Global financial crisis versus COVID-19: Evidence from sentiment analysis

Aktham Maghyereh1 | Hussein Abdoh2

1Department of Accounting and Finance, United Arab Emirates University, Abu Dhabi, UAE
2Department of Accounting and Finance, The Citadel: The Military College of South Carolina, Charleston, South Carolina, USA

Correspondence
Aktham Maghyereh, Department of Accounting and Finance, United Arab Emirates University, Abu Dhabi, UAE. Email: a.almaghaireh@uaeu.ac.ae and habdoh@citadel.edu

Funding information
United Arab Emirates University, Grant/Award Number: 31B135-UPAR-3-2020

Abstract
This study examines the relationship between sentiment and the realized volatility of returns for different asset classes (stocks, bonds, foreign currency, and commodities). Specifically, we aim to answer two key questions: first, how does sentiment relate to volatility during crises (mainly during the global financial crisis [GFC] and the COVID-19 pandemic)? Second, can sentiment be used to forecast volatility during crises? Using two nonparametric methods, mutual information and transfer entropy, we find that information sharing and transfer increased during the pandemic. We also find that sentiment information transfer to the volatility of assets differed between the GFC and the COVID-19 crisis. Since sentiment can reduce uncertainty around the realized variance of assets, we investigate the forecasting ability of sentiment during crises. We find that sentiment has a greater predictive power on realized volatility during crises, with a differential impact on volatility depending on the asset class. Our findings carry important implications for hedging, risk management and building models to predict variance during crises.

Abbreviations: BIC, Bayesian information criterion; ETE, effective transfer entropy; ETF, exchange-traded fund; GFC, global financial crisis; GIRF, generalized impulse response function; HAC, heteroskedasticity- and autocorrelation-consistent; MEM, maximum entropy method; MI, mutual information; SPGS, Standard & Poor's Goldman Sachs; TE, transfer entropy.
INTRODUCTION

It has been well documented that asset volatility can be explained by two quite distinct perspectives: classical asset-pricing theory and behavioural finance theory. The former posits that sentiment should not affect asset prices, while the latter asserts that investor sentiment can explain asset-price movements. Behavioural finance can be traced back to Keynes (1936) argument that people’s decision-making could be contaminated by irrational psychology: investors’ sentiments, emotions and moods. This creates changes in asset prices and hence increases volatility. On the theoretical side, Daniel et al. (1998) suggested that self-attribution of investors' private information over fundamental and public signals induces greater excess volatility. This, in turn, leaves room for sentiment to affect investors' trading decisions. On the empirical side, sentiment has been shown to impact asset volatility (e.g., Da et al., 2015; Ho et al., 2013; Kumari & Mahakud, 2015; Lee et al., 2002; Maitra & Dash, 2017; Shu & Chang, 2015).

These studies primarily focused on the sentiment–volatility relation in stock markets and during noncrisis periods. However, there is a lack of evidence about this relationship in different asset class markets, including bonds, foreign currencies and commodities. Moreover, to the best of our knowledge, no studies have compared the effects of investor sentiment on asset volatility during the 2008–2009 global financial crisis (GFC) and the COVID-19 pandemic. In this study, we examined two major factors related to sentiment–volatility relation. First, we explored the informational link between sentiment and asset volatility for different asset classes during normal and crisis periods. In this regard, we used two nonparametric methods: mutual information (MI) and effective transfer entropy (ETE). Second, we examined how sentiment can forecast in-sample and out-sample volatility.

Our analyses highlighted the following. First, the MI measure reveals a noticeable increase in the information transmissions between news-based economic sentiment and realized volatility of different financial assets during the two major global crises, but to varying degrees, depending on the asset class. Specifically, the information sharing between the economic news sentiment and the realized variance reached the highest level for oil, natural gas and the commodity index during the COVID-19 outbreak, while it peaked for gold, foreign currency and bonds during the GFC period. Silver, however, showed the highest level of MI outside both of these crises (during the 2012–2014 period). Second, ETE estimates indicated that sentiment is a net transmitter of information to asset volatility, with oil (the commodity index) receiving the highest (lowest) net ETE from sentiment. The ETE analysis revealed that sentiment could reduce the uncertainty about the realized variance of assets beyond the degree to which the realized variance reduces uncertainty about their own future values. Third, the ETE flow from sentiment to volatility increased at a higher rate relative to the flow from volatility to sentiment during the GFC, that is, sentiment increased the net ETE from sentiment to volatility. However,
not all asset classes have shown a similar increase in net ETE from sentiment during the COVID-19 pandemic. Fourth, a prediction model that included news sentiment yielded better out-of-sample performance in predicting the realized volatility for all asset classes than the corresponding benchmark of a simple autoregressive AR(1) specification. Fifth, the forecasting ability from sentiment to realized volatility increased most during the COVID-19 pandemic (GFC) for oil, natural gas, S&P 500, FTS 100 and the commodity index (foreign exchange rates and bonds).

This study contributes to the existing literature in the following ways. First, it reveals the importance of monitoring portfolio composition in different asset classes for shifts in sentiment during crises. Investors can better allocate funds across different asset classes by knowing the degree to which crises affect the sentiment–volatility relationship. Second, it adds to the available knowledge about volatility modelling and forecasting during crises, as it shows how sentiment predicts the future values of asset volatility. This, in turn, plays a vital role in asset pricing and risk management, not only for these assets but also for their financial derivatives (e.g., options). Third, past studies attempted to quantify the sentiment–volatility relation using path dependence (RS-GARCH) models or traditional linear causality (vector autoregressive [VAR]) models (e.g., Chen et al., 2021; Haroon & Rizvi, 2020; Ho et al., 2013; Kumari & Mahakud, 2015; Maitra & Dash, 2017; Qi et al., 2021; Shahzad et al., 2017). However, to the best of our knowledge, no study has examined this relationship using MI and transfer entropy methods. Unlike GARCH-type models, MI and transfer entropy are nonparametric methods (i.e., model-free measures) that do not require a functional form. Furthermore, transfer entropy quantifies the magnitude and direction of nonlinear information dynamics and possible asymmetric information flow between two time series variables under study. Specifically, it measures the dynamic directional information transfer rather than a measure of causality between variables (Dimpfl & Peter, 2019; Moldovan et al., 2020; Schreiber, 2000). Moreover, unlike traditional linear methods, transfer entropy captures the structural changes between two-time series, thereby providing a more reliable estimation of the effect of crises on information flow transmission. Fourth, regulators can examine the role played by sentiment in undermining financial asset volatility during crises and understand how two major crises (GFC and COVID-19) affected the sentiment–volatility relationship in different ways. Finally, this study is one of the few that has examined informational and causality linkages between sentiment and volatility across different spectra of asset classes.

The remaining parts of the paper proceed as follows: Section 2 briefly reviews the relevant literature. Section 3 presents the data source and descriptive statistics. Section 4 introduces the econometric methods used in the empirical analysis. Then, Section 5 shows the empirical results. Finally, the conclusions and implications are summarized in Section 6.

2 BRIEF LITERATURE REVIEW

Behavioural finance asserts that sentiment can influence investors' decision-making, even though it may not be aligned with an asset's fundamental value. This creates a deviation from the asset price maintained by fundamentals or from rational expectations about asset value (Edelen et al., 2010). One outcome of this deviation is an increase in price volatility. As such, sentiment and its association with emotions (e.g., pessimism or optimism) and general attitudes toward the financial market are positively linked with greater volatility, as documented by several studies (e.g., Brown, 1999; Da et al., 2015; Ho et al., 2013; Johnman et al., 2018; Verma
& Verma, 2007). Studying the relationship between sentiment and volatility has mainly been concentrated in the context of equity markets and, to a lesser extent, the oil and gold markets. Balcilar et al. (2017) show that sentiment significantly affects gold volatility, but only in the upper and lower quantiles. Yang et al. (2019) find that sentiment significantly predicts future oil volatility. However, we believe that studying other commodities (such as natural gas or silver) is important due to the financialization movement that has occurred in the commodities markets since early 2000. Therefore, a general sentiment index is sufficient to predict the volatility of all commodities. As a result of the financialization movement and the resulting increase in price comovements between different commodities and between different asset classes (e.g., Tang & Xiong, 2012), it is vital to analyse the impact of sentiment on volatility for a wide range of different assets. The present study helps to address this knowledge gap.

Sentiment can play an even more critical role in driving volatility during economic crises. This can primarily be attributed to the high uncertainty that accompanies these crises, as investors resort to their sentiment and/or beliefs when making investment decisions. Several studies have shown that the effect of sentiment on volatility is heightened during recessions. Garcia (2013) finds that sentiment from news content has a significant relationship with stock returns, particularly during recessions. Maitra and Dash (2017) document higher comovement between sentiment and volatility during crises than during calm periods on Indian stock markets. Similarly, Mathieu (2016) shows that the influence of investor sentiment on REIT and S&P 500 return volatility is greater during financial crises. Maghyereh and Abdoh (2020) find that the interdependence between investors’ sentiments and commodity returns differs according to return quantile and time-frequency.

There is a dearth of studies examining the role of sentiment in driving volatility during crises for assets other than equity. Moreover, the informational link between sentiment and volatility has received little attention. To bridge this gap, we employed Shannon’s (1949) entropy-based analysis. The entropy-based analysis is valuable because it is a nonparametric (model-free) approach and measures information transfer among nonlinear dependences in the autocorrelation structure of dynamic systems (Darbellay & Wuertz, 2000). Following Benedetto et al. (2020), we used two methods: MI based on the maximum entropy method proposed by Benedetto et al. (2016, 2019), and transfer entropy (TE) based on Shannon TE, first proposed by Schreiber (2000) and extended by Behrendt et al. (2019).

