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Commodity and financial markets’ fear before and during COVID-19 pandemic: Persistence and causality analyses

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ABSTRACT

Commodity and financial markets are leading points of attraction to investors, but are very sensitive to external crises, such as financial and health crises. An example is the overwhelming plunge in the prices of the assets being traded in most of these markets during the COVID-19 pandemic. The pandemic has raised market fear beyond what is historically known, thus calling for an empirical assessment of its degree of persistence. Interestingly, the issue of persistence in financial and commodity markets has not even been generally explored in the literature. Using fractional integration approaches, our findings show that all the considered market fear indices exhibit mean reversion before COVID-19 pandemic, implying that the effect of shocks is transitory. However, persistence is higher during the pandemic period, with fear indices of the gold market (GVZ), energy sector (VXXLE) and Eurocurrency market (EVZ) reaching the unit root zone. The Granger-causality test also reveals that equity market fear due to infectious diseases (EMV-ID) and global market fear (VIX) are responsible for the fear in virtually all other markets during the current COVID-19 pandemic period. Strong policy implications are associated with these findings.

1. Introduction

During periods of crises, pandemics, political unrests and other unappealing events especially at the global level, investors’ sentiments are often found to rise due to uncertainties caused by these events. This is because the events have the tendency of adversely affecting the performance of the economies of various countries, and the financial and commodity markets. The resultant effect of this is the fear it generates in investors which further triggers risks since market uncertainties are followed by emotional or sentimental behaviour that cannot be accurately predicted (Economou et al., 2018). Certainly, increased market uncertainty makes investors to be more sensitive to investment losses than gains (Giot, 2005), thus harming investment decisions (Chen and Chiang, 2020).

Among the many crises (ranging from financial to health to political) that have been historically reported, the current COVID-19 pandemic seems to be the one with the strongest impact on the global financial and commodity markets. Following the closure of domestic industries and countries’ borders, and the restriction placed on international trade, among other policies, global financial and commodity markets have been significantly paralyzed. For instance, no other crisis in history had a greater adverse impact on the performance of stock markets, including the Spanish Flu of 1918 (Baker et al., 2020) that resulted in the death of about 2% of the world population, and the latest global financial crisis of 2008 that resulted from credit crunch in the US. To further reveal the extent of the effect of the COVID-19 pandemic, Salisu and Vo (2020) confirm how investors began to sell off their stocks hurriedly following sharp fall in the global prices of crude oil. The early report of the Organisation for Economic Cooperation and Development (OECD) also reveals that the prices of commodities have plummeted, with the prices of stocks recording all-time lowest values in 10 years. Many empirical studies further reveal how the pandemic has been facilitating considerable cross-market transmission of risks (Adekoya and Oliyide, 2021; Umar et al., 2021).

Expectedly, a reflection of these market trends is seen in the measures of uncertainties across different financial and commodity markets. Peeping into the results of our descriptive analysis in Table 1, the markets fear more during the COVID-19 pandemic period than before it, except the Eurocurrency market. In fact, the average values of the global fear index, measured by the U.S. stock market implied volatility index (VIX), and the implied volatility indices of crude oil market (OVX) and the energy sector options (VXXLE) are exceedingly more than twice their
average values before the pandemic. Another recently introduced measure of uncertainty in equity markets that results from infectious diseases (i.e. infectious diseases-based equity market volatility (EMV-ID)) records a mean value of 22.09 during this period, compared to 0.39 for the pre-COVID-19 pandemic period, implying an increase of about 5528.89%.

With this high level of fear in the global markets as a result of the extremely risky conditions, making optimal investment decisions requires utmost carefulness and a measure of restored hope to investors. In particular, investors, either risk-averse or returns-maximizers, would need enough information to re-establish their confidence (Salisu and Vo, 2020), as knowledge about the behaviour of the essential markets would later present exceptional prospects to investors. In addition, the hope of normalcy to global trading activities hinges on the perception of investors of the safety of their investments. Thus, we believe that one of the most critical factors in restoring the confidence of potential investors is the understanding of the degree of persistence of the effect of shocks due to the COVID-19 pandemic on uncertainty or fear in the financial and commodity markets. If there is persistence of shocks to market fear, for instance, investors would be consistently drawn back to take strategic investment decisions, thereby making the full restoration of trading activities globally to be only expected in far distant time. Unfortunately, this would have severe implications for various economies, as there is a need for sustained investment to prevent any economy from plunging into depression (Salisu and Vo, 2020).

