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# COVID-induced sentiment and the intraday volatility spillovers between energy and other ETFs

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ABSTRACT

Did Covid19 induce market turmoil impact the intraday volatility spillovers between energy and other ETFs?. To examine this, we first estimate the realized volatility of ETFs using the 5-min high-frequency data. Next, we employ time-varying parameter vector autoregressions (TVP-VAR). Finally, we utilize the wavelet coherence measure to test the time-frequency impact of COVID-induced sentiment on the spillovers by employing investors' psychological and behavioural factors. We find that oil and stock markets are net transmitters while currency, bonds, and silver markets are net receivers. The wavelet analysis embarked significant impact of media coverage and fake news index towards shaping investors' pessimism for their investments. We proposed useful implications for policymakers, governments, investors, and portfolio managers.

## 1. Introduction

The uncertainty of the COVID-19 pandemic and its rapid spread across the globe due to high contagiousness created a doomscrolling crisis for the whole world. Officially declared a global pandemic by the World Health Organization (WHO, 2020) on March 11, 2020, the coronavirus outbreak created massive havoc with the death of millions of people across the globe and pushing 193 countries at irrevocable risk (Zhang et al., 2020). The catastrophic repercussions of COVID-19 tracked its drastic effect on the financial markets where the circuit breakers of US stock market triggered four times in ten days which occurred once in history during 1997. With its awe-inspiring enormity, the COVID-19 pandemic manifests one of the exorbitant recessions after the Great Depression of 1930. Aligned with it, US GDP recorded a 5% decline encompassing 4th quartile of 2019 to the last quartile of 2020.[1] In addition, the unemployment rate in the US experienced an incline from 4.4% to 14.7% and 13.3% in April 2020 and May 2020.[2] Correspondingly, its ever-increasing adverse impacts on the overall economic, financial, and global business sectors, the US market experienced heavy losses in the banks, industrials, consumer discretionary. Given this heightened economic volatile period, it is central to the attention of investors, portfolio managers, financial market participants, and policymakers to understand the volatility connectedness of financial markets, particularly US exchange-traded funds including energy commodities (US Oil and Natural Gas Fund), precious metals (Gold and Silver Fund), stocks, and bond markets funds.

The exchange-traded fund (ETF) is a class of asset that grasped the increasing attention of investors from the last few decades, which is a form of a collective investment vehicle (CIV).[3] Most ETFs are constructed for tracking securities, commodities, and precious metal

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[1] Please see: https://www.statista.com/statistics/188185/percent-change-from-preceding-period-in-real-gdp-in-the-us/

[2] Please see: https://www.statista.com/statistics/273909/seasonally-adjusted-monthly-unemployment-rate-in-the-us/

[3] Elton et al. (2019) explained this asset class as a collection of small number of funds organized as unit trusts which includes the first ETF (spider) whereas another smaller portion is arranged as 'holders' which simultaneously offers ownership of the underlying securities as well as voting rights.

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indices. ETFs acquire dual features of being closed-ended funds and open-ended funds where the former are traded at the securities exchanges, and the latter allows the creation and redemption of their shares which coincide with the constituent portfolios through authorized representatives (Kang et al., 2021; Liu et al., 2021). The open-ended ETFs offer effective arbitrage between the ETF and asset where authorized representatives get incentives to ensure that the difference between ETF price and net asset value remains low. The substantive popularity of ETFs around the globe is tracked in their growth in numbers and the net asset value of underlying securities, which reflects considerable development from USD 0.417 trillion to USD 5.89 trillion[4] between 2005 and 2020, respectively. Like the stock markets, the US ETFs market is also the world's largest market, facilitating efficient asset allocation, diversification, liquidity management, and hedging avenues. Importantly, growth in the ETFs has also safeguarded the investors' investments beyond tracking large country indices. In this way, ETFs create new investment potentials for the investors of energy commodities, precious metals, stocks and bonds, and very little is known about their volatility connectedness, especially during the COVID-19. Keeping in view the investors' attitudes towards COVID-19, informed investors could use the optimal portfolio management strategies by including US ETFs involving a versatile set of markets, for instance, energy commodities, metals, and stocks, which offer greater diversification and low risk to make rational decisions when markets are experiencing severe shocks. Evidence suggests that volatility spillovers are stronger when markets undergo bearish circumstances than bullish conditions (Naeem et al., 2020; Salisu and Vo, 2020).

Considering the above discussion, the current study offers novel contributions by examining the doomscrolling impacts of COVID-19 on the intraday volatility connectedness of US ETFs consisting of energy ETFs, precious metals, stocks, currency, and bond ETFs. Empirically, several studies have investigated the connectedness of US ETFs (Kang et al., 2021). However, clear evidence of intraday volatility connectedness among US ETFs particularly for a set of different energy and financial ETFs lacks in the prior literature. Various studies employed time-frequency techniques (Benlagha et al., 2022; Hadi et al., 2022; Tiwari et al., 2021; Khalfaoui et al., 2019) and wavelet analysis (Naeem and Karim, 2021; Karim and Naeem, 2022; Naeem et al., 2022a, 2022b; Sharif et al., 2020; Karim et al., 2022a, 2022b). Meanwhile, the contribution of study adds to the existing literature by employing the time-varying parameter vector auto-regression (TVP-VAR) approach proposed by Antonakakis and Gabauer (2017). This is contribution of the study as TVP-VAR surpasses the technique of Diebold and Yilmaz (2012); Diebold and Yılmaz (2014) in terms of providing free size for rolling-window, no problem of outliers and missing no observations in the dataset. Further, to validate our findings, we examined the impact of investors' psychological and behavioural factors on the volatility connectedness, where prevalent factors include a panic index, media coverage index, sentiment index, and fake news index. For obtaining this research objective, we employed wavelet coherence analysis to estimate the doomscrolling effect of COVID-19 using investors' psychological and behavioural factors on the volatility connectedness of US ETFs.

For analysis purposes, we used the data of seven ETFs, namely, US Oil Fund (USO), US Natural Gas Fund (UNG), SPDR Gold Shares Fund (GLD), iShare Silver Trust Fund (SLV), SPDR S&P 500 (SPY), 7–10 year Treasury Bond Fund (IEF), and Currency Share Euro trust Fund (FXE) for the period spanning January 2, 2020 to March 31, 2021. The analyses were carried out in three steps. First, we estimate the realized volatility of US ETFs using the 5-min intraday data. Second, we applied the time-varying parameter vector autoregression (TVP-VAR) for estimating the volatility connectedness among US ETFs. Finally, we employed the wavelet coherence approach to explore the time-frequency dependence of COVID-19 on the volatility connectedness across financial markets using four unique indexes of panic, media coverage, sentiment, and fake news.

We find high risk connectedness among US ETFs where USO transmitted major risk spillovers to other markets followed by SPY. The remaining ETFs indicated risk reception in the wake of COVID-19, whereas GLD and UNG remained disconnected from the network substantiating their shielding capacity during the crisis period and conquering the risk of the portfolios. Time-varying features of volatility connectedness acknowledged three major periods when markets experienced extreme volatility in spillovers when the pandemic started, followed by the moderate risk spillovers when markets started to normalize after the serious havocs of COVID-19. Finally, the third phase detects low volatility spillovers with high disconnection of US ETFs at the end of the sample period. The time-varying NET connectedness recalled the dominant contribution of USO in shaping the risk spillovers while other markets received volatility spillovers. Further, wavelet analysis indicated panic index lagged the volatility connectedness, sentiment index revealed perfect comovement, whereas both media coverage and fake news indexes showcased their leading role when compared with volatility connectedness. Hence, we can assess that media coverage and fake news indexes played a dominant role in determining the investors' attitudes towards market uncertainty. The sentiment index showed positive dependence implying that investors' sentiments co-moved with volatility connectedness of US ETFs. However, the panic index revealed that a low panic state was observed when risk spillovers were high and vice versa. In this way, we validated our study by employing investors' psychological attitudes to examine the doomscrolling effect of COVID-19 on the intraday volatility connectedness.

