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Abstract

This paper deals with the analysis of long-run relationships of fear indices for US stocks, commodities, and the energy sector with global fear indices for stocks and oil. Departing from the classical literature, fractional integration, and cointegration techniques are used to determine the degree of persistence in the long-run relationship of the indices. Our results are threefold. We first established a fractional cointegrating relationship between each of the global and oil fear indices and other fear indices. However, the long-run relationship tends to be weak for the technology stocks. In addition, the cointegrating framework reveals a nonstationary mean-reverting behaviour in the long-run relationship, implying that the effect of shocks from financial, economic, or other exogenous sources will be temporary though with long-lasting effects. These findings have crucial policy inferences for portfolio managers concerning investment decisions.

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JEL Classification: C22, G01; G15

1. Introduction

Economic integration through trade and investment flows has further improved the links among global equities (Lucey, 2017). This further led to improvement in the correlations among global equities, leading to discouraging diversification benefits by international investors trading on developed economies' stocks (Badshah, 2018). The 2007/2008 global financial crisis which originated from the US and the current Coronavirus (COVID-19) health crisis which originated from Wuham city, China, have weakened the global market dependencies, causing seemingly unrelated financial markets, and this gives chance for portfolio diversification among market participants. The 2007/08 financial crisis was caused by a credit crunch in the US and this is becoming an old tale of fading significance in global finance. Of greater importance is the current COVID-19 pandemic which spread fast to most countries throughout the world and killed several people within a short time of infection. It further led to the closure of industries in respective countries, thus causing another shock to stocks and other asset markets (Waheed et al., 2020; Sarwal et al., 2020). The COVID-19 health crisis has led to a dent in the stock market far beyond what the 2007/08 crisis had caused. During the 2007/08 crisis, the Chicago Board Options Exchange (CBOE) global volatility fear index (US VIX)[3] rose to 80.86 on 20/11/2008, while during the COVID-19 health crisis, it rose as high as 82.69 on 16/03/2020

[3] The US VIX is accepted as the global fear index. This is computed from the market performance of the S&P500 index. Meanwhile, another fear index (VXO) is based on S&P100, which is based on fewer US equities.

(see Table 1). So, financial marketers will henceforth refer to the COVID-19 pandemic as the global crisis that caused the strongest market uncertainty in the history of global stock markets.[4]

INSERT TABLE 1 ABOUT HERE

Considering the brief facts provided above, one of the most detrimental effects of such crises is the increased level of fear they create among market participants. This fear further triggers risks because it is often followed by emotional responses that cannot be adequately predicted (Economou et al., 2018). It is harmful to investment decisions (Chen and Chiang, 2020), as investors seem to have greater sensitivity to losses than gains (Giot, 2005). However, markets respond to shocks or fear differently. Several factors could be responsible for these different reactions. First, it depends on the source of the fear and the event that causes it in relation to the stocks being traded. For instance, Barros and Gil-Alana (2009) and Gul et al. (2010), respectively, find that recurring fear-provoking terrorist attacks had only a minimal effect on the financial markets of the Basque Country and Pakistan. Secondly, the level of market efficiency is also important. Johnston and Nedelescu (2006) note that efficient financial markets can completely absorb the market fear resulting from such terrorist events. The third case relates to the intrinsic worth, stability, and general acceptability of the assets. Gold seems to be one of such assets that fulfill these features, thus allowing it to enjoy hedging consideration against several market risks, including inflation and exchange rate risks (see Rehman et al., 2018; Junttila et al., 2018; Maghyereh et al., 2019; Adekoya et al., 2020). Lastly, it can also depend on the kind of stock portfolios traded on each stock market, as well as the level of capitalization. For instance, as detrimental as the COVID-19 pandemic was to the many

[4] The S&P500 index incorporates 500 top companies in the US stocks, chosen based on market capitalization. This index represents about 80% of the total value of the US stock market and represents quite well the movement in the US stock market, and has been used as a good proxy to judge the global stock market other than the US stock market. Two other US stock indices are the Dow Jones Industrial Average (DJIA) and the NASDAQ, which represent fewer US stocks compared to the S&P500 index. The DJIA is the oldest US stocks while NASDAQ is heavily technology weighted.

stock markets, the news report of CNN (2020) on May 12, 2020, reveals that some firms, including the technology giants, drug makers, and grocers have been able to push forward remarkably despite the stay-at-home orders. This is solely because the firm's products are largely based on orders and online transactions, leading to an almost zero slowdown in deliveries. Stocks of such firms are thus not expected to be significantly affected adversely by market uncertainty resulting from physical lockdowns.