Our findings showed that investor sentiment contains relevant information about future movements in financial volatility; therefore, we examine its usefulness for forecasting volatility and how that usefulness varies over time (e.g., during crises). Only a few studies have examined the usefulness of sentiment for forecasting future volatility values for different assets, especially using a frequency of data that is less than monthly (e.g., daily data).²

3 | DATA SET AND PRELIMINARY ANALYSIS

The daily data set used in this study included an index of news sentiment and four asset classes (stocks, bonds, currencies and commodities) from January 1, 2000, to October 31, 2020 (totalling 5227 observations).³ The chosen period spanned 20 years of financial history. It included the “dotcom” bust of 2000–2001, the September 11, 2001 terrorist attacks, the invasion of Iraq in 2003, the GFC from September 2008 to December 2009, the European sovereign debt crisis from April 2010 to June 2012 and, finally, the COVID-19 pandemic, from December 2019
to the present. However, as shown later, we focused on the GFC and COVID-19 pandemic in our discussion since they drove the main results of our study.

We empirically considered the impact of news on various financial assets using a news-based measure of economic sentiment, recently developed by Shapiro et al. (2020). The index is regularly updated on the San Francisco Fed’s website. This sentiment index is constructed based on economics-related news articles, using a lexical approach. The data contributing to the index include more than 238,685 economic and financial news articles from 16 major newspapers. The overall sentiment score is normalized to produce continuous values ranging from $-1$ to 0, indicating negative economic sentiment (a measure of the degree of the pessimism of agents about the state of the economy) and from 0 to 1, indicating positive economic sentiment (a measure of the degree of optimism of agents about the state of the economy).

The two stock markets used (and the indices that represent them) were from the United States (S&P 500) and the United Kingdom (FTSE 100). The bond market was represented by the Pimco Investment Grade Corporate Bond Index exchange-traded fund. The USD/EUR exchange rate represents the foreign exchange market. We chose the Standard & Poor’s Goldman Sachs Commodity Index to indicate the overall commodity market. We also used four commodities: Brent crude oil, natural gas, gold and silver. Data for all asset markets were obtained from the Thomson Reuters Datastream database.

To study the information content of news sentiment for realized volatility, we use daily squared returns to measure the ex-post realized volatility, that is, $R_{t}^{2}$ (see, e.g., Andersen & Bollerslev, 1998; Awartani et al., 2016; Foster & Nelson, 1996; Gong & Lin, 2017; 2018; Park & Ratti, 2008; Paye, 2012; Sadorsky, 2006). This measure is unbiased, but it can be noisy (e.g., Lopez, 2001; Patton, 2011).

Figure 1 presents the time-series plot of assets’ realized volatility and the news-sentiment index. The sentiment index reached its lowest (or negative) values during various crises, including the dotcom bust of 2000–2001, the September 11, 2001 terrorist attacks, the invasion of Iraq in 2003, the GFC from September 2008 to December 2009 and the European sovereign debt crisis from April 2010 to June 2012. The last two crises created the largest decline in the sentiment index. During the ongoing COVID-19 pandemic, we can clearly see another sharp decline in sentiment. Asset volatility corresponds to at least some of these crises. Asset volatilities have increased most during the COVID-19 pandemic, except for the gold, bonds and foreign exchange rates between the US dollar and the euro. As indicated in several studies, these assets may possess the feature of “flight-to-safety” during crises.

Panel A of Table 1 displays the mean, standard deviation, skewness, kurtosis of daily returns of all the series and the Jarque–Bera test for normality. The mean realized volatility was highest for natural gas and lowest for bonds and foreign exchange rates. The minimum volatility for all assets reached a value close to zero. Natural gas had the highest dispersion between maximum and minimum values, with a difference equal to 3.0511. Accordingly, its standard deviation was the highest, with a value equal to 0.0682, relative to standard deviations in volatility for the other assets. We observe a nonnormality in asset volatility distributions by looking at skewness and kurtosis. This was confirmed by the Jarque–Bera test, which rejected the null hypothesis that assets’ return volatilities are normally distributed. Panel B of Table 1 shows the correlation between the news-sentiment index and the volatility for each asset. The sentiment was negatively correlated with asset volatility, indicating that bullish changes in sentiment are associated with downward revisions in volatility (see, e.g., Lee et al., 2002).
METHODS

In this study, our interests primarily lay in measuring the incremental information content of news sentiment concerning the volatility of various asset classes. To achieve this, we used an entropy-based analysis approach borrowed from Shannon’s information theory (1949). The entropy-based analysis is valuable in that its non-parametric approach (or model-free test) can measure information transfer in nonlinear dependences of autocorrelation structures of dynamic systems (Darbellay & Wuertz, 2000). Following Benedetto et al. (2020), we used MI and TE methods. We briefly introduce these methods below.

FIGURE 1 Time trends of the sentiment and asset volatility values [Color figure can be viewed at wileyonlinelibrary.com]
TABLE 1  Summary statistics

|                | Sentiment | Oil       | Natural gas | Gold   | Silver  | Bonds    | S&P 500 | FTSE 100 | US$/EUR | Commodity index |
|----------------|-----------|-----------|-------------|--------|---------|----------|---------|----------|---------|-----------------|
| **Panel A**    |           |           |             |        |         |          |         |          |         |                 |
| Mean           | 0.0255    | 0.0001    | 0.002       | 2.16E–05| 6.28E–05| 4.14E–06| 2.87E–05| 2.62E–05| 6.69E–06| 4.07E–05       |
| Maximum        | 0.6196    | 0.032     | 3.0511      | 0.0019 | 0.0035  | 0.0003   | 0.0030  | 0.0025   | 0.0004  | 0.0029          |
| Minimum        | −0.7295   | 0.0000    | 0.0000      | 0.0000 | 0.0000  | 0.0000   | 0.0000  | 0.0000   | 0.0000  | 0.0000          |
| SD             | 0.2325    | 0.0006    | 0.0682      | 6.16E–05| 0.0002  | 9.32E–06| 0.0001  | 8.47E–05| 1.46E–05| 0.0001          |
| Skewness       | −0.2078   | 28.6346   | 39.6849     | 11.3342| 9.1286  | 10.8322  | 13.4508 | 12.7319  | 9.4405  | 11.8462         |
| Kurtosis       | 2.7165    | 1083.729  | 1640.102    | 236.572| 123.3908| 255.1886| 263.4697| 251.2452 | 177.6923| 248.0537        |
| Jarque-Bera    | 56.1260***| 2.60E+8***| 5.95E+08*** | 122,071***| 3,286,714***| 1,420,183***| 1,519,928***| 1,380,408***| 6,843,717***| 1,343,580***    |
|                | (0.0000)  | (0.0000)  | (0.0000)    | (0.0000)| (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000)         |
| **Panel B**    |           |           |             |        |         |          |         |          |         |                 |
| Sentiment      | 1.0000    | −0.2929***| −0.1207***  | −0.2284***| −0.2392***| −0.2923***| −0.3376***| −0.3411***| −0.2086***| −0.2740***      |
|                | (0.0000)  | (0.0214)  | (0.0000)    | (0.0000)| (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000)         |

Note: The data are based on daily observations and cover the period from January 1, 2000, to October 31, 2020, totalling 5328 observations for each series. The p values are in brackets.***, ** and * refer to significance levels at 1%, 5% and 10%, respectively.
4.1 Mutual information

MI measures the degree of information sharing between two discrete random variables by estimating their joint probability density functions, thus capturing all the information transfer (linear and nonlinear) that exists in the system. The concept of MI is intimately tied to so-called (Shannon) entropy \( H \), which measures the uncertainty in a random variable, or the average expected “amount of information” held in a random variable. Let \( X \) be a discrete random time-series with a probability distribution \( P(x_i) \) for \( i = 1, \ldots, n \), then, the Shannon entropy \( H(X) \) is defined by:

\[
H(X) = - \sum_{i=1}^{n-1} p_i \log p_i.
\]  

(1)

Then, the MI \( MI(X, Y) \) of two random two series, \( X \) and \( Y \), with a priori joint probability \( p(x_i, y_j) = p_{ij} \) can be obtained from the entropies of the two series \( H(X) \) and \( H(Y) \) and the joint entropy of both series \( H(X, Y) \), as follows:

\[
MI(X, Y) = H(X) + H(Y) - H(X, Y),
\]  

(2)

where \( H(X, Y) \) can be calculated as follows:

\[
H(X, Y) = - \sum_{i=1}^{n-1} \sum_{j=1}^{n-1} p_{ij} \log(p_{ij}(x, y)).
\]  

(3)

Since the prior probability of the two series and their joint probability is unknown, we followed Benedetto et al. (2016, 2019, 2020). We obtained the joint entropy \( \hat{h}(x, y) \) using the maximum entropy method, as follows:

\[
\hat{h}(x, y) = \frac{1}{2} \ln(2\pi e) + \frac{1}{4\pi} \int_{-\pi}^{\pi} \ln(\text{cross} - \text{PSD}_{x,y}(\omega))d\omega,
\]  

(4)

where \( \text{cross} - \text{PSD}_{x,y}(\omega) \) is the cross-power spectral density of two-time series \( x(n) \) and \( y(n) \) of length \( n = 1, \ldots, N \), which can be calculated by:

\[
\text{cross} - \text{PSD}_{x,y}(\omega) = \sum_{k=-\infty}^{\infty} C_{x,y}(k)e^{-j\omega k},
\]  

(5)

where \( C_{x,y}(k) \) is the cross-covariance between the two series.

