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Intraday volatility transmission among precious metals, energy and stocks during the COVID-19 pandemic

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ABSTRACT

In this study, we present the evidence of dramatic changes in the structure and time-varying patterns of volatility connectedness across equities and major commodities (oil, gold, silver and natural gas) in the US economy before and during the COVID-19 outbreak. We utilize high frequency 5-min trading data of most actively traded US ETFs to construct the volatility connectedness network. We compute the intraday volatility estimates using MCS-GARCH model and then employ Diebold and Yilmaz (2012) spillover index approach to approximate volatility spillovers between the financial markets. Our main findings showcase significant impact of COVID-19 pandemic on the volatility linkages of financial markets as the volatility connectedness among the different assets peaked during the outbreak. Other findings and implications of the study are further discussed.

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1. Introduction

The coronavirus outbreak began in December 2019 in Wuhan (China), afterwards the virus spread across the world. So far, the virus has infected a large number of people in almost 200 countries (Remuzzi and Remuzzi, 2020) and, still, remains a challenging task for global public health community. Aside the tragedies of death and disease, the COVID-19 pandemic has emerged as a global threat to world economies. Resultantly, various reports attribute the sluggish growth in world economies since 2019 to COVID-19 outbreak. Similarly, in the awake of the pandemic, the volatilities in financial markets significantly soared, which led to enormous losses for market participants. For instance, within one week equity worth $5 trillion was wiped out of global financial markets due to the outbreak. In the same way, commodities prices also experienced great fluctuations such as significant fall in oil prices (e.g., the negative price of West Texas Intermediate (WTI) crude oil futures) due to drop in the demand, and gold prices hit all-time high in the anticipation of weak economic recovery after the pandemic (Le et al., 2021). Given the extreme price movements in all of the major financial markets, investors and policy makers are left with many questions related to asset allocation and portfolio diversification.

Due to globalization, securitization, deregulation and the increasing development of information technology the integration among world major financial markets is generally on the rise, which significantly contributed to intensifying the previous episodes of financial crises such as Global Financial crisis 200-7-08 and European debt crisis 2012 (Jo, 2014; Öztek and Öcal, 2017; Bai et al., 2019). In addition, during the periods of financial meltdown, policy makers and investors take keen interest in understanding the magnitude and direction of spillovers between different asset classes to restore financial stability and enhance portfolio decisions (Bouriet al., 2020). This is also applicable to disastrous events such as COVID-19 pandemic as in periods of economic turmoil contagion increases the co-movement among the asset classes,

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Table 1
Descriptive statistics and correlations.

	SPY	USO	UNG	GLD	SLV
Mean	0.947	0.955	1.002	0.925	0.968
Median	0.851	0.866	0.942	0.812	0.895
Maximum	4.260	6.359	2.652	4.489	4.265
Minimum	0.375	0.483	0.593	0.475	0.572
Std. Dev.	0.401	0.380	0.244	0.396	0.290
Skewness	2.248	4.833	1.675	3.200	3.569
Kurtosis	11.382	42.926	7.193	17.607	23.083
Jarque-Bera	104127.8***	1942267.0***	33147.7***	292733.8***	522833.3***
Probability	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ADF	−19.467***	−20.788***	−22.864***	−23.736***	−23.286***
PP	−19.437***	−18.564***	−21.600***	−21.225***	−21.135***
KPSS	0.577	0.531	2.773	2.890	0.886
No. of Observations	27623	27623	27623	27623	27623
SPY	1.000				
USO	0.202***	1.000			
	(34.276)				
UNG	0.079***	0.132***	1.000		
	(13.207)	(22.157)			
GLD	0.414***	0.218***	0.165***	1.000	
	(75.606)	(37.139)	(27.781)		
SLV	0.312***	0.167***	0.106***	0.794***	1.000
	(54.649)	(28.227)	(17.707)	(217.117)	

Notes: ADF, PP and KPSS are the empirical statistics of the Augmented Dickey-Fuller (1979), and the Phillips-Perron (1988) unit root tests, and the Kwiatkowski et al. (1992) stationarity test, respectively. The asterisk (***) denotes the rejection of the null hypotheses of normality, unit root and significance of correlation at the 1% significance level. Values in parenthesis are t-statistics.

which further enhances the importance of the safe-haven asset (Baur and Lucey, 2010). Resultantly, there is growing interest in understanding the volatility connectedness network across different asset classes during the COVID-19 outbreak. And to examine whether spillover connectedness network across assets exhibit shift over the time due to the outbreak effects? Also, to investigate which asset class emerged as a superior hedge or safe-haven against the catastrophic shocks of the COVID-19? Explorations of these questions hold important implications related to risk management and portfolio diversification as once again the need for safe-haven assets during such exceptional times has resurfaced. In view of this, specifically in this paper we examine the effects of COVID-19 on connectedness network of equities and major commodities in the US economy. Pertinent to our objectives of the study we consider a network of five interrelated assets such as stocks, oil, gold, natural gas and silver, and then evaluate intra-day volatility transmission between the underlying markets before and during the pandemic. In this way our study contributes to the literature that uses connectedness measures to examine the risk-return spillovers between the assets during periods of economic downturn (Gebka and Serwa, 2006; Kang and Yoon, 2019; Antonakakis et al., 2019; Tiwari et al., 2020; Corbet et al., 2020, 2021).

The search for alternative investments in the face of trade integration and market risks has triggered higher connectedness among asset classes. Particularly, in the last two decades commodity markets have attracted a large influx of investors, which contributed to rapid growth of liquidity in commodity markets (Mensiet al., 2013; Balli et al., 2019; Naeem et al., 2020). Nowadays, investors consider commodities as pure alternative investments assets rather than as a channel to reinforce real economic activity via hedging of risks (Vivian and Wohar, 2012). Also, in view of the prevailing fragility and unfavourable shocks in conventional financial markets (especially stock markets), investors see commodities as an essential component of investment portfolios. In light of this, a large thread of academic literature has documented the causal relationship between commodities and financial markets, where often opportunities and associated risks are spilling from one to other (e.g., Roy and Roy, 2017; Yoon et al., 2019; Adekoya and Oliyide, 2020). In addition, the previous literature has also identified various channels driving the connectedness between commodity and financial markets.

Ever-increasing technological development and rise of algorithmic trading in the recent times have significantly contributed to growing the interactions between financial markets (Kirilenkoet al., 2017). In particular, portfolio managers pay keen interest to understand the speed of information flows and volatility spillovers originating from high frequency trading among financial markets to safeguard against contagion risk and adjust their asset allocation. In fact, precise knowledge of risk-return spillovers between financial markets during the crisis periods (marked with high contagion) provides even more valuable insights for portfolio diversification and hedging. In the same way, investor sentiments, algorithmic trading and rapid transmission of information through social media are cited among the major reasons for driving the financial contagion across financial markets during the COVID-19 outbreak (e.g., Corbet et al., 2020; Zhang et al., 2020). Keeping this in view, in this study we use high frequency data as oppose to daily and monthly data to provide more detailed understanding of the volatility spillover network between major commodities and equities during the pandemic. More importantly, the volatility estimations based on high frequency data portray more precise image of market risk, since they track much smaller intraday price movements. Hence, this offers portfolio managers and policy makers a great deal of important economic information for portfolio management and policy initiatives to stabilize financial markets.

The unsatisfactory performance of conventional GARCH models in modelling the intraday returns is well documented (Drost and Nijman, 1993; Andersen & Bollerslev, 1997, 1998). Moreover, the poor performance of these models is attributed to pronounced patterns of intraday volatility and trading activity. Keeping this in view, in this study we use multiplicative component GARCH (MCS-GARCH) model proposed by Engle and Sokalska (2012). The model decomposes the volatility of high frequency asset returns into multiplicative components, which are easy to estimate and interpret. The MCS-GARCH model expresses the conditional variance of intraday returns as a product of three components which include daily variance component, diurnal variance pattern and stochastic intraday volatility component. Thereby, the volatility estimates based on MCS-GARCH model are more stable and outperform conventional GARHC models. More importantly, the authors also suggest that the intraday volatility estimates from the model are particularly useful for devising optimal portfolio strategies. Accordingly, the study employs multiplicative component GARCH model to estimate intraday volatilities of network of five interrelated assets. Further, we use Diebold and Yilmaz (2012) spillover index approach to examine the volatility connectedness network among the underlying assets.