The remaining paper unfolds in the following manner: Section 2 provides a review of earlier empirical studies; Section 3 presents data and methodology; Section 4 explains the empirical results and justifications; finally, Section 5 concludes the study and several policy implications.

## 2. Literature review

### 2.1. US ETFs, COVID-19, and volatility connectedness

The effect of COVID-19 on the intraday volatility connectedness of financial markets has embraced a greater interest from scholars and practitioners. There is abundant evidence that examines the volatility connectedness of different financial markets, but literature examining the intraday volatility connectedness of US ETFs, particularly during COVID-19 is lacking. Ahmad et al. (2021) examined the spillovers role of implied volatilities of various commodity and stock markets with US equity sectors by employing the time and frequency spillovers. The authors reported that OVX spillovers are weakly connected with VIX, where stock market volatility is dominant. Meanwhile, they also documented strong spillovers between OVX and VIX during COVID-19. Farid et al. (2021) explored the intraday volatility transmission among various energy, stocks, and precious metals markets during COVID-19 outbreak using the MCS-GARCH technique and Diebold and Yilmaz (2012) connectedness approach. The authors reported a significant impact of COVID-19 on the volatility linkages as the volatility spiked during the COVID-19 pandemic. Corbet et al. (2021) studied the pandemic-related volatility spillovers of financial markets using the data of Chinese firms. The authors reported a significant impact of COVID-19 on the Chinese financial markets and evidenced consistent spillovers during the inception of COVID-19. Zhao et al. (2022) examined the tail risk spillovers between WTI returns and financial factors and illustrated that WTI is net risk receivers and various financial indicators are net risk transmitters. Luo et al. (2022) investigated the oil and gold volatilities using the sentiment indicators and found significant results. On climate policy risk front, the study of Ding et al. (2022) is substantial employing the method of DCC-MIDAS-climate policy approach.

[4] Please see: https://etfgi.com/

### 2.2. Earlier empirical studies using various methods

Lastrapes and Wiesen (2021) introduced a joint spillover index where they combined the popular Diebold and Yilmaz (2012) framework with conditional forecasts to decompose variance. Using the data of US sectors, the authors documented substantial differences in the results by employing two different techniques. Zhang et al. (2020) investigated the impact of COVID-19 pandemic on the global financial markets and identified substantial volatility spillovers before and after the pandemic. Moreover, the authors further suggested policy interventions by inculcating US' decisions to implement zero-percent interest rates for overcoming the financial uncertainties.

Kang et al. (2021) measured the frequency spillovers, connectedness and hedging effectiveness of oil and gold for US ETFs for short and long time horizons. The authors indicated strong volatility spillovers of VIX on the US ETFs both in the short and long-run. Meanwhile, the uncertainty factors indicated that US economic policy has minimal impact on the OVX, whereas OVX has a stronger spillover effect on US ETFs than gold in short and long-run. Regarding hedging effectiveness, the authors reported oil to be the most significant hedge for each ETF in both short and long-run. Corbet et al. (2020) examined the comovements and spillovers of oil and renewable firms under extreme market conditions, particularly during COVID-19. The study employed DCC-GARCH conditional correlation framework along with sectoral transmission mechanisms of volatility spillovers. The authors documented positive and economically meaningful spillovers during the start of the sample period, yet the findings, under extreme circumstances, revealed intense spillovers due to increasing demand for oil, gas, and coal during the COVID-19 pandemic. Bourghelle et al. (2021) examined the oil price volatility during COVID-19 pandemic, given the shock situation of COVID-19. The paper explored the volatility dynamics, explained the supply and demand shocks of oil, and concluded a sharp and abrupt pandemic reaction to the oil-induced shocks. Similarly, Jawadi and Sellami (2021) measured the effect of oil during the COVID-19 pandemic by using the data of exchange rates, real estate, and stock markets in the US and employed the return dynamics for estimation purposes. The study found that oil price considerably affects the US stock markets and exchange rates, but no significant impact on real estate markets is reported. Meaningfully, the authors showcase that following the adverse circumstances of COVID-19, oil price changes negatively affected the US dollar.

Ameur et al. (2020) investigated the extreme risk dependence between oil and gas markets by applying popular extreme risk measures of value at risk, conditional value at risk, delta conditional value at risk, and copulas for high-frequency data. The findings demonstrate that spillovers are intense from oil to gas market than gas to oil market and there is an asymmetry in the upward and downward risk spillovers, which entails significant policy insights. Tiwari et al. (2021) analyzed oil's return and volatility spillovers across major stock markets using the Diebold and Yilmaz (2012) spillover index and sensitivity analysis using lag structures and different forecast horizons. The findings highlight that spillovers are time-varying and dynamic, with varying volatilities across major financial markets. Khalfaoui et al. (2019) examined the volatility spillovers between oil and stock markets and suggested portfolio implications. The study employs the dynamic conditional correlation (DCC) and corrected dynamic conditional correlation (cDCC) GARCH models. The findings indicate that lagged volatility in the oil and stock markets is directly related to the current volatility in the respective markets. Husain et al. (2019) investigated the connectedness among crude oil prices, stock indices, and various metals prices in the USA using the Diebold and Yilmaz (2012) connectedness technique. The results indicate that stock index neither transmits nor receives spillovers, and economically distressed periods revealed high-risk spillovers. As evident from the above literature, very little evidence represents the volatility spillovers among US ETFs, specifically during COVID-19 which substantially illuminates the study's unique contribution.

## 3. Data and methodology

In this section, we first introduce our data of interest our econometric methodology. Our sample includes seven actively traded exchange-traded funds (ETFs), covering the period from January 2, 2020 to March 31, 2021, sampled at 5-min intervals. As for our econometric methods, we first calculate the realized volatility for each ETF. After that, we estimate a Time-Varying Parameter Vector Autoregression (TVP-VAR) model on the realized volatilities. This model enables us to capture the dynamic relationship between different markets these ETFs represent. After that, we apply the generalized forecast error variance decomposition (GFEVD) to estimate the volatility connectedness among US ETFs. Finally, we test the time-frequency impact of COVID-19 related indexes on the volatility connectedness using a wavelet coherence method.

The advantages of using 5-min (high frequency) data in examining volatility connectedness are multiple. First, 5-min data provides a finer level of detail, allowing for a more accurate assessment of volatility connectedness. Second, 5-min data provides a more accurate representation of the dynamics of financial markets, making it possible to detect and analyze rapid changes in volatility. In addition, high frequency data captures intraday volatility more effectively than lower frequency data, which is essential for understanding the interconnectedness of markets. Third, the high frequency nature of 5-min data provides a more detailed and accurate representation of market behavior, leading to more precise conclusions about volatility connectedness. Subsequently, understanding the connectedness of financial markets is important for risk management, and 5-min data provides a more accurate representation of market risk, allowing for more effective risk management strategies. Thus, the use of 5-min data in examining volatility connectedness provides a more complete picture of market behavior and enhances the ability to make informed decisions about market risk.

### 3.1. The ETF data and their realized volatility

We select seven ETFs that capture the dynamics of energy commodities, precious metals, and the overall performance of the stock market and macroeconomy. Our chosen ETFs include the following: (1) US Oil Fund (USO); (2) US Natural Gas Fund (UNG), (3) SPDR Gold Shares Fund (GLD), (4) iShare Silver Trust Fund (SLV), (5) SPDR S&P500 (SPY), (6) 7–10 year Treasury Bond Fund (IEF), (7) Currency Share Euro Trust Fund (FXE). Following Andersen and Bollerslev (1998), we calculate the 5-min realized volatility (RV) on day $t$ for each ETF as follows

$$RV_t = \sum_{\tau=1}^{N_t} r_{t,\tau}^2, \tag{1}$$

where $r_{t,\tau} = \ln P_{t,\tau} - \ln P_{t,\tau-1}$, and $P_{t,\tau}$ is the price of the ETF at the $\tau$-th sampling point on day $t$. In the US, the normal trading session in the equity market starts from 9:30 and ends at 16:00, which totals 6.5 h. Given that we sample the data at 5-min frequency, we have $n = 6.5 \times 60/5 = 78$ intraday observations for each trading day.

