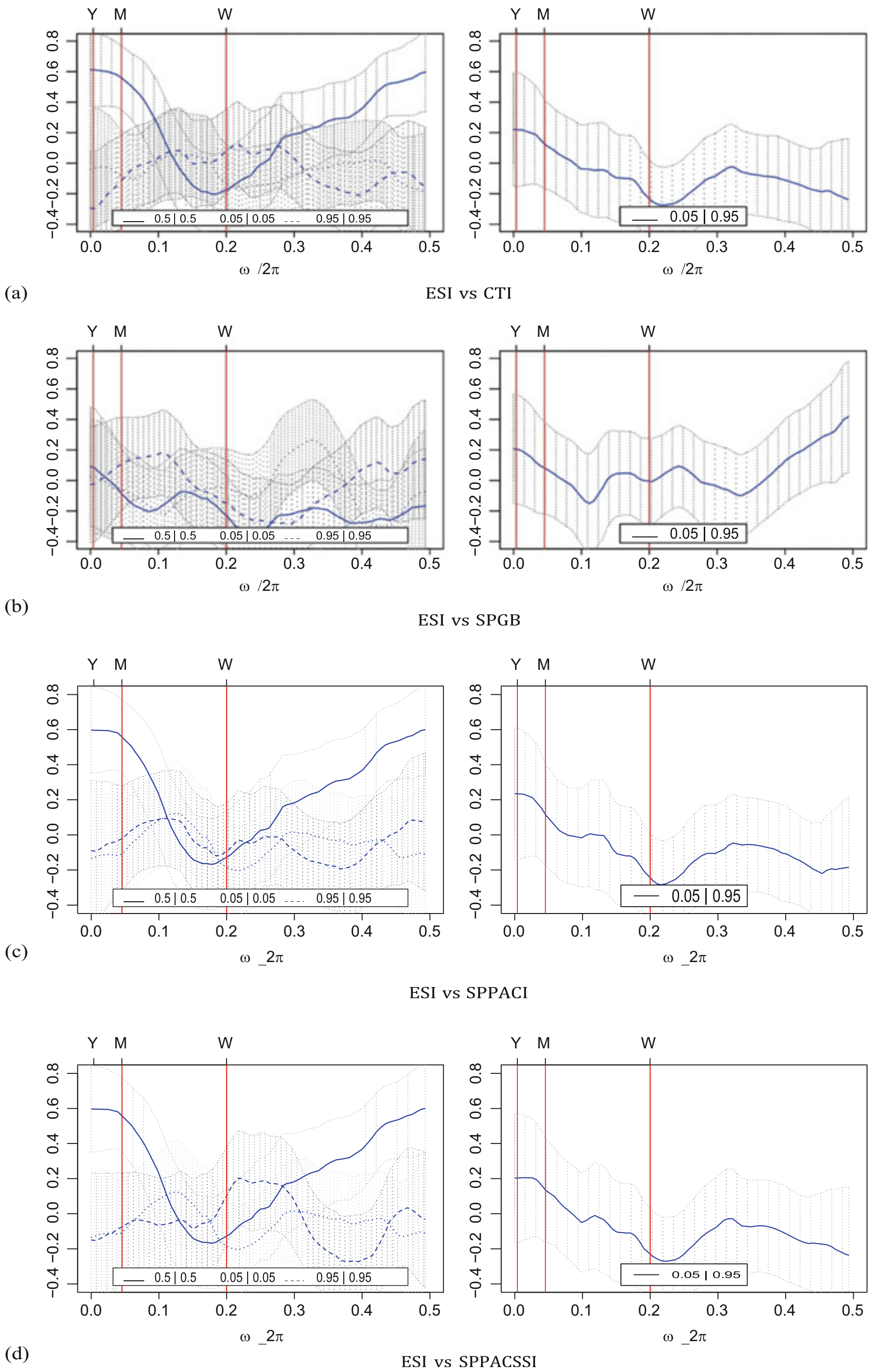

Fig. 4 Quantile coherency estimates for the 0.05|0.05, 0.5|0.5, and 0.95|0.95 of the joint distribution across different frequencies for the COVID-19 peak period sample. Note: Plots of the real part

on the performance of green bonds, which may translate to improved mobilization of financial resources to support climate transition.

Moreover, the plots in the right shows the evolution of coherency based on the quantile cross-spectral for 0.05|0.95 quantiles of the joint distributions. This enables us to shed light on dependence assuming that either economic sentiment or any of the four climate transition indices records large negative changes (0.05 quantiles) while one of the indices in the pair, exhibits large positive changes (0.95 quantiles). The results show that in the weekly time horizon, dependence is mostly negative and fairly weak for pairs comprising large negative changes (0.05 quantiles) of economic sentiment and large positive changes (0.95 quantiles) for each of the four climate transition indices. The weakest dependence under this time scale occurs with the green bond index. When the time scale if increased to monthly, results show that dependence switches from negative to positive, especially in the case of green bonds. However, results are mixed when the time scale increases to yearly. While dependence with green bonds becomes negative, it is positive with Paris-aligned climate sustainability screened index but switches from negative to positive at the end of the time horizon. In sum, these results suggest that the dependence between the performance of the four climate-themed financial indices considered with economic sentiment was stronger in the intermediate term following the large negative changes in economic sentiment due to the global uncertainty created by the outbreak of the COVID-19 health crisis.

Moving forward, Fig. 4 presents the evolution of coherency between economic sentiment and the four climate-themed indices during the peak of the COVID-19 pandemic which we spanned from January 02, 2020 to July 31, 2020. During this period as shown in Fig. 1, the level of economic sentiment was at its lowest levels. Regarding normal market returns (0.5 quantiles), results show a similar pattern of increased dependence across the weekly, monthly and yearly cycles for all the climate-themed indices except green bonds. Particularly, results show that at the peak of the COVID-19 pandemic, dependence with economic sentiment was mostly positive and stronger than the lower and higher quantiles. Although, dependence was negative and lowest at the beginning of the monthly cycle, it switches to positive and rose till the end of the yearly cycle. Dependence under this market condition, is stronger than the dependence under the other market conditions, it is also strongest in the short-term. However, the dependence with green bonds is mostly negative and strongest at the end of the weekly cycle.