The findings of the study show disastrous impact of COVID-19 on the financial markets. The global transmission of the virus led to soaring volatilities in the US financial markets. The empirical findings indicate significant effects of COVID-19 pandemic on the volatility linkages of financial markets as the volatility connectedness among the different assets peaked during the outbreak. The findings also exhibit that US stock market is the largest transmitter of volatility shocks in the system before and during the spread of virus. Additionally, our pair-wise spillover analysis exhibits various instances where volatility receivers switched to volatility transmitters during the outbreak. Finally, our findings also suggest that natural gas natural gas is least connected to other assets in terms of volatility spillovers, which reveal potential hedging and safe-haven function of natural gas against stocks and major commodities.

The rest of the paper is organized as follows. Section 2 provides brief literature review. Section 3 describes the methodology. The data description and preliminary analysis is presented in section 4. Section 5 presents empirical findings of the study. The last section concludes the paper.

2. Literature review

Extant literature has extensively covered the linkages among financial markets. More specifically, a large thread of literature has documented the risk and return spillovers between stocks and commodities, and across commodity classes. First, a strand of literature focuses on the linkages between commodities and financial markets. Wherein, the existing literature suggests various channels through which financial markets relate to commodities. These channels include inflation channel, interest rate channel and macro-economic factors based channel (e.g., Jain and Biswal, 2016; Ahmadi et al., 2016; Adekoya and Adebiyi, 2020; Akbar et al., 2019; Adekoya and Oliyide, 2020). Accordingly, numerous studies using variety of econometric methods present the evidence of spillovers among prices, returns and volatilities of commodities and stock markets. The related literature is summarized in Table 1.

Table A1
A summary of previous research on the relationship between commodities and stock markets.

Authors	Sample	Methodology	Variables	Main findings
Creti et al. (2013)	2001–11 Daily	DCC-GARCH	Stocks and 25 commodities (precious metals, energy, food, agriculture and livestock)	The findings suggest highly volatile and time varying correlations among commodity returns and stock markets. In particular during the crisis period of 2007–08.
Sadorsky (2014)	2000–12 Daily	ARMA-AGARCH and DCC-AGARCH	Stock, oil, copper and wheat	The findings indicate that strong volatility spillovers between commodities and stock returns in emerging markets post GFC 2007–08. In addition, oil is found to serve as a least expensive hedge for stock prices.
Mensi et al. (2017)	2000–16 Daily	Diebold and Yilmaz spillover index (2009, 2012) and DECO-FIGARCH	Stocks, gold, silver, platinum and palladium	The findings reveal strong volatility spillovers between commodities and stock markets, where stock markets serve as a source of volatility spillovers and precious metals are net receivers, especially during GFC and European Sovereign Debt Crisis.
Zhang (2017)	2000–16 Daily	Diebold and Yilmaz spillover index (2009, 2012, 2014) and DECO-GARCH	Stocks and oil	The findings indicate weak contribution of oil shocks to stock markets. However, large shocks matter for stock-oil connectedness.
Zhang et al. (2017)	1999–2015 Daily	VT-DCC and Block-DCC-GARCH	stock VIX, oil and gas	The findings show that US Henry Hub gas is significantly associated with stock market implied volatility indexes.
Junttila et al. (2018)	1989–2016 Daily	DCC-GARCH	Stocks, oil and gold	The findings suggest that the correlations between oil and equities increase during the periods of economic downturn, whereas the correlations of gold become negative. The findings advocate the hedge and safe-haven role of gold.
Mensi et al. (2018)	1997–2016 Daily	Wavelet decomposition method	Stocks, oil and gold	The findings show that stock returns in BRICS countries co-move with oil prices in lower frequencies. In particular strong price connectedness is observed post GFC.
Al-Yahyaee et al. (2019)	2005–16 Daily	Diebold and Yilmaz spillover index (2014) and DECO-FIAPARCH	Stocks, precious metals (gold, silver, palladium and platinum) and energy commodities (crude oil, heating oil and gasoline)	The findings show significant volatility spillovers between commodities and stock markets in GCC region.
Kumar et al. (2019)	2006–15 Daily	VARMA-DCC-GARCH	Stocks, oil and natural gas	The study found lack of long-term correlation between three markets in the Indian economy.
Wang and Wang (2019)	2000–18 Daily	Diebold and Yilmaz (2012) and Baruník and Křehlík (2018)	Stocks and Oil	The findings suggest that volatility spillovers between the two markets are mainly driven by short-term volatility. Also, heterogeneous results are found for net pairwise (frequency) spillovers between the oil sector and stock indexes in Chinese economy.
Boako et al. (2020)	1996–2018 Daily	Morlet Wavelet method	Stocks and commodities including energy, precious metals, agricultural and beverages	The findings show that stock returns and commodities co-move across multiple scales and establish a long-term integration in African countries.
Morema and Bonga (2020)	2006–20 Daily	VARMA-ADCC-GARCH	Stocks, oil and gold	The findings confirm strong volatility spillovers among three asset markets. Also, the linkages between commodities and stock market are crucial for portfolio management.
Uddin et al. (2020)	1996–2016 Daily	ARMA-GJR-GARCH and Copula approach	Stocks, oil, gold, silver, and platinum	The findings show that oil and gold co-move with US stock market under normal and extreme circumstances. Additionally, asymmetric tail dependence of silver and platinum is found with US stock market, in particular during economic slowdown periods.
Ali et al. (2020)<	2001–18 Daily	Cross-quantilogram	Stocks, energy, precious metals, industrial materials and agricultural	The findings unveil valuable hedging and safe-haven properties of precious and industrial metals against international stock markets

Second, another strand in literature focuses on the volatility spillovers between individual commodities and across commodity classes. In particular, financialization of commodity market after GFC 2007-08 has also led to high integration among different commodity classes (Caporin et al., 2020). In this regard, energy commodities are leading other commodity groups in terms of financialization (Zhang, 2018). Resultantly, Diebold et al. (2017) suggest that energy commodities often transmit shocks to other commodity groups, indicating strong connectedness with other commodity classes. In view of this, many authors have explored volatility interconnections and spillovers between various commodity classes including energy, precious metals, agricultural and industrial metals (Kang et al., 2017; Shahzad et al., 2019, among others).

Especially, an overwhelming focus has been given to document the inter- and intra-group volatility spillovers between energy commodities and precious metals (e.g., Sensoy, 2013; Batten et al., 2015). For example, Uddin et al. (2019) investigate the risk-return spillovers among precious metals. The authors discover asymmetric spillovers among the precious metals, which are more noticeable during the crisis period. Silver and gold are found to be net-transmitter of spillovers to other precious metals. Kang et al. (2017) use DECO-GARCH model and spillover index to estimate the spillovers between the oil futures and other five other commodity futures including gold and silver. The findings reveal strong bi-directional spillovers between the underlying commodities and the level of spillovers increased after GFC. In the same way, Al-Yahyaee et al. (2019) examine the risk and return spillovers among energy and precious metals futures. The findings of the study unveil significant risk-return spillovers between the two commodity classes in GCC region. The results also show that oil and precious metals excluding silver are net-transmitter of volatility in GCC markets. Using causality in variance tests, Yıldırım et al. (2020) examine the volatility spillovers between energy commodities and precious metals. The findings confirm volatility spillovers effects from oil to other commodities, which are pronounced during the crisis period. The authors also suggest that magnitude of spillovers decreases the benefits portfolio diversification in periods of economic slowdown. Similarly, Mensi et al. (2020) use spillover index and bivariate and multivariate wavelet coherence approaches to study volatility spillovers among energy commodities and precious metals. The findings disclose that volatility spillovers are dynamic and intensify during energy and financial crisis. In addition, with increase interest in exploring the volatility spillover network among and between energy commodities and precious metals, some studies also employ realized volatility measures based on high frequency data. For instance, Wang et al. (2020) use dynamic model averaging model to predict realized volatility spillovers among precious metals in Chinese market. Also, Hu et al. (2020) document the impact of macro factors on volatility spillovers network of energy commodities and precious metals.