Finally, the MI can be obtained based on Equation (2) as follows:

\[
\hat{MI}(X, Y) = h(x) + h(y) - \hat{h}(x, y) = \frac{1}{2} \ln(2\pi e) + \frac{1}{4\pi} \int_{-\pi}^{\pi} \ln(\text{PSD}_x(\omega))d\omega
\]

\[
+ \frac{1}{4\pi} \int_{-\pi}^{\pi} \ln(\text{PSD}_y(\omega))d\omega - \frac{1}{4\pi} \int_{-\pi}^{\pi} \ln(\text{cross} - \text{PSD}_{x,y}(\omega))d\omega.
\]  

(6)
4.2 Transfer entropy

Although MI is useful for capturing the information transfer in a system, it is a symmetric measure and hence cannot be used to determine the direction of information flow (i.e., mutual directional causation). Therefore, to complement our analysis, we used the TE method, which was introduced by Schreiber (2000). Using the TE method, we can detect linear and nonlinear information transfer and the asymmetries and dynamic transmission process.

Let $X$ and $Y$ denote two discrete and stationary processes with marginal probability distributions $p(i)$ and $p(j)$ and joint probability $p(i, j)$, whose dynamical structures correspond to a stationary Markov process of order $k$ and $l$ for discrete states of $X$ and $Y$, respectively. If the state of $Y$ does not influence the transition probabilities of $X$ (i.e., $(i, j) = 0)$, then the generalized Markov property satisfies the following assumption:

$$ p(i_{t+1} | i_t^{(k)}, j_t^{(l)}) = p(i_{t+1} | i_t^{(k)}) $$

where $i_t$ and $j_t$ represent the discrete states of $X$ and $Y$, respectively, at time $t$, $p(i_{t+1} | i_t^{(k)}, j_t^{(l)})$ and $p(i_{t+1} | i_t^{(k)})$ are the joint and conditional probability density functions, respectively, and $i_t^{(k)} = (i_t, ..., i_{t-k+1}), j_t^{(l)} = (j_t, ..., j_{t-l+1})$ denotes the $k$ and $l$ dimensional delay vectors of $X$ and $Y$. The deviation from this assumption can be quantified by the Kullback–Leibler divergence, which defines Shannon TE as:

$$ T_{EY \rightarrow X}(k, l) = \sum p(i_{t+1}, i_t^{(k)}, j_t^{(l)}) \log \frac{p(i_{t+1} | i_t^{(k)}, j_t^{(l)})}{p(i_{t+1} | i_t^{(k)})}. $$

The Markov block bootstrap procedure was used to obtain the statistical influence of the TE estimates in Equation (8).

Finally, to correct for the possible effects of small-sample bias in estimating the TE in Equation (8), we used the ETE, originally proposed by Marschinski and Kantz (2002) as follows:

$$ \text{ETE}_{Y \rightarrow X}(k, l) = T_{EY \rightarrow X}(k, l) - T_{E_{Y \text{shuffled}} \rightarrow X}(k, l) $$

where $T_{E_{Y \text{shuffled}} \rightarrow X}(k, l)$ is the TE using a shuffled series of $Y$.

By definition, $\text{ETE}_{Y \rightarrow X} \neq \text{ETE}_{X \rightarrow Y}$ implies asymmetric information transport between $X$ and $Y$. Moreover, $\text{ETE}_{Y \rightarrow X} > \text{ETE}_{X \rightarrow Y}$ indicates that the direction of the information flow moves from $Y$ (news sentiment) towards $X$ (realized volatility) and vice versa. Thus, the dominant direction of the information transfer can be determined by the difference between ETE estimates, with positive (negative) values indicating that the news sentiment (realized volatility) is the dominant direction of information transfer.

5 RESULTS

5.1 Main results

In Table 2, we present two unit root tests. The first is the augmented Dickey–Fuller (ADF) test (1979). We included a constant and a time trend in the specification used to infer stationarity.
However, this test does not account for structural breaks in the time series. Since the standard ADF unit root test has low power when structural breaks exist in the time series (see Perron, 1989), we also use the Lee and Strazicich (2003) unit root test. This test allows for the endogenous determination of the size and the break time, both in the level and the trend of the data generating process. The results of the test for two structural breaks are shown in Column 2 of Table 2. The null hypothesis for both tests was that the time series contained a unit root (nonstationarity). The null hypothesis for the two tests was rejected at either the 1% or 5% significance level, indicating that our time series of volatilities was stationary.

The main advantage of using the entropy-based method is that it did not require a model for the information transmission between our time series (i.e., nonparametric data). The time

| TABLE 2 | Unit root tests |
|---------|----------------|
|         | **ADF test**    | *Lee and Strazicich (2003)* |
| Sentiment | −4.8650***     | −3.9568** |
| Oil       | −14.5875***    | −49.4323*** |
| Natural gas | −25.8029***  | −73.1074*** |
| Gold      | −16.9397***    | −63.7605*** |
| Silver    | −17.1516***    | −61.3461*** |
| Bond      | −15.9716***    | −63.0997*** |
| S&P 500   | −11.6524***    | −52.3306*** |
| FTSE 100  | −12.6252***    | −58.7888*** |
| US$/EUR   | −17.6011***    | −70.4867*** |
| Commodity index | −14.6286*** | −61.2108*** |

*Note: The augmented Dickey–Fuller (ADF) test with the null hypothesis is defined as the series having a unit root. The asymptotic ADF critical values were −3.976, −3.418 and −3.1316 for the 1%, 5% and 10% significance levels, respectively. The Lee and Strazicich (2003) LM unit root test with two structural breaks critical values were −4.54, −3.84 and −3.50 for the 1%, 5% and 10% significance levels, respectively. Both unit root tests were carried out with optimal lag lengths, chosen using the Akaike information criterion.***, ** and * indicate significance at the 1%, 5% and 10% levels of significance, respectively.*
Table 3: Linear Granger causality test

| Null hypothesis                        | F-statistic | p Value |
|----------------------------------------|-------------|---------|
| Sentiment—Oil                          |             |         |
| Oil does not Granger cause sentiment    | 1.9595      | (0.1410)|
| Sentiment does not Granger cause oil   | 13.4328***  | (0.0000)|
| Sentiment—Natural gas                   |             |         |
| Natural gas does not Granger cause sentiment | 3.1992*   | (0.0814)|
| Sentiment does not Granger cause natural gas | 3.0736** | (0.0291)|
| Sentiment—Gold                         |             |         |
| Gold does not Granger cause sentiment   | 4.2663**    | (0.0141)|
| Sentiment does not Granger cause gold   | 30.9830***  | (0.0000)|
| Sentiment—Silver                       |             |         |
| Silver does not Granger cause sentiment | 2.3951*    | (0.0913)|
| Sentiment does not Granger cause silver | 28.1841*** | (0.0000)|
| Sentiment—Bonds                        |             |         |
| Bonds do not Granger cause sentiment    | 2.2938      | (0.1010)|
| Sentiment does not Granger cause bonds  | 58.4658***  | (0.0000)|
| Sentiment—S&P 500                      |             |         |
| S&P 500 does not Granger cause sentiment | 10.6011*** | (0.0000)|
| Sentiment does not Granger cause S&P 500 | 34.5359*** | (0.0000)|
| Sentiment—FTSE 100                     |             |         |
| FTSE 100 does not Granger cause sentiment | 14.5291*** | (0.0000)|
| Sentiment does not Granger cause FTSE 100 | 73.6966*** | (0.0000)|
| Sentiment—US$/EUR                      |             |         |
| US$/EUR does not Granger cause sentiment | 1.3185     | (0.2676)|
| Sentiment does not Granger cause US$/EUR | 21.5017*** | (0.0000)|
| Sentiment—Commodity index              |             |         |
| Commodity index does not Granger cause sentiment | 11.9134*** | (0.0000)|
| Sentiment does not Granger cause commodity index | 45.8490*** | (0.0000)|

Note: The F-statistic of the null hypotheses, that is, that there was no Granger causality. The order (p) of the VAR was selected using the Bayesian information criterion. The p values are in brackets.

***The rejection of the null hypothesis of no Granger causality at the 1% level of significance.

variations in MI between sentiment and asset volatility are presented in Figure 2. We can think of MI as a nonparametric covariance estimate between two-time series. Put another way, MI reflects the quantity of information content enclosed between two-time series. Since this was symmetric, we could not determine the direction of causality between the two-time series.

Figure 2 shows that MI, which was normalized to the value of one, increases significantly during crises. However, assets differ in their information sharing with sentiment in certain
crises. The MI of oil, natural gas and the commodity index with sentiment reached the highest level (one) during the COVID-19 pandemic. On the other hand, assets regarded as safe in our samples, such as gold, foreign currency and bonds, had a high level of MI during the GFC (2008–2009). The US and UK stock markets, as represented by the S&P 500 and FTS 100 indices, also exhibited the highest MI with sentiment during the GFC, rendering these safe assets ineffective at reducing risk from investing in stocks against the changes in sentiment during this period. Silver is a unique asset, as it showed the highest level of MI with sentiment during the 2012–2014 period. Overall, the findings suggest that during the GFC (COVID-19 pandemic), knowing the realized variance of the gold, bond, foreign currency and stock markets (oil, natural gas and the commodity index) from market sentiment could be performed.

**FIGURE 2** Mutual information. The evolution of the mutual relationship (information) between investor sentiment and the volatility of various asset classes over the sample period. The left scale represents the magnitude of entropy’s mutual information (normalized to 1). The thick solid line shows the mutual information, the dashed lines show the entropy of the time series, and the thin solid line shows joint entropy [Color figure can be viewed at wileyonlinelibrary.com]
with the best chance of success. Thus, investors in the commodity and stock markets may have included the general sentiment prevailing in their information set while making investment decisions.