Results for the lower (0.05 quantiles) of the distribution shows that dependence was mostly negative in the weekly and yearly cycles, except with green bonds, where it was positive in the yearly cycle. In the monthly cycle, dependence remained negative with SPPACSSI but positive with green bond and SPPACI. Regarding

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Fig. 4 (continued) of the quantile coherency estimates of Baruník and Kley (2019) for 0.05, 0.5, and 0.95 quantiles together with 95% confidence intervals. W, M, and Y denote weekly, monthly, and yearly periods, respectively. The ____, ------ and ___ line corresponds to the 0.5, 0.05 and 0.95 quantiles, respectively higher (0.95 quantiles) dependence, results show mostly negative dependence with CTI, SPPACI and SPPACSSI both in the weekly and yearly cycles while there is a switch from negative to positive dependence during the monthly cycle. However, the dependence with green bond shows a switch from negative to positive during the weekly cycle but remained negative throughout the monthly and yearly cycles. Results also shows that although dependence was strongest in the weekly cycle, this occurred with green bonds at the normal returns quantiles.

Lastly, plots at the right hand side in Fig. 4 shows the evolution of dependence based on the quantile cross-spectral for the 0.05|0.95 quantiles of the joint distributions. There are notable differences in the pattern of dependence across the three time horizons for the climate-themed indices, except for the green bonds. Specifically, results show that for the CTI, SPPACI and SPPACSSI, dependence with economic sentiment is generally negative under the weekly cycle before switching to positive at the later part of the monthly cycle and throughout the yearly cycle. Regarding the dependence with green bonds, results show that dependence with economic sentiment was mostly positive in both the weekly and yearly cycles while it was mainly negative in the monthly cycle. Taken together, the strongest dependence under the 0.05|0.95 quantiles occurred with green bonds in the short-term while in the long-term, dependence was slightly stronger with SPPACI. These results imply that during the peak of the COVID-19 pandemic, the 0.05|0.95 quantiles dependence between economic sentiment with the four climate-themed financial indices was mainly negative in short-term, except for green bonds. However, dependence became positive as the low levels of economic sentiment persisted into the monthly time horizon.

5 Conclusion

The on-going COVID-19 pandemic has significantly impacted the global macroeconomic conditions as well as the financial markets. This has attracted the interest of both researchers and policy markets regarding the potential effects of the pandemic on the progress towards achieving the SDGs, especially the 13th goal which concerns actions to combat climate change and its impacts. The role of the global financial markets in combating climate change has become indispensable, given the need to mobilize and channel the required financial resources to finance the transition towards a green and low-carbon economy. This study contributes to this debate by investigating the dynamic dependence between a newspaper-based economic sentiment index for the United States and four climate-themed financial indices since the COVID-19 pandemic using the quantile cross-spectral dependence technique of Baruník and Kley (2019). This approach considers upper, normal and lower tails (or quantiles) dependence across different time frequencies including daily, monthly and yearly. This technique enable a rich analysis with crucial implications for investors who seek to minimize the likelihood of extreme losses during this turbulent market period.

Generally, the results indicate that right-tail dependence between economic sentiment and the four climate-themed financial indices using daily data since the outbreak of the COVID-19 pandemic. For this purpose, we use the quantile cross-spectral technique of Baruník and Kley (2019), which allows dependence to vary across different time horizons and market conditions. Results show that when market conditions are very poor, dependence (coherency) is strongest between economic sentiment and the performance of green bonds in the intermediate time horizon. This suggests that when changes in economic sentiment persists into the monthly cycle, its effects on green bonds gets stronger than in the short and long-term. However, under normal market returns, results show a similar pattern of increased dependence across the weekly, monthly and yearly cycles for all the climate-themed indices except green bonds. Moreover, results show that at the peak of the COVID-19 pandemic, normal returns dependence with economic sentiment was mostly positive and stronger than the lower and higher quantiles. Lastly, the strongest dependence under the 0.05|0.95 quantiles of the joint distribution during the peak of COVID-19 pandemic occurred with green bonds in the weekly cycle.

In sum, these results suggest that the dependence between the performance of the four climate-themed financial indices considered with economic sentiment was stronger in the intermediate term following the large negative changes in economic sentiment due to the global uncertainty created by the outbreak of the COVID-19 health crisis. In addition, the findings suggest that the dependence between economic sentiment and the climate-themed indices (except green bonds), decreased mostly within their respective intermediate return quantiles during the peak of the COVID-19 pandemic. This shows that during the peak of the pandemic, the performance of climate-themed investments exhibited strong dependence with the level of economic sentiment in both the short- and long-terms than in the intermediate term. This implies that short- and long-term green investments may have been significantly affected by changes in economic sentiment as the number of COVID-19 cases and deaths increased. This has crucial implications for investors in green finance because understanding the dependence between economic sentiment and green financial assets returns during global economic/financial crisis is important in identifying factors that may drive the future potential of the global financial market in supporting climate transition over different time frequencies. Moreover, these findings imply that the potential of financial markets to support climate transition through attracting financial resources depends on the level of economic sentiment and may be biased due to market conditions (bullish or bearish) as well as the time frequency.

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The Impact of COVID-19 on the Volatility Transmission Across Equity and Commodity Markets

Salma Tarchella, Hela Mzoughi, and Fateh Belaid

Abstract The economic impact of the containment measures enacted in most countries as a result of the health crisis caused by the COVID-19 pandemic is unprecedented. Within this context, the main purpose of this analysis is to explore the impact of COVID-19 on the volatility transmission among American, European, and Chinese stock, energy, and commodity markets, both in the short and long-run. The empirical findings highlight that the COVID-19 pandemic has a strong impact on the linkages between the studied markets. The volatilities, correlations, and connectedness are stronger during the COVID-19 time lapse. However, these results vary between the short-run and the long-run investment horizons.

Keywords COVID-19 · Stock markets · Commodities · Interactions · Wavelet coherence · Wavelet causality

1 Introduction

The ongoing economic crisis is abviously a result of the health crisis caused by the COVID-19 pandemic showing negative economic, financial, social, cultural, environmental, and political consequences. Accentuated by the drastic containment imposed in most countries, the crisis led to a sharp reduction in trade and wide variations in exchange rates. Up to now, the outlook remains highly uncertain, as risks of new waves of contagion, a reversal of capital flows, and a further decline in international trade are still looming on the horizon. According to the Financial Times

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(2020),[1] there is a consensus among economists that the novel corona-virus would plunge the world into a global recession. The International Monetary Fund states that it expected a global recession that would be at least as bad as the 2008 financial crisis (Georgieva 2020).