Against this backdrop, the aim of this study is to examine the degree of persistence of fear in the global financial and commodity markets, while contributing to knowledge in a number of ways. One, empirical studies on the persistence of uncertainties in general is limited (see Plakandaras et al., 2019). While there are many studies on financial, commodity and macroeconomic variables, and how they are affected by policy-induced uncertainties, less information is known about the persistence of the measures of uncertainties. The few available ones are strictly based on economic policy uncertainties of countries, as captured by the recent studies of Yaya et al. (2020), Plakandaras et al. (2019) and Gil-Alana and Payne (2019). Their findings point to the same direction, generally indicating that economic policy uncertainty indices are persistent. For instance, Gil-Alana and Payne (2019) observe that the U.S. economic policy uncertainty index is persistent, requiring strong measures to restore economic normalcy since future values become very difficult to predict. Similar evidence is found for the G7 countries by Yaya et al. (2020), while adding that the series are fractionally cointegrated. The robust study of Plakandaras et al. (2019) which considers 72 uncertainty indices computed from different macroeconomic indicators reveals that virtually all the series are persistent, with chaotic dynamics only sporadically detected for a few indices during the periods of economic recession. Only the study of Yaya et al. (2021) specifically puts the market fears of stocks and commodities into consideration, although the focus of the authors is different from ours. To the best of our knowledge, however, this is the first study to apply persistence analysis to uncertainty or fear in financial and commodity markets.

Two, we conduct a comparative analysis for the periods before and during the COVID-19 pandemic in order to gauge the severity of the pandemic on market fears. Last but not the least, we determine if fears in other markets are driven by the equity market volatility due to infectious diseases (EMV-ID) and the global fear index (VIX) using the Granger-causality test. The aim here is to show whether the market fear induced by famous infectious diseases affects the fear in other markets during this period compared to the past, as this will help us to know the severity of the impact of the COVID-19 pandemic. This is further complemented with the global stock market index for completeness.

Accordingly, we test the following hypotheses:

1. $H_0$: Fears in the global commodity and financial markets are not persistence.
2. $H_0$: The COVID-19 pandemic does not have significant influence on the persistence of fears in the global commodity and financial markets.
3. $H_0$: EMV-ID and VIX do not significantly affect other fear indicators.

The remainder of this study is structured as follows: Section 2 develops the methodology, Section 3 describes the underlying data and discusses empirical findings, and Section 4 gives the conclusion.

2. Methodology

The objective of this study simply centers on the concept of long memory in time series as a way of determining the degree of persistence of the underlying series. The earliest approach of determining the persistence degree of time series data is the use of unit root tests, but the deficiency of this method comes up when there is an evidence of fractional integration in the series, i.e. a situation when the series is strictly neither I(0) nor I(1). Specifically, the power function of conventional tests of unit root is weak if integration property of the series is fractional in form (see Hasslers and Wolters, 1994; Diebold and Rudebusch, 1991). Motivated by this, this study employs the fractional integration techniques to examine the degree of persistence of market fears.

We begin the methodological framework with the parametric fractional integration approach by first characterizing a process integrated of order $d$ as follows:

\[(1 - L)^d y_t = \mu_t, \quad t = 1, 2, \ldots, \]

where $L$ is the lag operator ($L y_t = y_{t-1}$), $\mu_t$ follows a covariance stationary or a white noise (i.e. I(0)) process, $d$ denotes the fractional differencing parameter, and $y_t$ is the fear index under consideration.

To capture the expression on the left-hand side of equation (1) in its full form, the binomial expansion in terms of infinite order gives:

\[(1 - L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d - 1)L^2}{2!} - \frac{d(d - 1)(d - 2)L^3}{3!} + \ldots \]

(2)