The present paper dwells on the US stock markets, which trades commodities, technology, and energy stocks. The commodities are gold and silver, the technology stocks comprise of Amazon, Google, Apple, IBM, and Goldman Sachs. Others are S&P100 and Eurocurrency (US dollar/Euro) stocks. In Table 1, all the fear indices that existed during 2007/08 peaked in this crisis period, even the US technology stocks, silver, and energy sectors stocks that only existed after the 2007/08 financial crisis reported high fear indices before the COVID-19 health crisis, while the COVID-19 period saw markets registering even higher fear levels. These responses took place in March 2020 for most of the fear indices, while the oil fear index peaked on 21 April 2020. The two exceptions are the Eurocurrency and gold fear indices which reported a lower fear index compared to the former. In this light, it is worth examining the response of the specific commodity-based and US stock market-based fear to the global level fear. Further motivating this, the implied volatility indices have many merits and investment implications over the conventional historical volatility. Apart from being measures of market fear, the implied volatilities are forward-looking metrics that enable investors to calculate probability. In addition, they are useful in capturing investors' sentiments such that the connectedness of fear exhibited by market actors can be revealed (Maghyereh et al., 2016), and suitable metrics for risk management actions (Fassas and Siriopoulos, 2020) and market stress. With these intriguing features of fear gauges (implied volatilities), it would suffice that their relationship is examined as they have serious implications for investment decisions. In a comprehensive review offered in the next section, we note that this kind of analysis that relates global fear with a range of fear in specific markets is a very rare empirical practice in the literature. Rather, market fear has largely been related to stock or commodity (especially gold and oil) market returns.

Similarly, our methodological choice which helps to unravel the fractional cointegration between the series is novel and unique compared to those employed in past studies. Since fractional integration analysis is important for detecting the degree of persistence of the effects of shocks, policy implications from such findings are more valid and reliable than those offered in general studies. Note that fractional integration and cointegration techniques extend the classical literature based on unit roots and cointegration and that simply considers integer degrees of differentiation, 1 for the nonstationary series and 0 for the stationary ones. Allowing for fractional values, we allow for nonstationary mean-reverting series with shocks having long-lasting effects if the order of integration is in the range (0.5, 1). These time series econometrics techniques have come to complement unit roots and cointegration testing, as they render more meaningful policy explanations

The next section of the paper, Section 2 contains a literature review; Section 3 presents the method, while Section 4 describes the data. Section 5 is devoted to the empirical results and Section 6 concludes the paper.

2. Review of Literature

The most dangerous impact of market fear seems to be the creation of uncertainty spikes, thus rendering unpredictable the future trend of a particular financial market. As rightly noted by Chen and Chiang (2020), investment decisions are significantly harmed by uncertainty. This is unconnected from the fact that uncertainty results in bleak prospects of high future returns from the traded assets, especially stocks (Bloom, 2014; Christou et al., 2017; Chiang, 2019). Relying on this tendency, and following from the increasing integration of global financial markets, empirical attention has been drawn to the impact of market fear on both the commodity and stock markets. This is particularly worse when the fear is generated by either the financial markets of the developed countries with highly developed markets, such as the United States (see Bouri et al., 2017), or from highly traded commodities. Sarwar (2012) links the stock markets of the BRICS (Brazil, Russia, India, China, and South Africa) countries with the stock market fear of the US, measured through the US VIX. They establish that between 1993 and 2007, the US VIX accurately gauges the fear of the stock markets of Brazil, India, and China. This evidence seems to be corroborated by the subsequent work of Mensi et al. (2014). In particular, Mensi et al. (2014) disclose that the BRICS stock market returns respond adversely to US stock market uncertainty (measured by the VIX) during the bearish periods using a quantile regression technique. This is besides the fact that the stock markets of the countries co-move with the commonest global indicators, i.e. oil, gold, and S&P index. Badshah (2018) examines cross-market dependencies among VIX, the developed and emerging markets indices and their preliminary results show that VIX is a global driver of the listed stock markets. They further reveal that correlations of VIX to developed-market and emerging-market indices increase in turbulent periods. Considering the volatility connectedness across the U.S. and European implied volatility indices, Andrada-Felix et al. (2021) show that the connectedness changes over time, with a significant rise during the times of rising economic and financial tension.

