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Have returns and volatilities for financial assets responded to implied volatility during the COVID-19 pandemic?

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ABSTRACT

This paper uses transfer entropy measures to analyze the information sharing between the option implied volatility, the realized volatility and the returns of six financial assets during the COVID-19 pandemic. The measures indicate increases in the information transmissions during the pandemic which are uniform across the volatilities and the returns of all assets. In these transmissions, the option implied volatilities are found to play the central role, particularly in the returns of the assets as opposed to its realized volatilities. Thus, we may conclude that the predictability of the volatilities derived from option pricing models has improved during the pandemic and that this improvement has reduced the uncertainty of the future returns and the volatilities, albeit to a lower extent. These findings bear implications for constructing models that predict volatilities and returns during crises periods.

1. Introduction

The information about the future volatility is important for portfolio allocation, asset pricing and risk management. In order to predict volatility, financial markets’ participants often use the volatility embedded in option prices (Christensen and Prabhala, 1998; Fleming, 1998; Blair et al., 2010; Giot, 2003). However, many studies have claimed that this option implied volatility (the OIV hereafter) is a poor predictor of the future realized variance. For instance, Canina and Figlewski (1993) indicate that the OIV is an inaccurate measure of the future risk of the S&P 100. Similarly, Agnolucci (2009) find that oil options are priced with volatilities that are different from the true future risk of oil. Other studies have cast doubts on the unbiasedness of the implied volatility prediction compared to other predictors. The study of Szakmary et al. (2003) is along these lines and it finds that despite outperforming the historical volatility predictor, still the OIV exhibits biases. These are attributed largely to the misspecification of the option pricing model used to derive the measure.1

In this paper, we revisit to evaluate the predictive content of the implied volatility for the future variance and we conduct our analysis over six financial assets: oil, gold, silver, foreign exchange, bonds and equities.2 Our study is distinguished from the previous literature on the predictability of implied volatility in many aspects. First, we use an entropy-based approach that is capable of measuring the mutual information shared between the OIV and the future realized variance. The approach reveals the dominant source

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2 Studies focus mainly on equity indexes (e.g., Nuij et al., 2014; Cao et al., 2010) and some on oil (See, Agnolucci, 2009).

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of the shared information, and in that sense, it is directional. Second, we investigate the information sharing and the transmission mechanism not only with the future realized volatilities, but also with the future realized returns. This is important and it has implications regarding the role played by the OIV and sentiment in the determination of the premiums of equities and other assets. Finally, our study tracks the information sharing and the transmissions during the crisis periods with particular emphasis on the recent COVID pandemic period. Few studies examine the predictive role of the OIV during crises.

To the extent that the OIV is a gauge of market sentiment, our work is thus related to the issue of whether market sentiments during crisis have spoiled the predictability of OIV. It is well known that the investor sentiment intensifies during crises (Zouaoui et al., 2011) such as during the COVID-19 pandemic, thus leading to less association between the implied volatility, the realized volatility and the returns. It is well known that the investor sentiment drives option prices and thus the OIV (See, Seo and Kim, 2015), and hence, it can influence the transmission of information between the OIV, the realized variance and returns during various time periods. In the literature, to assess the predictive content of the OIV, most studies compare against multi variate GARCH forecast of the realized variance. However, the use of Entropy in the analysis has many advantages over GARCH. Different from GARCH which is parametric, Entropy is non-parametric and hence, it avoids any misspecification biases that may arise due to the wrong functional form or the distributional assumptions of the errors. Because of its parametric functional form, the GARCH allows for the investigation of the predictive content of the OIV, but it does not allow for assessing how realized volatility influences the prices of options and thus, the option implied volatility as it is the case in Entropy methods. It is not possible, for instance, to see if the risk/returns share any information with the OIV. This can be important if the markets’ future uncertainty prediction proxied by the OIV is influenced by the current variance.

Other disadvantages of GARCH includes its misspecification over longer time horizons and its sensitivity to outliers and structural breaks. On the contrary, Entropy is robust to these as well as to the economic turbulences and to the changes in regulations (See Papana et al., 2016; Dimpfl and Peter, 2018). These methods are able to measure the role of the financial variable in the mutual information shared between two variable and hence, it also reveals the direction of the transmission and the causality as indicated by Bekiros et al. (2017).

Therefore, instead of comparing the forecast accuracy by using time series GARCH models as in Lv (2018) and Haugom et al. (2014), this paper assesses the predictive ability of the OIV through the information it shares with the future variance and returns. In particular, we use mutual information (MI) to measure the extent of transmission between the variables and then transfer entropy (TE) to estimate the amount of information that crosses from one variable to the other. As mentioned previously, many studies highlight the positive association between OIV and the future variance. But our focus in this paper lies on how this association has changed during the COVID 19 pandemic crisis which may have intensified stresses and sentiments. Thus, we expect that the pandemic may have influenced the predictability of options to forecast future realized volatility and returns.

Our results can be summarized as follows. The mutual information measure reveals a noticeable increase in the transmissions between the OIV, the realized volatility and the returns during the COVID 19 pandemic crisis period. These findings are found to be uniform across all assets. For instance, the information sharing between the OIV and the realized variance is found to be highest in the oil market as 91% of the joint information of the oil’s option implied volatility and the oil’s realized volatility is a shared mutual information. The percentage is higher at 96% when we measure the mutual information that the OIV shares with oil returns.

In the period that preceded the pandemic these percentages were 54% and 71% for the oil realized volatility and the oil returns respectively. The same analysis applies to the rest of assets: the information sharing is higher during the pandemic and the mutual information between the OIV and the realized returns constitutes a higher proportion of the joint information than it is with realized volatility.

Furthermore, the transfer entropy analysis reveals that the direction of the transmissions is skewed in the favor of the OIV particularly during the pandemic. This means that the information crosses from the implied option volatility to either the returns or the realized variances are higher than in the opposite direction. In comparison to the periods before the pandemic, the difference in net transmissions has increased for most assets thus, we may conclude that the OIV provides a more accurate forecasts of the future variances/returns of assets during the pandemic.

To see if these findings still stand using another method, we estimate a time-varying parameter vector autoregressive model as in Antonakakis et al. (2020) (TVP–VAR hereafter), and from the variance decompositions of the forecast errors of this model we computed the dynamic directional connectedness measures as in Diebold and Yilmaz (2012, 2014). These measures re-confirm that connectedness and information sharing has heightened abruptly during the pandemic, but it also indicates that the association has

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3 It is well known that the investor sentiment intensifies during crises (Zouaoui et al., 2011). Hence, we expect it to do so during the COVID-19 pandemic, thus leading to an increased association between the implied volatility, the realized volatility and the returns.

4 Entropy quantifies the strength of information transfer between two variables dynamically. It can also show the causality from one variable to another and it is equivalent to Granger causality. It is also robust to non-linearity. This method is first used by Schreiber (2000) to recognize asymmetric information transfer in nonlinear systems.

5 Transfer Entropy is asymmetric, and it is designed to measure both linear and nonlinear causality among financial time series (Hlavackova-Schindler et al., 2007; Benedetto et al., 2019a).

6 The MI sharing of oil before the pandemic was around 0.5. Note also that the amount of mutual information sharing of oil during the pandemic is even higher than it was during the oil market crash from 2014 to 2016 and/or during the global financial crisis in 2008.

7 The exceptions are the net transmissions to the returns and the variances of the 10-year Treasury note, the net transmissions to the realized variance of gold and to the realized variance of the exchange rate; these all declined during the COVID period.
started to decline after March 2020. Furthermore, the measures show that the OIV is a net transmitter of information to both the realized variances and the returns of all assets during nearly every crisis sample including the pandemic.

These findings bear policy implications for academics and researchers as well as investors. First, models to predict variance and returns during the pandemic should consider the heightened predictive power of OIV and its differential predictive power over realized variance and returns compared to other periods. Second, the emergence of OIV as a net transmitter of shocks to asset returns and variances during the phases of the pandemic endorses a dynamic and time-varying portfolio diversification to mitigate portfolio risk.

The rest of the paper is organized as follows: in the next section we provide a synopsis of the literature. In section 3, we describe our data set and provide a preliminary investigation of the sample. Section 4, given details on how entropy methods are used to analyze information transmission. In section 5, we provide empirical results and analysis of the entropy measures’ output. Finally, in section 6, we write some concluding remarks. The appendix of the paper contains sketches of the Time Varying Parameter Vector Autoregressive Model (the TVP-VAR) and the measures of connectedness of Diebold and Yilmaz (2012, 2014).

2. Literature review

The COVID–19 virus had infected 14,368,133 people and killed 602,953 in 215 countries and territories by July 19, 2020 (Worldometer, 2020). The pandemic has cratered economies, employment, and equity markets. Government-imposed quarantines and social distancing generated enormous economic repercussions. Not surprisingly, the pandemic has amplified uncertainty in financial markets.

In the literature, there is only few published studies that examine the effect of the pandemic on financial markets. For instance, Lahmin and Bekiros (2020) apply the Renyi entropy to investigate stability and irregularity in 16 international stock markets and 45 cryptocurrencies. They find that cryptocurrencies become more unstable, and irregular compared to equities which is affected but to a lower extent. They conclude that investment in cryptocurrencies is riskier than investment in equities during the pandemic. On the connectedness among markets during the pandemic, there is the work of Adekoya and Oliyide (2020) who examine the association between the commodity and the financial markets. They applied causality-in-quantiles tests and find that the volatility among markets has become more interlinked particularly at the lower and the middle-level quantiles.