Equation (2) is characterized by slow and monotonic declining weights. Hence,

| Fear gauge | Mean Pre-COVID | Mean COVID period | % change | Maximum Pre-COVID | Maximum COVID period | Jarque-Bera Pre-COVID | Jarque-Bera COVID period |
|------------|---------------|-------------------|----------|-------------------|----------------------|----------------------|------------------------|
| OVX        | 33.1904       | 84.1345           | 153.49%  | 78.9800           | 325.1500             | 282.0126             | 66.3492                |
| GVZ        | 16.5594       | 21.4790           | 29.71%   | 39.9500           | 48.9800              | 936.6207             | 18.5801                |
| SLV        | 28.6226       | 37.3408           | 30.46%   | 80.6400           | 100.6600             | 1753.9185            | 60.3253                |
| XLE        | 22.7825       | 51.6823           | 126.85%  | 57.4700           | 130.6100             | 1528.2301            | 10.1163                |
| EVZ        | 0.2729        | 7.9612            | -14.15%  | 19.8700           | 19.3100              | 305.0692             | 57.8939                |
| VIX        | 16.1845       | 32.4895           | 100.74%  | 48.0000           | 82.6900              | 282.0126             | 66.3492                |
| EMV-ID     | 0.3925        | 22.0934           | 5528.89% | 12.5500           | 68.3700              | 249527.62            | 6.7785                 |

Table 1 Statistical description of data.
The flop of the conventional unit root is shown in the possibility of the fractional differencing parameter \( d \) to take values other than 0 and 1. Such values have implications for how soon or far the effect of shocks disappears. For instance, if \( d > 0 \), it implies that the series in question exhibits long memory or long-range dependency behaviour because it infers a strong degree of association or dependency among the observations in distant time. Interestingly, the fractional integration is so flexible that the general case of \( d > 0 \) can be further broken to infer distinct implications. If \( 0 < d < 0.5 \), the series under consideration is covariance stationary, implying that the long memory behaviour of the series is still within the stationarity zone. If \( 0.5 < d < 1 \), the series is said to be non-stationary mean reverting. Nevertheless, the series is said to exhibit mean reversion if \( 0 < d < 1 \), meaning that the effect of shocks is transitory, although it will last longer for the case of \( 0.5 < d < 1 \) than the case of \( 0 < d < 0.5 \). If \( d = 0 \), perfect stationarity is the case, as the impact of shocks will disappear naturally within a very short while, time if \( d \geq 1 \), there is persistence, indicating that the effect of shocks will be permanent except for the implementation of strong policies to recover initial average trend.

Having described the fractional integration model, we follow two main approaches in estimating \( d \). These are the semiparametric and parametric approaches. The Gaussian semi-parametric approach follows that of Robinson (1995) which is based on the Local Whittle function in the frequency domain. It basically uses a band of frequencies that degenerates to zero. This is specified as:

\[
\hat{d} = \text{arg min}_d \left( \log C(d)/n - 2 \sum_{j=1}^{k} \frac{1}{j} \log \lambda_j \right),
\]

(4)

for \( d \in (-1/2, 1/2); C(d) = \sum_{j=1}^{k} I(\lambda_j) \lambda_j^d, \lambda_j = 2 \pi j / n, 1 + k^{-1/2} \),

where the bandwidth parameter is denoted by \( k \), while the periodogram of the series under consideration is given as \( I(\lambda_j) \). Additionally, if we assume that the fourth moment is finite and other mild conditions are fulfilled, Robinson (1995) shows that \( \sqrt{n(\hat{d} - d_0)} \rightarrow N(0, 1) \) as \( n \rightarrow \infty \), where \( d_0 \) is the real value of \( d \) under the additional requirement that \( k \rightarrow \infty \) slower than \( T \).

For the parametric analysis, it is based on the dual approaches of Dahlhaus (1989) and Robinson (1994) which employ the Whittle function in the frequency domain and the Lagrange Multiplier test, respectively. A major advantage of this technique is that it produces consistent and reliable estimate of \( d \) even when the series is non-stationary. Therefore, for any real value of \( d_0 \) in equation (1), we test the null hypothesis of \( H_0 : d = d_0 \) consistent with Robinson (1994). Therefore, the residual of the regression model is captured by \( \bar{y}_t \) as shown below:

\[
y_t - \Delta^{d} \bar{y}_t + x_t, \quad t = 1, 2, \ldots \tag{5}
\]

where \( y_t \) retains the definition in equation (1), and \( z_t \) is a vector of deterministic terms of order \( k > 1 \). Conventionally, equation (5) can take any functional forms: model without any deterministic terms, model with only intercept, and model with both intercept and linear trend.

Lastly, we account for structural breaks in the fractional integration analysis. This is because the presence of structural shifts in the series can lead to bias results if not put into consideration. Studies, such as Ben Nasr et al. (2014) and Ashley and Patterson (2010) show that the presence of structural breaks can literally induce fractional integration or long memory when they do not exist in actual fact.