Ramelli and Wagner (2020) illustrate how markets are adjusting to the rapid emergence of a previously neglected risk. These results suggest that the market fairly quickly began to respond to concerns about the possible economic consequences of the novel coronavirus. They affirm that the reaction happened in quite an orderly fashion, focusing on international trade. In late February and early March, there have been significant price movements in the global market. But behind these feverish price movements, certain trends are emerging. In particular, the cross section of stocks reveals that investors have started to worry about the potential amplifications of the COVID-19 shock through financial channels. Alfaro et al. (2020) show that unexpected changes in the trajectory of COVID-19 infections predict US stock returns, in real time. Indeed, using logistic models, they find that COVID-19 related losses in market value at the firm level rise with capital intensity and leverage, and are deeper in industries more conducive to disease transmission. Moreover, Gerding et al. (2020) find that stock price reactions were more pronounced in countries having higher debt/GDP ratios. In the same perspective, Al-Awadhi et al. (2020) use a daily data on the 1579 stocks of both Hang Seng Index and Shanghai Stock Exchange Composite Index over the period from January, 10 to March, 16, 2020. They shed light a negative and statistically significant relationship between stock returns and both the daily change in total confirmed cases and the daily change in total cases of death.

Within this context, to assess the impact of the COVID-19 pandemic on the dynamic linkages across regional financial stock markets in termes of volatility transmission is an important issu to explore. To this end, we attempt to develop a simple, but straightforward, empirical approach to examine the impact of COVID-19 on the volatility transmission among[2] American, European, and Chinese stock, energy, and commodity markets, both in the short and long-run investment horizons. The proposed empirical approach relies on the wavelet approach.

The organization of the rest of this paper is as follows: Section 2 exposes empirical methodology. Section 3 presents the data and empirical results. Section 4 displays the robustness check results, and Sect. 5 concludes.

[1] Financial Times: Global recession already here, say top economists.: https://www.ft.com/content/be732afe-6526-11ea-a6cd-df28cc3c6a68

[2] The selection of these markets is motivated by many reasons. First, the Chinese stock market is highly integrating and a substantial increase in the dependence between it and other market (Wu et al. 2019; Xiao 2020). Second, the Chinese market acts as the epicenter of both physical and financial contagion (Corbet et al. 2020). Finally, the American and the European are two superpowers that are also affected by this novel virus.

2 Methodology

To study the interactions between China, American, and European stock markets on several time-scales, we use the wavelet technique. The use of this technique has several salient features; the most important one is the possibility of breaking down the data into several time scales.[3] Let's consider the returns of our variables be a time-series function f(t), under wavelet transform, which can be decomposed as follows:

$$f(t) = \sum_k s_{J,k}\varphi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \ldots + \sum_k d_{1,k}\psi_{1,k}(t), \quad (j, k \in \mathbb{Z})$$

Where: J represents the number of multi-resolution levels, in our study we take $J = 5$.[4] k depicts the ranges from 1 to coefficient numbers in each level. $\varphi_{J,\ k}$(t) and $\psi_{j,\ k}$(t) illustrate the approximating wavelet functions, while the coefficients $s_{J,\ k}$, $d_{J,\ k}, \ldots, d_{1,\ k}$ are the wavelet transform coefficients. Following recent past studies such as Urom et al. (2021), we use the discrete wavelet transform (DWT) and its developments regarding the maximum overlap (MODWT), which allows for a multi-resolution analysis (MRA) within time-domain segments called "scales". Progressively, high-frequency fluctuations are illustrated via the shortest scale, whereas low-frequency fluctuations are illustrated via the largest ones. The coefficients $d_{J,\ k}, \ldots, d_{1,\ k}$ disclose a rising finer scale deviation from the smooth trend and $s_{J,\ k}$ is the smooth coefficient that models the trend. Then, the initial f(t) series under wavelet approximation ($J = 5$) can be expressed as follows:

$$\mathrm{f(t)} = \mathrm{S_5(t)} + \mathrm{D_5(t)} + \mathrm{D_4(t)} + \mathrm{D_3(t)} + \mathrm{D_2(t)} + \mathrm{D_1(t)}$$

S_5(t) indicates the smooth signal and D_1(t)..D_5(t) indicate detailed ones. Then, the continuous wavelet transform (CWT) is considered to develop the wavelet coherence (WTC).[5]

3 Data and Empirical Results

In our empirical analysis, we consider variables for market portfolios of China, America, and Europe such as the Shanghai Composite (SSEC), S&P 500, and Euro STOXX 50 indices. Also for commodities, we consider oil (West Texas Intermediate

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[3] To learn more about the advantages of using this technique, see In and Kim (2006).

[4] J should describe the maximum integer such that 2^j has a value less than the number of observations.

[5] Even the DWT is very used in economic research, the CWT it is also, due to their advantages related to data decomposition of many variables at the same time, see Grinsted et al. (2004).

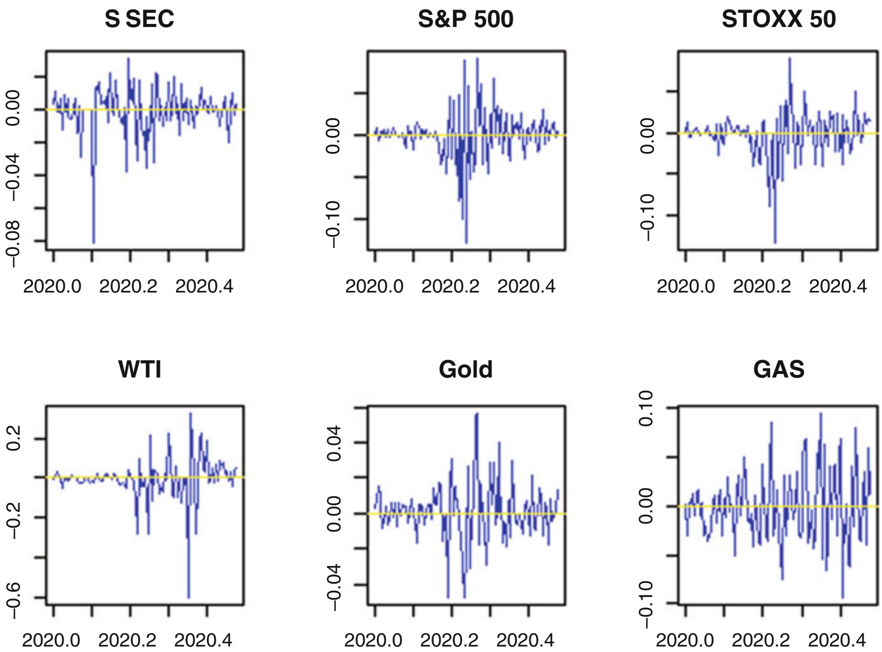


Fig. 1 Daily returns

crude oil futures contract), gas (natural gas futures contract), and gold (futures contract on gold). Our data are sourced from DataStream and Energy Information Administration for the period from first January 2020 to 29th May 2020. Figure 1 shows a period of volatility clustering for all the series during the pandemic period. Specifically, the Chinese stock market is affected at the beginning of February 2020 whereas S&P 500, STOXX 50, WTI, Gold, and GAS present a notable at the beginning of March (one month later), following the propagation of the pandemic.