Third, the study is also related to strand of literature that investigates the risk-return spillovers among alternative assets classes, in particular during the periods of financial meltdown. Thus, once again due to the catastrophic effects of COVID-19 outbreak on economic and financial variables, a steam of studies have attempted to shed light on the impact of outbreak on the connectedness network of different asset classes. For example, using TVP-VAR connectedness approach Bouri et al. (2020) show increased network connectedness among five assets including crude oil, gold, stocks, currencies, and bonds during the pandemic. Le et al. (2021) explore the tail dependency network of assets during the outbreak. The results show that tail dependency in both lower and upper joint distributions of asset returns increased during the COVID-19 outbreak. Amar et al. (2021) use spillover index approach of Diebold and Yilmaz (2012) and continuous time-frequency of Torrence and Webster (1999) to showcase the relationship between commodities and stock market in the major oil-producing and consuming economies during the COVID-19 outbreak. The findings suggest strong interdependence among the underlying market, which peaked during the pandemic. Adekoya and Oliyide (2020) investigate volatility spillovers among commodities and other financial markets. The results showcase strong volatility spillovers among commodities and financial markets. Also, the findings highlight significant impact of COVID-19 measures on driving connectedness between the underlying markets. Similarly, Cui et al. (2021) examine the risk connectedness among oil and stock markets for major oil-importing and oil-exporting economies. The findings indicate the risk connectedness among the market reached its peak during the GFC and COVID-19 crises. In addition, in order to search for safe-haven assets during the outbreak period of high financial contagion, some authors also re-examine the hedging and safe-haven properties of different assets including energy commodities and precious metals during the global pandemic (e.g., Ji et al., 2020; Conlon and McGee, 2020; Conlon et al., 2020; Sherif, 2020; Salisu et al., 2020).

3. Methodologies

3.1. MCS GARCH

The study uses MCS GARCH model that helps to capture the conditional variance for the high frequency (intraday) financial returns. Previously various authors have employed the method to accurately estimate volatility dynamics in the financial markets (e, g., Raza et al., 2018, 2019; Banerjee and Paul, 2020). Consider the financial data intraday returns$\gamma_{l,m}$, where j (1,2,3 … …,J) represents the day and q the equal period of interval at which intraday returns are estimated. The model specifies the conditional variance is the multiplicative product of diurnal, daily and stochastic (high frequency/intraday) volatility, so that intraday financial returns process may be described as:

$$\gamma_{l,m} = \mu_{l,m} + \varepsilon_{l,m}$$

$$\varepsilon_{l,m} = \beta_{l,m} v_{l,m} \tag{1}$$

$$v_{l,m} = w_{l,m} \sigma_l p_m$$

where $w_{l,m}$ is the stochastic (high frequency/intraday) volatility, σ_l is a daily extrinsically measured forecast volatility,p_m the diurnal volatility in the equal period of interval,$w_{l,m}$ finally represent the standardized innovation which follow a specific distribution.

The symmetric/asymmetric forecast volatilityσ_l results are derived through the multifactor risk model exogenously, but the results can also be obtained through simple daily GRACH (forecast) model. The GRACH model is given bellow:

$$\gamma_l = \mu_l + \sigma_l p_l$$

$$\mu_l = \phi \gamma_{(l-1)} \tag{2}$$

$$ln(\sigma_l^2) = \omega_o + \alpha_1 |p_{l-1}| + \gamma_1 p_{l-1} + (\beta_1 \sigma^2{}_{l-1})$$

where σ_l and μ_l are conditional volatility and mean of financial data returnsγ_l, p_l should be between zero and one due to the properties of standard innovationγ_l and here σ^2measures the sign effect and magnitude effect.

The process of seasonal (diurnal) part of is given below:

$$s_m = \frac{1}{L} \sum_{l=1}^{L} (\varepsilon^2{}_{l,m} / \sigma^2{}_l(\tag{3}$$

Then residuals of the diurnal is divided by daily volatility and obtained the e normalized residuals:

$$\widehat{\varepsilon}_{l,m} = \varepsilon_{l,m} / (\sigma_l s_m) = w_{l,m} v_{l,m} \tag{4}$$

They help generate the stochastic component of volatility $w_{l,m}$ by using GARCH model.

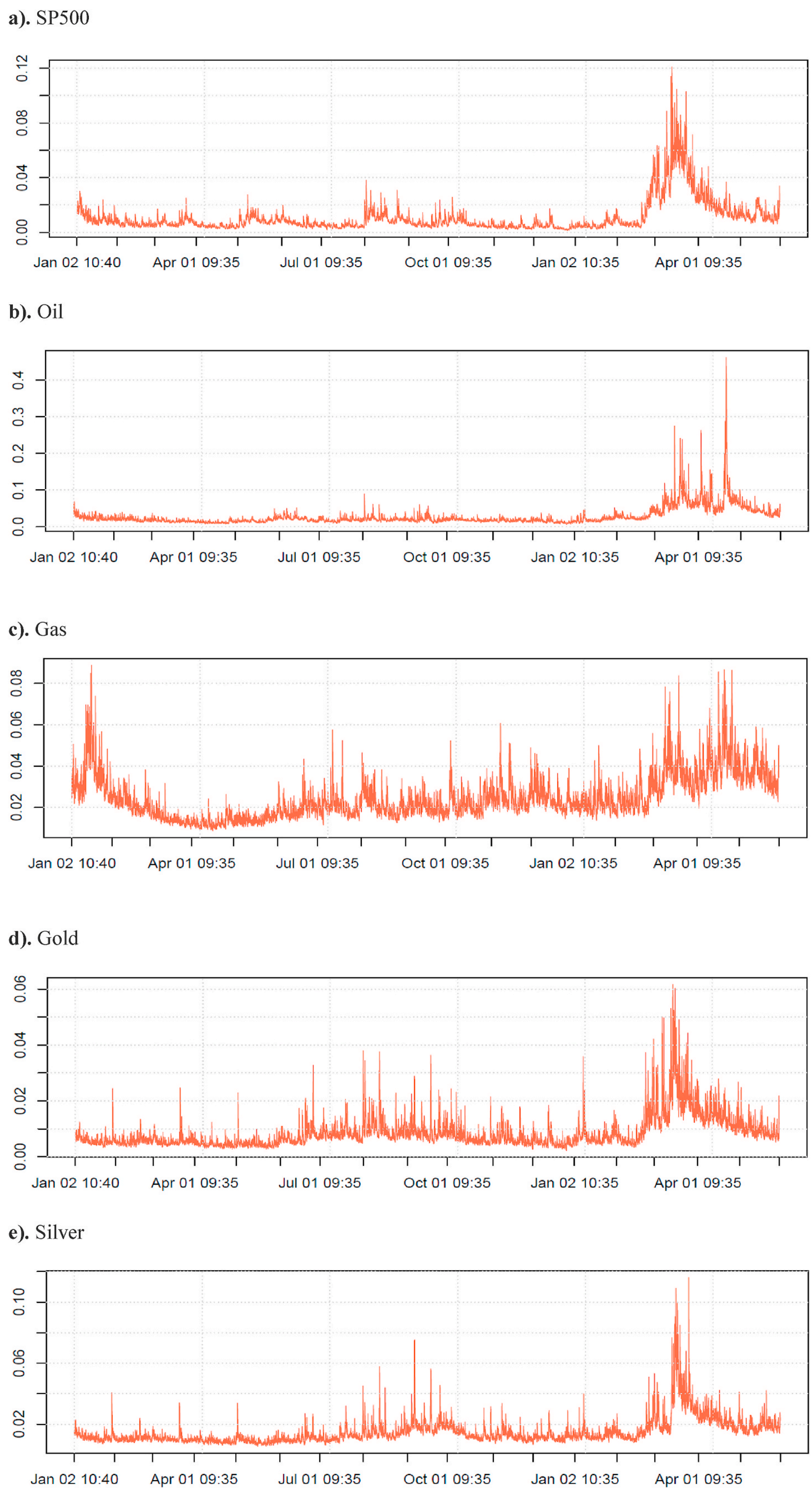


Fig. 1. Intraday volatilities without seasonal component.