3. Data and discussion of results

3.1. Data source and description

Due to the consideration of the COVID-19 pandemic period in the analysis, we employ daily datasets of notable fear gauges of commodity (OVX, GVZ, SLV and XLE), Eurocurrency (EVZ) and equity (VIX and EMV-ID) markets in order to obtain fairly large data observations. Except for EMV-ID which was computed by Baker et al. (2020), other indices were constructed by the Chicago Board Options Exchange (CBOE). Howbeit, they are all sourced from the economic database of the Federal Reserve Bank of St. Louis (see https://www.fred.stlouisfed.org). To cover our aim which is to examine the impact of the current pandemic on the performance (persistence and causality) of the markets fear gauges, the full sample is partitioned into the periods before and during the COVID-19 pandemic. Thus, the period before the pandemic spans between March 16, 2011 and December 30, 2019, while the period for the COVID-19 pandemic spans from December 31, 2019 to July 10, 2020.

We first justify the need to examine the impact of the COVID-19 pandemic on the fear level in these markets through their trends as offered in the graphical plots in Fig. 1. Without any disputation, the year 2020, which was associated with the pandemic, demonstrates a high level of fear or uncertainty across most of the markets compared to the previous years. As observed, all the fear indices exhibit high upward spike in many days of 2020, although GVZ and EVZ seem to have similar occasional trend in the past too. Except for these two indices, the low volatility observed in others in the previous years appears to be suddenly overturned during the pandemic. In addition, we give a summary of the relevant descriptive statistics of the series in Table 1 where we compare the two sub-samples under consideration. It is observed that the average fear index is exceedingly greater during the pandemic than before it, except for EVZ whose values are 9.2729 and 7.9612 for the periods before and during the pandemic respectively. Amazingly, average fear index during the pandemic is more than twice the period before it in virtually other markets. It is particularly worse for the EMV-ID whose value during this period is 22.0934 compared to the 0.3925 for the period before the pandemic, indicating about 5528.89% increase. Although amazing, it is justified since the EMV-ID index directly tracks the equity market volatility that is due to infectious diseases. Other markets with exceedingly high percentage change in their mean values include the crude oil (153.49%) and aggregate energy (126.85%) markets. All the indices except EVZ are also seen to record higher maximum values during this period. Finally, the Jarque-Bera test rejects the null hypothesis of normal distribution for all the indices regardless of the sample period.

We complete the description of the data by examining their stationarity features using both the conventional Augmented Dickey-Fuller (ADF) test and its structural breaks version (ADF-SB). The power function of the former test is weak in rejecting the unit root null hypothesis in the presence of structural breaks. For the pre-COVID period, all the series are confirmed to be stationary by both tests (see Table 2). However, the ADF test fails to reject the unit root null hypothesis for all the indices during the COVID period, until their first differences are taken. We

\footnote{Although most of the indices were computed for earlier periods, fear indices of silver and energy sector started by 16/03/2011. For the sake of comparison therefore, the datasets for the pre-COVID-19 period are re-sample to have equal start dates. On the other hand, 12/31/2019 is regarded as the beginning of the pandemic because that was the day the first crisis was reported in the originating country, China.}
suspect that this is due to the occurrence of structural shifts along the paths of the series, as induced by the pandemic. Accordingly, we apply the ADF-SB test which then shows that OVX, SLV, VIX and EMV-ID are stationary at level. In short, the results of the unit root test also indicates that the current pandemic has affected the stationarity behaviour of the fear indices, thus likely impacting their persistence.

### 3.2. Fractional integration results

We now proceed to the main empirical results, starting with the results of the Gaussian semiparametric technique\(^3\) which imposes no functional form on the residuals (see Adekoya, 2020a). It is observed from Table 3 which presents the results for the period before COVID-19 pandemic that with the exception of VIX and EMV-ID, the fractional differencing parameter \(d\) is close to being 1 in most cases. This implies the non-rejection of the null hypothesis of \(d=1\) so that the fear indices are said to be persistent. For the exceptional indices, the results appear mixed for VIX although a higher number of the periodogram lengths (\(k = T^{0.6}, k = T^{0.7}\) and \(k = T^{0.8}\)) support mean reversion since \(d\) is less than 1. However, mean reversion in the range of covariance stationarity is established for EMV-ID, as the unit root hypothesis is rejected in support of \(0<d<0.5\) throughout. Turning to the results for the COVID-19 pandemic period (see Table 4), we see that the \(d\) estimates are greater than those reported in Table 3, suggesting higher degree of persistence during this period. In fact, the unit root hypothesis is rejected in favour of \(d>1\) in many cases, especially at the lower periodogram lengths (i.e. \(k = T^{0.4}, k = T^{0.5}\) and \(k = T^{0.6}\)). EMV-ID still shows mean reversion in most cases, but now at the nonstationary region.