After calculating the realized volatility, we plot the time series dynamics of the ETFs in Fig. 1. We can see that USO, GLD, SPY, IEF, and FXE exhibit large spikes around March 2020, the timing fits the outbreak of COVID-19 in major economies. UNG and SLV, on the other hand, exhibits more time-varying variations during our sample period.

We present the summary statistics for each ETF volatility in Table 1. In particular, we report the mean, standard deviation, skewness, kurtosis, and the Jarque-Bera statistic based on the null of normality. We can see that USO has the highest mean volatility, followed by UNG, SLV, and SPY. Meanwhile, all of the seven ETFs have a high kurtosis that exceeds 3 and a Jarque-Bera test statistic in the magnitudes of >300. Among the seven ETFs, the Jarque-Bera test statistics for USO and FXE are 244,694 and 1,117,354, suggesting the existence of volatility jumps

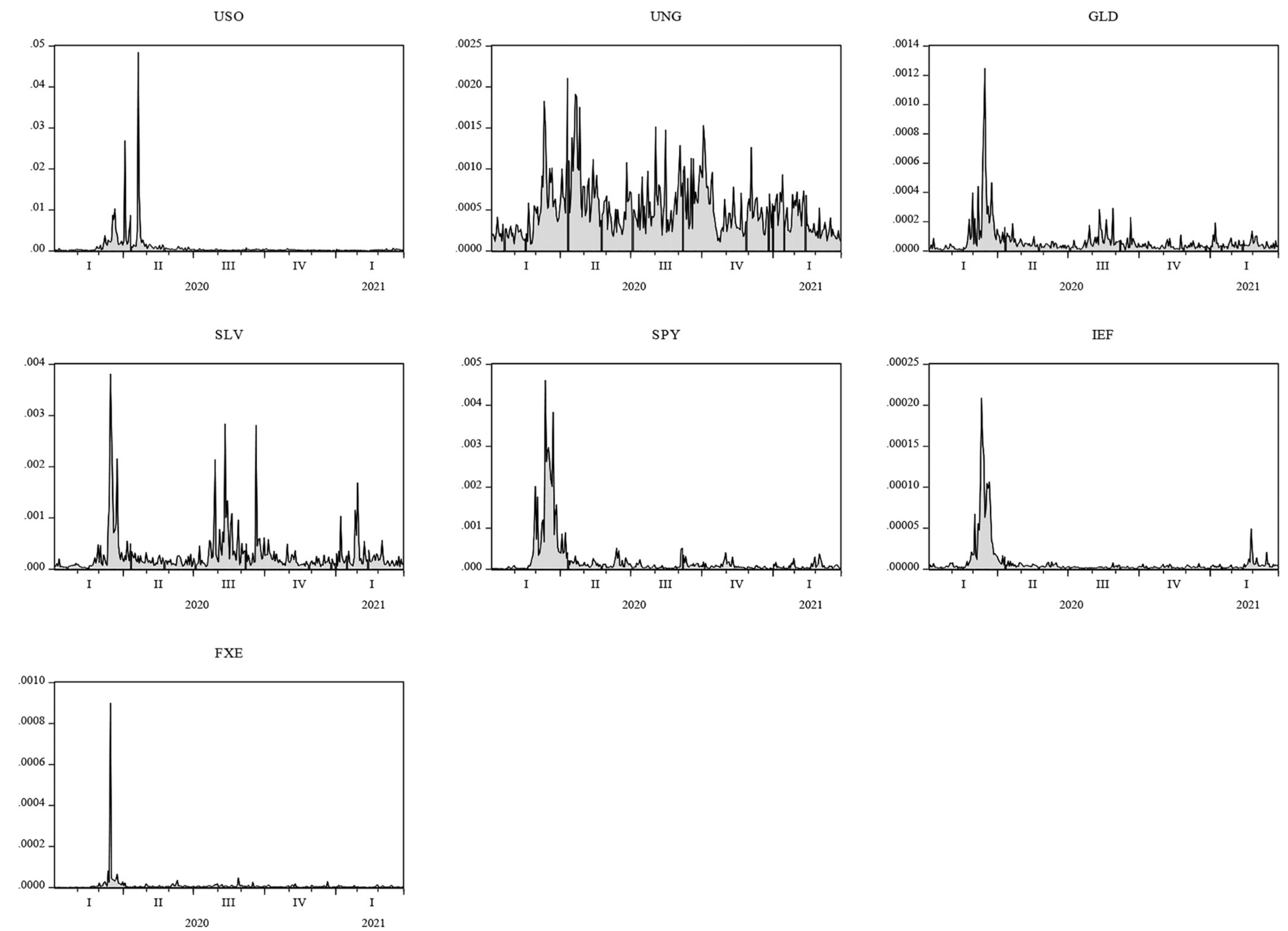


**Fig. 1.** Evolution of realized volatilities of the Seven ETFs.
Note: This figure shows the time evolution of realized volatilities estimated from high-frequency data from January 2, 2020 to March 31, 2021. The numbers I, II, III, IV mark the four quarters (Q1 to Q4) in a year.

**Table 1**
Descriptive statistics.

| ETFs | Symbol | Mean | Std. Dev. | Skewness | Kurtosis | Jarque-Bera | ADF |
|---|---|---|---|---|---|---|---|
| US Oil Fund | USO | 0.00087 | 0.00338 | 10.74 | 138.06 | 244,694.70 [a] | −12.16 [a] |
| US Natural Gas Fund | UNG | 0.00051 | 0.00034 | 1.67 | 6.68 | 323.98 [a] | −4.35 [a] |
| SPDR Gold Shares Fund | GLD | 0.00007 | 0.00011 | 6.40 | 56.74 | 39,936.23 [a] | −3.84 [a] |
| iShare Silver Trust Fund | SLV | 0.00028 | 0.00043 | 4.73 | 30.34 | 10,950.80 [a] | −7.53 [a] |
| SPDR S&P500 | SPY | 0.00021 | 0.00052 | 5.10 | 32.63 | 12,849.51 [a] | −3.30 [a] |
| 7–10 year Treasury Bond Fund | IEF | 0.00001 | 0.00002 | 5.74 | 41.08 | 20,693.72 [a] | −3.57 [a] |
| Currency Share Euro Trust Fund | FXE | 0.00001 | 0.00005 | 16.85 | 293.29 | 1,117,354.00 [a] | −16.36 [a] |

Note: a indicates 1% significance.

that are consistent with the time series dynamics in Fig. 1. The high values of the two measures indicate that *none* of the ETF volatilities follow a normal distribution. Moreover, all ETFs how a positive skewness, which is consistent with the existence of a long right tail, or extremely large volatilities. In sum, all the time series properties shown in Table 1 are consistent with the market turmoil observed during our sample period.