The static estimates of Shannon TE are shown in Table 4. Following Behrendt et al. (2019), the ETE was determined using a number of shuffles equal to 50 and 300 bootstrap replications. The Markov order was set at $k = i = 1$ and $k = i = 2$ for the original series and $k = i = 1$ for the residual series. The difference refers to the difference between ETE estimates. Positive (negative) values indicate that news sentiment (realized volatility) was dominating the direction of information transfer.

All ETE estimates in Table 4 indicate that sentiment was a net transmitter of information to the spot markets of volatility. More specifically, the highest net (or difference) TE value was seen for oil, where sentiment could transfer information to realized volatility on a net basis by 0.0109. The ETE from sentiment to the commodity index was almost the same as the ETE from the commodity index to sentiment, making it hard to determine what predicts the other. However, for the majority of asset classes, it was clear that sentiment revealed information about the volatilities of these assets. In particular, sentiment can reduce the uncertainty around the realized variance of assets beyond the degree to which the realized variance reduces uncertainty about their future values. Thus, sentiment is valuable for forecasting the future level of asset volatility. In this case, building a model to predict variance requires the sentiment level to be known. Next, we used dynamic entropy-transfer estimates over the sample period to investigate whether this forecasting ability of sentiment holds during crises.
| TABLE 4 | Static transfer entropy |
|--------|-------------------------|
|        | TE   | ETE   | SE   | p Value |
| Sentiment—Oil                     |
| Sentiment → Oil                   | 0.0174 | 0.0160 | 0.0160 | 0.0000 |
| Oil → Sentiment                   | 0.0067 | 0.0051 | 0.0006 | 0.0000 |
| Difference                         | 0.0107 | 0.0109 |
| Sentiment—Natural gas              |
| Sentiment → Natural gas            | 0.0171 | 0.0154 | 0.0006 | 0.0000 |
| Natural Gas → Sentiment            | 0.0080 | 0.0063 | 0.0007 | 0.0000 |
| Difference                         | 0.0091 | 0.0091 |
| Sentiment—Gold                     |
| Sentiment → Gold                   | 0.0099 | 0.0081 | 0.0006 | 0.0000 |
| Gold → Sentiment                   | 0.0051 | 0.0034 | 0.0006 | 0.0000 |
| Difference                         | 0.0048 | 0.0047 |
| Sentiment—Silver                   |
| Sentiment → Silver                 | 0.0241 | 0.0224 | 0.0006 | 0.0000 |
| Silver → Sentiment                 | 0.0172 | 0.0155 | 0.0007 | 0.0000 |
| Difference                         | 0.0069 | 0.0069 |
| Sentiment—Bonds                    |
| Sentiment → Bonds                  | 0.0114 | 0.0096 | 0.0006 | 0.0000 |
| Bonds → Sentiment                  | 0.0087 | 0.0070 | 0.0006 | 0.0000 |
| Difference                         | 0.0027 | 0.0026 |
| Sentiment—S&P 500                  |
| Sentiment → S&P 500                 | 0.0160 | 0.0144 | 0.0006 | 0.0000 |
| S&P 500 → Sentiment                | 0.0141 | 0.0125 | 0.0006 | 0.0000 |
| Difference                         | 0.0019 | 0.0019 |
| Sentiment—FTSE 100                 |
| Sentiment → FTSE 100                | 0.0115 | 0.0100 | 0.0006 | 0.0000 |
| FTSE 100 → Sentiment               | 0.0072 | 0.0058 | 0.0006 | 0.0000 |
| Difference                         | 0.0043 | 0.0042 |
| Sentiment—US$/EUR                  |
| Sentiment → US$/EUR                 | 0.0135 | 0.0111 | 0.0006 | 0.0000 |
| US$/EUR → Sentiment                | 0.0063 | 0.0047 | 0.0006 | 0.0000 |
| Difference                         | 0.0072 | 0.0063 |
Since the distribution of asset volatilities was leptokurtic (the kurtosis value was more than 3 for each asset, as shown in Table 1), we used ETE across quantiles, as shown in Table 5. We could identify how extreme changes in sentiment or asset volatility transmitted information by observing the 75%–100% (0%–25%) quantiles. In low quantiles, the TE between sentiment and asset volatility was weak. However, in high quantiles, the informational link between sentiment and asset volatility became stronger and less symmetrical. The transmission of asset volatility information to sentiment was not equal to the transmission of sentiment to volatility.

Figure 3 shows the results of the dynamic ETE over the sample period. The dashed line represents the dynamic ETE from news sentiment to realized volatility ($ETE_{Y\rightarrow X}$). In contrast, the solid line represents the dynamic ETE from realized volatility to news sentiment ($ETE_{X\rightarrow Y}$). By definition, $ETE_{Y\rightarrow X} \neq ETE_{X\rightarrow Y}$ implies asymmetric information transfer between $X$ and $Y$. Moreover, $ETE_{Y\rightarrow X} > ETE_{X\rightarrow Y}$ indicates that the direction of information flow is from $Y$ (news sentiment) towards $X$ (realized volatility) and vice versa.

It can be seen that the dashed line is generally above the solid line during crises, so the direction of information flow is from sentiment towards the realized variance. However, assets show different time variations in information flow during crises. We observed a larger flow of information from sentiment to the oil market between 2003 (which corresponded with the invasion of Iraq) and 2012 (which corresponded with the end of the sovereign debt crisis). There was a noticeable increase in information flow during the GFC. A similar picture appeared with all assets, where ETE flow from sentiment to volatility increased higher relative to the flow from sentiment to sentiment during the GFC. This pattern has not appeared in all assets during the COVID-19 pandemic. Stock markets (S&P 500 and FTS 100), foreign exchange markets and oil markets only showed a significant increase in the ETE from sentiment to their return volatility during the pandemic. This has not been the case for gold, silver, bonds, natural gas, or the commodity index, indicating that sentiment played a greater role in disseminating information from sentiment to volatility during the GFC than during the COVID-19 pandemic. Finally, it should be noted that the bidirectional transfer of information between sentiment and natural gas volatility has become low (near to zero) since 2012.

### Additional test

We further used a two variable VAR framework to investigate the dynamic responses of realized volatility of different asset classes to innovations in news-sentiment measures. In the
VAR model, both variables (i.e., realized volatility and sentiment) were considered to be endogenous; then, using the generalized impulse response function (GIRF) of Koop et al. (1996) and Pesaran and Shin (1998), we illustrate the dynamic impact of news-sentiment shock on the volatility of financial assets. The optimal lag specification in the VAR model was determined by minimizing the Akaike and Schwarz information criteria.

Figure 4 depicts the GIRFs of realized volatility of different asset classes to a one standard deviation increase in the news-sentiment shock. In this figure, the horizontal axis shows the

| TABLE 5 | Bootstrapped transfer entropy quantiles |
|----------|-----------------------------------------|
|          | 0%          | 25%         | 50%         | 75%          | 100%        |
| Sentiment—Oil |
| Sentiment → Oil | 0.0002 | 0.0010 | 0.0013 | 0.0018 | 0.0043 |
| Oil → Sentiment | 0.0003 | 0.0010 | 0.0013 | 0.0018 | 0.0047 |
| Sentiment—Natural gas |
| Sentiment → Natural gas | 0.0003 | 0.0010 | 0.0015 | 0.0019 | 0.0038 |
| Natural Gas → Sentiment | 0.0005 | 0.0013 | 0.0016 | 0.0021 | 0.0051 |
| Sentiment—Gold |
| Sentiment → Gold | 0.0004 | 0.0012 | 0.0015 | 0.0020 | 0.0034 |
| Gold → Sentiment | 0.0004 | 0.0012 | 0.0016 | 0.0021 | 0.0043 |
| Sentiment—Silver |
| Sentiment → Silver | 0.0004 | 0.0012 | 0.0016 | 0.0021 | 0.0039 |
| Silver → Sentiment | 0.0005 | 0.0013 | 0.0016 | 0.0020 | 0.0040 |
| Sentiment—Bonds |
| Sentiment → Bonds | 0.0003 | 0.0011 | 0.0014 | 0.0019 | 0.0034 |
| Bonds → Sentiment | 0.0005 | 0.0012 | 0.0016 | 0.0021 | 0.0039 |
| Sentiment—S&P 500 |
| Sentiment → S&P 500 | 0.0002 | 0.0010 | 0.0014 | 0.0018 | 0.0032 |
| S&P 500 → Sentiment | 0.0005 | 0.0012 | 0.0015 | 0.0020 | 0.0050 |
| Sentiment—FTSE 100 |
| Sentiment → FTSE 100 | 0.0003 | 0.0011 | 0.0014 | 0.0018 | 0.0037 |
| FTSE 100 → Sentiment | 0.0003 | 0.0009 | 0.0012 | 0.0016 | 0.0036 |
| Sentiment—US$/EUR |
| Sentiment → US$/EUR | 0.0003 | 0.0011 | 0.0014 | 0.0018 | 0.0037 |
| US$/EUR → Sentiment | 0.0003 | 0.0009 | 0.0012 | 0.0016 | 0.0036 |
| Sentiment—Commodity index |
| Sentiment → Commodity index | 0.0004 | 0.0011 | 0.0015 | 0.0020 | 0.0036 |
| Commodity index → Sentiment | 0.0003 | 0.0012 | 0.0017 | 0.0021 | 0.0040 |

Note: The bootstrapped transfer entropy quantiles are represented. The estimates were performed based on 300 bootstrap replications.
number of days after the impulse shocks, and the vertical axis gives the magnitude of the responses. The confidence intervals (shaded areas) at the 95% level were obtained using a bootstrap procedure with 1000 replications. The GIRF (black line) shows how long and to what extent realized volatility responds to an unanticipated positive change in news sentiment. In all

FIGURE 3 Dynamic effective transfer entropy. The dynamic effective transfer entropy estimates plots using a growing window approach based on Equation (8). The estimates were performed using a number of shuffles equal to 100 and 300 bootstrap replications. The dashed line represents the dynamic ETE from sentiment asset volatility (ETEY→X). The solid line represents the dynamic ETE from asset volatility sentiment (ETEY→Y). [Color figure can be viewed at wileyonlinelibrary.com]
cases, Figure 4 indicates that the response of realized volatility to positive news sentiment is negative. However, the responses are relatively short-lived, as they remain statistically significant for approximately just 2 days after the initial change. Overall, the results indicate that a positive shock in economic sentiment (i.e., agents become more optimistic about the state of the economy) contains incremental information for various asset classes, hence decreasing their realized volatilities. However, this information may not necessarily be rational or consistent with assets’ fundamentals, as we discussed earlier in the introduction. The negative response of realized volatility of different asset classes to positive news-sentiment change supports several studies’ conclusions (e.g., Johnman et al., 2018; Kumari & Mahakud, 2015; Lee et al., 2002) that bullish sentiment leads to a downgraded revision of volatility. Compared with the size of the decrease in realized volatility, positive sentiment caused a more persistent decline in the volatility of the S&P 500 and silver. Increased persistence may play a role in strengthening the usefulness of sentiment for forecasting asset volatility.