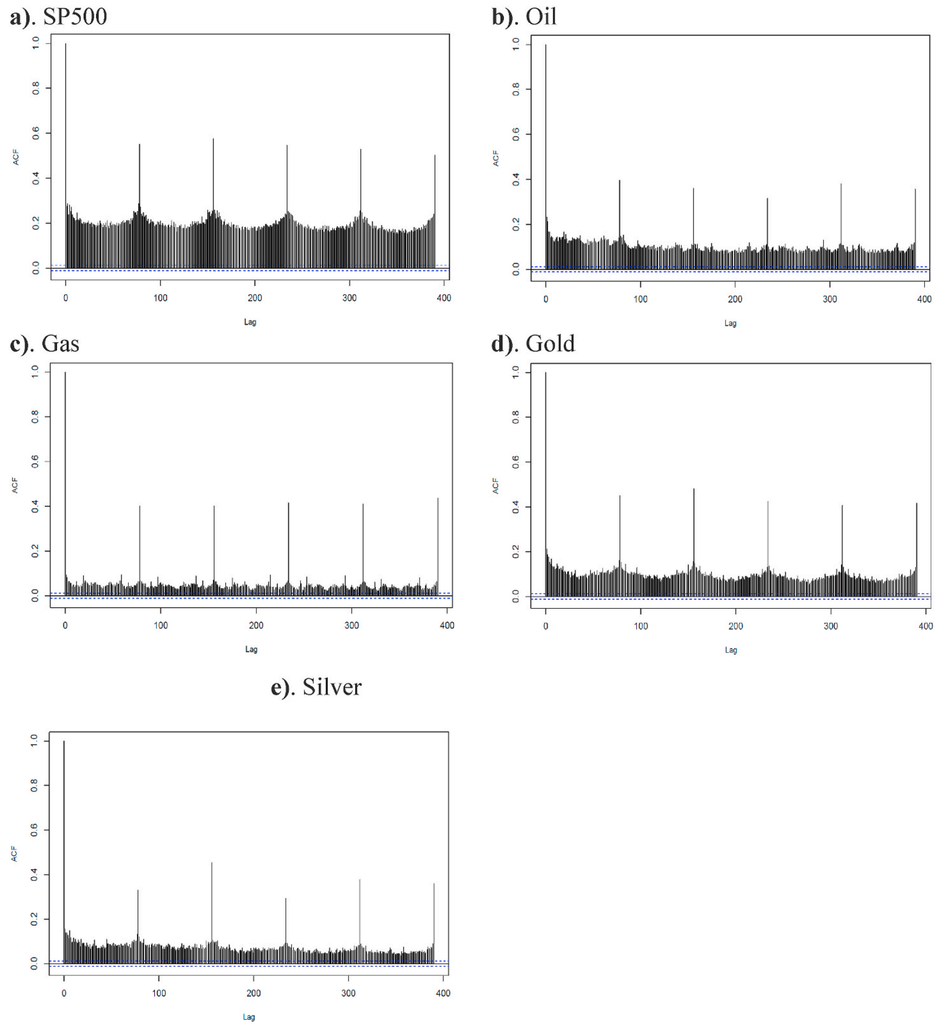


Fig. 2. Autocorrelation functions of absolute intraday returns.

3.2. Diebold and Yilmaz (2012)

The Diebold-Yilmaz spillover method is based upon forecast error variance decomposition (VAR process). Hence, let the VAR model with p variables and m lags, which can be written as:

$$Y_l = \theta(Q)Y_l + \varepsilon_l \tag{5}$$

where Y_l indicate a $p \times 1$ vector of problem variables $\theta(Q) = \sum_f \theta_f K^f$ is a $p \times p$ m-th order lag (polynomial matrix) of coefficients, L is the lag operator, ε_l , Σ denotes white noise and covariance matrix.

The moving average process in VAR is represented by

$$Y_l = \Psi(Q)\varepsilon_{l-i} \tag{6}$$

where Ψ (Q) is a $p \times p$ matrix (infinite lag polynomials) can be measured recursively. The generalized forecast error variance decomposition (FEVD) can be estimated as:

$$\phi_{i,g}(F) = \frac{\sum_{gg}^{-1}\sum_{f=0}^{F}\Psi_f\Sigma)(\Psi_f\Sigma)(\Psi_f\Sigma)_{i,g}]^2}{\sum_{f=0}^{F}(\Psi_g\Sigma\Psi'_g)_{ii}} \tag{7}$$

where Ψ_f depict $p \times p$ matrix for calculating the coefficients of moving average having f lags, Σgg is the gth diagonal element, F denotes the selected forecast and $\phi_{i,g}$ is the variance of forecast error of concerned variable.

In the generalized form of VAR framework is the combination of cross-and own-variable variance, i.e. $\sum_{f=1}^{F}\phi_{i,g}(F) \neq 1$. (Not necessarily to equal one). Hence, the sum of columns does not add up by definition in the variance decomposition matrix and the process is given below:

$$\tilde{\phi_{i,g}}(F) = \frac{\phi_{i,g}(F)}{\sum_{f=1}^{p}\phi_{i,g}(F)} \tag{8}$$

The pair wise connectedness is measured through $\phi_{i,g}(F)$ from g to i at horizon F in the different time domain. Moreover, normalized variance matrixes reflect the level of connectedness among different studied variable can be easily introduced.

4. Data and preliminary analysis

We use five actively traded US exchange traded funds (ETFs) to represent the US financial markets. First, the SPDR S&P 500 trust ETF (SPY) tracks down the performance of S&P 500 stock index. The index is considered as one of the main benchmarks for tracking the performance of the US stock market. The index is made up of 500 large- and mid-cap U.S. stocks which are selected based on industry, market capitalization and liquidity. Second, the US oil fund ETF (USO) tracks the prices of WTI crude oil. The fund was first launched by US commodity fund on April 10, 2006. The fund primarily invests its assets in crude-oil futures and other oil related future contracts. The fund tracks the performance of

Table 2
Estimation results from ARMA (1,1)-mcsGARCH(1,1) model on intraday returns.

	SPY	USO	UNG	GLD	SLV
φ_0	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ψ_1	0.7278***	0.2281**	0.6071***	0.6763***	0.0655
	(0.1046)	(0.1063)	(0.0737)	(0.1001)	(0.0482)
ψ_2	−0.7528***	−0.2939***	−0.6387***	−0.7080***	−0.2019***
	(0.1002)	(0.1041)	(0.0705)	(0.0956)	(0.0471)
ω	0.0149***	0.0244***	0.0343***	0.0270***	0.0306***
	(0.0018)	(0.0079)	(0.0085)	(0.0030)	(0.0047)
α_1	0.0995***	0.0871***	0.0716***	0.1089***	0.0821***
	(0.0053)	(0.0129)	(0.0106)	(0.0074)	(0.0073)
β_1	0.8895***	0.8903***	0.8953***	0.8623***	0.8857***
	(0.0057)	(0.0198)	(0.0183)	(0.0090)	(0.0109)
Asymmetry	−0.0889***	−0.0354***	−0.0068	−0.0403***	−0.0623***
	(0.0151)	(0.0127)	(0.0129)	(0.0131)	(0.0117)
Tail	1.7482***	1.1576***	1.2598***	1.1280***	1.5112***
	(0.1124)	(0.0694)	(0.0646)	(0.0589)	(0.1155)
Diagnostic tests					
LL	162074.6	135986.2	137461.6	169912.7	153485.2
AIC	−11.734	−9.8453	−9.9521	−12.302	−11.112
Q(20)	[0.5385]	[0.1522]	[0.8632]	[0.5990]	[0.4605]
$Q^2(20)$	[0.0143]	[0.1236]	[0.8106]	[0.2461]	[0.9937]
K–S	[0.2468]	[0.1355]	[0.5643]	[0.2435]	[0.9594]
LiMcLeod	[0.8282]	[0.2654]	[0.1294]	[0.2733]	[0.1613]
Hosking	[0.8446]	[0.7200]	[0.1710]	[0.1745]	[0.1932]