Some studies have looked at the impact of the increase in deaths and infections on the returns and volatilities of financial markets. Along these lines is the study of Kamdem et al. (2020) who use a short-long memory model to measure the influence on commodity prices. The authors find a strong negative relationship between death/infected numbers and commodity prices. The study by Just and Echaust (2020) is similar, but it uses Markov switching models instead, and it finds that the spread of the Coronavirus in Europe has significantly impacted the returns, the implied volatilities and the implied correlations of the US stock markets. Other studies that document an increase in risk and uncertainty of the US market following the spread of the disease are: Baek et al. (2020), Baig et al. (2020) and Albulescu (2020).

None of these works have investigated the shared information content between the OIV, the future realized volatility and the returns. The only study that focuses on these inter-relationships is the work of Benedetto et al. (2020) who infer the mutual information and the entropy between the OIV and the realized volatility of the Brent and the WTI oils. They find that the information that the OIV shares with the realized volatilities of both oils has recently increased, thus indicating an increased the predictability of options prices of the future variance of oil.

Our study is directly related to this study, but we extend beyond in many directions. First, our work is not restricted to the oil market, and instead, we investigate other interesting markets such as the equity market, the bond market, the foreign exchange market, the gold market and the silver market. This is important as it shows in which market the predictability has improved the most. Second, the analysis of the predictability of the OIV is extended to the returns and not only to the future variances. It is well known that risk require premium in financial markets. Therefore, it will be interesting to assess the predictability of markets’ expected risk (OIV) of these premiums and returns. Third, our focus is placed on the predictability value of OIV during the COVID 19 crisis and previous crisis episodes; an issue which is ignored by Benedetto et al. (2020) and the previous literature.

Next, we turn to discuss data, description and preliminary investigation.

3. Data and preliminary analysis

The OIV indices of all the assets are constructed and published by the Chicago Board of Options Exchange (CBOE). These indices are derived from transacted option prices, and thus it is forward looking and it represents the market consensus about the future volatility. The OIVs are used by many researchers as proxies for investor fear gauges (IFGs) and to track investor sentiment (Dennis et al., 2006; Awartani et al., 2016; Maghyereh et al., 2016; Ji and Fan, 2016; Gong and Lin, 2018; Fassas and Siriopoulos, 2020). In crisis, the high

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8 The US unemployment rate rose from 3.6% in Jan to 14.7% in April 2020, the highest since the Great Depression (Washington Post, 2020). The S&P 500 index declined by 31%, from 3240.09 on Dec 30, 2019, to 2237.40 on March 23, 2020.

9 More than 100 countries went through full or partial lockdowns by March 31, 2020 (Dunford et al., 2020). https://www.bbc.com/news/world-52103747.

10 Dimpf and Peter (2019) investigate volatility spillovers among oil, gold, equities, and foreign exchange rates using group entropy methods. However, we are different as we focus on the transmission between the variables of the same market and not across the group of markets.
sentiment of fear raises the risk premiums and the OIV itself in financial markets.\textsuperscript{11}

The original implied volatility indices are based on solving for the volatility variable in the Black and Scholes model/other model, which is criticized for biases that result from failure to specify the data generating process of the underlying. The main issue is that options of various maturities and strikes have implied different future volatilities (Simon, 2002; Gonzalez-Perez, 2015).\textsuperscript{12}

Therefore, On Sep 22, 2003, the CBOE have stopped computing implied volatility indices based on the Black and Scholes model and started to compute it on the basis of the fair value of future volatility as in Demeterfi et al. (1999). The new OIV indices are now computed from the prices of calls and puts with no pricing model, rendering them model-free. It represents the market expected volatility over the next 30 days.\textsuperscript{13}

Our data include the daily closing prices and the OIV indexes of four asset classes: commodities, currencies, bonds, and equities. The three commodities and its OIVs are the Brent crude, the CBOE Crude Oil ETF Volatility Index (the OVX), the gold, the CBOE Gold ETF Volatility Index (the GVZ), and the silver and the CBOE Silver ETF Volatility Index (the VXSLV). The FX market is represented by the USD/EUR exchange rate. The CBOE Eurocurrency ETF Volatility Index (the EVZ) is used to denote the volatility of the EU/US$ exchange rate.

The 10-year US Treasury note represents the bond market. The CBOT 10-year T-note Volatility Index (the TYVIX) is used for the OIV of the bond returns. The S&P 500 index is used as a proxy of the US stock market. The CBOE Volatility Index (the VIX) is used to represent the US stock market’s OIV. This index is the most famous and it is based on the prices of options that are written on the S&P 500 index as the underlying asset.\textsuperscript{14}

All the data is derived from the Thomson Reuters’ Datastream according to its availability. The start time of the OIV varies according to the asset: The Brent crude and the S&P 500 index data extends from May 10th, 2007 to November 10th, 2020; gold and EU/US$ exchange rate extends from June 2nd, 2008 to November 10th, 2020; the silver data is from March 17th, 2011 to November 10th, 2020.

The sample period includes various crises episodes: the Global Financial Crisis (GFC) which starts on July 2nd, 2007, and ends December 31st, 2009; The European Debt Crisis (EDC) which extends from May the 1st, 2010 to September the 6th, 2012; the Oil Market Crash (OMC) from June 20th, 2014 to January 2nd, 2016; and finally, the COVID 19 crisis that starts in January 2nd, 2020 and it runs to the end of the sample period in November 10th, 2020.\textsuperscript{15} The long time period of the sample allows for examining the information transmission between the OIV, the realized variance and the returns of the six assets during the pandemic crisis and it also allows for comparison with the transmissions during normal times as well as during previous crises episodes such as the Global Financial Crisis, the European Debt Crisis and the Oil Market Crash.

From the price data, we computed continuously compounded daily returns for each time series ($r_t$) as $r_t = \ln \left( \frac{p_t}{p_{t-1}} \right)$, where $p_t$ is the daily price observed at time t. To study the informational content of realized volatility, we use daily squared returns to measure the ex-post volatility (See, Foster and Nelson, 1996; Andersen and Bollerslev, 1998; Sadorsky, 2006; Park and Ratti, 2008).\textsuperscript{16} The squared returns measure is unbiased but it is noisy (Lopez, 2001; Patton, 2011).\textsuperscript{17} As the OIV is typically annualized; we constructed the daily OIV by dividing annualized figures by the square root of 252. Table 1 itemizes proxies of the assets that we use in this study.

Table 2 presents the descriptive statistics of the returns and the volatilities of the assets. The mean of OIV is remarkably higher than the mean of the realized variance: 1.456 for oil, 0.9144 for gold, 1.449 for silver, 1.3564 for bonds, and 1.456 for the P 500 index as a proxy of the US stock market. The CBOE Volatility Index (the VIX) is used to represent the US stock market’s OIV. This index is the most famous and it is based on the prices of options that are written on the S&P 500 index as the underlying asset.\textsuperscript{14}

As Fig. 2 shows, peaks in both types of volatility appear during the pandemic, but the increase in the amplitude of the OIV is greater. It is also observed that the increase in the realized volatility is associated with a decrease in returns. In fact, when volatility reaches high levels during crises, the realized returns become negative. The oil figure seems to be different from others mainly due to the relative huge impact of the pandemic on its implied volatility, realized volatility and returns relative to other crisis periods.

Table 2 describes the data, and it shows positive skewness and positive excess kurtosis. In addition, the distribution is not normal as indicated by the significance of the Jarque–Bera statistic. Accordingly, we focus on transfer entropy to estimate causality between the series. As Barnett et al. (2009) indicate, Granger causality yields the same results for transfer entropy even when variables are not normally distributed.

\textsuperscript{11} Whaley (2009) argues that the VIX gauges investors’ fears during bear markets and enthusiasm otherwise.

\textsuperscript{12} See Whaley (2000) and Orlando and Taglialetela (2017) for more details.

\textsuperscript{13} For the calculation of OIV indices see the CBOE’s “VIX white paper” at https://www.cboe.com/micro/vix/vixwhite.pdf.

\textsuperscript{14} Our motivation for choosing these financial assets is based on the data availability of their implied volatility indices.

\textsuperscript{15} The choice of the time periods of the GFC is based on studies of Fry-McKibbin et al. (2014), Dungey and Gajurel (2014), Wanga et al., 2017, and Chang et al. (2020). The European Debt Crisis period is based on the research of Samarakoon (2017), Mohti et al. (2019). The Oil Market Crash Period is based on Dutta (2018), Chen et al. (2020), Berk and Çam (2020). The start of the COVID sample period is based on Mazur et al. (2020), Chang et al. (2020), Adekoya and Oliyide (2020).

\textsuperscript{16} Researchers often use intra-day returns to calculate realized variance. The daily returns are used due to the unavailability of high-frequency data of the sampled assets.

\textsuperscript{17} Note that we tried GARCH volatility instead of squared returns and we get the same results. Results based on GARCH are available from the authors upon request.
Before applying transfer entropy, we verify the stationarity of our time series (Dimpfl and Peter, 2018). Table 3, presents unit root tests. The specification of inferring stationarity accounts for structural breaks in the time series. It also includes a time trend and a constant. The standard ADF unit root test has low power in the presence of structural breaks (Perron, 1989), so we invoke the Lee and Strazicich (2003) unit root test, which allows for the endogenous determination of the size and the timing of breaks in the level and in the trend of the data-generating process.