One fact is known for uncertainty or fear in the international markets. It is often sponsored by activities or events that directly or indirectly influence trading activities. This accounts for the reason why the fear indices are said to be persistent. For the exceptional indices, the results appear mixed for VIX although a higher number of the periodogram lengths (\(k = T^{0.6}, k = T^{0.7}\) and \(k = T^{0.8}\)) support mean reversion since \(d\) is less than 1. However, mean reversion in the range of covariance stationarity is established for EMV-ID, as the unit root hypothesis is rejected in support of \(0<d<0.5\) throughout. Turning to the results for the COVID-19 pandemic period (see Table 4), we see that the \(d\) estimates are greater than those reported in Table 3, suggesting higher degree of persistence during this period. In fact, the unit root hypothesis is rejected in favour of \(d>1\) in many cases, especially at the lower periodogram lengths (i.e. \(k = T^{0.4}, k = T^{0.5}\) and \(k = T^{0.6}\)). EMV-ID still shows mean reversion in most cases, but now at the nonstationary region.

Contrary to major assumptions around the distribution of the disturbance term that it has a zero mean, they further show that only when a non-zero mean is assumed can the semiparametric estimator perform better. Based on these revelations, the semiparametric results may suffer from unreliability since market noise is usually not persistent, as it fizzes out often quickly. Furthermore, the semiparametric method performs poorly in short samples, just as for the COVID-19 pandemic period.

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\(^3\) Other semiparametric test (log-periodogram regression method) of Geweke and Porter-Hudak (1983) essentially produces similar results.

### Table 2

| Fear gauge | Pre-COVID | COVID |
|------------|-----------|-------|
|            | ADF | ADF-SB | t-stat. | t-stat. | Break dates | ADF | ADF-SB | t-stat. | t-stat. | Break dates |
| OVX        | -3.7422*** | -6.3388**** | 9/26/2014 | -11.1361b**** | May 3, 2020 |
| GVZ        | -5.9051b**** | -6.6235*** | 3/28/2013 | -11.2114b**** | 3/13/2020 |
| SLV        | -5.9733b**** | -7.1110*** | 3/28/2013 | -10.1162b**** | November 3, 2020 |
| XLE        | -5.2080*** | -6.6533*** | 8/29/2014 | -10.986b**** | September 3, 2020 |
| EVZ        | -3.9183*** | -7.2054*** | 8/22/2014 | -12.272b**** | September 3, 2020 |
| VIX        | -7.2058*** | -8.6965*** | 11/25/2011 | -13.7438b**** | 2/21/2020 |
| EMV-ID     | -12.5086**** | -14.5380b**** | 10/22/2014 | -9.9642b**** | June 3, 2020 |

*** and ** indicate significance at 1% and 5% critical levels respectively. a and b denote stationarity at level and first difference respectively.
that we are considering. Due to these limitations, we re-estimate the fractional differencing parameter $d$ using the parametric approach of Robinson (1994).

The parametric method allows for three model specifications: no deterministic terms, intercept, and intercept and linear time trend. The best model specification is determined by the significance of the linear time trend and the intercept. As obviously seen in Table 4, the model without any deterministic terms proves to be the best in all cases. During the period before COVID-19, all market fears are mean reverting with the highest $d$ value recorded for OVX (0.9190) and the lowest for EMV-ID (0.2328). The mean reversion is however faster for EMV-ID as it falls within the stationarity range. For the COVID-19 pandemic period, the $d$ estimates for all the four indices, except EMV-ID, are around the unit root boundary (i.e. $d=1$) which is consequently associated with persistence. EMV-ID is still mean reverting, but in the non-stationary region rather than being covariance stationary as observed before the pandemic. Hence, the effect of shocks will last longer during this period than before even though it will still disappear.