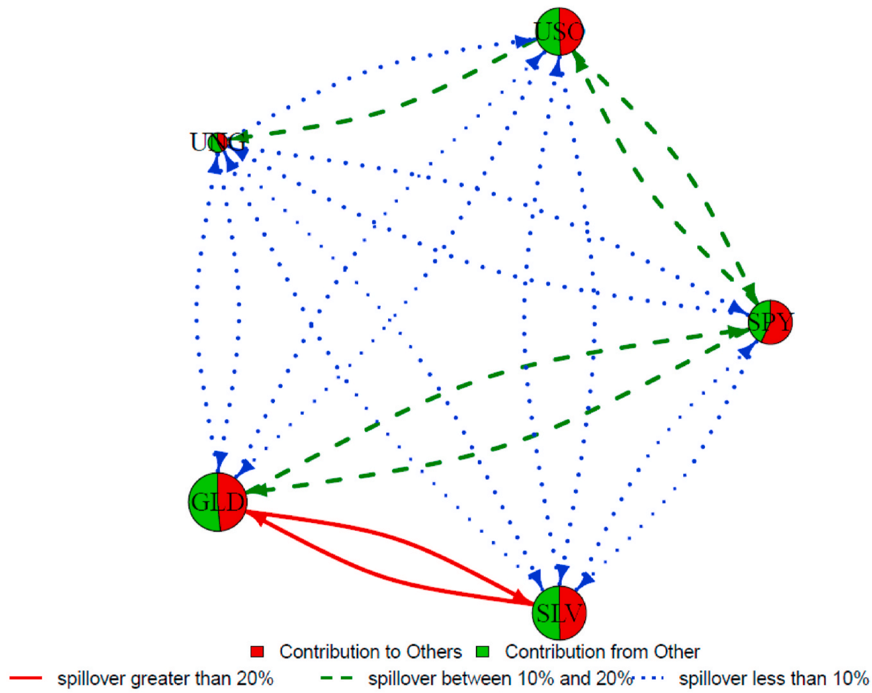
Notes: We report the maximum likelihood (ML) estimates and the z statistics (in parentheses) for the parameters of the volatility models. The lags *p, q, r* and *m* are selected using the log likelihood (LL) for different combinations of values ranging from 0 to 2. Q(k) and Q^2(k) are the Ljung-Box statistics for serial correlation in the model residuals and squared residuals, respectively, computed with k lags. ARCH(k) is the Engle LM test for the ARCH effect in the residuals up to the *k*th order. K–S denotes the Kolmogorov-Smirnov test (for which the p-values are reported), representing the adequacy of the Student-t distribution model. Hosking (1981) and Li and McLeod (1981) are the autocorrelation tests until lag 20. The p-values [in the square brackets] below 0.05 indicate the rejection of the null hypothesis. The asterisks (***), (**) and (*) represent significance at the 1%, 5% and 10% levels, respectively.

crude oil market by tracking the daily percentage changes of the spot price of WTI crude oil. Third, the US natural gas fund ETF (UNG) tracks the prices of natural gas. It is the largest natural gas ETF fund with shares listed on NYSE Arca. The fund enables the investors to invest in natural gas without investing in futures market. Fourth, SPDR gold shares trust ETF (GLD) traces the performance of the gold market by tracking the price of gold bullion in the over-the-counter (OTC) market. The fund is considered to provide easy and cost-efficient way to gain exposure to gold market. Finally, iShares silver trust ETF (SLV) illustrates the performance of the silver prices. All the indices are denominated in USD. We employ high-frequency-5 min data of the mentioned ETFs from 02, January 2019 to 29, May 2020 for the empirical analysis. We choose 5 min high-frequency price data as it strikes a logical balance between microstructure noise and accurate estimations (Degiannakis, 2008; Andersen and Todorov, 2010; Luo and Ji, 2018). Also, the sample duration enables us to effectively model the spillover connectedness network among the underlying markets before and during the COVID-19 pandemic.

For the empirical analysis continuously compounded returns are calculated by converting the price series into log first difference. Table 1 displays the descriptive statistics of the five US ETFs representing the five alternative financial assets. As shown in Table 1, UNG has the highest mean return during the sample period, followed by SLV and USO. Not surprisingly, the statistics also show that among all the ETFs highest standard deviation is noted for SPY, which reflects the unprecedented volatility experienced in US stock market during the outbreak. On the contrary, among all the financial markets the lowest volatility is reported for natural gas. In addition, the results of skewness, kurtosis, and Jarque Bera tests clearly show that all the series are not normal with positive skewness. The results of Augmented Dickey-Fuller (1979), and the Phillips-Perron (1988) unit root tests, and the Kwiatkowski et al. (1992) stationarity test suggest that all return series are stationary. Finally, the results of historical correlations analysis among the financial markets show positive moderate correlations between US equities and other financial assets excluding natural gas. The results also manifest high positive correlation between two precious metals in US during the sample period. Additionally, the results also show that natural gas is least correlated with other assets in our sample duration, which once again highlight the superior performance of UNG over other ETFs.

Next, Fig. 1 illustrates intraday volatility patterns of US financial markets during the sample period. It is evident from the graphs that volatility in the US financial markets soared after the COVID-19 virus was declared as a global pandemic. A large volatility jump is noted for all markets post World Health Organization (WHO)'s announcement. Here, our findings distinctly second the evidence that suggests the widespread panic caused quick sell-outs and havoc in financial markets around the globe (Zhang et al., 2020; Akhtaruzzaman et al., 2020). Resultantly, investor's beared major losses and financial markets tumbled due to great uncertainty linked with the pandemic. Further, it can be seen from the graphs that high-rise in the volatility of financial markets persists till the end of April 2020 and then markets seem to recover and rebound quickly. Consequently, volatilities declined across the US financial markets. Additionally, apart from the COVID-19 pandemic crash we also note recurrent episodes of high volatility in US natural gas market, which correspond to low natural gas prices in 2019 due to oversupply problem in US natural gas industry.

Further, as the MCS GARCH model is effective in capturing the intraday seasonality pattern, thus in this study we directly fit the MCS GARCH on the original return series of US ETFs. Fig. 2 displays the absolute autocorrelation functions (ACF) of original return series. ACF of absolute original return series of all ETFs excluding UNG show the U-shaped seasonality pattern of asset return volatilities. Furthermore, Table 2 presents the obtained parameters from the model fit. The results show that most of the parameters of the mean model (ARCH) and the volatility model (GARCH) are significant across all the ETFs. Also, the high values of β1 for all the assets suggest significant high impact of previous period volatility on the current volatility. We also note significant positive value of the asymmetry parameter (γ_1) for majority of the



Note: This network graph illustrates the degree of total connectedness in a system that consists of the US stock market, oil, natural gas, gold and silver volatilities over the full sample period. Total connectedness is measured using the Diebold-Yilmaz framework. The size of the node shows the magnitude of contribution of each variable to system connectedness, while the color indicates the origin of connectedness. In particular, the red color implies contribution from the variable under consideration to the other variables of the system and the green color means contribution from the other variables to the variable under analysis. The color and shape of the arrows refer to the strength of connectedness. The red colour and full line arrows represent spillovers more than 20% while green and blue colour arrows show spillover between 10% to 20% and less than 10%, respectively.

Fig. 3. Diebold-Yilmaz (2012) spillover network for the full sample.