Results of the test indicate two structural breaks, and we insert the test statistics of the two tests in Columns 2 and 3 of the Table. The null hypothesis of both tests is that the time series contains a unit root. As shown in the table, Table 2, descriptive statistics.

Fig. 1 reveals that volatility changes abruptly at least once during the pandemic.

Notes: *** indicates 1% significance.

18 Fig. 1 reveals that volatility changes abruptly at least once during the pandemic.
To get a preliminary idea on the relationship between OIV, realized volatility and returns, we implement the non-linear causality test of Diks and Panchenko (2006). The test is a nonparametric Granger causality test that is based on the integral of dynamic correlations between the variables. The test is related to an earlier version of a causality test that is first proposed by Hiemstra and Jones (1994), but it drops the assumption that the variables should be mutually and individually iid variables.

Table 5 presents the test statistics together with the p values. As can be seen in the table, while the OIV significantly influences the realized volatility at the 1% level, the opposite is not true. The same result applies to the returns: the causality runs from the OIV to the returns and not the other way around. However, at the 10% significance level, the returns and the realized variance of some assets Granger cause the OIV. Therefore, the causality test highlights the value of the OIV in forecasting the realized variance and the returns of the assets. The test remains skeptical of the predictability of the OIV using either the realized variance or the returns.

4. Method

We seek to measure the incremental information content of the IFG (measured by OIV) of returns and volatilities of the asset classes before and during the pandemic. To do so we employed Shannon’s (1949) entropy-based analysis. The Entropy-based analysis is valuable because of its non-parametric (model-free) approach that measures the information transfer among nonlinearly dependent autocorrelated structures of dynamic systems (Darbellay and Wuertz, 2000).

Following Benedetto et al. (2020) we use two methods: The mutual information (MI) based on the maximum entropy method (MEM), which is proposed by Benedetto et al. (2016, 2019) and the transfer entropy (TE) which builds on the Shannon transfer entropy

| Table 3 | Unit root tests. | ADF Test | Lee and Strazicich (2003) |
|-----------------|-----------------|----------|---------------------------|
| Brent Oil       |                 |          |                           |
| OVX             | −4.3305***      | −7.9978***|
| BOR             | −6.0862***      | −56.6370***|
| BOV             | −40.2390***     | −40.3273***|
| Gold            |                 |          |                           |
| GVX             | −4.3324***      | −3.8446***|
| GR              | −60.0862***     | −57.1187***|
| GV              | −40.3349***     | −40.3196***|
| Silver          |                 |          |                           |
| VXSLV           | −3.7796***      | −3.4886**|
| SR              | −48.3483***     | −29.3027***|
| SV              | −15.3938***     | −12.9167***|
| EU/US$ Exchange Rate |         |          |                           |
| EUVIX           | −4.1054***      | −4.9064***|
| EU/US$R         | −56.3232***     | −50.0896***|
| EU/US$V         | −50.4341***     | −49.9684***|
| 10-year Treasury Note          |          |          |
| TVYIX           | −4.6267***      | 2.7641*|
| TYR             | −55.7732***     | −3.3778**|
| TYV             | −29.1935***     | −21.1141***|
| US Stock Market (S&P 500)       |          |          |
| VIX             | −5.79186***     | −4.7023***|
| SPR             | −68.7795***     | −68.7782***|
| SPV             | −42.0836***     | −42.0617***|

Notes: For the ADF test the null hypothesis is that the series has a unit root versus stationarity. Asymptotic ADF critical values are −3.9662, −3.4137 and −3.1286 at 1%, 5%, and 10% significance, respectively. For the Lee and Strazicich (2003) LM unit root test with two structural breaks critical values are −3.5660, −3.0230, and −2.7480 at 1%, 5%, and 10% significance, respectively. Both unit root tests are carried out with optimal lag length chosen using the Akaike information criterion. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

the null hypothesis is rejected at the 1% and the 5% significance level in both tests, thus, indicating that the time series of the returns and the volatilities are stationary.

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For more details on this test see Bekiros and Diks (2008).

This is an alternative test of non-linear Granger causality, but this test suffers from the lack of power and from over-rejection problems (Diks and Panchenko, 2006).

At the 10% level, the returns Granger causes the OIV in silver and foreign exchange. Similarly, the realized variance Granger causes the OIV in equities and the foreign exchange.

The Panchenko’s C++ code file was used for the non-linear causality test.
The MI quantifies the information sharing between two discrete random variables by estimating their joint probability density function, thus capturing the linear and the nonlinear information transfer in the system. However, the MI is symmetric and hence, it cannot determine the direction of the information flow or the mutual directional causation. Therefore, to complement our analysis, we first proposed by Schreiber (2000) and then extended by Behrendt et al. (2019). The two methods quantify the information transfer between systems in disciplines such as physics, physiology, social media, financial markets, biology, engineering, and earth sciences. For applications to financial markets, see Benedetto et al. (2015), Benedetto et al. (2016), Chunxia et al. (2016), and He and Shang (2017).

Note: The symbol “/>” implies does not Granger-cause. The optimal Embedding dimension = 2. The series in first differences. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

**Table 5**

Average values of mutual information for GFC, EDC, OMC and COVID-19 periods.

|                         | Global Financial Crisis (GFC) | European Debt Crisis (EDC) | Oil Market Crash (OMC) | Before COVID-19 pandemic | COVID-19 pandemic (Jan. 2, 2020–Nov. 11, 2020) |
|-------------------------|-------------------------------|----------------------------|-------------------------|--------------------------|-----------------------------------------------|
|                         | (Jul. 2, 2007–Dec. 31, 2009)  | (May 1, 2010–Sep. 6, 2012) | (Jan. 20, 2014–Jan. 2, 2016) | (Jan. 2, 2018–Dec. 31, 2019) |                                               |
| Brent Oil               | O VX/BOR                      | 0.7471                     | 0.8042                  | 0.9002                   | 0.7157                                        | 0.9610                                        |
|                         | O VX/BOV                      | 0.3900                     | 0.5464                  | 0.5875                   | 0.5477                                        | 0.9130                                        |
| Gold                   | GVX/GR                        | 0.9689                     | 0.8098                  | 0.6670                   | 0.5392                                        | 0.6756                                        |
|                         | GVX/GV                        | 0.9317                     | 0.7423                  | 0.4566                   | 0.3092                                        | 0.4005                                        |
| Silver                 | VXSLV/GR                      | –                          | 0.9433                  | 0.8220                   | 0.6599                                        | 0.7779                                        |
|                         | VXSLV/GV                      | –                          | 0.7417                  | 0.6246                   | 0.4393                                        | 0.5642                                        |
| EU/US$ Exchange Rate   | EUVIX/EU/US                   | 0.9045                     | 0.8586                  | 0.7572                   | 0.6403                                        | 0.7552                                        |
|                         | SV                            | 0.8871                     | 0.7820                  | 0.6265                   | 0.5675                                        | 0.5928                                        |
| 10-year Treasury Note  | TYVIX/TYR                     | 0.7751                     | 0.9105                  | 0.8193                   | 0.5712                                        | 0.7567                                        |
|                         | TYVIX/TVY                     | 0.8729                     | 0.8681                  | 0.6251                   | 0.4345                                        | 0.5747                                        |
|                         | US Stock Market (S&P 500)     |                            |                         |                          |                                               |                                               |
|                         | VIX/SPR                       | 0.8643                     | 0.8562                  | 0.5981                   | 0.5496                                        | 0.7798                                        |
|                         | VIX/SPV                       | 0.6203                     | 0.9074                  | 0.3946                   | 0.3228                                        | 0.5635                                        |

Notes: Table 4 shows the average magnitude of the mutual relation between Implied volatility (IV) and underlying asset return/Realized Volatility (RV). The values of mutual information are normalized to the value of 1.

a Start date of the sample: June 2, 2008.

b Start date of the sample: March 17, 2011.
use the TE, which is an asymmetric measure that detects linear and nonlinear information transfer and dynamic causation during transmission. The next section introduces both methods.\textsuperscript{24}

a. Mutual information

Assume that the source $X$ produces $n$ signals, then the Shannon entropy of $X$ ($H(X)$) is defined as

$$H(X) = H(p_1, p_2, \ldots, p_i) = - \sum_{i=1}^{n} p_i \log_2 p_i \tag{1}$$

The $P(x_i)$ is the probability that signal $x_i$ shows up in the characters of the received message. Note here that if the chance is high, then it is less informative from the view point of the receptors. Rarer signals are more informative. The more information received by the receptors from signaling, the more certainty they have about the future development of the process and vice versa.

For example, a two-outcome set with 50/50 odds, results in the highest amount of uncertainty. For instance, suppose that the two outcomes are rise and fall of the S&P500 index. On the other hand, if the odds are 70/30, then the entropy will be around 0.88, thus indicating a much lower uncertainty.