Next, we attempt to analyze the interconnection between these markets within a wavelet approach. First, we decompose our series into five different frequency components and a smoothed component.[6]

Figure 2 shows a separation of the effects across time-scales and frequency bands between SSEC, S&P 500, STOXX 50, WTI, Gold, and GAS in both before and after the COVID-19 period. The considered pre-COVID-19 period goes from January second, 2019, and December 30, 2019. Figures 2a, b, and c present the wavelet correlation between SSEC, S&P 500, and STOXX 50 before the COVID-19 whereas the others are after the pandemic occurrence. Graphically, the correlation between S&P 500 and SSEC is higher after the spread of the novel corona-virus; while the

[6]The choice of a filter length $L = 8$ responds to the reasonable strategy suggesting that using the smallest L that gives reasonable results and provides the most accurate time-alignment between wavelet coefficients at various scales and the original time-series.

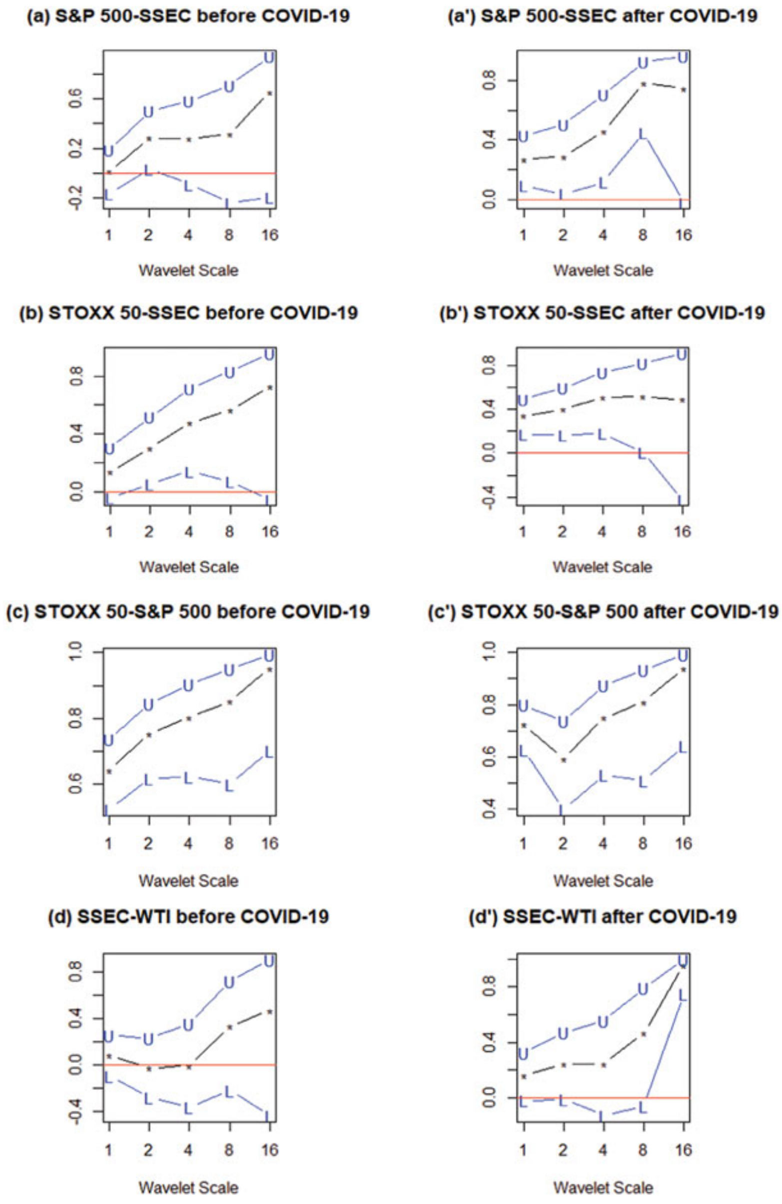


Fig. 2 Wavelet correlation before and after COVID-19. Note: The solid lines in black correspond to the wavelet covariance and correlation coefficients. The blue lines made up of "U" and "L" line represents respectively the upper and lower limits of a 95% confidence level

correlation between STOXX 50 and S&P 500 is higher than that STOXX 50 and SSEC showing a significant connection.