5.3 Forecasting volatility based on news sentiment

This section constitutes in-sample and out-of-sample results about the usefulness of the information contained within news sentiment for predicting the realized volatility of different assets classes. To perform the in-sample analysis of the forecasting power of the sentiment, we
first adopt the simplest and most widely used model specification (see e.g., Li & Yu, 2012; Lu et al., 2021; Paye, 2012) in the following form (AR-NS):

$$RV_t = \alpha + \beta_1 RV_{t-1} + \beta_2 NS_{t-1} + \epsilon_t,$$

(10)
where $RV_{t-1}$ represents 1 lag order of realized volatility ($RV_t$), $NS_{t-1}$ refers to the news-sentiment index, and $\varepsilon_t$ is the zero-mean normally distributed residual. In the above specification, the null hypothesis of no in-sample predictability is $H_0 : \beta_2 = 0$. We applied a heteroskedasticity- and autocorrelation-consistent estimator to obtain a robust estimate.

It is worth noting that sentiments may have an asymmetric predictive power effect on returns. Ding et al. (2004) and Zhang and Semmler (2009) examine the asymmetric impact of sentiment on stock returns and find that stock returns react strongly to optimism but less so to pessimism. The recent paper by Frydman et al. (2021) examines the effects of market sentiments on stock returns and distinguishes the role of optimism and pessimism. They find that the fundamental impact on future returns depends on sentiment regimes (optimism and pessimism extremes). We borrow this idea from this literature and differentiate the sentiment index into positive (optimistic) and negative (pessimistic) economic sentiments. Accordingly, optimistic sentiment is defined as $NS_t^+ = \max(0, NS_t)$, and the pessimistic sentiment is $NS_t^- = \min(0, NS_t)$. We run the following predictive equation (AR-ANS):

$$RV_t = \alpha + \beta_1 RV_{t-1} + \beta_2 NS_{t-1}^+ + \beta_3 NS_{t-1}^- + \varepsilon_t.$$  

In this specification, the asymmetric effects of sentiment are captured by the parameters $\beta_2$ and $\beta_3$. When the coefficient $\beta_3$ is different from $\beta_2$, the optimism and pessimism sentiments have different predictive power effects on future asset volatility.

Furthermore, we focus on the impact of the sentiment on asset volatility during recessions. To investigate this, we add a new interaction variable between a recession indicator and market sentiment to the model in Equation (10). We opt to use the Aruoba–Diebold–Scotti (ADS) Business Condition Index (Aruoba et al., 2009) to reflect the economic conditions. This index is designed to track the cyclical fluctuations of the real economy at a high observation frequency (daily). ADS’s positive values indicate better-than-average business conditions, whereas progressively negative values indicate worse-than-average conditions or recession. Figure A1 in Appendix A plots the ADS index with NBER recessions shaded. As we can see, the ADS indicator is strongly cohered with the NBER chronology, plunging (become progressively negative) during NBER recessions. Thus, our predictive regression model is set as follows (AR-ADSNS):

$$RV_t = \alpha + \beta_1 RV_{t-1} + \beta_2 NS_{t-1}^+ + \beta_3 ADS_{t-1} + \beta_4 NS_{t-1}^- + \beta_5 ADS_{t-1} \times NS_{t-1}^- + \varepsilon_t.$$  

The coefficient $\beta_3$ is our estimate of interest. More specifically, a negative $\beta_3$ means that a higher sentiment tends to reduce volatility when there is a recession (i.e., crises).

Finally, to examine the asymmetric effects of sentiment (optimism and pessimism) on asset volatility under different market conditions, we consider a regression specification of the form (AR-ADSANS):

$$RV_t = \alpha + \beta_1 RV_{t-1} + \beta_2 NS_{t-1}^+ + \beta_3 ADS_{t-1} \times NS_{t-1}^+ + \beta_4 NS_{t-1}^- + \beta_5 ADS_{t-1} \times NS_{t-1}^- + \varepsilon_t$$  

20 | MAGHYEREH AND ABDOH
Table 6 shows the in-sample forecast of realized volatility based on the news-sentiment measure. The estimation results showed that the coefficient corresponding to the news sentiment was statistically different from zero in all cases. The change in the sentiment index (NS) negatively affected the realized volatility of all asset classes, consistent with the impulse function presented earlier. This finding was robustly held in both models specified in Panels A and C. In Panel B, we find that sentiment has an asymmetric effect on realized volatility where optimistic sentiments increase realized volatility, but their pessimistic sentiments have the opposite effect. Nevertheless, the economic magnitude of this asymmetric effect prevails mostly in natural gas. Thus, our findings support prior reports that positive sentiment increases volatility (e.g., Chen et al., 2013). Panel C and D reflect Equation (12) and Equation (13), respectively. We find that a recession significantly increases the power of sentiment in explaining asset volatilities. However, this magnifying impact mainly occurs when sentiment is low (pessimistic sentiments). Overall, we show that sentiment has in-sample predictability for daily realized volatility in all asset classes. This predictability was highest during the recession and for oil and natural gas. Overall, using sentiment improved the in-sample one-step-ahead forecasting of asset volatility.

To assess the out-of-sample predictability of news sentiment, we split the full sample into two series of data blocks. The first was used to estimate the model parameters, and the second was used to assess the out-of-sample predictability. Our estimation period ran from January 2, 2000, to December 31, 2010, and our forecasting period ran from January 3, 2011, to May 31, 2020. Following Welch and Goyal (2008), out-of-sample forecasts were generated based on a recursive approach (expanding estimation windows). We adopted the AR-NS, AR-ANS, AR-ADSNS, and AR-ADSANS specifications as our predictive regression models and a simple autoregressive AR (1) specification as a benchmark (see, e.g., Li & Yu, 2012; Lu et al., 2021; Paye, 2012):

\[
RV_t = \alpha + \beta RV_{t-1} + \varepsilon_t. \tag{14}
\]

To evaluate the statistical evidence of forecast accuracy relative to the benchmark, we use the modified Diebold and Mariano (1995) test proposed by Harvey et al. (1997), henceforth referred to as the MDM statistic. The MDM statistic for the null hypothesis of equal forecast accuracy is defined as:

\[
\text{MDM statistic} = \frac{\Delta d}{\sqrt{\text{Var} (\Delta d)}} \sim N(0, 1), \tag{15}
\]

where \(\Delta d = \frac{1}{m} \sum_{t=n+1}^{m+n} \Delta d_t\) and \(\text{Var} (\Delta d)\) are the estimated long-run variance of \(\{\Delta d_t\}_{t=n+1}^{m+n}\) and \(n\) and \(m\) are the length of the in-sample and out-of-sample periods, respectively. \(\Delta d_t\) is the average loss difference between forecasts produced under the benchmark and the nested model forecasts, defined as: \(\Delta d_t = L (\hat{V}R_t^f) - L (\hat{V}R_t^b)\), where \(L (\hat{V}R_t^f)\) and \(L (\hat{V}R_t^b)\) are the loss functions for the predictive regression model and the benchmark, respectively. By definition, a significant and positive value of the MDM statistic indicates that the predictive regression model outperformed the benchmark. In contrast, a significant and negative value of the MDM statistic indicates the opposite.