Now consider two signaling random time series $X = \{x_i\}_{i=1}^{N}$ and $Y = \{y_i\}_{i=1}^{N}$ that produce $N$ signals each with a priori joint probability $p(x_i, y_i) = p_{2i}$; the Shannon’s joint entropy is defined as

$$H(X, Y) = - \sum_{i=1}^{n} \sum_{j=1}^{n} p_{2i}(x, y) \log_2(p_{2i}(x, y)) \tag{2}$$

In a similar way, the joint entropy measures how much uncertainty is embedded in the joint distribution of the two variables.

The mutual information (MI) shared by the signaling variables can be written as a function of the joint entropy as:

$$MI(X, Y) = H(X) + H(Y) - H(X, Y), \tag{3}$$

The MI in (3) measures the signaling of the marginal entropies outside the joint. In that sense, it is similar to the covariance between two variables, but it is different in that it is non-linear and non-parametric. Therefore, the mutual entropy can be used as a measure of the amount of information that the individual variables are getting from one another from outside the joint system. Fig. 1 displays a Venn diagram of the marginal and joint entropies to depict the relationship.

Since the prior probability of the two series and their joint probability are unknown, we follow Benedetto et al. (2016) and Benedetto et al. (2019) to obtain the joint entropy ($\hat{h}(x, y)$) and use the MEM to compute the joint entropy as

$$\hat{h}(x, y) = \frac{1}{2} \ln(2 \pi e) + \frac{1}{4\pi} \int_{-\pi}^{\pi} \ln(cross - PSD_{xy}(\omega)) \, d\omega, \tag{4}$$

where cross – PSD\textsubscript{xy}(\omega) is the cross-power spectral density of the time series of $x(n)$ and $y(n)$ of length $n = 1, \ldots, N$ which is calculated according to

$$cross - PSD_{xy}(\omega) = \sum_{k=-\infty}^{\infty} C_{xy}(k)e^{-j\omega k} \tag{5}$$

In Eq. (5), $C_{xy}(k)$ is the cross-covariance between the two series.

Finally, MI can be obtained based on Eq. (3) as

$$\hat{MI}(X, Y) = h(x) + h(y) - \hat{h}(x, y) = \frac{1}{2} \ln(2 \pi e) + \frac{1}{4\pi} \int_{-\pi}^{\pi} \ln(PSD_{x}(\omega)) \, d\omega$$

$$+ \frac{1}{4\pi} \int_{-\pi}^{\pi} \ln(PSD_{y}(\omega)) \, d\omega - \frac{1}{4\pi} \int_{-\pi}^{\pi} \ln(cross - PSD_{xy}(\omega)) \, d\omega \tag{6}$$

In Eq. (6), the $\hat{MI}(X, Y)$ represents a sample measure of the amount of information that is shared by the variables outside the joint entropy. If the $\hat{MI}(X, Y) > 0$, then the two variables exchange signals and thus, they are interdependent. The larger the $\hat{MI}(X, Y)$, the stronger the nonlinear association between the two variables.\textsuperscript{25}

b. Transfer entropy

\textsuperscript{24} Most notations and text in this section are taken from Benedetto et al. (2016, 2019) and Benedetto et al. (2020).

\textsuperscript{25} We use Matlab codes provided by Benedetto et al. (2020) to estimate mutual information.
As mentioned previously, the MI measure is symmetric and hence, it does not inform on the variable that contributes more information to the other. This is important as the MI does not allow for inference on the causality or directional transmissions between the variables. To correct for this shortcomings, Schreiber (2000) introduces the TE by combining the Shannon entropy with the Kullback–Leibler distance measure under the assumption that the underlying processes are Markovian that evolve temporarily (See, Kullback and Leibler, 1951).

Similar to the MI approach, assume that \(X\) and \(Y\) denote two discrete and stationary random processes that represent the time series \(\{x_t\}_{t=1}^N\) and \(\{y_t\}_{t=1}^N\) respectively. Further assume that the dynamic structures of the corresponding processes are stationary Markovian processes of order \(k\) and \(l\) for \(X\) and \(Y\), respectively. If the state of \(Y\) does not influence the transmission probabilities of \(X\) (i.e., \(TE_{Y\rightarrow X}(k,l) = 0\)), then the generalized Markov property satisfies the assumption

\[
p(i_{t+1}|i_{t}^{(k)}, j_{t}^{(l)}) = p(i_{t+1}|i^{(k)})
\]

(7)

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

\[
TE_{Y\rightarrow X}(k,l) = \sum p(i_{t+1}, i_{t}^{(k)}, j_{t}^{(l)}) \log \frac{p(i_{t+1}|i_{t}^{(k)}, j_{t}^{(l)})}{p(i_{t+1}|i^{(k)})}
\]

(8)

where \(TE_{Y\rightarrow X}\) measures the information flow from process \(Y\) to process \(X\). The reverse TE measures the information flow in the opposite direction in an analogous manner. If \(ETE_{Y\rightarrow X} = ET_{X\rightarrow Y}\) then the information transmission among \(X\) and \(Y\) is a symmetric, and it is skewed. For instance, if \(ETE_{Y\rightarrow X} > ET_{X\rightarrow Y}\) then the flow from \(Y\) to \(X\) is higher than from \(X\) to \(Y\), and we may conclude that changes in the \(Y\) process may predict and/or cause \(X\).

A Markov block bootstrap procedure obtains the statistical influence of the transfer entropy estimates in Eq. (8). Finally, to anticipate small-sample bias in the estimates of the TE, we use the Effective Transfer Entropy, ETE as follows (Marschinski and Kantz, 2002):

\[
ETE_{Y\rightarrow X}(k,l) = TE_{Y\rightarrow X}(k,l) - TE_{Y\text{ shuffled} \rightarrow X}(k,l)
\]

(9)

where \(TE_{Y\text{ shuffled} \rightarrow X}(k,l)\) is the transfer entropy using shuffled series of \(Y\).\(^{26}\)

5. Empirical results

a. Mutual information

\(\text{Table 5}\) displays the MI measure between OIV and realized volatility/returns of each asset.\(^{27}\) It displays the MI measure over the various crisis periods that are considered in this study. As mentioned previously, the MI is a proxy estimate of the non-parametric covariance between two time series because it reflects the quantity of information enclosed between them, but still, we cannot

\(^{26}\) The R package “\text{RTransferEntropy}“ is used as described in Behrendt et al., (2010b) to estimate the effective transfer entropy.

\(^{27}\) Note that the MI measure is normalized to 1.
discern the direction of causality because it is symmetric.

The table shows that the MI between the OIV, the realized volatility and the returns has increased significantly during the pandemic. Moreover, the information sharing of the OIV with the returns is higher than what implied volatility shares with the realized variance. This is uniform across all assets and crisis time periods.

Compared to the period before the COVID pandemic, the MI between the OIV and the realized volatility has increased from 0.5477,
0.3092, 0.4393, 0.5675, 0.4345, 0.3228 to 0.913, 0.4005, 0.5642, 0.5928, 0.5747, 0.5635 for oil, gold, silver, exchange rates, bonds and equities respectively. The pandemic has also magnified the information transmission between the OIV and the assets’ returns, as the increase in the MI values exceeds those of realized volatility of gold, foreign exchange and bonds. Specifically, the MI between the OIV and the returns rises by 0.0451, 0.0896 and 0.0453 for gold, foreign exchange and bonds respectively.

Fig. 3. Mutual information.

Note: Figure 3 shows the evolution of informational relations between Implied Volatility (IV) and underlying asset return/Realized Volatility (RV) over the sampled period. The black line is mutual information. Mutual information is normalized (normalized to 1) of entropy. Red and blue dotted lines trace entropy in the series. The vertical axis represents the magnitude of the exchange of information (in percentage), and the horizon axis is the time line.
Panel A: Returns

Brent Oil

Panel B: Volatility

Gold

Silver

EU/US$ Exchange Rate

10-year Treasury Note

US Stock Market (S&P 500)

Notes: Figure 4 plots estimates of dynamic ETE via a growing window approach based on Eq. (8). Estimates involve a number of shuffles equaling 100 and 300 bootstrap replications. The red line traces dynamic ETE from Implied Volatility (IV) to underlying asset return/Realized Volatility (RV) ($ETE_{IV\rightarrow RV}$). The blue line traces dynamic ETE from asset return/RV to underlying IV ($ETE_{RV\rightarrow IV}$). The vertical axis represents the magnitude of transfer entropy/or information flow, and the horizon axis is the time line.

Fig. 4. Dynamic effective transfer entropy.
Therefore, we may conclude that the OIV predictability has improved during the pandemic particularly in predicting the returns as opposed to the realized variance. The greatest change in the amount of the MI that the OIV shares is found to be in the oil market whereas the lowest change is recorded in the foreign exchange market. The increase of information sharing during the pandemic is high even when it is compared to the period of the oil market crash, the OMC period: Jun. 20, 2014–Jan. 2, 2016.

In different crisis periods the OIV sharing of information changes according to the asset class. For instance, the highest sharing with oil is found during the pandemic, while the highest sharing of silver and bonds is found during the European Debt Crisis: May 1, 2010–Sep. 6, 2012. The MI during the global financial crises is highest in the foreign exchange and gold markets: Jul. 2, 2007–Dec. 31, 2009.