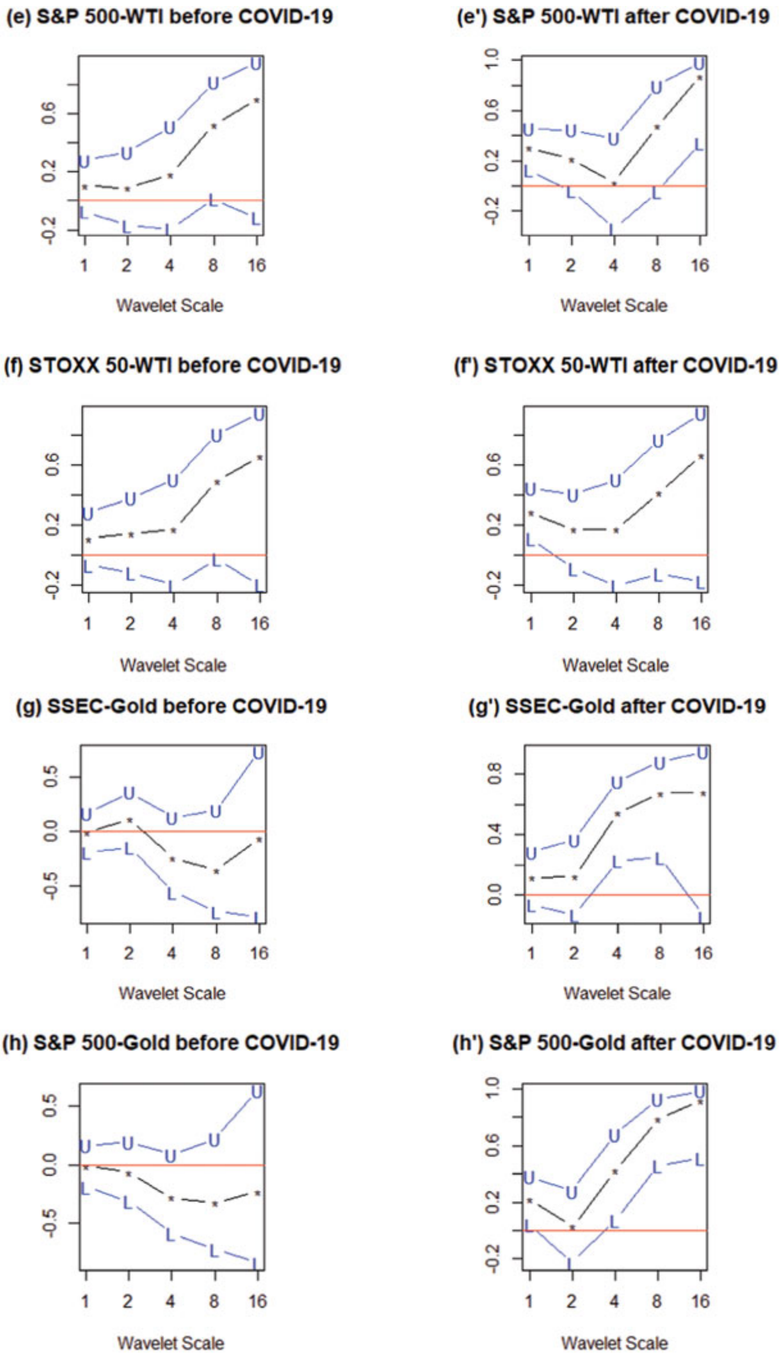


Fig. 2 (continued)

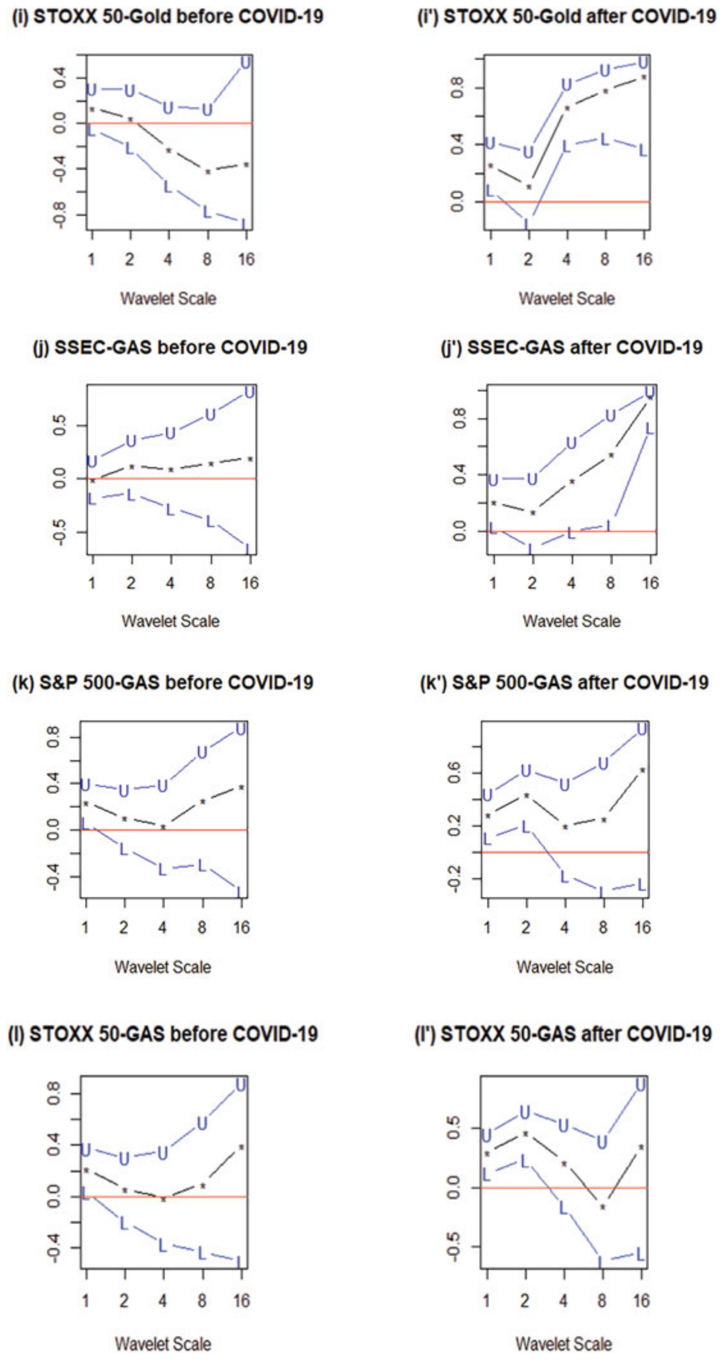


Fig. 2 (continued)

As for the relationship between stocks and commodities, they are all positive and stronger in the long run than in the short run and more intensive after COVID-19; yet they are negative for some couple before COVID-19's occurrence. These findings highlight that correlation between stock markets of China, the US, and the EU is affected by the ongoing pandemic. The positive relation with commodities suggests a weak benefit of diversification especially in the long run and the hedging is less attractive after the COVID-19, particularly in the long-term investment horizons. The two strategies seem to be inefficient during the turbulence period such as the ongoing crisis due to the COVID-19 pandemic.

Figure 3 shows a strongly significant co-movement between SSEC, S&P 500, and STOXX 50 over the post-COVID-19 period whereas the interactions are weak before. The three stock markets are in phase but the Chinese market is more volatile than the American and the European ones. These latest seem to react similarly to the bad news and follow systematically the downward movement in Chinese stock market.

The STOXX 50 and S&P 500 co-move strongly over time-scales and frequencies, except for the high frequencies (2–4 days). Figure 3c and c' show that the arrows are mostly turned right-up, especially in the long-term investment horizons (over 16–32 days) whether it is before or after the COVID-19 period. Moreover, in the long term investment horizon, the American market seems to be more volatile than the European market over the long term horizon whereas in the short term the STOXX 50 is more volatile than S&P 500, specifically during March 2020 (2–4 days) and in the end of April 2020 (4–8 days). This is due to the increasing number of deaths recorded in European countries than the American United States. Thus, the shock transmission is led in the short-run investment horizon to the European markets and to American markets in the long-run horizon. As for the oil market, Fig. 3d and d′ show a weak dependency whether before or after the ongoing coronavirus pandemic.