### 3.3. The role of structural breaks

Because of the sensitivity of financial and commodity markets to external events such as health and financial crises, fears in these markets are likely to exhibit structural shifts. The graphical illustrations in Fig. 1 reveal notable spikes in the trends of the indices, thereby suggesting possible breaks. We prove this by a more formal test, Augmented Dickey-Fuller unit root test with structural breaks (ADF-SB), and one break date each is identified for all the indices both before and during COVID-19 pandemic. Not accounting for these breaks if they exist can produce spurious results in the analysis of persistence degree of time series (see Adekoya, 2020b; Yaya et al., 2020). In line with these studies, we first employ the Bai-Perron structural breaks test (see Bai and Perron, 2003) to detect inherent break dates. The Bai-Perron test is preferred above the ADF-SB test in that it is able to detect a maximum of five break dates, unlike the latter that is limited to one.

Table 5 presents the break dates. A minimum of two break dates are identified for each series in both periods. In general, the period before the pandemic witnesses higher number of break dates in virtually all the indices and this could be because of its larger sample size. These break dates are thus accounted for in the fractional integration estimation and the results are reported in Tables 6 and 7. We notice that at least one break date is significant for each of the indices in both periods, except for SLV (during the period before the pandemic), and XLE and VIX (during the pandemic period) where none of their break dates are found to be significant. Although there is a decrease in the value of the $d$ estimates in all cases, the impact of structural breaks seems to be more effective during the pandemic period. The mean reversion bounds of the indices are not changed during the pre-COVID period despite the slight reduction in the $d$ estimates. However, for the four fear indices namely OVX, SLV, VIX and EMV-ID, there are significant alterations. OVX, SLV and VIX now exhibit non-stationary mean reverting behaviour contrary to their pure non-stationary behaviour when structural breaks are not accounted for, while EMV-ID becomes covariance stationary. Interestingly, these four fear indices, except SLV, have the highest average percentage change as reported in Table 1. It is thus obvious that the COVID-19 pandemic period is associated with notable changes in market fears.

| Fear gauge | Pre-COVID | COVID period |
|------------|-----------|-------------|
|            | No deterministic terms | With intercept | With linear time trend | No deterministic terms | With intercept | With linear time trend |
| OVX        | 0.9190 (0.0174) | 0.9197 (0.0175) | 0.9197 (0.0175) | 0.9671 (0.0629) | 0.9783 (0.0708) | 0.9769 (0.0713) |
| GVZ        | 0.8570 (0.0177) | 0.8574 (0.0178) | 0.8570 (0.0178) | 1.0142 (0.0611) | 1.0286 (0.0682) | 1.0277 (0.0685) |
| SLV        | 0.8913 (0.0176) | 0.8892 (0.0182) | 0.8880 (0.0184) | 1.0520 (0.0668) | 1.0872 (0.0769) | 1.0862 (0.0775) |
| XLE        | 0.9186 (0.0182) | 0.9220 (0.0184) | 0.9220 (0.0184) | 1.0728 (0.0535) | 1.0983 (0.0650) | 1.0909 (0.0662) |
| EVZ        | 0.8606 (0.0170) | 0.8592 (0.0172) | 0.8575 (0.0173) | 1.0014 (0.0618) | 1.0040 (0.0683) | 0.9870 (0.0650) |
| VIX        | 0.8680 (0.0184) | 0.8716 (0.0187) | 0.8717 (0.0187) | 0.9754 (0.0564) | 0.9661 (0.0604) | 0.9574 (0.0617) |
| EMV-ID     | 0.2328 (0.0153) | 0.2328 (0.0153) | 0.2321 (0.0153) | 0.6340 (0.0628) | 0.6270 (0.0618) | 0.6144 (0.0632) |

The best model has its values in bold. Values in parentheses are standard errors.
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**Table 6**

| Fear gauge | D         | D1        | D2         | D3         | D4         |
|------------|-----------|-----------|------------|------------|------------|
| OVX        | 0.912     | -0.0458  | 0.1050**   | -0.1529*** | -0.0118    |
|            | (0.0177)  | [0.94]   | [2.14]     | [-3.14]    | [-0.24]    |
| GVZ        | 0.8504    | -0.0311  | -0.0877*   | 0.2043***  | -0.0440    |
|            | (0.0177)  | [0.60]   | [1.68]     | [3.93]     | [-0.85]    |
| SLV        | 0.8905    | -0.0062  | -0.0664    | -0.0531    | -          |
|            | (0.0177)  | [0.13]   | [1.47]     | [-1.14]    |            |
| XLE        | 0.9142    | -0.1002**| 0.0664     | -0.1227**  | 0.0546     |
|            | (0.0184)  | [-1.78]  | [1.18]     | [-2.18]    | [0.97]     |
| EVZ        | 0.8558    | -0.0525  | 0.0850**   | -0.2028*** | -          |
|            | (0.0172)  | [-1.10]  | [-1.78]    | [4.25]     |            |
| VIX        | 0.8576    | -0.0915  | 0.2428***  | -0.1260*   | 0.2518***  |
|            | (0.0187)  | [-1.22]  | [3.23]     | [1.68]     | [3.34]     |
| EMV-ID     | 0.2666    | 0.6565***| -0.6770*** | 0.2100     |            |
|            | (0.0133)  | [4.16]   | [-3.76]    | [1.10]     |            |