US ETFs, which indicates stronger reaction of financial markets to bad news in comparison to good news. Finally, the tail coefficients are also significant across all the financial markets.

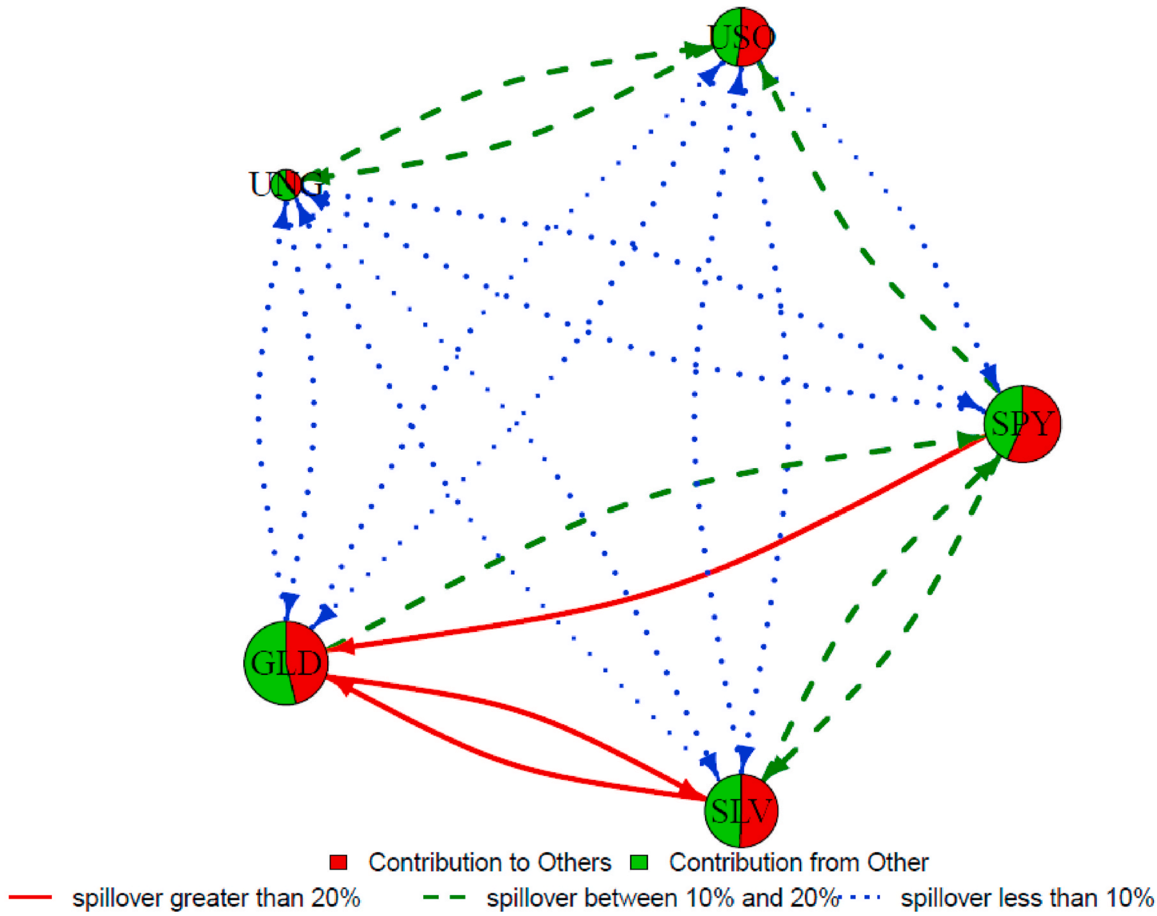
5. Main results and findings

5.1. Static analysis

In order to study the volatility spillovers among US financial markets before and during the COVID-19 pandemic, we construct state-of-art volatility connectedness network of five interrelated assets namely stocks, oil, natural gas, gold and silver using Diebold and Yilmaz (2012) spillover index approach. Fig. 3 illustrates the spillover network of complete sample period. The analysis highlights important insights about the volatility linkages among US financial markets.

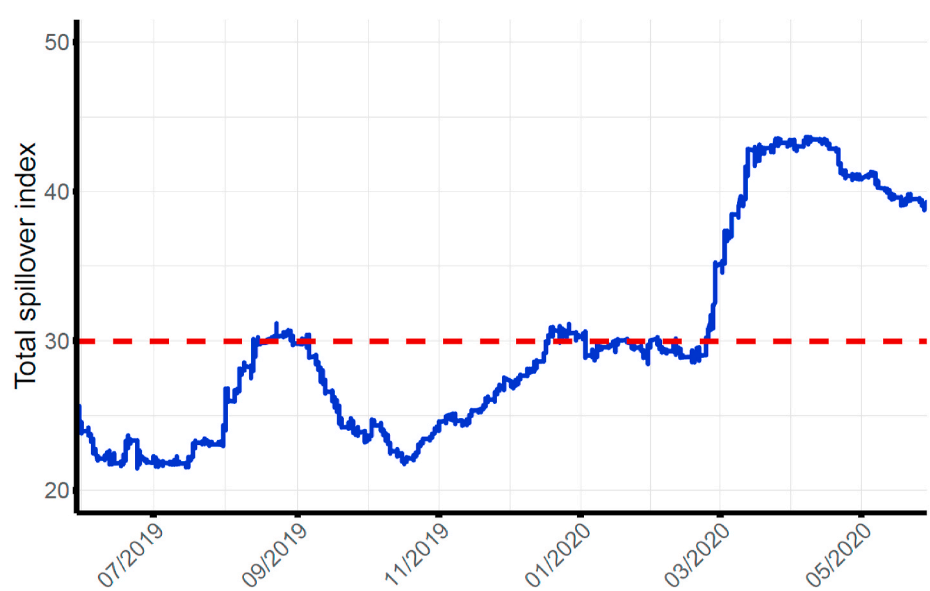
First, the empirical results reveal strong bi-directional volatility spillovers between precious metals in US over the full sample period. The findings match the earlier obtained evidence in the preliminary analysis that suggested strong positive co-movement between gold and silver. The findings are also validated by a strand of literature that argues strong volatility dependence across precious metals, in particular gold and silver (Reboredo and Ugolini, 2015; Dutta, 2018; Mensi et al., 2019). Second, the results also unveil moderate bi-directional volatility spillovers between US stocks and oil prices. The findings are similar to studies of Arouri et al. (2011) and Ewing and Malik (2016) that found bi-directional volatility transmission between oil prices and stock market in the US economy. Further, we also find some volatility linkages between stocks and gold prices. The findings are some way different from Husain et al. (2019) who suggest lack of significant volatility spillovers between US stock index and precious metals. Instead, our findings oppose the popular notion of weak volatility linkages between stocks and gold and rather suggest safe-haven property of gold against US stocks is not stable. Furthermore, we find unilateral volatility transmission from crude oil to natural gas market. Overall, the findings indicate that the gold market and stocks are the largest transmitters of volatility spillovers to volatility connectedness network.