As for the relation before COVID-19 between S&P 500 and WTI and STOXX 50 and WTI, the figures highlight strong dependency over the 32–64 days frequency bands and the arrows are pointing down, implying that American and European stock markets lead to determinate the WTI price. Next, the Figs. 3e′ and f′ point out a weak dependency between American and European stock markets and WTI price over the 4–16 days frequency bands, starting from February to the end of April due to the severe spread of the virus and the conflict between Saudi Arabia and Russia.[7]

Likewise, the connectedness between stocks and commodities (Gold) after COVID-19 is more interesting than before. Indeed, the arrows turn to the right down denoting that the S&P 500 and SSEC lead and Gold are strongly affected. An exception, for the 4–8 days investment horizon, where the arrows turn to left-up, which meaning that the S&P 500 and Gold are not in phase at the beginning of the pandemic period. The gold price increased at the starting of the pandemic period

[7] The stoppage of economic activities in the world has pushed oil consumption down sharply and even into negative demand.

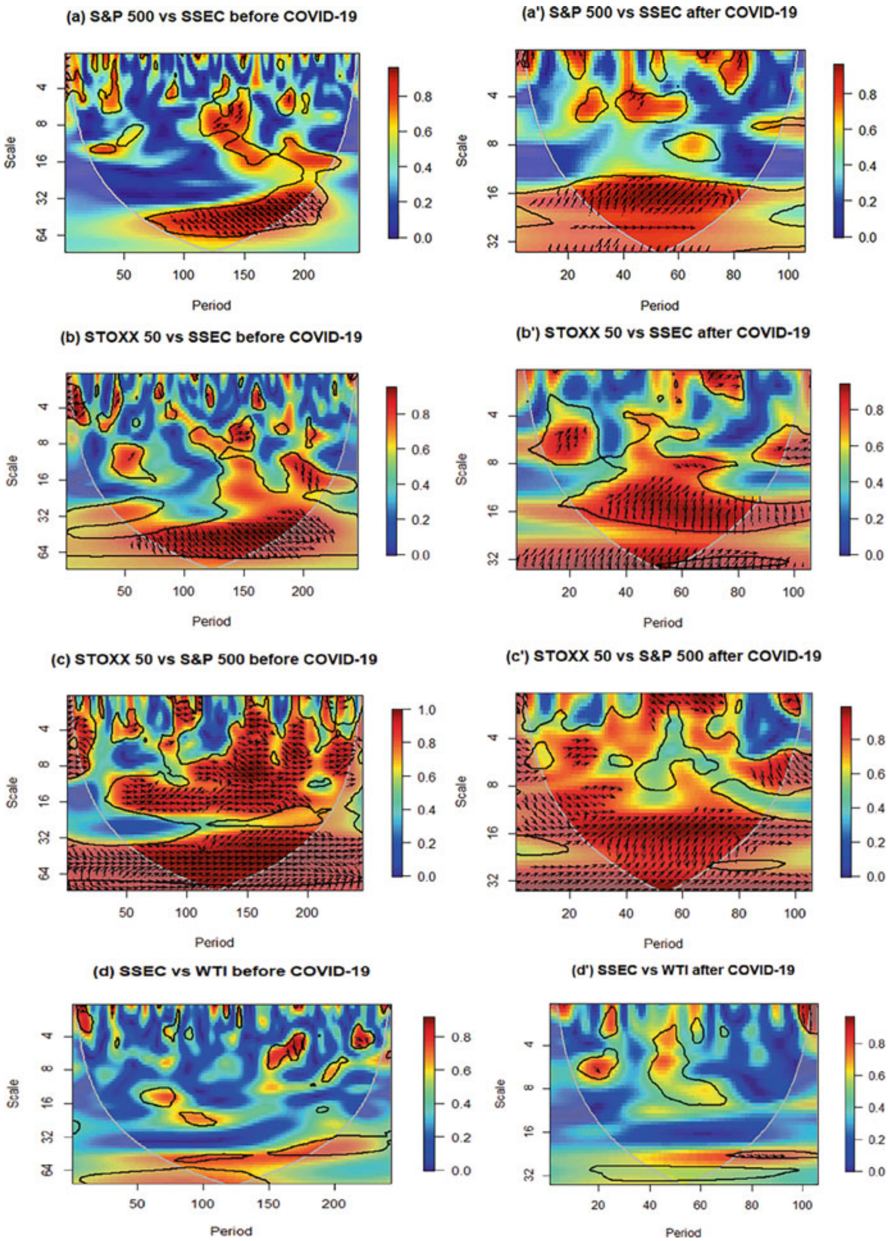


Fig. 3 Wavelet coherence plots by pair-wise estimates before and after COVID-19. Note: The thick black contour designates the 5% significance level estimate from the Monte Carlo simulations using the phase randomized surrogate series