***, ***, and * represent significance at 1%, 5% and 10% critical levels respectively. Values in parentheses are standard errors while those in brackets are t-statistics.

**Table 7**

| Fear gauge | D         | D1        | D2         | D3         | D4         |
|------------|-----------|-----------|------------|------------|------------|
| OVX        | 0.9128    | 0.0532    | 0.5980***  | -0.2450*   | -0.0392    |
|            | (0.0673)  | [0.42]    | [4.71]     | [-1.94]    | [0.31]     |
| GVZ        | 0.9986    | 0.1643**  | -0.0355    | -          |            |
|            | (0.0638)  | [2.18]    | [-0.47]    |            |            |
| SLV        | 0.8927    | 0.4811*** | -0.0830    | -          |            |
|            | (0.0666)  | [5.54]    | [-1.06]    |            |            |
| XLE        | 1.0421    | -0.0077   | 0.2484***  | -0.0455    | -          |
|            | (0.0547)  | [-0.09]   | [2.74]     | [-0.51]    |            |
| EVZ        | 0.9800    | 0.1063    | -0.0905    | -          |            |
|            | (0.0640)  | [1.32]    | [-1.15]    |            |            |
| VIX        | 0.9412    | 0.1465    | -0.1482    | -          |            |
|            | (0.0611)  | [1.28]    | [-1.40]    |            |            |
| EMV-ID     | 0.3933    | 29.5224***| -15.5489***| -11.0643   |            |
|            | (0.0520)  | [4.35]    | [-2.08]    | [-1.48]    |            |

***, ***, and * represent significance at 1%, 5% and 10% critical levels respectively. Values in parentheses are standard errors while those in brackets are t-statistics.

The combined results of both indices are presented in Table 8 with the results of EMV-ID being in the upper panel. The table shows that the null hypothesis of no causality is strictly rejected for all the fear indices during the period before COVID-19. This is unlike the pandemic period where the null hypothesis is resoundingly rejected for OVX, SLV and XLE. This causal evidence is certainly not unexpected for this period as the pandemic has been proven to affect many equity markets. Emotional responses from other markets thus follow the fear triggered in equity markets (see Economou et al., 2018). Also, Giot (2005) reveals that investors are very sensitive to losses or gains. This implies that uncertainty in equity markets that affects investors’ returns adversely can trigger fear in investors in other markets. Meanwhile, GVZ and EVZ are not Granger-caused by EMV-ID. Not surprising, we recall that they have the least percentage change as reported in Table 1. In fact, EVZ which is the tracker for the fear in the Eurocurrency market, records negative change indicating that its average value is lower during the COVID-19 period. Eurocurrency market fear seems not to be induced by the pandemic. On the other hand, gold (whose market fear tracker is GVZ) belongs to a class of commodity assets that has enjoyed stability due to its high intrinsic worth, and this has even made it to be considered as a suitable hedge for certain economic risks including exchange rate and inflation risks (see Junttila et al., 2018; Rehman et al., 2018; Adekoya and Oliyide, 2021; Adekoya et al., 2021a,b). This stability accounts for the reason why it is just fairly affected by the current pandemic compared to others.

Turning to the causal effect of VIX, we see from the lower panel of Table 8 that GVZ and SLV are affected before the pandemic, but there is an improved performance during the health crisis. During the pandemic, the null hypothesis cannot be rejected only for XLE. We also believe this aligns with a priori expectation. Baker et al. (2020), among others, explain that COVID-19 has the greatest impact on global stock market performance. With this, VIX, which proxies the global stock market fear, has the tendency to drive fear in other markets.