Table 2 presents the Pearson correlation of the ETF volatilities. Interestingly, the correlation between SPY and IEF, which equals 0.775, is the highest. Next are the correlations between GLD-SLV and GLD-SPY. The volatilities of SPY, which peaked around March 2020 when COVID-19 outbreak, had reflected investors' fear of the market certainty (Farid et al., 2021; Farid et al., 2023). Overall, GLD and SLV has low, yet

**Table 2**
Correlation matrix between the realized volatilities of US ETFs.

| | USO | UNG | GLD | SLV | SPY | IEF | FXE |
|---|---|---|---|---|---|---|---|
| USO | 1 | | | | | | |
| UNG | 0.409 | 1 | | | | | |
| GLD | 0.192 | 0.181 | 1 | | | | |
| SLV | 0.083 | 0.167 | 0.730 | 1 | | | |
| SPY | 0.249 | 0.228 | 0.734 | 0.453 | 1 | | |
| IEF | 0.192 | 0.286 | 0.589 | 0.297 | 0.775 | 1 | |
| FXE | 0.052 | 0.034 | 0.690 | 0.534 | 0.403 | 0.242 | 1 |

positive correlations with the two energy ETFs, USO and UNG. This finding corroborates earlier findings in Akhtaruzzaman et al. (2021a) that previous metals like gold served as safe haven assets to hedge risks from the energy market, but this property is lost during the COVID-19 pandemic.

### 3.2. Time-varying parameter vector autoregressive (TVP-VAR) model and generalized forecast error variance decomposition (GFEVD)

#### 3.2.1. Model specification

When using the traditional VAR model, to capture the time-varying dynamics of dependencies among variables, a common practice is to opt for the *rolling window approach* (Diebold and Yilmaz, 2012). But a major disadvantage of this approach is the arbitrariness in choosing the length of the rolling window. To cope with this problem, Antonakakis and Gabauer (2017) suggest using the Time-Varying Parameter Vector Autoregressions (TVP-VAR) approach where the task of choosing a rolling window size is dispensed with. Following Antonakakis and Gabauer (2017) and Akhtaruzzaman et al. (2021b), we specify the TVP-VAR model as follows:

$$y_t = B_t z_{t-1} + u_t = \sum_{i=1}^{p} B_{it} y_{t-i} + u_t \tag{2a}$$

$$vec(B_t) = vec(B_{t-1}) + \varepsilon_t \tag{2b}$$

where in Eq. (2a), $y_t$ is the $n \times 1$ vector of all the assets of interest (in our case, the seven ETFs); $z_t = (y_{t-1}', y_{t-2}', \dots, y_{t-p}')'$ is the $np \times 1$ long vector of lagged terms of $y_t$; $B_t = (B_{1t}, B_{2t}, \dots, B_{pt})$ is the $n \times np$ coefficient matrix, and it follows the random walk process governed by Eq. (2b). Denote the information obtain up until $t-1$ as $I_{t-1}$. Based on information $I_t$, the error terms $u_t$ and $e_t$ in Eq. (2a) and Eq. (2b) follow $u_t \mid I_{t-1} \sim N(0, \Sigma_{ut})$ and $e_t \mid I_{t-1} \sim N(0, \Sigma_{\varepsilon t})$, respectively. The lag order $p$ of the TVP-VAR($p$) model is selected by the Bayesian Information Criterion (BIC), and the estimation is done by Kalman filters.

#### 3.2.2. Generalized forecast error variance decomposition (GFEVD)

According to the Wold theorem, a VAR ($p$) model can be transformed into a VMA ($\infty$), i.e., an infinite-order vector moving average process. Similarly, for a TVP-VAR ($p$) model, it has a TVP-VMA ($\infty$) representation

$$y_t = \sum_{i=1}^{p} B_{it} y_{t-i} + u_t = \sum_{j=0}^{p} A_{jt} u_{t-j} \tag{3}$$

where the coefficient $\{A_{jt}\}$ satisfies

$$A_{jt} = \begin{cases} \Phi_1 A_{j,t-1} + \Phi_2 A_{j,t-2} + \cdots + \Phi_p A_{j,t-p} & j > 0 \\ I_n & j = 0 \\ O_n & j < 0 \end{cases} \tag{4}$$

For a VAR model, based on the VMA ($\infty$) representation, we can apply the traditional variance decomposition approach to examine how a variable respond to an orthogonalized shock. The resulting impulse response is called orthogonalized impulse response (OIRF) approach. However, by construction, ORIF depends on the Cholesky decomposition of the error variance, which is not invariant to the ordering of variables (Antonakakis et al., 2020; Antonakakis and Gabauer, 2017). To cope with this ordering problem, Pesaran and Shin (1998) developed the Generalized Forecast Error Variance Decomposition (GFEVD) based on the generalized impulse response function (GIRF) proposed in Koop et al. (1996). Similarly, using a TVP-VMA representation, the H-step-ahead GIRF for the $j$-th variable is calculate as

$$\Psi_{j,t}(H) = \sigma_{jj,t} A_{H,t} \Sigma_t e_j \tag{5}$$

where $\sigma_{jj,\,t}$, or the square root $\sigma^2_{jj,\,t}$, is the $j$-th diagonal element of the conditional variance $\Sigma_t$, $A_{H,\,t}$ is specified in Eq. (3), and $e_j$ is the $n \times 1$ selection vector where the $j$-th element equals one while other elements are all zero. Due to shock to variable $j$, the pairwise directional connectedness from $j$ to $i$ is

$$\widetilde{\phi}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \Psi_{ij,t}(H)^2}{\sum_{j=1}^{n} \sum_{t=1}^{H-1} \Psi_{ij,t}(H)^2} \tag{6}$$

where $\Psi_{ij,\,t}(H) = e_i' \Psi_{j,\,t}(H)$ is the $i$-th element of $\Psi_{j,\,t}(H)$. As an analogy to the VAR-based total directional connectedness developed by Diebold and Yilmaz (2012), we calculate the time-varying version of total directional connectedness as follows

$$C_{i\rightarrow\cdot,t}(H) = \frac{\sum_{j=1, j\neq i}^{n} \widetilde{\phi}_{ji,t}(H)}{\sum_{j=1}^{n} \widetilde{\phi}_{ji,t}(H)} \times 100 \tag{7a}$$

$$C_{i\leftarrow\cdot,t}(H) = \frac{\sum_{j=1, j\neq i}^{n} \widetilde{\phi}_{ij,t}(H)}{\sum_{j=1}^{n} \widetilde{\phi}_{ij,t}(H)} \times 100 \tag{7b}$$

where Eq. (6a) is the total directional connectedness from variable $i$ to others, and Eq. (6b) is the total directional connectedness from other variables to variable $i$. The time-varying total connectedness of the TVP-VAR system is by adding up all $\widetilde{\phi}_{ij,t}(H)$, which is

$$C_t(H) = \frac{1}{n} \sum_{i=1, i\neq j}^{n} \sum_{j=1}^{n} \widetilde{\phi}_{ij,t}(H) \times 100 \tag{8}$$

### 3.3. Wavelet coherence

After estimating the total connectedness measure based on a TVP-VAR model, we can also assess the time-frequency comovement among total connectedness and COVID related indexes using the wavelet coherence measures developed by Torrence and Compo (1998) and Torrence and Webster (1999) and elaborated on in Grinsted et al. (2004).

#### 3.3.1. Specification

Suppose we have a time series $y_i$. Denote $W_t^{y_i}(s)$ is the *wavelet transformation* of $y_i$, calculated as

$$W_t^{y_i}(s) = \sum_{\tau=0}^{T-1} y_i(\tau) \cdot \frac{1}{\sqrt{s}} \Psi\left(\frac{\tau - t}{s}\right), \tag{9}$$

where $t$ indicates day $t$, the sampling interval is one day, $s$ marks the wavelet scale, and $T$ is the length of the time series (in days). The function $\Psi(\cdot)$ denotes a localized wavelet, of which the common choice is the Morlet wavelet, i.e., $\Psi(\eta) = \pi^{-1/4} \exp\,(i\omega_0\eta - \eta^2/2)$. Suppose we have another time series $y_j$, then the *cross-wavelet power spectrum* between $y_i$ and $y_j$ can be calculated as

$$W_t^{y_i y_j}(s) = \left\langle W_t^{y_i}(s), W_t^{y_j}(s) \right\rangle. \tag{10}$$

where $\langle W_t^{y_i}(s), W_t^{y_j(s)} \rangle$ is the product of $W_t^{y_i}(s)$ and $W_t^{y_j}{*}(s)$, with $W_t^{y_j}{*}(s)$ being the complex conjugate of $W_t^{y_j}(s)$. When $y_i = y_j$, Eq. (10) becomes the *wavelet power spectrum* of $y_i$, $W_t^{y_i y_j}(s)$.