Next, in order to understand the effects of COVID-19 outbreak on the volatility connectedness of US financial markets, we present the spillover network for the COVID19 sub-sample starting from 01 January 2020 until 29 May 2020. Once again the results in Fig. 2 display US stocks as the largest transmitter of volatility during the virus spread. The findings are explained by the fact that investors view US stock market as a barometer of the economic and financial conditions of the US (Das et al., 2019). Hence, turbulences in the US equity market often translate into significant variations in asset prices and augmented volatility in other financial markets. The findings are further validated by Adekoya and Oliyide (2020), who also argue that stock market acts as a net-transmitter of volatility to other asset classes during the COVID-19 outbreak. Also, the findings reveal strong volatility transmission from US stocks to oil and gold markets, which once more exhibit that financial contagion during the COVID-19 outbreak originated in the stock market and then spread to other financial markets. In addition, similar to our static analysis we find strong bi-directional volatility spillovers between precious metals such as gold and silver. Finally, our findings advocate the potential safe-haven function of natural gas to hedge the volatility in other financial markets during the pandemic. Since, natural gas market



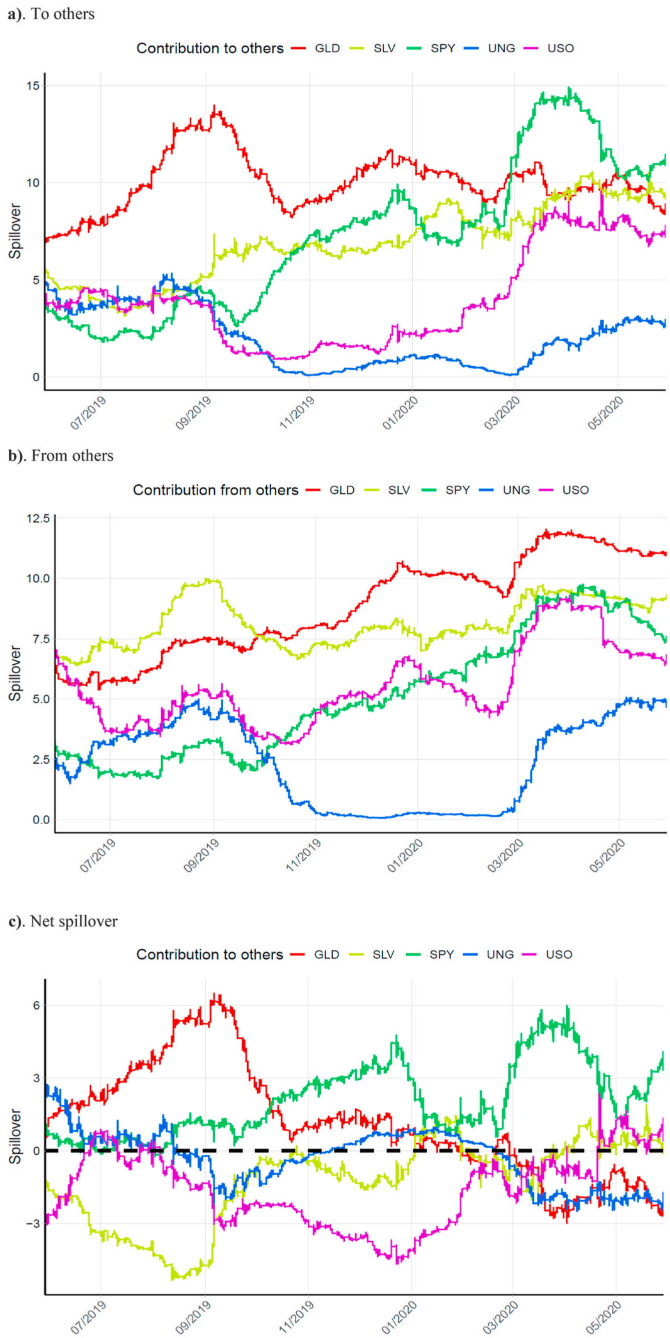
Note. See notes to Figure 3.

Fig. 4. Spillover network for the COVID19 sub-sample from 01 January 2020 until 29 May 2020.



Note: This figure displays the time-varying behavior of the total volatility spillover index among the five variables considered computed using the approach of Diebold and Yilmaz (2012). These dynamic total spillover indices are calculated from the forecast error variance decompositions using a rolling window size of 10 days (7800 intraday volatility observations) and a forecast horizon of H=2 days.

Fig. 5. Rolling window DY total spillover index.



Note: These figures displays the time-varying behavior of To others, From others and pairwise net volatility spillover for the five variables considered computed using the approach of Diebold and Yilmaz (2012). These dynamic spillover indices are calculated from the forecast error variance decompositions using a rolling window size of 10 days (7800 intraday volatility observations) and a forecast horizon of H=2 days.

Fig. 6. Rolling window spillover indices.

in the US is least connected to other major financial markets during the sample period.

5.2. Dynamic analysis

In order to establish whether spillover connectedness network across assets exhibit shift over the time due to the outbreak effects, we present time-varying total volatility spillover index among the five variables computed using the approach of Diebold and Yilmaz (2012). Fig. 4 clearly manifest the significant impact of COVID-19 pandemic in driving volatility connectedness among the US financial markets as the volatility spillovers among the markets peaked in the month of March 2020. The findings indicate that contagion effects driven by market sentiment of fear quickly transmitted across US financial markets. In consequences, financial markets became highly volatile leading to severe economic losses. It can also be inferred from the findings that high volatility connectedness among US financial markets during the outbreak mirrors reduced portfolio diversification opportunities for investors across alternative assets classes. The findings are somewhat in line with Amar et al. (2021), who also showcase higher interdependence among stock and commodity markets during the outbreak period for a set of countries. Additionally, our findings are also corroborated by recent growing evidence that suggests volatility connectedness among different asset classes spiked during the COVID-19 outbreak (e.g., Bouri et al., 2020; Le et al., 2021; Naeem et al., 2021).

Fig. 5 exhibits time-varying total volatility spillovers from each asset class to other major financial assets in the US. The results of full sample period show that equities and gold are the net-transmitter of volatility to other assets. However, during the COVID-19 pandemic, stock, gold and oil emerge as the largest contributor of the volatility shocks in the system. In addition, natural gas transmits least volatility spillovers to other financial markets. In the same way, Fig. 5 also shows that natural gas receives least volatility spillovers from other assets before and during COVID-19 outbreak. On the contrary, rest of the financial markets receive augmented level of volatility shocks during the period of virus spread. Finally, the results of net spillovers are also presented in Fig. 5. Interestingly, the findings unveil that silver emerges as the largest contributor of net volatility spillovers to other asset categories during the outbreak. The finding reinforce the notion that financialization of commodity market has attracted investors to view different commodities as a mainstream financial assets and essential component of investment portfolios.

In the end, we present the bi-lateral net volatility spillovers among the financial markets in Fig. 6. Once again the results show that US stock market is net transmitter of volatility spillovers to other financial markets before and during the pandemic. Wang et al. (2020) also display that US stock market acts as a net-transmitter of volatility shocks to other financial markets. In this regard, we observe high volatility connectedness between the stocks, oil and gold. However, natural gas has the lowest level of volatility connectedness with stocks, which highlights the potential use of natural gas to hedge stock market risk in the US economy (see Fig. 7).

Now, regarding oil and natural gas we note that before the outbreak natural gas is the net transmitter of volatility to oil market as this period corresponds to turbulent times in US natural gas industry (prices hit the lowest in the three years). In opposite, during the COVID-19 pandemic crude oil switches from net receiver to net transmitter of volatility between the two underlying markets. In the same way, gold is the transmitter of volatility to oil market before the COVID-19 outbreak, but during the pandemic crude oil shifts from net receiver to net transmitter of volatility to gold market. The findings are similar to the earlier evidence that indicates bi-directional contagion effects between the two underlying markets before and during the pandemic period (Gharib et al., 2021). In addition, silver is found to be a net-transmitter of volatility shocks to crude oil market during the full sample period.

Furthermore, the results also show that natural gas is the net receiver of volatility spillovers from gold and silver during the virus outbreak period. Wherein, low volatility connectedness exists between the natural gas and silver. The findings once again show the potential use of natural gas to hedge price fluctuations in precious metals like silver. Finally, we note that gold is net transmitter of volatility shocks to silver before the outbreak, however silver emerges as the net-transmitter in the pandemic times. Overall, our pair-wise results exhibit various instances where volatility receivers switched to volatility transmitters and vice versa during the outbreak. Bouri et al. (2020) also display various such cases while documenting the return connectedness among financial markets during COVID-19 outbreak.