### 4. Conclusion

Uncertainties in financial and commodity markets reflect the level of

| Causal variable: EMV-ID | Pre-COVID-19 | During COVID-19 |
|-------------------------|--------------|-----------------|
|                         | F-stat.    | Probability   | F-stat.    | Probability   |
| OVX                     | 0.7831      | 0.3763         | 9.3712***  | 0.0027        |
| GVZ                     | 0.0118      | 0.9134         | 1.8753     | 0.1732        |
| SLV                     | 0.0008      | 0.9778         | 6.3039**   | 0.0133        |
| XLE                     | 1.3368      | 0.2477         | 5.3689**   | 0.0221        |
| EVZ                     | 2.2423      | 0.1344         | 2.3319     | 0.1292        |
| Causal variable: VIX    |              |                |             |               |
| OVX                     | 1.9348      | 0.1644         | 10.1627*** | 0.0018        |
| GVZ                     | 5.8696**    | 0.0155         | 19.0455*** | 0.0003        |
| SLV                     | 2.7527*     | 0.0972         | 29.4613*** | 0.0000        |
| XLE                     | 0.5285      | 0.4673         | 1.5437     | 0.2163        |
| EVZ                     | 0.8212      | 0.3649         | 31.1946*** | 0.0000        |

***, ***, and * represent significance at 1%, 5% and 10% critical levels respectively.

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We do not examine causal effect between VIX and EMV-ID because they are both measures of equity market uncertainty. Apart from the fact that EMV-ID adds infectious diseases in its measurement, the notable difference between both series is that VIX is options based while EMV-ID is text counts-based.
trends. The second round of our results discloses that, to a large extent, market fear of gold, energy sector and Eurocurrency may be permanent markets, as well as equity market fear due to infectious diseases (EMV-the fear in the crude oil (OVX), silver (SLV) and global stock (VIX) EVZ reaching the unit root zone. Hence, although the effect of shocks on fractional integration parameter for all the series, with GVZ, XLE and GVZ, seven market fear indices before and during the COVID-19 pandemic. Two main approaches are considered. The first is the fractional integration technique which is important in determining the exact degree of persistence. The other is Granger-causality test for the examination of the possibility of infectious diseases-based equity market volatility (EMV-ID) and the global market fear index (VIX) in driving fear in other markets.

We discover from the empirical results, having accounted for the significant influence of structural breaks, that the entire market fear indices exhibit mean reverting behaviour before the COVID-19 pandemic period, indicating that the impact of shocks is only transitory. More specifically, the impact of the shocks will die out faster for EMV-ID whose d estimate depicts covariance stationarity. On the other hand, the COVID-19 pandemic period witnesses higher values for the fractional integration parameter for all the series, with GVZ, XLE and EVZ reaching the unit root zone. Hence, although the effect of shocks on the fear in the crude oil (OVX), silver (SLV) and global stock (VIX) markets, as well as equity market fear due to infectious diseases (EMV-ID) will still die out, such process will be slower compared to the period before the pandemic. On the other hand, the effect of shocks on the market fear of gold, energy sector and Eurocurrency may be permanent unless there are stronger measures to recover their initial average trends. The second round of our results discloses that, to a large extent, equity market fear due to infectious diseases (EMV-ID) and global market fear (VIX) are responsible for the fear in virtually all markets during the COVID-19 pandemic period. To show the impact of the pandemic more specifically, EMV-ID does not Granger-causes any of the indices during the pre-COVID-19 period, while VIX is only significant for GVZ and SLV.

Therefore, the attention of governments, policy makers, portfolio managers and potential investors should be drawn to the fact that global health crisis and, by generalization, other forms of globally felt crises, have the tendency of inducing higher persistence in market fear. This calls for the need to guard against the occurrence of future occurrence of crisis, or timely measures to contain its spread, such as in cases of health pandemics. Notwithstanding, policies or scientific discoveries that reduce the potency of the coronavirus will drastically reduce market fear. This implies that the currently shuttered global business arena would still be restored to normalcy following the mean reversion evidence in most of the markets. In addition, although high volatility and persistence revealed in this study can present considerable risks, shrewd investors can still generate solid short term returns when the markets are appropriately harnessed. Lastly, it is important for investors in other markets to monitor the movements in the equity market uncertainty that is induced by infectious diseases and the global market uncertainty following causal evidence.

Credit author statement

Oluwasegun B. Adekoya: Conceptualization, Data curation, Methodology, Analysis, Supervision. Johnson A. Oliyide: Writing-Original draft preparation, Reviewing, Editing, Validation.

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