Using the *cross-wavelet power spectrum*, we compute the *wavelet coherence* between $y_i$ and $y_j$. Mathematically, it is calculated as

$$R_t^2(s) = \frac{\left|\mathscr{S}\left(s^{-1} W_t^{y_i y_j}(s)\right)\right|^2}{\mathscr{S}\left(s^{-1}\left|W_t^{y_i}(\tau)\right|^2\right) . \mathscr{S}\left(s^{-1}\left|W_t^{y_j}(s)\right|^2\right)} \in [0, 1], \tag{11}$$

where $|W_t^{y_i}(\tau)|^2$ and $|W_t^{y_j}(s)|^2$ are the *wavelet power spectrum* between $y_i$ and $y_j$; $W_t^{y_i y_j}(s)$ is their cross-*wavelet power spectrum*; $\mathscr{S}(\cdot)$ is the smoothing operator, defined as:

$$\mathscr{S}(W(s)) = \mathscr{S}_{scale}(\mathscr{S}_{time}(W_t(s))). \tag{12}$$

where $S_{time}$ is the smoothing operator along the time dimension, and $S_{scale}$ is the smoothing operator along the wavelet scale dimension, specified as $\mathscr{S}_{time}(W(s)) = \left(W_t(s) \cdot c_1^{-1/2\delta^2 s^2}\right)$ and $\mathscr{S}_{time}(W(s)) =$

$W_t(s) \cdot c_2 \text{rect}(0.6s)$, with $\text{rect}(\cdot)$ being the rectangular function.

Now, denote $\rho_{xy,\ t}(s)$ as the wavelet-based *dynamic correlation* between $x$ and $y$, defined as:

$$\rho_{y_i y_j,t}(s) = \frac{\Re\left(W_t^{y_i y_j}(s)\right)}{\sqrt{\left|W_t^{y_i}(\tau,s)\right|^2 \cdot \left|W_t^{y_j}(s)\right|^2}} \in [-1,1], \tag{13}$$

where $\Re\left(W_t^{y_i y_j}(s)\right)$ is the real part of the *cross-wavelet power spectrum*. Apparently, this measure captures the comovement of $y_i$ and $y_j$, which can be used to capture the pairwise comovement of two assets (Rua, 2010).

## 4. Empirical results and discussion

### 4.1. Connectedness among US ETFs

Table 3 presents the connectedness among US ETFs where total connectedness index (TCI) reveals system-wide connectedness of variables at 40%. The NET directional connectedness demonstrates that USO is leading the connectedness of the system by transmitting major spillovers to other ETFs followed by SPY, which transmits moderate spillovers to others during COVID-19. Conversely, FXE, SLV, IEF, UNG, and GLD are net recipients of spillovers in an orderly manner. The NET volatility transmission of USO is in line with Ji et al. (2022); Kang et al. (2021) and Mensi et al. (2020), who reported that the highest volatilities are transmitted by oil. Alternatively, our findings oppose the findings of Farid et al. (2021), who reported USO as net recipient of risk spillovers during COVID-19 pandemic. Meanwhile, SPY transmits moderate spillovers to other ETFs concurrent with Zhang et al. (2020) and Wang et al. (2020), who documented strong risk transmission from SPY to the rest of the markets. However, our findings counter the evidence of Karim et al. (2022c, 2022d), Husain et al. (2019), who narrated SPY neither transmits nor receives risk spillovers during the COVID-19 pandemic.

Correspondingly, the strong risk spillovers are received by FXE followed by SLV, IEF. However, UNG and GLD illustrate minimal risk reception displaying their low volatility in the system-wide connectedness, particularly during COVID-19. In addition, it is also highlighted that UNG and GLD, due to their strong integration in the financial markets, are less susceptible to the shocks coming from the outbreak of COVID-19 (Anwer et al., 2022; Alawi et al., 2022; Karim et al., 2022c, 2022d; Billah et al., 2022; Adekoya and Oliyide, 2021). Earlier empirical evidence (Le et al., 2021; Naeem et al., 2021; Elsayed et al., 2020) also illustrated that markets exhibited strong risk spillovers during the coronavirus pandemic.

Fig. 2 exhibits the time-varying total connectedness of US ETFs for the period encompassing January 2, 2020 to March 31, 2021. The pattern of risk spillovers splits the plot into three time periods delivering high volatility spillovers (January 2, 2020 to May 2, 2020), moderate volatility spillovers (May 2, 2020 to August 2, 2020), and low volatility spillovers (August 2, 2020 to March 31, 2021). Overall, it can be observed that time-varying volatility connectedness demonstrated significant ups and downs with pronounced risk spillovers initially that seemed to be moderate during the middle of the sample period and eventually disappeared by the end of the sample period. The initial spike in the graph denotes the period of high-risk spillovers where the connectedness of US ETFs substantially inclined to reach the maximum TCI level at 72% during March 2020, reflecting the declaration of a worldwide emergency state. It also manifests that markets were exposed to highest volatilities, uncertainties of economic and financial circumstances, and uneven conditions prevailing globally. Soon after the havocs of the pandemic slightly calmed down, the second period of time-varying volatility connectedness highlighted moderate risk spillovers that touched the TCI level at 40%. Immediately after August 2020, the volatility connectedness gradually declined, stressing that markets returned to normalized circumstances with lower risk connectedness.

Our findings imply a significant doomscrolling effect of COVID-19 outbreak in shaping the volatility spillovers among the US exchange-traded funds. Based on the arguments of Elsayed et al. (2020), Le et al. (2021), and Salisu and Vo (2020), it is asserted that the crisis period, driven by the market sentiment of fear, spread across the globe that resulted in higher volatility spillovers among the markets. The higher risk spillovers also denote declined diversification of asset portfolio opportunities for the investors who experienced extreme losses in the face of a global pandemic. Moreover, our findings imply that investor attitudes are quite a rationale for adopting diversification strategies during the crisis and market turbulence. However, during high-risk spillovers, following flight-to-safety, investors tend to shift from one asset class to another to secure their investments which adequately justifies the high levels of risk spillovers (Sarwar et al., 2020; Hamdi et al., 2019).

Fig. 3 displays the time-varying NET connectedness of US ETFs, which corroborates the findings presented in Table 3. The time-varying dynamics highlight that USO transmitted highest risk spillovers to other ETFs, particularly during the onset of COVID-19 pandemic, while the rest of the ETFs received marginal risk spillovers. Our findings corroborate Mensi et al. (2020) and Kang et al. (2021), who also documented net transmission of risk spillovers from oil to other markets, while our results counter the findings of Tiwari et al. (2021), who reported oil to be the net recipient of risk spillovers. In other words, we can say that USO remained highly volatile and exhibited major exposure to the doomscrolling effects of COVID-19 whereas the rest of ETFs showcased net reception of risk spillovers during the onset of COVID-19 pandemic. Overall, it is stressed that USO revealed high susceptibility while other ETFs indicated less exposure to the COVID-19 havocs. GLD and UNG remained disconnected from the network in line with Farid et al. (2021), Ji et al. (2020), and Elsayed et al. (2020), who spotted them as refuge assets shielding the investments from uncertain circumstances. Meanwhile, from the investors' point of view, the slight exposure of GLD and UNG to the volatilities and shocks caused by COVID-19 pandemic validates diversification opportunities of GLD and UNG against other ETFs as they shield the investments from uncertainties and uneven economic periods (Siddique et al., 2022; 2023).