Table 7 shows the results of the MDM test, with the corresponding \(p\) values. In all prediction models (sentiment predictor only: AR-NS; positive and negative sentiment
## Table 6  In-sample predictability of daily realized volatility

|            | Oil     | Natural gas | Gold    | Silver   | Bonds   | S&P 500 | FTSE 100 | US$/EUR | Commodity index |
|------------|---------|-------------|---------|----------|---------|---------|----------|---------|-----------------|
| **Panel A: AR-NS** \( RV_t = \alpha + \beta_1 RV_{t-1} + \beta_2 NS_{t-1} + \varepsilon \) |         |             |         |          |         |         |          |         |                 |
| \( \alpha \) | 8.12E−5** | 0.00201*    | 1.93E−5*** | 5.34E−5*** | 3.76E−6*** | 2.25E−5*** | 2.37E−5*** | 6.55E−6*** | 3.58E−5*** |
|             | (0.0000) | (0.0326)    | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| \( \beta_1 \) | 0.36942*** | 0.10075*    | 0.13946*** | 0.18508*** | 0.13216*** | 0.17678*** | 0.284989*** | 0.04506*** | 0.16303*** |
|             | (0.0000) | (0.0564)    | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| \( \beta_2 \) | −0.00021*** | −0.00019*** | −2.91E−5*** | −8.87E−5*** | −6.71E−6*** | −7.68E−5*** | −7.28E−5*** | −6.56E−6*** | −6.60E−5*** |
|             | (0.0000) | (0.0000)    | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Adj. \( R^2 \) | 0.14236 | 0.03889     | 0.03558 | 0.05293  | 0.05405  | 0.13291  | 0.08452  | 0.03965  | 0.05598 |
| **Panel B: AR-ANS** \( RV_t = \alpha + \beta_1 RV_{t-1} + \beta_2 NS_{t-1} + \beta_3 NS_{t-1} + \varepsilon \) |         |             |         |          |         |         |          |         |                 |
| \( \alpha \) | 1.30E−5  | 0.00398**   | 1.12E−5*** | 2.95E−5*** | 2.68E−6*** | 2.61E−6*** | 7.88E−6*** | 4.60E−6*** | 1.70E−5*** |
|             | (0.3787) | (0.0125)    | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| \( \beta_1 \) | 0.36079*** | 0.10125*    | 0.12754*** | 0.17305*** | 0.12261*** | 0.14140*** | 0.25495*** | 0.03438*** | 0.14050*** |
|             | (0.0000) | (0.0592)    | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| \( \beta_2 \) | 0.00014** | 0.01037**   | 1.38E−5*** | 3.73E−5*   | −1.02E−6 | 2.72E−5** | 1.01E−5** | 3.79E−6*** | 3.36E−5*** |
|             | (0.0426) | (0.0181)    | (0.0446) | (0.0638) | (0.3231) | (0.0144) | (0.0268) | (0.0212) | (0.0000) |
| \( \beta_3 \) | −0.00058*** | −0.01057*   | −7.53E−5*** | −0.00022*** | −1.29E−5*** | −0.00019*** | −0.00017*** | −1.76E−5*** | −0.00017*** |
|             | (0.0000) | (0.0915)    | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Adj. \( R^2 \) | 0.14708 | 0.04230     | 0.04526 | 0.06247  | 0.06157  | 0.15246  | 0.1040   | 0.04397  | 0.07368 |
| **Panel C: AR-ADSNS** \( RV_t = \alpha + \beta_1 RV_{t-1} + \beta_2 NS_{t-1} + \beta_3 ADS_{t-1} \times NS_{t-1} + \varepsilon \) |         |             |         |          |         |         |          |         |                 |
| \( \alpha \) | 7.64E−5*** | 0.00194**   | 1.91E−5*** | 5.23E−5*** | 3.72E−6*** | 2.16E−5*** | 2.28E−5*** | 6.47E−6*** | 3.47E−5*** |
|             | (0.0000) | (0.0416)    | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Oil | Natural gas | Gold | Silver | Bonds | S&P 500 | FTSE 100 | US$/EUR | Commodity index |
|-----|-------------|------|--------|-------|---------|----------|---------|----------------|
| β₁  | 0.366220*** | 0.10077* | 0.13845*** | 0.18292*** | 0.13090*** | 0.27956*** | 0.16044*** | 0.04373*** | 0.15457*** |
|     | (0.0000)    | (0.0552) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0014) | (0.0000) |
| β₂  | −2.64E−05*  | −0.00217* | −2.05E−05*** | −4.46E−05** | −4.96E−06*** | −3.94E−05*** | −3.64E−05*** | −3.22E−05** | −1.47E−05* |
|     | (0.0679)    | (0.0508) | (0.0000) | (0.0123) | (0.0000) | (0.0001) | (0.0000) | (0.0226) | (0.0546) |
| β₃  | −0.00028*** | −0.00362* | −1.32E−05*** | −6.79E−05*** | −2.70E−05** | −5.82E−05*** | −4.97E−05*** | −7.97E−05*** | 0.0000 |
|     | (0.0004)    | (0.0691) | (0.0790) | (0.0021) | (0.0167) | (0.0000) | (0.0000) | (0.0058) | (0.0000) |
| Adj. R² | 0.15221 | 0.04291 | 0.03613 | 0.05461 | 0.0550 | 0.13656 | 0.08992 | 0.04337 | 0.06278 |

Panel D: AR-ADSANS ($RV_t = α + β₁RV_{t-1} + β₂NSS⁺_{t-1} + β₃ADS⁻_{t-1} × NSS⁺_{t-1} + β₄NSS⁻_{t-1} + β₅ADS₋_{t-1} × NSS⁻_{t-1} + ε_t$)

| α   | 1.03E−05 | 0.00400** | 1.10E−05*** | 2.91E−05*** | 2.66E−06*** | 2.12E−06*** | 7.44E−06*** | 4.57E−06*** | 1.66E−05*** |
|     | (0.4846) | (0.0123) | (0.0000) | (0.0000) | (0.0000) | (0.0001) | (0.0000) | (0.0000) | (0.0000) |
| β₁  | 0.35405*** | 0.10133* | 0.12267*** | 0.17041*** | 0.120319*** | 0.24654*** | 0.28723*** | 0.03282*** | 0.12603*** |
|     | (0.0000) | (0.0922) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| β₂  | 0.00014** | 0.00624* | 5.45E−05* | 4.51E−05* | −1.23E−6 | 3.04E−05** | 1.15E−05** | 4.20E−06** | 4.09E−05*** |
|     | (0.0129) | (0.05237) | (0.0527) | (0.0754) | (0.3407) | (0.0293) | (0.03133) | (0.0423) | (0.0050) |
| β₃  | 2.50E−5 | −0.00744 | 1.65E−5* | −1.06E−5 | 5.60E−7 | 1.95E−6* | 1.27E−6* | −5.03E−7* | −7.51E−6 |
|     | (0.8028) | (0.4904) | (0.0826) | (0.7056) | (0.6950) | (0.0899) | (0.0919) | (0.0825) | (0.6401) |
| β₄  | −9.98E−5** | −0.01156 | −4.10E−5*** | −0.00014*** | −8.44E−06*** | −0.00010*** | −7.39E−05*** | −1.12E−05** | −5.30E−05*** |
|     | (0.0411) | (0.3758) | (0.0004) | (0.0001) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0064) |
| β₅  | −0.00067*** | −0.00124 | −4.75E−5*** | −0.00012*** | −6.09E−06*** | −0.00012*** | −0.00013*** | −8.74E−06*** | −0.00017*** |
|     | (0.0000) | (0.9286) | (0.0001) | (0.0009) | (0.0010) | (0.0000) | (0.0000) | (0.0030) | (0.0000) |
| Adj. R² | 0.15613 | 0.0334 | 0.04847 | 0.06444 | 0.06352 | 0.15916 | 0.11416 | 0.042559 | 0.08516 |

Note: The estimations from an in-sample analysis. p Values are in brackets. *** and * were significant at the 1%, 5% and 10% levels, respectively.
**TABLE 7** Diebold–Mariano test of out-of-sample forecast accuracy

| Model       | Oil     | Natural gas | Gold     | Silver    | Bonds    | S&P 500   | FTSE 100  | USS/EUR   | Commodity index |
|-------------|---------|-------------|----------|-----------|----------|-----------|-----------|-----------|-----------------|
| AR-NS       | 2.5432**| 2.0303**    | 2.0789** | 2.8150*** | 2.4314** | 2.9356*** | 2.2679**  | 2.3880**  | 2.5132**         |
|             | (0.0109)| (0.0478)    | (0.0376) | (0.0048)  | (0.0150) | (0.0033)  | (0.0233)  | (0.0169)  | (0.0119)         |
| AR-ANS      | 2.2446**| 2.1589***   | 1.7694*  | 2.4867**  | 2.5864***| 2.5043**  | 2.8092*** | 2.3173**  | 2.0283**         |
|             | (0.0247)| (0.0246)    | (0.0768) | (0.0128)  | (0.0096) | (0.0122)  | (0.0000)  | (0.0204)  | (0.0425)         |
| AR-RECNS    | 2.7064***| 2.6700***   | 2.0903** | 2.7096*** | 2.3450** | 2.5043**  | 2.3096**  | 2.5631**  | 2.6061***        |
|             | (0.0068)| (0.0094)    | (0.0365) | (0.0067)  | (0.0190) | (0.0122)  | (0.0209)  | (0.0103)  | (0.0091)         |
| AR-RECANS   | 2.6307***| 2.2578**    | 2.2584** | 2.5859*** | 2.7254***| 2.6839*** | 2.0928**  | 2.7837*** | 2.4949**         |
|             | (0.0085)| (0.0208)    | (0.0239) | (0.0097)  | (0.0064) | (0.0072)  | (0.0363)  | (0.0053)  | (0.0125)         |

Note: The reports out-of-sample performances of news sentiment in predicting the volatility of various assets. The predicting models used are sentiment predictor only (AR-NS), positive and negative sentiment predictors (AR-ANS), sentiment during the recession (AR-ADSNS), and positive and negative sentiments during the recession (AR-ADSANS). The benchmark model represents the AR model (Equation 14), which includes only volatility history information. The results of the modified Diebold–Mariano (MDM) test of equal point forecast accuracy and p values. The null hypothesis of the MDM test is that the expected loss of forecast error is equal. The MDM test’s alternative hypothesis is that the sentiment model’s predictive accuracy is more accurate than the benchmark model. The out-of-sample evaluation period was from January 3, 2011, to May 31, 2020. The p values are shown in brackets. *** , ** and * were significant at the 1%, 5% and 10% levels, respectively.
predictors: AR-ANS; sentiment during recession: AR-ADSNS; and positive and negative sentiments during recession: AR-ADSANS) the MDM statistics were positive and statistically significant at the 1% or 5% levels. These findings suggest that the prediction model yielded a better out-of-sample performance for predicting the realized volatility for all assets than the corresponding benchmark (the autoregressive AR (1), Equation 14). In addition, this

**FIGURE 5** Rolling-window testing the dependence of realized volatility on news sentiment. Estimated news sentiment and realized volatility coefficients (black) and their 95% confidence intervals (blue). These coefficients were extracted based on a rolling-window estimation of Equation (11), where the window was set to 200 days.
forecasting power rises when differentiating between positive and negative sentiment. Finally, the prediction model benefits from including recession indicators and the sentiment index. Hence, we concluded that news sentiment possesses significant predictive content in forecasting the realized volatility of various financial assets, especially during recessions.