Fig. 3 reports the temporal range of the MI measure during the period. The MI values of all asset returns increase suddenly and substantially during March 2020. This phenomenon corresponds to the announcement of the national emergency and the lockdowns regulations globally. A hike in uncertainty that surrounds the economy has improved the role that the OIV plays in predicting realized volatility and returns. In fact, the MI reaches a value of 1 during some phases of the pandemic for oil, thus, indicating a complete exchange of information between the OIV, the returns and the realized variance.

Furthermore, Fig. 3 shows that there is no discernible trend in the MI before the pandemic with the exception of gold and silver. For these two assets the MI is decreasing over time. Finally, the MI between the OIV and the realized volatility remains highest for an extended period of time from Nov 2008 to Nov 2014. Finally, the figure shows that the MI that the OIV shares with the returns is higher than what it shares with the realized volatility. This is uniform across all assets and time periods.

b. Transfer entropy

Fig. 4 reports the results of the effective transfer entropy (ETE). Following Behrendt et al. (2019), we shuffle 50 to 300 bootstrap replications to get the ETE measure. The red line represents the dynamic ETE from the oil to the underlying asset’s returns/realized variance (ETE\(_{Y\rightarrow X}\)). The blue line represents the dynamic ETE from asset’s returns/realized variance to the OIV (ETE\(_{X\rightarrow Y}\)). By definition, the ETE\(_{Y\rightarrow X}\) \(\neq\) ETE\(_{X\rightarrow Y}\) implies asymmetric transmissions between X and Y. Moreover, if ETE\(_{Y\rightarrow X}\) > ETE\(_{X\rightarrow Y}\) then the information flows from the OIV toward the returns/the realized variance more than it crosses vice versa.

Table 6 displays the ETE estimates across assets and time periods. The estimates show that the OIV is a net transmitter of information to the realized volatility and to the returns of all markets except the silver market during the European Debt Crisis. These results describe the extent to which the OIV can reduce uncertainty about asset returns and variances beyond the degree to which the returns and variances reduce the uncertainty about their own future values (see Barnett et al., 2009).

The highest net effective transfer entropy during the pandemic is found in the oil and the US equity markets. The net information transmission from the OIV to the oil return and realized variance is 0.0317 and 0.0269 respectively. For US equities, the comparable values are 0.0361 and 0.0303 respectively. It is worth to mention here that the net transmission from the OIV to the returns is higher than the net transmissions to the realized variance. This is true across various crisis periods and assets. Therefore, we may conclude that while the OIV helps in forecasting the future volatility, it is more helpful in reducing the future returns uncertainty.

The changes in net transmission indicate that the predictability of the OIV is conditional on the asset as well as on the time period considered. It also depends on the predicted variable. For instance, during the COVID pandemic crisis, the OIV is the most useful in predicting the future variance of oil, silver and US equities. However, during the oil market crash, the OIV is useful in forecasting the returns and the realized variance of the foreign exchange market as well as the variance of the treasury bonds. The returns of the US equity market and the yields of the treasury bonds are best predicted during the Global Financial Crisis.

Note also that the OIV is not the center of the transmission in the silver market during the European Debt Crisis period. But for other periods, the OIV is still the center of transmissions even for silver. A possible explanation is that the silver option market may not be as developed and as liquid as other option markets and probably this may have affected the information transmitted from the OIV in this market.

Overall, our results show that the OIV informs on the future variance and the returns. Accordingly, models that predict the variance and the returns during the pandemic should consider these findings in two respects. First, the predictive role of the OIV is generally critical. Second, its predictive ability differs for the realized variance and the returns. As mentioned, the OIV has been effective in predicting the returns of most assets more than the realized variance during crises including the pandemic.

Fig. 4 reports estimates of the ETF across the sampled periods. The red line traces dynamic ETF from the OIV to the realized variance/returns. The blue line traces the reverse directionality: from the realized variance/the returns to the OIV. As seen in the figure, the red line is always above the blue line, indicating a net flow from the OIV to the realized variance/returns in most of the sample periods including the pandemic. Our findings re-confirm the Benedetto et al. (2020) that the predictive power of the OIV increases during crises times.29

c. Additional analysis

To double-check the findings under another data-generating process, we used two novel methods: (1) the time-varying Granger causality procedure developed by Shi et al. (2018,2020), and (2) the dynamic connectedness approach of Diebold and Yilmaz (2012,
Table 6
Average values of effective transfer entropy for GFC, EDC, OMC and COVID-19 periods.

|                                    | Global Financial Crisis (GFC) | European Debt Crisis (EDC) | Oil Market Crash (OMC) | Before COVID-19 pandemic | COVID-19 pandemic |
|------------------------------------|------------------------------|----------------------------|------------------------|--------------------------|------------------|
|                                    | (Jul. 2, 2007-Dec. 31, 2009) | (May 1, 2010-Sep. 6, 2012) | (Jun. 20, 2014-Jan. 2, 2016) | (Jan. 2, 2018-Dec. 31, 2019) | (Jan. 2, 2020-Nov. 11, 2020) |
| **Panel A: Returns**               |                              |                            |                        |                          |                  |
| Brent Oil                          |                              |                            |                        |                          |                  |
| OVX -> BOR                         | 0.0066                       | 0.0251                     | 0.0309                 | 0.0295                   | 0.0318           |
| BOR -> OVX                         | 0.0027                       | 0.0017                     | 0.0001                 | 0.0007                   | 0.0001           |
| **Difference**                     |                              |                            |                        |                          |                  |
| Gold                               |                              |                            |                        |                          |                  |
| GVX -> GR                          | 0.0119                       | 0.0164                     | 0.0193                 | 0.0219                   | 0.0251           |
| GR -> GVX                          | 0.0049                       | 0.0001                     | 0.0012                 | 0.0043                   | 0.0049           |
| **Difference**                     |                              |                            |                        |                          |                  |
| Silver                             |                              |                            |                        |                          |                  |
| VXSLV -> SR                        | -                            | 0.0407                     | 0.0127                 | 0.0125                   | 0.0168           |
| SR -> VXSLV                        | -                            | 0.0774                     | 0.0026                 | 0.0005                   | 0.0005           |
| **Difference**                     | -                            | -0.0366                    | 0.0100                 | 0.0120                   | 0.0163           |
| EU/US$ Exchange Ratea              |                              |                            |                        |                          |                  |
| EUVIX -> EU/US$                   | 0.0111                       | 0.0073                     | 0.0179                 | 0.0185                   | 0.0219           |
| EU/US$ -> EUVIX                   | 0.0107                       | 0.0042                     | 0.0007                 | 0.0084                   | 0.0062           |
| **Difference**                     |                              |                            |                        |                          |                  |
| 10-year Treasury Note              |                              |                            |                        |                          |                  |
| TVIX -> TYR                        | 0.0154                       | 0.0108                     | 0.0094                 | 0.0114                   | 0.0109           |
| TYR -> TVIX                        | 0.0033                       | 0.0003                     | 0.0003                 | 0.0018                   | 0.0019           |
| **Difference**                     |                              |                            |                        |                          |                  |
| US Stock Market (S&P 500)         |                              |                            |                        |                          |                  |
| VIX -> SPR                         | 0.0382                       | 0.0395                     | 0.0291                 | 0.0346                   | 0.0391           |
| SPR -> VIX                         | 0.0018                       | 0.0034                     | 0.0019                 | 0.0012                   | 0.0030           |
| **Difference**                     |                              |                            |                        |                          |                  |
| US Stock Market (S&P 500)         |                              |                            |                        |                          |                  |
| VIX -> VIX                         |                              |                            |                        |                          |                  |
| **Panel B: Realized Volatility**   |                              |                            |                        |                          |                  |
| Brent Oil                          |                              |                            |                        |                          |                  |
| OVX -> BOV                         | 0.0052                       | 0.0163                     | 0.0255                 | 0.0240                   | 0.0284           |
| BOV -> OVX                         | 0.0029                       | 0.0034                     | 0.0028                 | 0.0016                   | 0.0015           |
| **Difference**                     |                              |                            |                        |                          |                  |
| Gold                               |                              |                            |                        |                          |                  |
| GVX -> GV                          | 0.0047                       | 0.0210                     | 0.0198                 | 0.0219                   | 0.0225           |
| GRV -> GVX                         | 0.0035                       | 0.0003                     | 0.0035                 | 0.0041                   | 0.0065           |
| **Difference**                     |                              |                            |                        |                          |                  |
| Silver                             |                              |                            |                        |                          |                  |
| VXSLV -> SV                        | -                            | 0.0095                     | 0.0092                 | 0.0097                   | 0.0097           |
| SV -> VXSLV                        | -                            | 0.0883                     | 0.0071                 | 0.0051                   | 0.0027           |
| **Difference**                     | -                            | -0.0788                    | 0.0021                 | 0.0046                   | 0.0071           |
| EU/US$ Exchange Ratea              |                              |                            |                        |                          |                  |
| EUVIX -> EU/US$                   | 0.0261                       | 0.0090                     | 0.0217                 | 0.0188                   | 0.0154           |
| EU/US$ -> EUVIX                   | 0.0179                       | 0.0041                     | 0.0031                 | 0.0066                   | 0.0061           |
| **Difference**                     | 0.0083                       | 0.0049                     | 0.0186                 | 0.0122                   | 0.0093           |
| 10-year Treasury Note              |                              |                            |                        |                          |                  |
| TVIX -> TYV                        | 0.0149                       | 0.0084                     | 0.0131                 | 0.0124                   | 0.0090           |
| TYV -> TVIX                        | 0.0080                       | 0.0040                     | 0.0009                 | 0.0012                   | 0.0015           |
| **Difference**                     | 0.0070                       | 0.0044                     | 0.0121                 | 0.0113                   | 0.0076           |
| US Stock Market (S&P 500)         |                              |                            |                        |                          |                  |
| VIX -> SPV                         | 0.0135                       | 0.0327                     | 0.0304                 | 0.0322                   | 0.0356           |
| SPV -> VIX                         | 0.0020                       | 0.0036                     | 0.0000                 | 0.0031                   | 0.0043           |
| **Difference**                     | 0.0116                       | 0.0291                     | 0.0304                 | 0.0290                   | 0.0313           |