**Table 3**
Connectedness table.

| | USO | UNG | GLD | SLV | SPY | IEF | FXE | Contribution FROM others |
|---|---|---|---|---|---|---|---|---|
| USO | 83 | 8.4 | 0.8 | 0.2 | 5.1 | 2.4 | 0.1 | 17 |
| UNG | 20.9 | 69.9 | 1 | 1.4 | 2.4 | 4 | 0.4 | 30.1 |
| GLD | 5.3 | 2.3 | 38 | 16.5 | 20.8 | 3.4 | 13.7 | 62 |
| SLV | 6.2 | 2.6 | 23 | 46.8 | 7.1 | 1.1 | 13.3 | 53.2 |
| SPY | 8.4 | 3.7 | 9.2 | 3.1 | 64.4 | 8.9 | 2.2 | 35.6 |
| IEF | 9.6 | 5.5 | 2 | 1.2 | 14.6 | 65.9 | 1.2 | 34.1 |
| FXE | 4.1 | 1.1 | 22.4 | 15 | 4.3 | 0.9 | 52.1 | 47.9 |
| Contribution TO others | 54.7 | 23.6 | 58.4 | 37.5 | 54.4 | 20.6 | 30.8 | **TCI = 40%** |
| NET directional connectedness | 37.7 | −6.5 | −3.7 | −15.7 | 18.7 | −13.4 | −17.1 | |

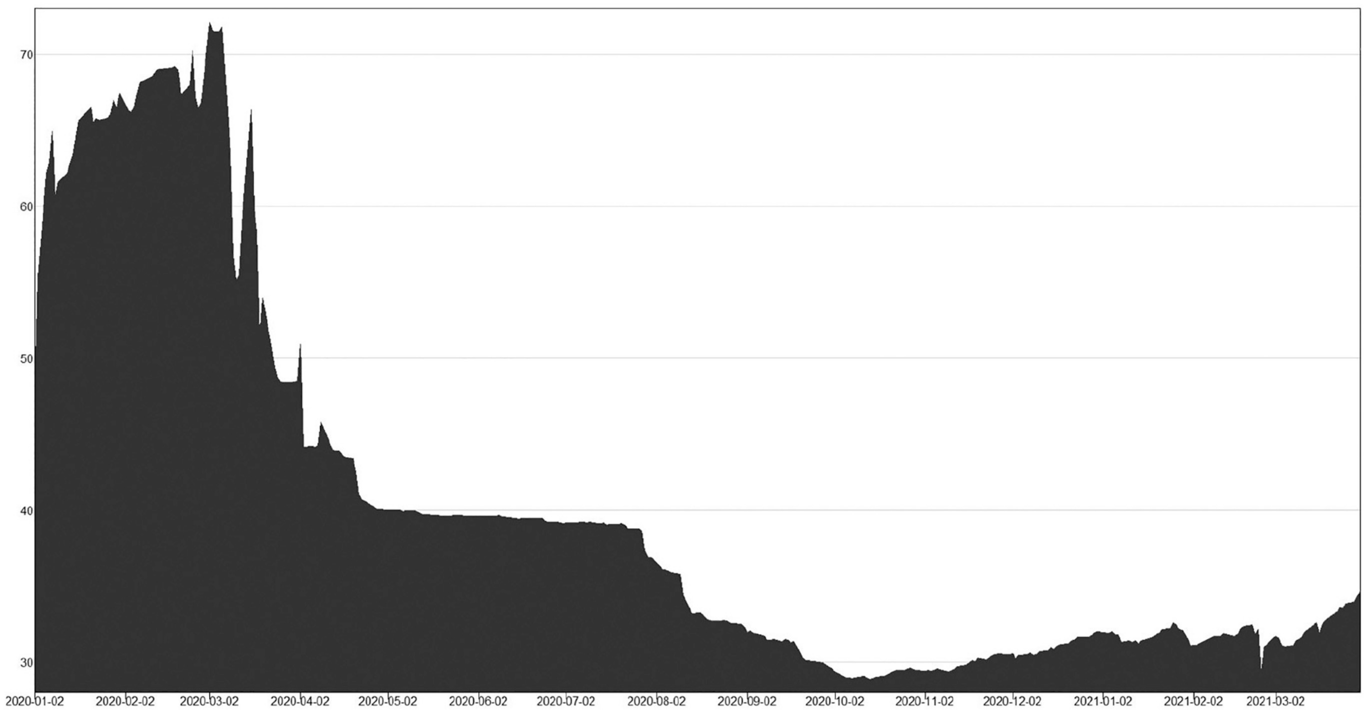


**Fig. 2.** Time-varying total connectedness.

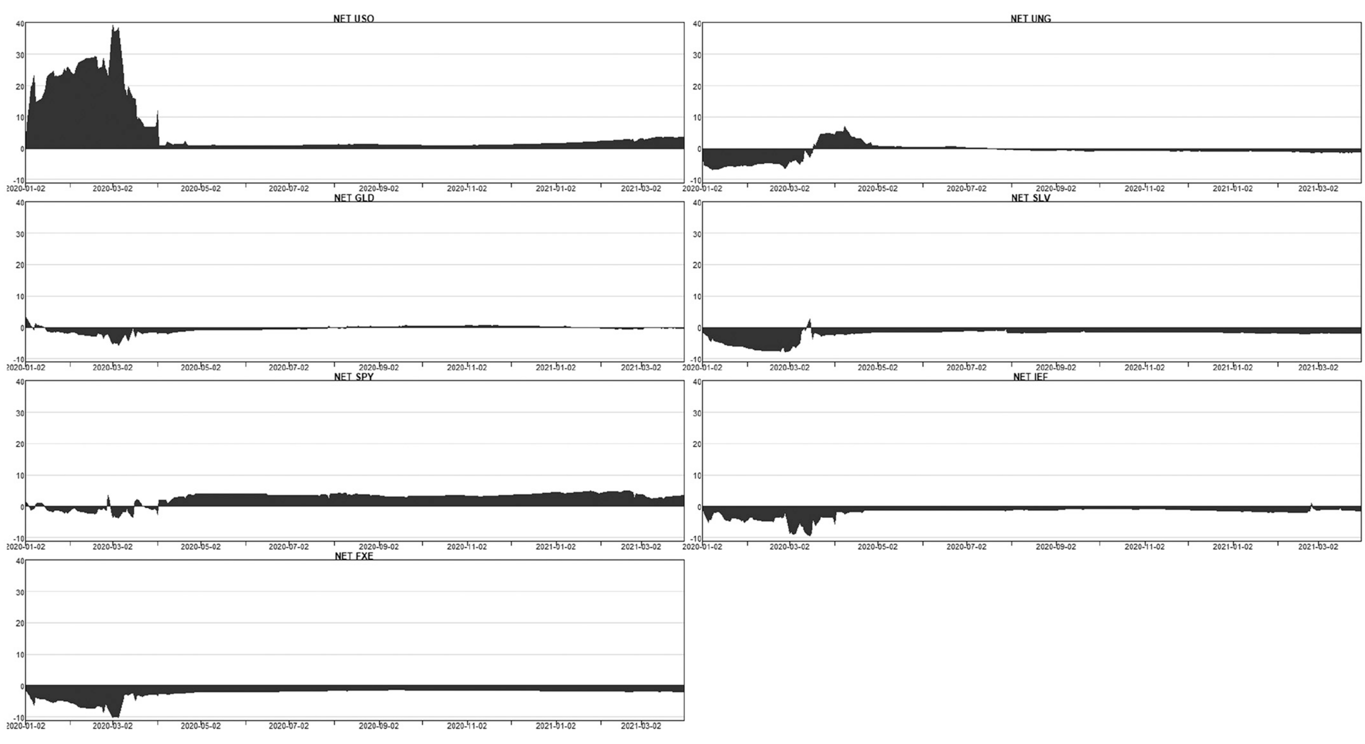


**Fig. 3.** Time-varying NET connectedness.
Note: This figure shows the time-varying NET connectedness of US ETFs using TVP-VAR model from January 2, 2020 to March 31, 2021.