Bouri et al. (2018) later mirror Mensi et al. (2014), but briefly depart in terms of methodology. They are able to show from their Bayesian Graphical Structural Vector Autoregressive (BGSVAR) model that accommodates contemporaneous and lagged causality effects that the global and within-the-group implied volatilities of the stock market are responsible for the implied volatilities of each BRICS country. In addition, they disclose only small effects of commodity market volatility for the countries, with the exception of South

Africa. The study of Sarwar and Khan (2016) rather focuses on Latin America, while incorporating some interesting innovations, such as the behavior of the nexus between the series considered before, during, and after the financial turmoil of 2008. Their Granger-causality test and GARCH-based model were used to assess the behavioural response of the stock markets of Latin America and the larger equity of the emerging markets to uncertainty in the US stock market (as captured by the VIX). They observe from their empirical analysis that the intensification of the US stock market uncertainty depresses the stock returns of the emerging markets, but increases their variance.

In a recent event-based study of Bash and Alsaifi (2019), they note that market fear resulting from uncertainty is responsible for the aggregate abnormal returns in all the firms considered, indicating an adverse impact of the uncertainty on stock returns. Rather than strictly focusing on stock markets, another interesting paper of Mensi et al. (2017) is based on the dependence structure of the volatility indices of commodity markets, which are oil, corn, and wheat, and they establish a time-varying asymmetric tail dependence. This is similar to the study of Bouri et al. (2017) that finds strong cointegration and an asymmetric relationship between oil, gold, and the Indian stock markets.

As is clearly seen above, the VIX has been the most prominent and commonly examined stock market volatility (or fear gauge) index in relation to the stock and commodity markets returns of most countries. This is probably because of the stock market size of the US and the significant role it plays. Observing this, therefore, a few other studies have started looking into other market volatility indices. For instance, Zhu et al. (2019) briefly broaden the scope of assessment by looking into some other similar fear indices such as the Equity Market Volatility (EMV) index which was developed based on the text counts of various newspapers articles. Comparing VIX and EMV, Zhu et al. (2019) show that a larger in-sample impact on the stock market volatility of the US is found for VIX, while those of EMV trackers are greater using the out-of-sample prediction. They additionally uncover the superior strength of the policy-based EMV tracker in predicting US stock market volatilities over the VIX and other EMV tracker measures. Chen et al. (2018) forecast the volatilities of the spot Brent and WTI oil returns using the information content of the CBOE crude oil Energy Trust fund (ETF) volatility index (OVX). Their findings provide evidence in favour of the oil price predictability of the implied volatility index. The broader study of Economou et al. (2018) considers the nonlinear cointegrating relationship between three fear indices, namely CBOE VIX, the Financial Times Stock Exchange (FTSE)and DAX volatility indices, and stock markets of the UK, the US, and Germany. While the US stock market asymmetrically induces the fear indicator generally, the asymmetric impact is specific to the life span and size of the adjustment process.

Thus far, we observe that the relationship between global market fear and other specific components of commodity-based and US stock market-based fear has not been substantially verified from the available empirical evidence. There are strong motivations to conduct such empirical analysis, following the turbulence caused by the current COVID-19 pandemic on various international markets. More importantly, is the fact that past studies have not studied the degree of fractional cointegration among market fears. Yet, findings from such analysis matter for strategic investment decisions. Thus, our contributions are robust to all these empirical omissions.