Notes: Table 5 shows average ETE between Implied Volatility (IV) and underlying asset return/Realized Volatility (RV).

a Start date of the sample: June 2, 2008.
b Start date of the sample: March 17, 2011.
6. Time-varying Granger causality

We utilize a novel time-varying Granger causality test recently developed by Shi et al. (2018; 2020). This econometric procedure is valuable in that it considers the stylized facts that is observed in the financial market data such as heteroskedasticity, deterministic trend, and nonlinearity. It also tracks the changes in the causal relationships over time. Therefore, this method is a novel measure that examines the change in any causal relation and detects the exact dates of the origination and the collapse of the episode of causality. The new test of time-varying Granger causality is based on a recursive evolving window algorithm procedure. It is an extension of both the forward expanding window algorithm method of Thoma (1994) and the rolling window algorithm method of Swanson (1998).

The blue line in Fig. 5 shows the heteroskedastic-consistent least upper bound of the Wald statistic sequences of the causality between the OIV, the realized variance and the returns with its corresponding 5% critical values, which is bootstrapped and it is represented by the black lines. The test confirms our earlier results in that the direction of causality runs from the OIV to the realized volatility/returns. It also confirms that casualty is stronger during the pandemic.

The figure also shows that the causality in the oil market is the highest causality among all assets during the pandemic period thus, supporting our earlier conclusion on the strong MI found between the OIV, the realized volatility and the returns of the oil market during the COVID period. However, the causality between the OIV with the oil returns has reached its maximum during the oil market crash period compared to other crisis periods.

During the COVID period, the figure shows that there is a significant feedback effect from the realized variance to the OIV in all of the markets except the gold and the treasury bill markets. The feedback effect from the returns is weak and insignificant except in the oil market.

7. Dynamic connectedness approach

This novel procedure allows the VAR parameters and the variances to fluctuate via a stochastic volatility Kalman Filter estimation with forgetting factors instead of using the Diebold and Yılmaz approach that relies on rolling-window VAR. This method captures the net transmission mechanisms of shocks of one variable to another and the total dynamic connectedness between them. Appendix A reviews TVP–VAR connectivity model.

Fig. 6 displays the index of the total connection between the OIV and the realized variance and the returns across different time periods. The greatest connection is found between the OIV and the returns appears to be in the equity market with a maximum value of around 50%. That is, the cross-connectedness with the OIV explains 50% of variance of forecast errors of equity returns. The value of the index varies over time, but it shows a clear trend during some sub-periods. In particular, there has been a sudden heightened connectedness during the pandemic, but it is not sustained. Connectedness then declines after March 2020 for most assets, confirming our findings from the entropy-based tests. Periods before and during are characterized by heterogeneous fluctuation in the connectedness. The period before (during) exhibits small (large) fluctuations. Nonetheless, large fluctuations are limited to narrow time phases during the pandemic. Connectedness between the OIV and the realized variance of bonds and the returns of the foreign exchange are nearly zero by year-end 2019. This finding shows that the relation between the OIV and the asset returns and the variance has manifested during the pandemic (see Fig. 6).

Fig. 7 also displays the time-varying net directional and the pairwise connectedness between the OIV and the realized volatility and the returns of each asset. We uncover whether each asset’s OIV is a net transmitter (positive value) or a net receiver of shocks (negative value) at each time during the sample. It appears that the OIV is a net transmitter of shocks to the realized variance and to the returns in nearly every period. More important, the transmission of shocks from the OIV increases remarkably during the pandemic particularly for silver and bonds.

Overall, the emergence of OIV as a net transmitter of shocks to asset returns and variances during phases of the pandemic highlights the importance of using dynamic portfolio diversification to mitigate portfolio investment risk.

8. Conclusion

In finance, the literature is interested in the role that the OIV plays in the prediction of the future risk and the future returns of the financial markets. This study contributes to the literature by investigating how the predictability of the options implied volatility (OIV) of the future realized variance/returns has changed over the COVID 19 pandemic for six of major investable assets: the US equity, the US treasury bonds, the oil, the gold, the $ foreign exchange and the silver.

This procedure was first proposed by Phillips et al. (2015a, b), Phillips and Shin (2018; 2020) to detect both real-time bubbles and crises. The TVP–VAR connectedness procedure outperforms a standard rolling-window VAR. It does not require setting the size of the rolling window, so its results are insensitive to the selection of the window size. Hence, there is no need to set arbitrary window-size, and it uses the entire sample without loss of observations. It is insensitive to outliers and/or skewness. It also adjusts immediately to structural changes and events, thus, enabling us to track connectedness between variables clearer and faster.
Fig. 5. Time-varying Granger causality test results.
Unlike the related literature, our work approaches the implied volatility predictability issue by using entropy-based methods that are non-parametric and non-linear. In that sense our method circumvents the specification biases inherent in parametric methods, and it is thus able to captures non-linear dependence between the variables. Furthermore, we focus and infer during various crisis episodes and across many assets.

Our results are interesting and intuitive. We find that the information crosses between the OIV and the realized variance/returns has heightened significantly during the pandemic indicating increased predictability of the OIV during crisis periods. However, the transmission is found to be higher with returns compared to the realized variances and hence, we may conclude that the OIV shares more information about the future returns than it shares about the future risk. The predictability of the OIV is found to depend on the asset and on the time period.

Fig. 5. (continued).
Fig. 6. Connectedness index.

Notes: Figure 4 plots the dynamic CI based on TVP–VAR with lag of 2 and a 12-step-ahead forecast. CI measures time-varying CI. It measures total information flow among variables. The vertical axis is the total spillover (connectedness) index (in percentage), and the horizon axis is the time line.
These findings show the higher relative importance of the OIV in forecasting the returns and risk during the crisis periods compared to other periods. They also show that the predictability is contingent on the asset. For instance, the OIV is more useful for prediction in the oil and the equity markets than it is in other markets. Therefore, risk managers of portfolios that contain oil and equities need to exploit the information contained in the OIV to improve the accuracy of their risk forecasts and thus, their measurement of risk.

The main limitation of this work is that it does not provide a prediction or a prediction measure of the accuracy of the out of sample forecasts that are conditional on the previous values of the OIV. Such computations are necessary to assess the true value of entropy in inferring the relevant factors that predict volatility. This issue is left for future research.

Fig. 7. Net total directional connectedness.
Appendix A

Time-Varying Granger Causality

Let a set of \( y \) variables, which are two strictly stationary process, with components \( y_t = (y_1, y_2)' \). The lag-augmented VAR (LA-VAR) regression for testing Granger causality from \( y_2 \) (news sentiment) to \( y_1 \) (asset returns) can be written as

\[
y_t = \Pi y_{t-1} + \varnothing y_{t-2} + \varepsilon_t, \quad t = 1, \ldots, T \tag{A1}
\]

where \( \Pi_{2 \times (2p+1)} = [\Phi_0, \Phi_1, \ldots, \Phi_p] \) is the first order autoregressive coefficient and \( \varnothing \) is the augmented term with \( \varnothing \) being a zero matrix under the DGP. The error term \( \varepsilon_t \) is assumed to be an iid sequence. In order to test the null hypothesis that \( y_2 \) does not Granger cause \( y_1 \) (i.e., \( H_0 : y_2 \not\Rightarrow y_1 \)), the standard Wald (W) can be denoted as:

\[
W = [R \text{vec}(\hat{\Pi})]' [R(X^X)^{-1}R]^{-1} [R \text{vec}(\hat{\Pi})] \tag{A2}
\]

where \( \text{vec}(\hat{\Pi}) \) is a row vector \( 2 \times (2p+1) \) coefficients of \( \hat{\Pi} \) and \( R \) is a \( p \times (2p+1) \) restriction matrix for the Granger causality running from \( y_2 \) to \( y_1 \).

To investigate the potential causal relationship between two financial series using the recursive evolving procedure Shi et al. (2018; 2020) estimate \( W \) for each subsample regression over \( [f_1, f_2] \) with a sample size fraction of \( f_0 \) in the recursive evolving algorithm and estimate heteroskedasticity consistent sup Ward statistic sequence \( (S_W) \) as follows:

\[
S_{W f_0} = \sup_{f_1 \leq f \leq f_2} \{ W_{f_0 f} \} \tag{A3}
\]

where \( \wedge_0 = \{(f_1, f_2) : 0 < f_0 + f_1 \leq f_2 \leq 1, \text{ and } 0 \leq f_1 \leq 1 - f_0 \} \), \( f \) is the (fractional) observation of interest, \( f_0 \) is the minimum (fractional) window size, \( f_1 \) and \( f_2 \) are the starting and terminal points of the sequence of regressions, respectively. Origination (\( f_e \)) and termination (\( f_f \)) dates in the causal relationship are calculated based on the following recursive evolving algorithms:

\[
\tilde{f}_e = \inf_{f_1 \leq f \leq f_0} \{ f : S_{W f} > scv \} \quad \text{and} \quad \tilde{f}_f = \inf_{f_1 \leq f \leq f_0} \{ f : S_{W f} < scv \} \tag{A4}
\]

where scv is the sequence of the bootstrapped critical values of \( S_W \) statistics. If the Ward statistic sequence exceeds its corresponding

Note that most notations and text in this section are taken from Shi et al. (2018; 2020).
critical value, a significant change in causality is detected.