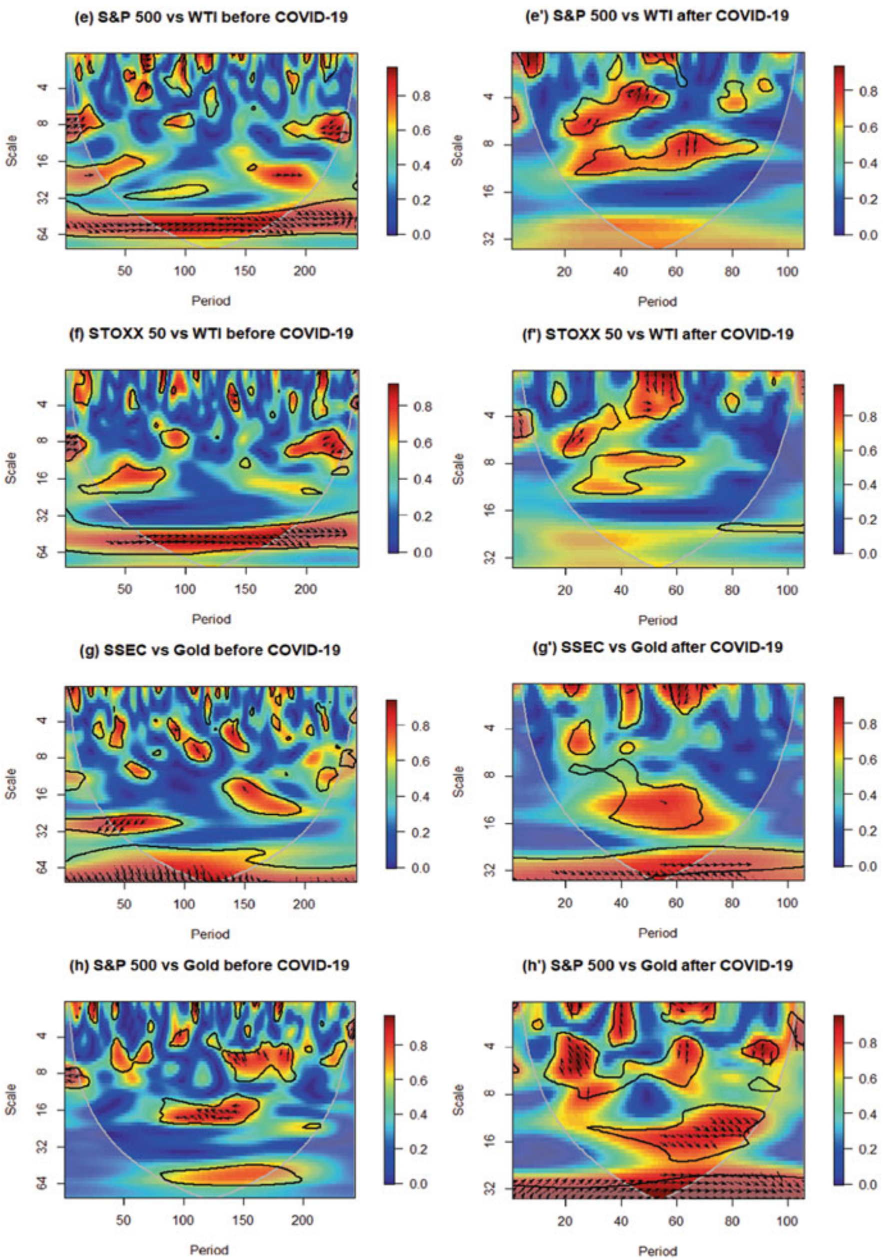
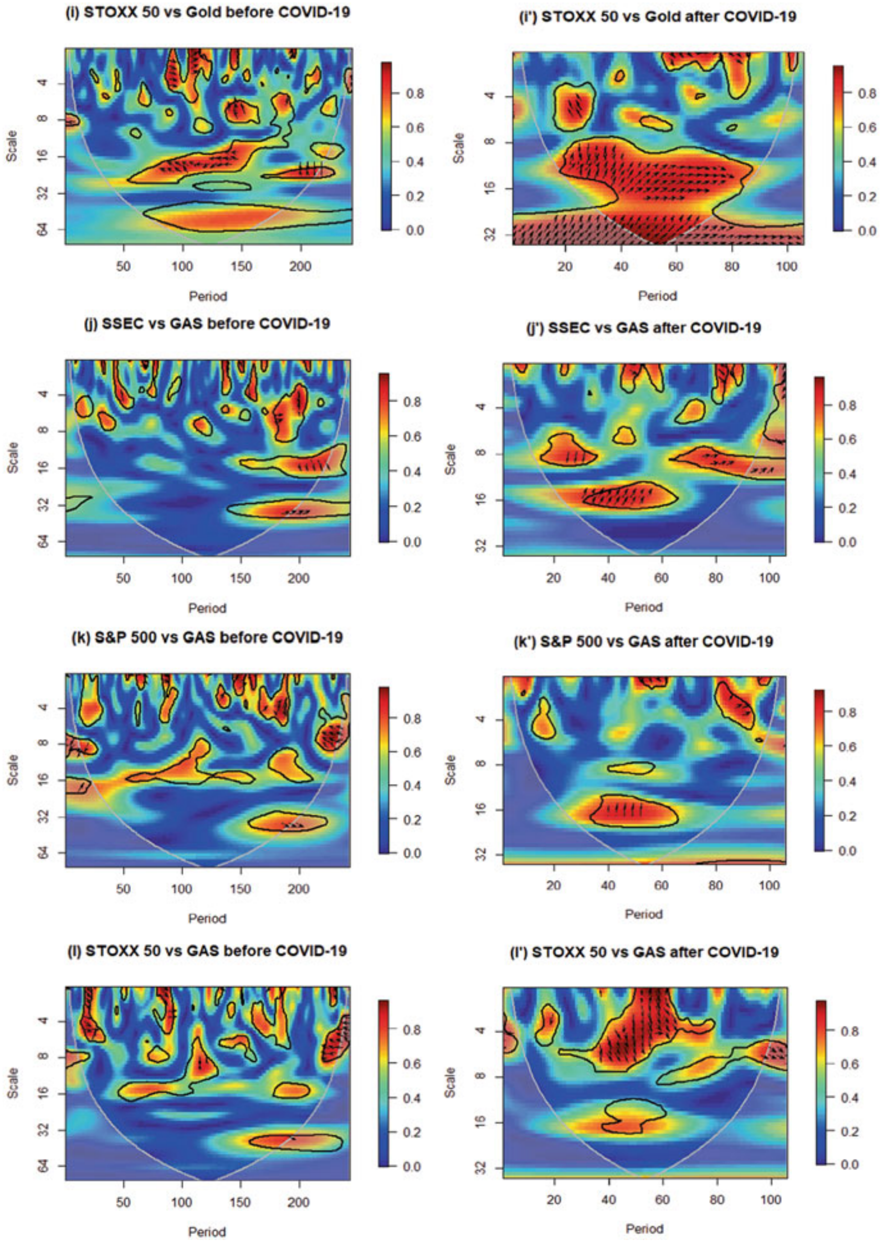


Fig. 3 (continued)



50	100	150	200
18/03/2019	31/05/2019	09/08/2019	24/10/2019

20	40	60	80	100
24/01/2020	21/02/2020	20/03/2020	20/04/2020	18/05/2020

Fig. 3 (continued)

then it decreased at the beginning of March 2020, which may be due to supply chain disruptions that affected the gold supply because of the lockdown imposed due to the COVID-19 spread.

Furthermore, the dependence between STOXX50 and Gold is strong over the 32-day's frequency band and in the 8–16 days investment horizon starting from the end of January 2020 to the midst of April. The Gold leads the European markets. This finding is in line with the findings of Baur and McDermott (2010, 2016) affirming that gold is a safe haven.

The interaction between SSEC and natural gas is more important after COVID-19 conversely of the American stock market. Indeed, for the first relation, there are more hot red zones than before COVID-19 with small zones and the arrows point to the right-up after COVID-19, indicating that the gas price is leading for these small zones.

As for the European implied volatility, the results of the relation between STOXX 50 and GAS before and after COVID-19 show the existence of huge zones of high coherence located over the short-run investment horizons. While before the COVID-19 these two markets move in the opposite direction and the European stock price is leading, they are in phase and the European stock price is leading through March and May 2020, i.e. during the COVID-19 period.

To sum up, our findings point out that the ongoing COVID-19 crisis is expected to have a greater effect on the co-movements between stock markets of China, the U. S, and E.U and energy commodity markets given the significant dependence after the pandemic occurrence.