### 4.2. Wavelet analysis

To further investigate the impact of COVID-19 on intraday volatility connectedness of US ETFs, we employed the wavelet coherence technique using four indexes of Panic index, Media Coverage index, Sentiment index, and Fake News index. Fig. 4(a) presents the impact of COVID-19 on the connectedness of US ETFs using the panic index where larger fragments and stronger dependence are detected for the given period. The impact is substantial at the beginning and middle of the plot, which gradually diminished at the end of the sample period over 4–64 days' frequency bands. The diagonally downward direction of arrows suggests that panic index is lagging the volatility connectedness, implying that US ETFs' volatility connectedness leads to investors' panic during the inception of the COVID-19 pandemic. Further, rightward

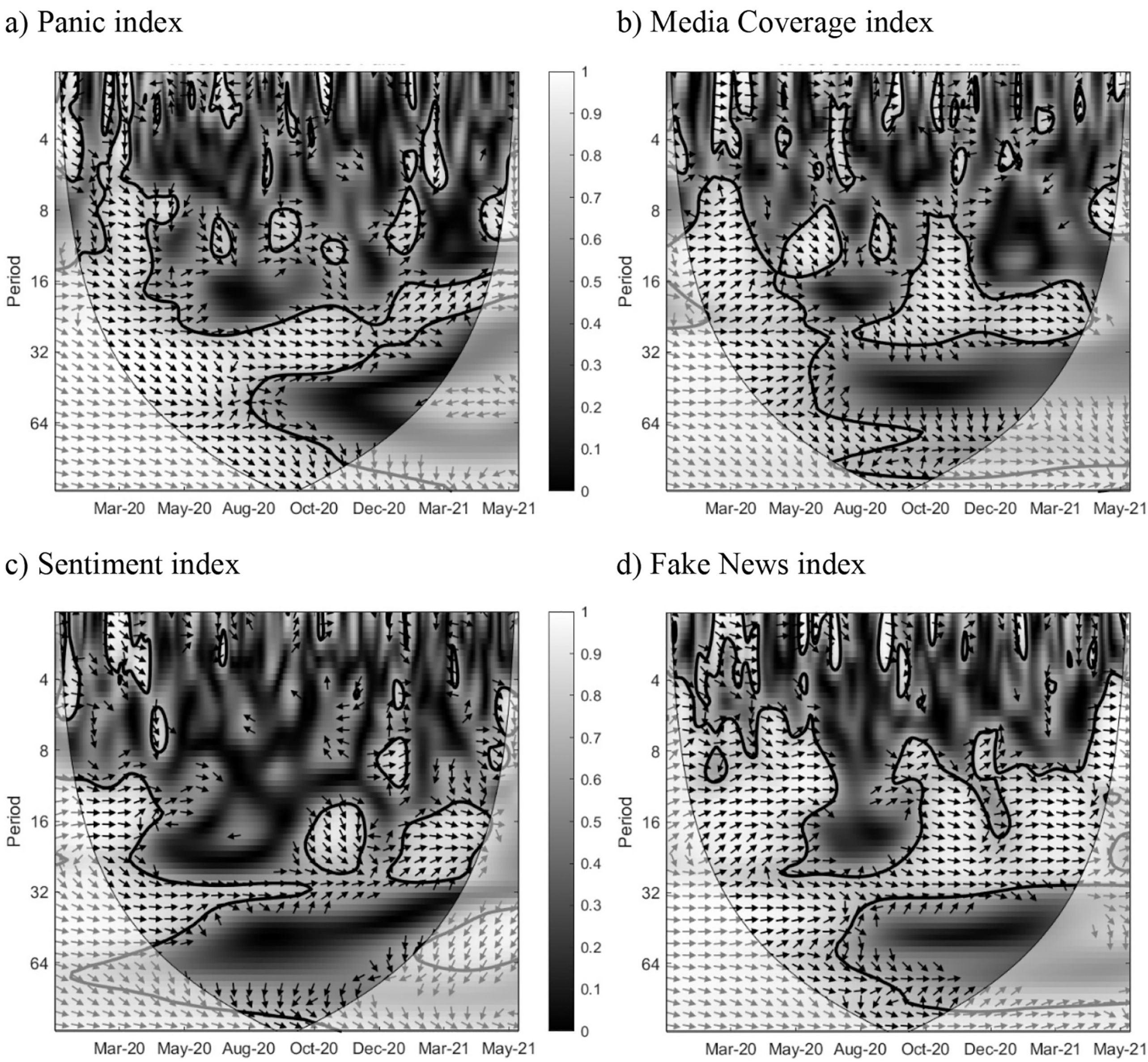


**Fig. 4.** Impact of COVID-19 on the connectedness.
Note: Wavelet coherence between the total connectedness and COVID related indexes. The 5% significance level against the noise is shown as a thick contour. The relative phase relationship is shown as arrows (with in-phase pointing right, anti-phase pointing left, and COVID related index leading connectedness by 90-degree pointing straight down).

direction of arrows signposts perfect covement between volatility connectedness of US ETFs and panic index which implies that with the increase in the volatility connectedness, the panic index also tend to increase (Rua and Lopes, 2015). Interestingly, at the end of the period, smaller fragments show diagonally upward direction of arrows which manifests that panic index leads the volatility connectedness, that is, with the decrease in the volatility connectedness, investors' panic turned out to be higher even the economically distressed period fade away.

Fig. 4(b) demonstrates the impact of COVID-19 on US ETFs risk connectedness by employing the media coverage index. Similar to Fig. 4 (a), the wavelet patterns reveal larger fragments during the start and middle of the sample period. However, smaller wavelets are reported during the end of the sample period. The diagonally upward direction of arrows manifests that media coverage index leads to US ETFs risk connectedness, implying that volatility connectedness among US ETFs was lower than the media coverage at the beginning of the pandemic (Appiah et al., 2023; Arfaoui et al., 2023; Farid et al., 2023). Noticeably, the diagonally downward direction of arrows illustrates an opposite nexus where media coverage index lags the intraday risk connectedness of US ETFs. Conversely, Fig. 4(c) plots wavelets of sentiments index where minimal comovement between volatility connectedness of US ETFs and sentiment index is reported. The figure illustrates smaller fragments of dependence with the rightward direction of arrows at the start and end of the sample period. Hence, we can infer that the dependence between sentiment index and connectedness is perfect yet smaller. In other words, with the increase in volatility spillovers, investors' sentiments tend to vary accordingly.

Finally, Fig. 4(d) presents the dependence between fake news index and volatility connectedness of US ETFs during the COVID-19 pandemic where larger fragments of comovement are displayed at the start of the outbreak, which gradually shrinks to smaller fragments and then again turned to be a larger fragment of dependence. The arrows' diagonally upward direction indicates that fake news leads the volatility spillovers, implying that rumors spread faster than the reported risk connectedness of US ETFs. The rightward direction of arrows suggests a perfect comovement between fake news and risk spillovers, spotting the increase in the intraday volatility connectedness also increases the fake news. From the investors' viewpoint, these psychological and behavioural factors play a significant role in determining and designing their portfolios in the face of COVID-19 pandemic. Overall, panic index showed lagged effect, which asserts that panic of investors lagged the risk connectedness (Naeem et al., 2022c,d). Media coverage index leads the volatility spillovers implying that COVID-19 coverage surmounted the investment challenges for investors. Captivatingly, the sentiment index showed perfect comovement with risk spillovers of US ETFs, inferring that investors' sentiments showed direct dependence with the volatility connectedness, and with sentiments of investors, the volatility connectedness tends to differentiate accordingly (Karim et al., 2023; Naeem et al., 2023b,a). Meanwhile, fake news leads the intraday volatility connectedness, emphasizing that fake news played a significant role in shaping the volatility spillovers for investors who falsely relied on the risk spillovers while managing the risk of their portfolios during the pandemic COVID-19.