In our case, we investigate the existence of a causal relationship between IV and future variance and returns for six assets using the recursive evolving procedures, lag length of the bivariate VAR is chosen using the Bayesian information criteria (BIC) with a maximum lag order of 12. In implementation of the recursive testing procedure, the minimum window size $f_0$ is set to 0.2, which includes 704 observations. The critical values of recursive evolving approaches are obtained from a bootstrapping procedure with 499 replications.

**TVP-VAR model**

Let $y_t$ and $y_{t-1}$ be represented by $N \times 1$ and $Np \times 1$ dimensional vectors, respectively. The TVP-VAR model can be written as

$$y_t = \beta y_{t-1} + \epsilon_t, \quad \epsilon_t | F_{t-1} \sim N(0, S_t)$$  \hspace{1cm} (A5)

$$\beta_t = \beta_{t-1} + \nu_t, \quad \nu_t | F_{t-1} \sim N(0, R_t),$$  \hspace{1cm} (A6)

where $\beta_t$ is an $N \times N$ dimensional time-varying coefficient matrix. $\epsilon_t$ is an $N \times 1$ vector of disturbances with $N \times N$ time-varying variance-covariance matrix. $\nu_t$ is an $N^2 \times 1$ dimensional vector. $R_t$ is an $N^2 \times N^2$ dimensional matrix.

Once time-varying coefficients $\beta_t$ and $S_t$ from the TVP-VAR model are estimated, the generalized impulse response functions and generalzied forecast error variance decompositions (GFEVD) can be calculated as in the generalized connectedness procedure of Diebold and Yılmaz (2014). The H-step ahead (scaled) GFEVD of the $i^{th}$ variable from shocks to variable at time $t$ denoted by $\theta_{y_i}^H(H)$ can be calculated as

$$\theta_{y_i}^H(H) = \sigma^2 \left( \sum_{h=1}^{H-1} (\epsilon'_h H_s \sum \epsilon_h)^2 \right) \sigma^2 \left( \sum_{h=1}^{H-1} (\epsilon'_h H_s \sum \epsilon_h) \right)^2,$$  \hspace{1cm} (A7)

where $\sum$ is the variance matrix of the vector of errors $\epsilon$, and $\sigma^2$ is the standard deviation of the error term of the $i^{th}$ variable. $\epsilon_i$ is a selection vector with 1 in the $i^{th}$ element and 0 otherwise. To get a unit sum for each row of the variance decomposition we normalize each entry of the matrix by the row sum as

$$\tilde{\theta}_{y_i}^H(H) = \frac{\theta_{y_i}^H(H)}{\sum_j \theta_{y_j}^H(H)}$$  \hspace{1cm} (A8)

In Eq. (A8) the decomposition, including own shocks to each variable, sums to 1—i.e., $\sum_{j=1}^N \tilde{\theta}_{y_i}^H(H) = 1$, and total decomposition of the two variables sums to $N$—i.e., $\sum_{j=1}^N \tilde{\theta}_{y_j}^H(H) = N$. Based on $\tilde{\theta}_{y_i}^H(H)$ we can compute the time-varying connectedness index (CI) as

$$TCI_i^H(t) = \frac{\sum_{i, j=1}^N \tilde{\theta}_{y_i}^H(H)}{\sum_{i, j=1}^N \tilde{\theta}_{y_j}^H(H)} \times 100 = \frac{\sum_{i, j=1}^N \tilde{\theta}_{y_i}^H(H)}{N} \times 100$$  \hspace{1cm} (A9)

The index in Eq. (A9) measures total information flow among markets (i.e., oil and US equities). It is an off-diagonal addition to the proportions of the forecast error variance of $y_i$ to shocks to $y_j$ when $i \neq j$.

The directional connectedness variable $i$ receives it from variable $j$ (FROM) ND can be calculated as

$$S^i_{ij}(H) = \frac{\sum_{j=1}^N \tilde{\theta}_{y_i}^H(H)}{\sum_{j=1}^N \tilde{\theta}_{y_j}^H(H)} \times 100$$  \hspace{1cm} (A10)

Similarly, directional connectedness of variable $i$ to $j$ (TO) is computed as

$$S^f_{ij}(H) = \frac{\sum_{j=1}^N \tilde{\theta}_{y_i}^H(H)}{\sum_{j=1}^N \tilde{\theta}_{y_j}^H(H)} \times 100$$  \hspace{1cm} (A11)

Finally, by the difference between Eqs. (A10) and (A11) we can construct net total directional connectedness as

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We also conducted the analysis using a minimum window size $f_0$ of 0.25 and 0.30 (which corresponding with 882 and 1057 days respectively) to check the sensitivity to the window size. We found that our results are robust to window size selection. To conserve space, the results are not reported in the paper but they are available from the authors upon request.

The text and notation in this section are from Antonakakis et al. (2020).
$S'_i(H) = S'_i(H) - S'_i(H)$

(A12)

Total net directional connectedness in Eq. (A12) indicates which market prevails in the transmission of information.

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This is to certify that there is no conflict of interests to declare. This unpublished manuscript is not under consideration elsewhere. We have approved the manuscript and agree with submission to Journal of Commodity Markets.

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Credit author statement

With regard to authors roles in this manuscript, the first author handled the conceptualization, methodology, software functions and the second author handled the validation, formal analysis and writing the original draft. Third author handled the analysis review and editing function.

References

Adekoya, O.B., Oliyide, J.A., 2020. How COVID-19 drives connectedness among commodity and financial markets: evidence from TVP-VAR and causality-in-quantiles techniques. Resour. Pol. 101898 (in press).

Agnoletti, F., 2009. Volatility in crude oil futures: a comparison of the predictive ability of GARCH and implied volatility models. Energy Econ. 31 (2), 316–321.

Albulescu, C.T., 2020. COVID-19 and the United States financial markets’ volatility. Finance Res. Lett. (in press).

Andersen, T.G., Bollerslev, T., 1998. Answering the skeptics: yes, standard volatility models do provide accurate forecasts. Int. Econ. Rev. 885–905.

Antonakakis, N., Chatziantoniou, I., Gabauer, D., 2020. Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. J. Risk Financ. Manag. 13, 1–23.

Awtarani, B., Aktham, M., Cherif, G., 2016. The connectedness between crude oil and financial markets: evidence from implied volatility indices. J. Commod. Mark. 4 (1), 56–69.

Baek, S., Mohanty, S., Glambosky, M., 2020. COVID-19 and stock market volatility: an industry level analysis. Finance Res. Lett. 101748 (in press).

Baig, A.S., Hassan Anjum Butt, H.A., Haroon, O., Rizvi, S.A.R., 2020. Deaths, panic, lockdowns and US equity markets: the case of COVID-19 pandemic. Finance Res. Lett. (in press).

Barnetti, L., Barrett, A.B., Seth, A.K., 2009. Granger causality and transfer entropy are equivalent for Gaussian variables. Phys. Rev. Lett. 103 (23), 238701.

Behrendt, S., Dimpfl, T., Peter, F.J., Zimmermann, D.J., 2019. Birentropy—quantifying the flow between different time series using effective transfer entropy. SoftwareX 10, 100265.

Bekiros, S., Diks, C., 2008. The relationship between crude oil spot and futures prices: cointegration, linear and nonlinear causality. Energy Econ. 30, 2673–2685.

Bekiros, S., Nguyen, D.K., Junior, L.S., Salah Uddin, G., 2017. Information diffusion, cluster formation and entropy-based network dynamics in equity and commodity markets. Eur. J. Oper. Res. 256 (3), 945–961.

Benedetto, F., Giunta, G., Mastroeni, L., 2015. A maximum entropy method to assess the predictability of financial and commodity prices. Digit. Signal Process. 46, 19–31.

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

Benedetto, F., Mastroeni, L., Quaresima, G., Vellucci, P., 2020. Does OVX affect WTI and Brent oil spot variance? Evidence from an entropy analysis. Energy Econ. 104815.

Benedetto, F., Mastroeni, L., Vellucci, P., 2019. Modeling the flow of information between financial time series by an entropy-based approach. Ann. Oper. Res. 1–18.

Berk, L., Čan, E., 2020. The shift in global crude oil market structure: a model-based analysis of the period 2013–2017. Energy Pol. 142, 111497.

Blair, B.J., Poorn, S.H., Taylor, S.J., 2010. Forecasting S&P 500 volatility: the incremental information content of implied volatilities and high-frequency index returns. In: Handbook of Quantitative Finance and Risk Management. Springer, Boston, MA, pp. 1333–1344.

Canina, L., Figlewski, S., 1993. The informational content of implied volatility. Rev. Financ. Stud. 6 (3), 659–681.