4 Robustness Test

Table 1 presents the results of the causal relationship between selected variables after COVID-19 using the wavelet-based Granger Causality test for different investment horizons. The raw series show that there are two bidirectional causalities between SSEC and STOXX50 and between the S&P 500 and gold. Moreover, there are four unidirectional causalities from the S&P 500 to SSEC, from STOXX50 to S&P 500, from STOXX 50 to gold, and from GAS to STOXX 50. Statistically, the unsurprisingly Chinese stock price falling has a significant impact on the American stock market over very long-term investment horizons and on the European stock market over mid-and long-term scales.

The causalities between S&P 500 and STOXX 50 are bidirectional over the medium and long-term horizons whereas the bidirectional causalities between SSEC and S&P 500 are identified just on the long-term investment horizons and for the one of SSEC and STOXX 50 are identified in both the mid-and long-term scales. Also, the findings show that WTI price volatility is causing the Chinese stock market just in the very long-run (S5) and causing the American and the European stock markets for all the frequency bands; while the fall of WTI price during the

Table 1 Wavelet-based Granger causality test

Time-domain		Frequency bands (days)					
	Raw series	D1 (2–4)	D2 (4–8)	D3 (8–16)	D4 (16–32)	D5 (32–64)	S5 (> 64)
SSEC→S&P 500	1.133	3.428**	1.9374	0.130	1.522	7.893***	14.229***
S&P 500→SSEC	2.900*	0.382	3.517**	0.865	7.692***	1.497	4.193**
SSEC→STOXX 50	3.078*	1.484	0.037	4.403**	5.409***	14.251***	20.59***
STOXX 50→SSEC	3.507**	0.513	0.978	4.080**	4.848***	0.264	4.797**
S&P 500→STOXX 50	0.669	1.549	9.606***	7.443***	2.3025*	8.853***	6.707***
STOXX 50→S&P 500	7.403***	7.628***	1.944	9.781***	4.23**	8.090***	16.977***
SSEC→WTI	0.085	0.095	0.221	0.466	1.030	0.387	0.996
WTI→SSEC	0.477	1.223	0.095	0.058	0.164	0.452	5.75***
S&P 500→WTI	0.400	2.422*	8.569***	0.865	0.230	1.499	6.635***
WTI→S&P 500	0.072	3.808**	4.542**	3.128**	2.587*	2.493*	4.521**
STOXX 50→WTI	0.713	0.184	2.351	0.195	1.800	0.897	7.394***
WTI→STOXX 50	0.977	3.399**	2.542*	2.737*	2.819*	3.155**	11.159***
SSEC→Gold	1.720	1.612	1.046	0.496	0.537	7.15***	0.324
Gold→SSEC	1.605	2.103	1.253	3.158**	1.237	2.566*	5.672***
S&P 500→Gold	2.619*	5.646***	0.386	2.289	1.590	7.305***	15.191***
Gold→S&P 500	6.680***	4.669**	6.389***	5.519***	0.574	5.939***	9.339***
STOXX 50→Gold	6.741***	6.653***	0.355	7.114***	2.442*	9.497***	15.876***
Gold→STOXX 50	0.882	1.204	2.125	4.610**	1.693	22.915***	38.867***
SSEC→GAS	0.967	2.170	0.156	4.864***	1.231	2.856*	5.891***
GAS→SSEC	2.130	0.204	2.12	1.876	0.929	4.502**	4.811**
S&P 500→GAS	0.267	0.089	0.897	1.757	0.705	6.032***	5.197***
GAS→S&P 500	1.628	3.949**	0.218	0.189	2.361*	0.265	11.319***
STOXX 50→GAS	1.991	1.648	2.186	4.753**	0.930	6.095***	6.963***
GAS→STOXX 50	5.127***	7.981***	6.512***	5.069***	1.775	1.684	33.697***

Note: The data reflects the W-statistic. *, **and *** refer the acceptance of the causal relationship at 10%, 5%, and 1% significance levels respectively

COVID-19 period is caused just by the S&P 500 in D1, D2, and S5 and by STOXX 50 in S5.

As for the Gold, causality is strongly influencing the U.S stock prices for all the selected frequencies, except for the D4 frequency band and weakly influencing the Chinese stock market and the E.U stock market; whereas the Gold price is strongly caused by STOXX 50 for all the frequency bands except for the D2 frequency band and by S&P 500 for D1, D5, and S5. Lastly, the wavelet causality tests show that the GAS price volatility is causing Chinese stock price in very long-term investment horizons, the S&P 500 in D1, D4 and S5 and STOXX 50 over the short- term scales and in very long-term investment horizons; whilst, the GAS price in the COVID-19 period is caused by the selected stock markets mostly over the long-term investment horizons.

5 Conclusion

The ongoing COVID-19 pandemic is considered one of the most current turmoil periods having a significant impact on the linkages among global markets. Our paper is useful for investors and policymakers in order to reduce the risk of contagion in the future, implementing better financial strategies. Using wavelet analysis, our findings point out that the COVID-19 outbreak has a greater effect on the co-movements between stock and energy commodity markets. Indeed, the co-movements between the return series are affected by the novel corona-virus over time-scales; especially in the long-run investment horizons. Thus, it suggests weak evidence of diversification benefits of Chinese, American, and European stock markets with energy commodity markets. For the case of SSEC and S&P 500 and SSEC and STOXX 50, the Chinese market is leading only during the COVID-19 period, which means that, despite the spread of the virus to America and Europe, the Chinese market is more volatile, throughout this period, than American and European markets and any decrease in Chinese stock prices during this pandemic period is followed by the depreciation in American and European stock prices.

The wavelet-based Granger Causality test exhibits significant causalities for different investment horizons. The strong causality of the international stock market is detected between S&P 500 and STOXX 50, where there are many bidirectional causalities across scales than SSEC and S&P 500 and SSEC and STOXX 50. Furthermore, the causalities between stock markets and WTI is important, where the effect of the WTI price volatility is causing S&P 500 and STOXX 50 for all the frequency bands. Yet, the WTI price is weakly caused by American and European stock markets during the COVID-19 period due to the hijacking of the investor decision-making process for investing in oil futures. The influence of the American and European stock prices is in line with the findings of Torun et al. (2020) highlighting the impact of previous oil price shocks. Lastly, the wavelet-based causality running from Gold price to American stock market is stronger than to Chinese stock market and European stock market; while the wavelet-based causality running from GAS price to European stock market is stronger than to Chinese stock market and American stock market due to the wide use of gas in Europe, especially during winter, which happened to be the peak period of the pandemic's outbreak.

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