We also checked the robustness of the forecasting scheme based on rolling estimation and the forecasting procedure. This method captures the evolution of news sentiment on volatility over time. This was crucial, as our sample extended over periods of financial turbulence, such as the GFC and the COVID-19 pandemic. A daily rolling window of 200 trading days was used to implement this exercise using the AR-NS model above.20

The time-varying coefficients \( \beta_{\tau} \) in Equation (10), along with its 95% confidence intervals, are shown in Figure 5. It was evident that the coefficients that showed the influence of news sentiment on the realized volatility changed over time but remained significant. During most periods, there was a negative and significant reaction of realized volatility to increases in news sentiment. More importantly, Figure 5 shows that the coefficients reached their maximum during the 9/11 attacks, the invasion of Iraq in 2003, the GFC in 2008–2009, the oil price crash between 2014 and 2016, and during the COVID-19 outbreak from December 2019 to the present. These results confirmed that news sentiment plays an increasing role in information transfer during crises. However, the dependence of realized volatility on news sentiment increased the most during the COVID-19 pandemic (the GFC) for oil, natural gas, S&P 500, FTS100, and the commodity index (foreign exchange rates and bonds). In summary, these findings suggest that, first, sentiment has greater predictive power for realized volatility during crises, and second, that sentiment had a differential impact on volatility during the two crises depending on the asset class.

6 | CONCLUSIONS

This study aimed to reveal the relationship between news sentiment and the realized return volatility for major asset classes (stocks, bonds, currency and commodities). The research highlighted the role of sentiment in driving volatility during two major global crises, namely the GFC of 2008–2009 and the ongoing COVID-19 pandemic.

The empirical evidence we have documented in this study is consistent with the extant literature in that behavioural finance, as represented here by sentiment, plays a significant role in causing and predicting volatility. The evidence also showed that sentiment plays a more important role in driving volatility during crises, but to varying degrees, depending on the asset class. More specifically, we found that sentiment was a net transmitter of information to most asset classes, with oil receiving the greatest value from sentiment. The ability to forecast sentiment from realized volatility increased the most during the COVID-19 pandemic (GFC) for oil, natural gas, S&P 500, FTS 100, and the commodity index (foreign currency and bonds). Additionally, there was some support for the belief that assets regarded as safe, such as gold, bonds and currency, were less affected by crises. We found this belief has been better validated during the COVID-19 pandemic than it was during the GFC.

Our findings provide practical implications for portfolio management and forecast modelling. For example, investors can shift investment allocation across asset classes during crises in such a way as to minimize the risk to their portfolio investment against changes in market sentiment. In addition, volatility modeling and forecasting during crises can use our findings concerning the relationship between sentiment and volatility. Our findings could be
extended by studying the outcome of sentiment on volatility and the subsequent returns. In particular, future studies could compare the risk-premium of sentiment on different asset classes during normal periods and times of crisis.

**AUTHOR CONTRIBUTION**

Hussein Abdoh: formal analysis; validation; writing – original draft; writing – review & editing.

**ACKNOWLEDGEMENT**

The authors thank the anonymous reviewers of this manuscript. The first author would like to acknowledge the financial support provided by United Arab Emirates University (grant number 31B135-UPAR-3-2020).

**DATA AVAILABILITY STATEMENT**

All data are obtained via individual data channels, such as the Thomson Reuters Datastream database and Federal Reserve Bank of San Francisco. The models and data analysis are applied through computer software, such as MATLAB, R and Stata. All data and codes will be available from the authors upon request.

**ORCID**

Aktham Maghyereh [http://orcid.org/0000-0002-6907-2622](http://orcid.org/0000-0002-6907-2622)

Hussein Abdoh [https://orcid.org/0000-0002-6907-2622](https://orcid.org/0000-0002-6907-2622)

**ENDNOTES**

1 In a simulation study, Dimpfl and Peter (2019) show that standard linear approaches such as vector autoregressions and Granger causality tests are inappropriate to detect information transfer.

2 For an example of studies that investigated the ability of the investment to forecast volatility, please see Lee et al. (2002), Antweiler and Frank (2004), and Baker and Wurgler (2006).

3 We used short-horizon data (daily) to retain a high number of observations and consequently to adequately capture the speed and intensity of the dynamics.

4 [https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/](https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/)

5 The lexical method of sentiment analysis is built upon natural language processing (NLP), which relies on a predefined list of words associated with emotions of financial, economic news, referred to as lexicon emotions.

6 Shapiro et al. (2020) assessed the accuracy of their model and found it performed better than any models constructed using machine-learning techniques.

7 The daily continuously compounded returns for each asset, $r_t$, were computed as $r_t = \ln(\frac{p_t}{p_{t-1}})$, where $p_t$ is the daily price at time $t$.

8 It should be noted that researchers often use intra-day returns to calculate realized volatility. However, due to the unavailability of higher frequency data for the assets in our sample, we employed daily returns.

9 Many studies have indicated that gold generally performs a “safe haven” role (Baur & Lucey, 2010; Ciner et al., 2013; Li & Lucey, 2017; Maghyereh & Abdoh, 2022a, 2022b; Reboredo, 2013). Given the traditional motives of “flight-to-safety” from stocks to bonds, Baele et al. (2020) showed that these motives correspond to heightened levels of volatility and a reduction in sentiment levels. According to Campbell et al. (2009), bonds are only really a safe haven if inflation is procyclical. The liquidity motive amid crises may encourage
investors to hold currencies during uncertain times. Accordingly, these assets may witness the lowest return volatilities during crises.

The two methods have rapidly and recently been applied to quantify information transfer between systems in several fields of research, including physics, physiology, social media, financial markets, biology, engineering, and earth sciences. For the application of these methods in the context of financial markets, see Benedetto et al. (2015, 2016); Chunxia et al. (2016); Benedetto et al. (2020); and Xiao and Wang (2020).

Note that most notation and text in this section are taken from Benedetto et al. (2016, 2019, 2020) and Behrendt et al. (2019).

Joint entropy $H(X, Y)$ measures how much uncertainty (entropy) is embedded in a joint system of two random variables.

The reverse transfer entropy, which measures the information flow from $X$ to $Y$ (i.e., $T_{E_{X \rightarrow Y}}(l, k)$), can be obtained analogously.

This method was first used by Schreiber (2000) as a method for recognizing asymmetric information transfer in nonlinear systems. Dimpf and Peter (2018) applied this method to investigate volatility spillovers between oil, gold, stock, and foreign exchange rates. More recently, Benedetto et al. (2020) used the method to determine the flow of information between the implied oil volatility (OVX), and the spot variance of West Texas Intermediate (WTI) and Brent returns.

The results provided in this table were based on 300 bootstrap replications.

Dynamic ETE was performed using a growing window approach, with the number of shuffles equal to 50 and 300 bootstrap replications.

Data on the ADS index covering the period January 1, 2000, to October 31, 2020, are downloaded from https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/ads.

Diebold (2022) provides evidence that the ADS Index is accurately provided signals of the real-time “Great Recession” of 2007–2009 and the ongoing Pandemic Recession.

$\text{Var}(\Delta d)$ was estimated using the heteroscedasticity and autocorrelation consistent (HAC) estimator.

We considered alternative window lengths of 100, 150, 250 and 300 observations for robustness. The results (unreported here but available from the authors upon request) remained qualitatively similar.

REFERENCES

Andersen, T. G., & Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. International Economic Review, 39(4), 885–905.

Antweiler, W., & Frank, M. Z. (2004). Is all that talk just noise? The information content of internet stock message boards. The Journal of Finance, 59(3), 1259–1294.

Aruoba, S.B., Diebold, F.X. & Scotti, C. (2009). Real-time measurement of business conditions. Journal of Business and Economic Statistics, 27, 417–427.

Awartani, B., Maghyereh, A., & Cherif, G. (2016). The connectedness between crude oil and financial markets: Evidence from implied volatility indices. Journal of Commodity Markets, 4(1), 56–69.

Baele, L., Bekkaert, G., Inghelbrecht, K., & Wei, M. (2020). Flights to safety. The Review of Financial Studies, 33(2), 689–746.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. The Journal of Finance, 61(4), 1645–1680.

Balcilar, M., Bonato, M., Demirer, R., & Gupta, R. (2017). The effect of investor sentiment on gold market return dynamics: Evidence from a non-parametric causality-in-quantiles approach. Resources Policy, 51, 77–84.

Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. Financial Review, 45(2), 217-229.

Behrendt, S., Dimpfl, T., Peter, F. J., & Zimmermann, D. J. (2019). RTransferEntropy—Quantifying information flow between different time series using effective transfer entropy. SoftwareX, 10, 100265.
Benedetto, F., Giunta, G., & Mastroeni, L. (2015). A maximum entropy method to assess the predictability of financial and commodity prices. *Digital Signal Processing, 46*, 19–31.

Benedetto, F., Giunta, G., & Mastroeni, L. (2016). On the predictability of energy commodity markets by an entropy-based computational method. *Energy Economics, 54*, 302–312.

Benedetto, F., Mastroeni, L., & Vellucci, P. (2019). Modeling the flow of information between financial time series by an entropy-based approach. *Annals of Operations Research, 299*, 1235–1252.