Cao, C., Yu, F., Zhong, Z., 2010. The information content of option-implied volatility for credit default swap valuation. J. Financ. Mark. 13 (3), 321–343.

Chang, Ch-L., McAleer, M., Wang, Y.-A., 2020. Herding behaviour in energy stock markets during the Global Financial Crisis, SARS, and ongoing COVID-19. Renew. Sustain. Energy Rev. 134, 110349.

Chen, Z., Craig, K.A., Karpovics, M., 2020. Once bitten twice shy? Evidence from the U.S. banking industry during the crash of the energy market. Energy Econ. 92, 10498.

Christensen, B.J., Prabhala, N.R., 1998. The relation between implied and realized volatility. J. Financ. Econ. 50 (2), 125–150.

Chunxia, Y., Xueshui, Z., Luoluo, J., Sen, H., He, L., 2016. Study on the contagion among American industries. Phys. Stat. Mech. Appl. 444, 601–612.

Diks, C., Panchenko, V., 2006. A new statistic and practical guidelines for nonparametric Granger causality testing. J. Econ. Dynam. Contr. 30, 1647–1669.

Darbellay, G.A., Wuertz, D., 2000. The entropy as a tool for analysing statistical dependences in financial time series. Phys. Stat. Mech. Appl. 287 (3-4), 429–439.

Demeterfi, K., Derman, E., Kamal, M., Zou, J., 1999. More than you ever wanted to know about volatility swaps. Goldman Sachs Quant. Strat. Res. Notes 41, 1–56.

Diniz, P., Mayhew, S., Stivers, C., 2006. Stock returns, implied volatility innovations, and the asymmetric volatility phenomenon. J. Financ. Quant. Anal. 381–406.

Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66.

Diebold, F.X., Yilmaz, K., 2014. On the network topology of variance decompositions: measuring the connectedness of financial firms. J. Econom. 182 (1), 119–134.

Dimpfl, T., Peter, F.J., 2018. Analyzing volatility transmission using group transfer entropy. Energy Econ. 75, 368–376.

Dimpfl, T., Peter, F.J., 2019. Group transfer entropy with an application to cryptocurrencies. Phys. Stat. Mech. Appl. 516, 543–551.

Dungey, M., Gajurel, D., 2014. Equity market contagion during the global financial crisis: evidence from the world’s eight largest economies. Econ. Syst. 38, 161–177.

Dutta, A., 2018. Oil and energy sector stock markets: an analysis of implied volatility indexes. J. Multinatl. Financ. Manag. 44, 61–78.

Fassas, A.P., Siriopoulos, C., 2020. Implied Volatility Indices-A Review. The Quarterly Review of Economics and Finance (in press).

Fleming, J., 1998. The quality of market volatility forecasts implied by S&P 100 index option prices. J. Empir. Finance 5 (4), 317–345.

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

Fry-Mckibbin, R., Hsiao, C.Y.-L., Tang, C., 2014. Contagion and global financial crises: lessons from nine crisis episodes. Open Econ. Rev. 25, 521–570.

Giot, P., 2003. The information content of implied volatility in agricultural commodity markets. J. Futures Mark.: Fut. Options Other Deriv. Prod. 23 (5), 441–454.
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Gong, X., Lin, B., 2018. The incremental information content of investor fear gauge for volatility forecasting in the crude oil futures market. Energy Econ. 74, 370–386.

Gonzalez-Perez, M.T., 2015. Model-free volatility indexes in the financial literature: a review. Int. Rev. Econ. Finance 40, 141–159.

Hauguen, E., Langlois, J., Molinari, P., Westgaard, S., 2014. Forecasting volatility of the US oil market. J. Bank. Finance 47, 1–14.

He, J., Shang, P., 2017. Comparison of transfer entropy methods for financial time series. Phys. Stat. Mech. Appl. 482, 772–785.

Hiemstra, C., Jones, Y.S., 1994. Testing for linear and nonlinear Granger causality in the stock price-volume relation. J. Finance 49, 1639–1664.

Hlavackova-Schindler, K., Palus, M., Vejmelka, M., Bhattacharya, J., 2007. Causality detection based on information theoretic approaches in time series analysis. Phys. Rep. 441, 1–46.

Ji, G., Fan, Y., 2016. Modelling the joint dynamics of oil prices and investor fear gauge. Res. Int. Bus. Finance 37, 242–251.

Jiang, G.J., Tian, Y.S., 2005. The model-free implied volatility and its information content. Rev. Financ. Stud. 18 (4), 1305–1342.

Just, M., Echaust, K., 2020. Stock market returns, volatility, correlation and liquidity during the COVID-19 crisis: evidence from the Markov switching approach. Finance Res. Lett. 101775 (in press).

Kamdem, J.S., Essomba, R.B., Berinyinuy, J.N., 2020. Deep learning models for forecasting and analyzing the implications of COVID-19 spread on some commodities markets volatilities. Chaos, Solit. Fractals 140, 110215.

Kullback, S., Leibler, R.A., 1951. On information and sufficiency. Ann. Math. Stat. 22 (1), 79–86.

Lahmin, S., Bekiros, S., 2020. Renyi entropy and mutual information measurement of market expectations and investor fear during the COVID-19 pandemic. Chaos, Solit. Fractals 139, 110084.

Lee, J., Strazicich, M.C., 2003. Minimum Lagrange multiplier unit root test with two structural breaks. Rev. Econ. Stat. 85 (4), 1082–1089.

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

Lv, W., 2018. Does the OVX matter for volatility forecasting? Evidence from the crude oil market. Phys. Stat. Mech. Appl. 492, 916–922.

Magh prey er, A.I., Awar tani, B., Bouri, E., 2016. The directional volatility connectedness between crude oil and equity markets: new evidence from implied volatility indexes. Energy Econ. 57, 78–93.

Mar schinski, R., Kantz, H., 2002. Analysing the information flow between financial time series. Eur. Phys. J. B-Condens. Matter Complex Syst. 30 (2), 275–281.

Mazur, M., Dang, M., Vega, M., 2020. COVID-19 and the March 2020 Stock Market Crash. Evidence from S&P500. Finance Research Letters (in press).

Mohti, W., Dionisi, A., Vieira, I., Ferreira, P., 2019. Financial contagion analysis in frontier markets: evidence from the US subprime and the Eurozone debt crises. Phys. Stat. Mech. Appl. 525, 1388–1398.

Nui j, W., Milea, V., Hogenboom, F., Frasin car, F., Kaynak, U., 2014. An automated framework for incorporating news into stock trading strategies. IEEE Trans. Knowl. Data Eng. 26 (4), 823–835.

Orlando, G., Taglialatela, G., 2017. A review on implied volatility calculation. J. Comput. Appl. Math. 320, 202–220.

Papana, A., Kyrtsou, C., Kugiumtzis, D., Diks, C., 2016. Detecting causality in non-stationary time series using partial symbolic transfer entropy: evidence in financial data. Comput. Econ. 47, 341–365.

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

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

Perron, P., 1989. The great crash, the oil price shock, and the unit root hypothesis. Econometrica: J. Econ. Soc. 1361–1401.

Phillips, P.C.B., Shi, S., Yu, J., 2015a. Testing for multiple bubbles: historical episodes of exuberance and collapse in the S&P 500. Int. Econ. Rev. 56 (4), 1043–1078.

Phillips, P.C.B., Shi, S., Yu, J., 2015b. Testing for multiple bubbles: limit theory of real-time detectors. Int. Econ. Rev. 56 (4), 1079–1134.

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

Samarakoon, L.P., 2017. Contagion of the eurozone debt crisis. J. Int. Financ. Mark. Inst. Money 49, 115.

Shi, S., Phillips, P.C.B., Hurn, S., 2018. Change detection and the causal impact of the yield curve. J. Time Anal. 39, 966–987.

Shi, S., Phillips, P.C.B., Hurn, S., 2020. Causal change detection in possibly integrated systems: revisiting the money income relationship. J. Financ. Econom. 18, 158–180.

Simon, D.P., 2002. Implied volatility forecasts in the grains complex. J. Futures Mark. 22 (10), 959–981.

Swanson, N.R., 1998. Money and output viewed through a rolling window. J. Monetary Econ. 41 (3), 455–474.

Szakmary, A., Ors, E., Kim, J.K., Davidson III, W.N., 2003. The predictive power of implied volatility: evidence from 35 futures markets. J. Bank. Finance 27 (11), 2151–2175.

Thoma, M.A., 1994. Subsample instability and asymmetries in money-income causality. J. Econom. 64 (1–2), 279–306.

Wanga, G.-J., Xie, C., Lin, M., Stanley, H.E., 2017. Stock market contagion during the global financial crisis: a multiscale approach. Finance Res. Lett. 22, 163–168.

Whaley, R.E., 2009. Understanding the VIX. J. Portfolio Manag. 35 (3), 98–105.

Whaley, R.E., 2000. The investor fear gauge. J. Portfolio Manag. 26 (3), 12–17.

Worldometer, 2020. Worldometer COVID-19 Data [Internet]. Available from: https://www.worldometers.info/coronavirus/#countries.

Zouaoui, M., Nouyrigat, G., Beer, F., 2011. How does investor sentiment affect stock market crises? Evidence from panel data. Financ. Rev. 46 (4), 723–747.