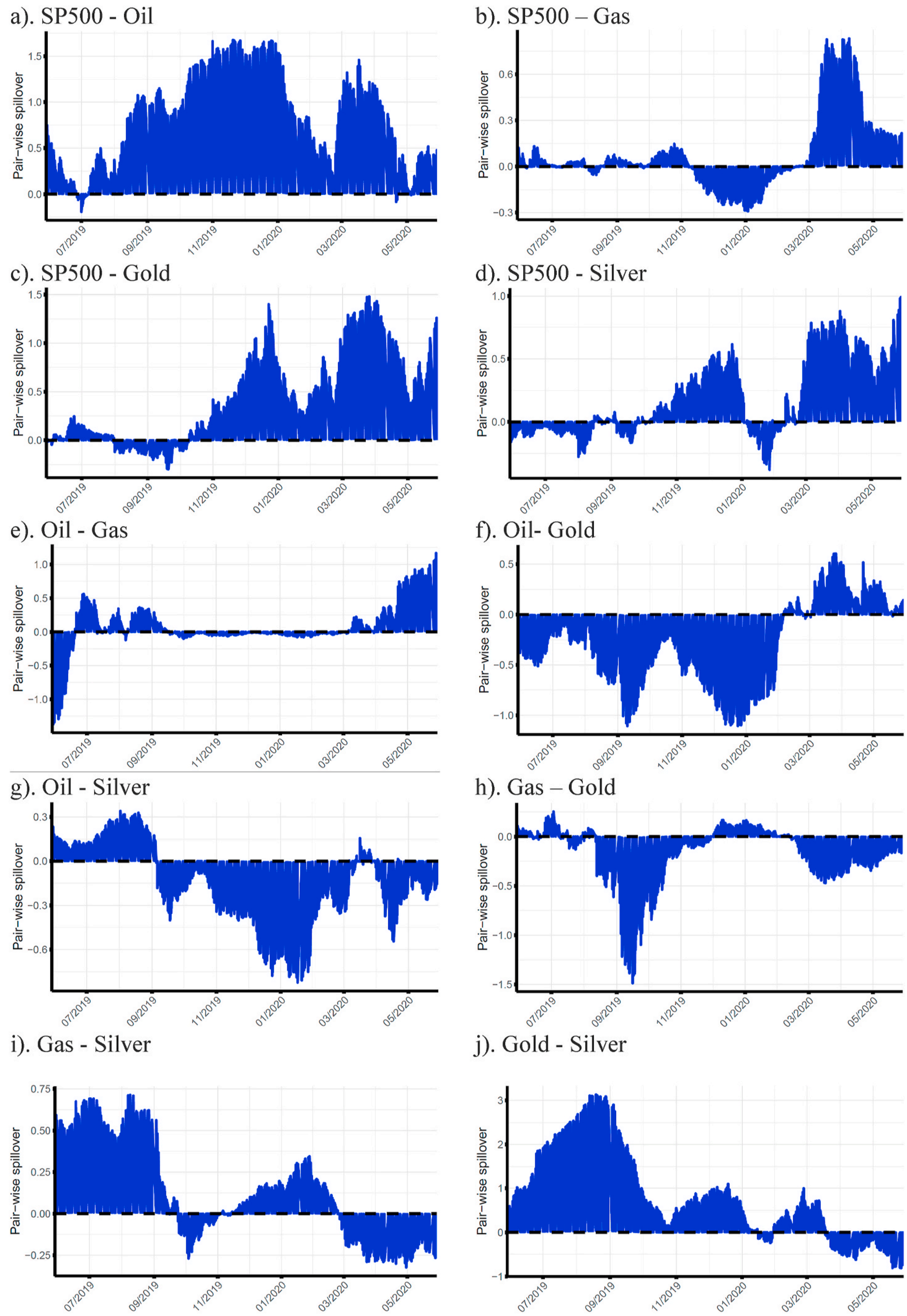


Fig. 7. Pair-wise net spillovers.

6. Conclusions

The COVID-19 pandemic has caused great disruptions in the financial markets around the world. In fact, increased stress in financial markets has led to growing contagion among financial markets, which has prompted policy makers around the globe to take wide range of monetary and financial easing measures. Taking this into consideration in this study we investigate the volatility transmission among major financial markets in the US economy before and during the pandemic.

In particular, the study examines the volatility connectedness network of equities and major commodities including gold, oil, silver and natural gas by utilizing 5-min trading data of US ETFs. We compute the intraday volatility estimates using MCS-GARCH model, which is well recognized to produce superior and stable diurnal volatility estimates. Further, we construct the volatility connectedness network of assets using Diebold and Yilmaz (2012) spillover index approach. Additionally, we also document the time-varying dynamics of volatility spillovers among the underlying assets before and during the virus spread, which unveils the outbreak effects on US financial markets.

Our empirical findings are as follows: First, our full sample network analysis shows that stocks and gold are two largest contributors of volatility shocks to the volatility connectedness network. Second, our sab-sample analysis of COVID-19 outbreak period also reveals that US stock market continues to act as the largest transmitter of volatility spillovers to major commodity markets in the US. The findings stress the fact that investors consider US equity market as the leading indicator of the economic and financial conditions of the US economy. Third, our dynamic analysis confirms the significant impact of the COVID-19 pandemic on volatility spillovers among assets; since we note volatility connectedness among US financial markets peaked during the virus spread period. The findings showcase reduced portfolio diversification and hedging opportunities for investors across alternative asset classes. Fourth, our findings from static and dynamic analysis exhibit that natural gas is least connected to other assets in terms of volatility spillovers, which reveal potential hedging and safe-haven function of natural gas against stocks and major commodities. Moreover, the results showcase that natural gas emerges a superior hedging and safe-haven option for investors in the financial markets during the pandemic crisis. Accordingly, investors and portfolio managers seeking portfolio diversification and hedging opportunities in environment of high risk such as COVID-19 pandemic can consider natural gas market for investment. Finally, our findings from pair-wise spillover analysis illustrate various cases of net receivers switching to net transmitter of volatility spillovers and vice versa during the outbreak.

The findings of the study hold important implications for policy and financial markets. Our findings advocate that policy makers should pay careful attention to volatility connectedness network among assets to restore financial stability and safeguard investments. In fact, lack of understanding of volatility spillovers linkages among different asset classes fuels systematic financial contagion. Therefore, policy makers should continuously monitor informational spillovers among different financial markets to design timely policy interventions to eliminate the contagion risk arising from inter-connectedness of financial markets. Also, investors can utilize the information regarding the net shocks transmitter or receiver nature of the different asset classes to optimize their portfolio investment strategies.

Note: This network graph illustrates the degree of total connectedness in a system that consists of the US stock market, oil, natural gas, gold and silver volatilities over the full sample period. Total connectedness is measured using the Diebold-Yilmaz framework. The size of the node shows the magnitude of contribution of each variable to system connectedness, while the color indicates the origin of connectedness. In particular, the red color implies contribution from the variable under consideration to the other variables of the system and the green color means contribution from the other variables to the variable under analysis. The color and shape of the arrows refer to the strength of connectedness. The red colour and full line arrows represent spillovers more than 20% while green and blue colour arrows show spillover between 10% and 20% and less than 10%, respectively.

Note: This figure displays the time-varying behavior of the total volatility spillover index among the five variables considered computed using the approach of Diebold and Yilmaz (2012). These dynamic total spillover indices are calculated from the forecast error variance decompositions using a rolling window size of 10 days (7800 intraday volatility observations) and a forecast horizon of H = 2 days.

Note: These figures displays the time-varying behavior of To others, From others and pairwise net volatility spillover for the five variables considered computed using the approach of Diebold and Yilmaz (2012). These dynamic spillover indices are calculated from the forecast error variance decompositions using a rolling window size of 10 days (7800 intraday volatility observations) and a forecast horizon of H = 2 days.

CRediT authorship contribution statement

Saqib Farid: Conceptualization, Writing – original draft, Methodology, Writing – review & editing. **Ghulam Mujtaba Kayani:** Conceptualization, Writing – original draft, Writing – review & editing. **Muhammad Abubakr Naeem:** Conceptualization, Methodology, Software, Formal analysis, Writing – original draft. **Syed Jawad Hussain Shahzad:** Supervision, Methodology, Software, Formal analysis, Writing – review & editing.

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