Benedetto, F., Mastroeni, L., Quaresima, G., & Vellucci, P. (2020). Does OXV affect WTI and Brent oil spot variance? Evidence from an entropy analysis. *Energy Economics, 89*, 104815.

Brown, G. W. (1999). Volatility, sentiment, and noise traders. *Financial Analysts Journal, 55*(2), 82–90.

Campbell, J. Y., Sunderam, A., & Viceira, L. M. (2009). *Inflation bets or deflation hedges? The changing risks of nominal bonds* (No. w14701). National Bureau of Economic Research.

Chen, M. P., Chen, P. F., & Lee, C. C. (2013). Asymmetric effects of investor sentiment on industry stock returns: Panel data evidence. *Emerging Markets Review, 14*, 35–54.

Chen, Z., Liang, C., & Umar, M. (2021). Is investor sentiment stronger than VIX and uncertainty indices in predicting energy volatility? *Resources Policy, 74*, 102391.

Chunxia, Y., Xueshuai, Z., Luoluo, J., Sen, H., & He, L. (2016). Study on the contagion among American industries. *Physica A: Statistical Mechanics and its Applications, 444*, 601–612.

Ciner, C., Gurdgiev, C., & Lucey, B. M. (2013). Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates. *International Review of Financial Analysis, 29*, 202–211.

Dai, Z., Engelberg, J., & Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. The *Review of Financial Studies, 28*(1), 1–32.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *The Journal of Finance, 53*(6), 1839–1885.

Darbellay, G. A., & Wuertz, D. (2000). The entropy as a tool for analysing statistical dependences in financial time series. *Physica A: Statistical Mechanics and its Applications, 287*(3-4), 429–439.

Diebold, F. M., & Mariano, R. (1995). Comparing predictive accuracy. *Journal of Business and Economic Statistics, 20*(1), 253–265.

Diebold, F.X., (2022). *Real-time real economic activity: Entering and exiting the pandemic recession of 2020*. PIER Working Paper Archive 22–001, Penn Institute for Economic Research, Department of Economics, University of Pennsylvania.

Dimpfl, T., & Peter, F. J. (2018). Analyzing volatility transmission using group transfer entropy. *Energy Economics, 75*, 368–376.

Dimpfl, T., & Peter, F.J. (2019). Group transfer entropy with an application to cryptocurrencies. *Physica A: Statistical Mechanics and its Applications, 516*, 543–551.

Ding, D.K., Charoenwong, C., & Seetoh, R., (2004). Prospect theory, analyst forecasts, and stock returns. *Journal of Multinational Financial Management, 14* (4–5), 425–442.

Edelen, R. M., Marcus, A. J., & Tehranian, H. (2010). Relative sentiment and stock returns. *Financial Analysts Journal, 66*(4), 20–32.

Foster, D. P., & Nelson, D. B. (1996) Continuous record asymptotics for rolling sample variance estimators. *Econometrica, 64*, 139–174.

Frydman, R., Mangee, N., & Stillwagon, J., (2021). How market sentiment drives forecasts of stock returns. *Journal of Behavioral Finance, 22*(4), 351–367.

García, D. (2013). Sentiment during recessions. *The Journal of Finance, 68*(3), 1267–1300.

Gong, X., & Lin, B. (2018). The incremental information content of investor fear gauge for volatility forecasting in the crude oil futures market. *Energy Economics, 74*, 370–386.

Haroon, O., & Rizvi, S.A.R. (2020). COVID-19: Media coverage and financial markets behavior—A sectoral inquiry. *Journal of Behavioral and Experimental Finance, 27*, 100343.

Harvey, D., Leybourne, S., & Newbold, P. (1997). Testing the equality of prediction mean squared errors. *International Journal of Forecasting, 13*(2), 281–291.

Ho, K. Y., Shi, Y., & Zhang, Z. (2013). How does news sentiment impact asset volatility? Evidence from long memory and regime-switching approaches. *The North American Journal of Economics and Finance, 26*, 436–456.
Johnman, M., Vanstone, B. J., & Gepp, A. (2018). Predicting FTSE 100 returns and volatility using sentiment analysis. Accounting and Finance, 58, 253–274.

Keynes, J. M. (1936). The general theory of employment, interest, and money. Springer.

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. Journal of Econometrics, 74(1), 119–147.

Kumari, J., & Mahakud, J. (2015). Does investor sentiment predict the asset volatility? Evidence from emerging stock market India. Journal of Behavioral and Experimental Finance, 8, 25–39.

Lee, J., & Strazicich, M. C. (2003). Minimum Lagrange multiplier unit root test with two structural breaks. Review of Economics and Statistics, 85(4), 1082–1089.

Lee, W. Y., Jiang, C. X., & Indro, D. C. (2002). Stock market volatility, excess returns, and the role of investor sentiment. Journal of Banking and Finance, 26(12), 2277–2299.

Li, S., & Lucey, B. M. (2017). Reassessing the role of precious metals as safe havens—What colour is your haven and why? Journal of Commodity Markets, 7, 1–14.

Lopez, J. A. (2001). Evaluating the predictive accuracy of volatility models. Journal of Forecasting, 20(2), 87–109.

Lu, X., Ma, F., Wang, J., & Zhu, B. (2021). Oil shocks and stock market volatility: New evidence. Energy Economics, 103, 105567.

Maghyereh, A. & Abdoh, H. (2020). The tail dependence structure between investor sentiment and commodity markets. Resources Policy, 68, 101789.

Maghyereh, A. & Abdoh, H. (2022a). COVID-19 pandemic and volatility interdependence between gold and financial assets. Applied Economics, 54(13), 1473–1486.

Maghyereh, A., & Abdoh, H. (2022b). Can news-based economic sentiment predict bubbles in precious metal markets. Financial Innovation, 8, 35.

Maitra, D., & Dash, S. R. (2017). Sentiment and stock market volatility revisited: A time–frequency domain approach. Journal of Behavioral and Experimental Finance, 15, 74–91.

Marchinski, R., & Kantz, H. (2002). Analysing the information flow between financial time series. The European Physical Journal B—Condensed Matter and Complex Systems, 30(2), 275–281.

Mathieu, A. (2016). Investor sentiment and the return and volatility of REITs and Non-REITs during the financial crisis. In Essays on the Impact of Sentiment on Real Estate Investments (pp. 40–64). Springer Gabler.

Moldovan, A., Cataron, A., & Andonie, R. (2020). Learning in feedforward neural networks accelerated by transfer entropy. Entropy, 22(1),102.

Park, J., & Ratti, R. A. (2008). Oil price shocks and stock markets in the US and 13 European countries. Energy Economics, 30(5), 2587–2608.

Patton, A. J. (2011). Volatility forecast comparison using imperfect volatility proxies. Journal of Econometrics, 160(1), 246–256.

Paye, B.S. (2012). ‘De’ja vol’: Predictive regressions for aggregate stock market volatility using macroeconomic variables. Journal of Financial Economics, 106, 527–546.

Perron, P. (1989). The great crash, the oil price shock, and the unit root hypothesis. Econometrica: Journal of the Econometric Society, 57, 1361–1401.

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. Economics Letters, 58(1), 17–29.

Qi, XZ., Ning, Z., & Qin, M. (2021). Economic policy uncertainty, investor sentiment and financial stability—An empirical study based on the time varying parameter-vector autoregression model. Journal of Economic Interaction and Coordination, 1–21. (in press).

Reboredo, J. C. (2013). Is gold a safe haven or a hedge for the US dollar? Implications for risk management. Journal of Banking & Finance, 37(8), 2665–2676.

Sadorsky, P. (2006). Modeling and forecasting petroleum futures volatility. Energy Economics, 28(4), 467–488.

Schreiber, T. (2000). Measuring information transfer. Physical Review Letters, 85(2), 461–464.

Shahzad, S.J.H., Raza, N., Balcilar, M., Ali, S., & Shahbaz, M. (2017). Can economic policy uncertainty and investors sentiment predict commodities returns and volatility? Resources Policy, 53, 208–218.

Shannon, C. E. (1949). Communication theory of secrecy systems, Bell Systems Tech Journal, 28, 656–715.
Shapiro, A. H., Sudhof, M., & Wilson, D. (2020). *Measuring news sentiment*. Federal Reserve Bank of San Francisco.

Shu, H. C., & Chang, J. H. (2015). Investor sentiment and financial market volatility. *Journal of Behavioral Finance, 16*(3), 206–219.

Tang, K., & Xiong, W. (2012). Index investment and the financialization of commodities. *Financial Analysts Journal, 68*(6), 54–74.

Verma, R., & Verma, P. (2007). Noise trading and stock market volatility. *Journal of Multinational Financial Management, 17*(3), 231–243.

Welch, I., & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *The Review of Financial Studies, 21*(4), 1455–1508.

Xiao, D., & Wang, J. (2020). Dynamic complexity and causality of crude oil and major stock markets. *Energy, 193*, 116791.

Yang, C., Gong, X., & Zhang, H. (2019). Volatility forecasting of crude oil futures: The role of investor sentiment and leverage effect. *Resources Policy, 61*, 548–563.

Zhang, W., & Semmler, W., (2009). Prospect theory for stock markets: Empirical evidence with time-series data. *Journal of Economic Behavior and Organization, 72* (3), 835–849.

**How to cite this article:** Maghyereh, A., Abdoh, H. (2022). Global financial crisis versus COVID-19: Evidence from sentiment analysis. *International Finance, 1–31.*

https://doi.org/10.1111/infi.12412

**APPENDIX A**

See Figure A1

**FIGURE A1** Aruoba–Diebold–Scotti business conditions index. Shading shows NBER-dated recessions. Federal Reserve Bank of Philadelphia.