## 5. Conclusion and implications

The prime objective of this study is to examine the doomscrolling impact of COVID-19 on the intraday volatility connectedness of US ETFs. For this purpose, we used the data of seven ETFs, namely, USO, UNG, GLD, SLV, SPY, IEF, and FXE, for the period encompassing January 2, 2020 to March 31, 2021. Estimations were carried out in three steps; 1) we estimate the realized volatility of US ETFs using the 5-min intraday data, 2) we applied the time-varying parameter vector autoregressions (TVP-VAR) for estimating the volatility connectedness among US ETFs, and 3) we employed the wavelet coherence approach to explore the time-frequency dependence of COVID-19 on the volatility connectedness across financial markets using four unique indexes of panic, media coverage, sentiment, and fake news. We find considerable risk connectedness among the various US ETFs where USO transmitted major risk spillovers to other markets, followed by SPY. The leftover ETFs indicated risk reception, particularly during COVID-19, whereas GLD and UNG remained disconnected from the network substantiating their refuge status during the crisis period and overcoming the risk of the portfolios.

Time-varying dynamics of volatility connectedness identified three major periods when markets experienced extreme uncertainty at the commencement of the pandemic. The second phase indicates moderate risk spillovers when markets start to normalize after the serious havoc of COVID-19. The third phase detects low volatility spillovers with high disconnection of US ETFs at the end of the sample period. The time-varying NET connectedness reiterated the dominant contribution of USO in shaping the risk spillovers while leftover markets received volatility spillovers. Further, wavelet analysis indicated panic index lagged the volatility connectedness, sentiment index revealed perfect comovement, whereas both media coverage and fake news indexes showcased their leading role when compared with volatility connectedness. Hence, we can assess that media coverage and fake news indexes played a sizable role in determining the investors' attitudes towards the uncertainty of the market. Contrarily, the sentiment index showed positive dependence iterating that investors' sentiments co-moved with volatility connectedness of US ETFs. However, panic index revealed that a low panic state was observed when risk spillovers were high and vice versa. In this way, we validated our study by employing investors' psychological attitudes to examine the effect of COVID-19 on the intraday volatility connectedness.

With these findings, we devise implications for policymakers, governments, regulation authorities, portfolio managers, investors, and financial market participants during the COVID-19 pandemic. Policymakers can relish these findings to redefine their existing policies to reduce the effects of external shocks on investments. Governments can take up useful policies while carefully examining the expected risks that appeared out of global pandemics. Similarly, regulation authorities need to set plans and act accordingly when markets undergo harsh economic and financial circumstances. While cautiously evaluating the risks of their portfolios, Portfolio managers can judge whether to put highly volatile investments in the mainstream investments or they can be sidelined. In this way, adding the potentials of the investment with less susceptibility to the external unexpected stress events can shield the investments from serious losses. Investors can benefit from these findings by optimistically choosing those ETFs which offer greater diversification and low risk, given the impacts of COVID-19 on the financial markets. In terms of psychological and behavioural factors, it is necessary to strategically design the portfolio mix based on real facts figures rather than fake news, which tends to entice pessimism and disappointments in the investors regarding their portfolios and investment avenues. Thus, these findings offer beneficial opportunities for policymakers, portfolio managers, and investors to carefully assess and define their investment objectives by considering the haphazard economic conditions.

On the policy implications front, the pandemic led to a sharp increase in market volatility, which impacted the performance of ETFs and led to concerns about their stability and resilience. The increased market volatility and the role of ETFs in the spread of market shocks led to calls for greater regulation of the ETF industry. In addition, the rapid selling of ETFs during the pandemic led to liquidity concerns, highlighting the need for more robust market infrastructure to ensure the smooth functioning of ETFs. Moreover, the pandemic and the market turbulence it caused raised questions about the protection of investor interests and the need for more stringent investor protection measures. The role of ETFs in the financial system, particularly in the transmission of market shocks, led to discussions about their potential impact on the stability of the financial system. In summary, the COVID-19 pandemic has prompted a reassessment of the role of ETFs in the financial system and has led to calls for greater regulation and oversight of the ETF industry to ensure the protection of investor interests and the stability of the financial system.

There are some academic implications of the study for research scholars and academicians. For instance, the pandemic provided a unique opportunity to study the behavior of ETFs and their impact on financial markets during a period of extreme volatility. Moreover, the pandemic prompted a reassessment of the liquidity and market efficiency of ETFs, leading to new academic research on these topics. The pandemic led to a renewed focus on risk management in the ETF industry and the development of new risk management strategies along with portfolio diversification and the role of ETFs in achieving diversification, leading to new academic research in this area. Finally, the use of algorithmic trading in the ETF industry has come under scrutiny, leading to new academic research on the impact of algorithms on ETF trading and market behavior.

The limitations of the study are as follows: the pandemic caused significant market volatility and data collection may be limited, leading to a potential bias in the results. The rapid changes in financial markets during the pandemic may have led to changes in the behavior and performance of ETFs, making it difficult to draw general conclusions. The COVID-19 pandemic is a relatively recent event, and a longer time horizon is necessary to fully assess the impact of the pandemic on ETFs.

However, further research is needed to understand the long-term effects of the COVID-19 pandemic on ETFs and their role in financial markets and to understand the market structure of ETFs and their impact on financial markets, particularly in periods of extreme volatility. Moreover, future studies can examine the impact of regulation on the ETF industry and the effectiveness of current regulation in protecting investor interests and ensuring market stability. Scholars can compare the performance and behavior of ETFs across different countries and regions, particularly during periods of market stress. Further research is needed to develop and improve risk management strategies for ETFs, particularly in periods of market stress.

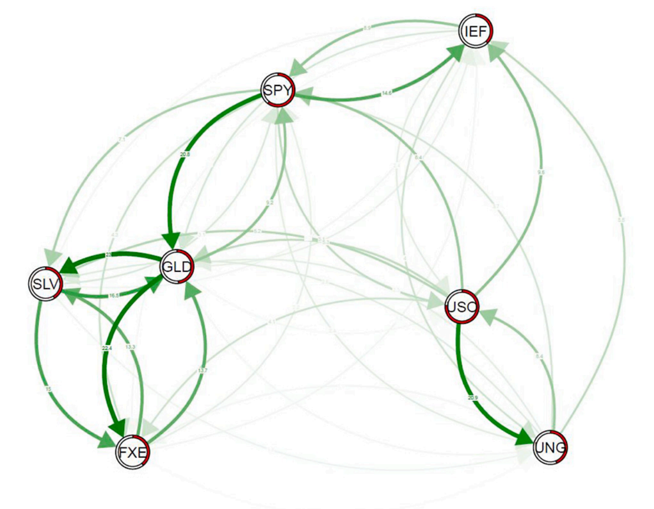


**Fig. A1.** Network diagram of realized volatility spillover using the TVP-VAR approach.
Note: The network graph illustrates the degree of pairwise directional connectedness of a system that consists of the daily realized volatilities of the US ETFs covering the complete sample period. TVP-VAR is employed for computing total connectedness. Colours on the borders show the origination of the connectedness. The red colour points towards the contribution of spillovers from a particular market to the other market in the whole system. Edge size of each figure indicates magnitude of total directional connectedness. Lag = 1 (SIC criteria); forecast horizon = 10 days.

**CREDIT Author Statement**

Naeem: Idea conception, data management.
Karim: analysis, drafting.
Yarovaya: Editing, drafting.
Lucey: editing, drafting

Note: This figure shows the time-varying total volatility connectedness between the seven ETFs volatilities based on a TVP-VAR model. The sample period is from January 2, 2020 to March 31, 2021.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.106677.

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