3. Statistical Methodology

As earlier stated in the paper, we use fractional integration and cointegration methods. Therefore, the main advantage is the higher flexibility it allows in the model specification by the use of fractional differentiation, compared with the standard unit root methods and cointegration techniques. In fact, it is well known that most unit root procedures have extremely low power if the true data generating process is fractionally integrated (see, e.g., Diebold and Rudebusch, 1991; Hassler and Wolters, 1994; Lee and Schmidt, 1996 among many others) and the same happens in the context of cointegration (Dittman, 2000; Smallwood and Norrbin, 2003; etc.).

Our strategy starts by estimating the fractional differencing parameter in each series. This is achieved first by using the semiparametric log-periodogram regression approach of Geweke and Porter-Hudak (GPH, 1983), with an updated estimator in Robinson (1995a), and the Local Whittle Semi-parametric estimator of Robinson (1995b).

The GPH approach uses the spectrum $f(\lambda)$ function expressed as,

$$f(\lambda)=\left|1-\exp(-i\lambda)\right|^{-2d} f^{*}(\lambda) \tag{1}$$

where Fourier frequencies are set as $\lambda_j = 2\pi j/N$ at low frequencies for $j=1,\ldots,m$, and j is the size of the periodogram, i.e. $j = N^k$ where T is the size of the time series and k is some fractional values i.e. $k \in (0,1)$. For an Autoregressive Moving Average (ARMA) process, $d=0$ and $f^{*}(\lambda)$ represents the Fourier function of the process, while $f(\lambda)$ is the Fourier function for the corresponding Autoregressive Fractionally Integrated Moving Average (ARFIMA) process of which its fractional integration parameter d is to be estimated and i is the order of the exponent. Thus, (1) is easily expressed as,

$$f(\lambda)=\left\{4\sin^{2}(\lambda/2)\right\} f_{0}(\lambda), \tag{2}$$

and by using the periodogram of the data,

$$I(\lambda)=\frac{1}{2\pi T}\left|\sum_{t=1}^{N} e^{it\lambda}\left(y_t-\bar{y}\right)^{2}\right| \tag{3}$$

in (2), the fractionally differenced parameter d is estimated as the slope of the log regression,

$$\log\left\{I(\lambda_j)\right\}=c-d\log\left\{4\sin^{2}(\lambda/2)\right\}+\varepsilon_i \tag{4}$$

where ε_i are the residuals from the model.

By using the periodogram in (3), the LW estimator represents an approximation to the MLE in the frequency domain, since for large *N,*

$$I(\lambda_j) \sim e^{f(\lambda_j)^{-1}} \tag{5}$$

with the likelihood function,

$$L\{I(\lambda_j),...,I(\lambda_m),\theta\} = \prod_{j=1}^{m} \frac{1}{f_\theta(\lambda_j)} e^{-I(\lambda_j)f(\lambda_j)^{-1}} \tag{6}$$

with $\theta = (C,d)$ becoming,

$$L(d,C) = \sum_{j=1}^{m} \left\{ \log C - 2d \log(\lambda_j) - \frac{I(\lambda_j)}{C\lambda_j^{-2d}} \right\} \tag{7}$$

in the neighborhood of the zero frequency. By differentiating (7) with respect to *C*, the local Whittle estimator is then given as,

$$\hat{d} = \arg\min \left(\log \left[m^{-1} \sum_{j=1}^{m} \left\{ \frac{I(\lambda_j)}{\lambda_j^{-2d}} \right\} \right] - 2dm^{-1} \sum_{j=1}^{m} \log(\lambda_j) \right) \tag{8}$$

Apart from these two semiparametric approaches, other parametric methods will be implemented. These include the Lagrange Multiplier (LM) test (Robinson, 1994), which has the advantage that it allows us to test any real value *d* including the values in the nonstationarity region (d ≥ 0.5). The estimation relies on three levels of deterministic terms: no intercept, intercept only, and an intercept with a time trend as in the Dickey-Fuller unit root test. Thus, with the confidence band computed in this case, one can test the null hypothesis,

$$H_o : d = d_o, \tag{9}$$

for any real value d_o. Based on the confidence interval, and with the upper bound of the confidence limit for the estimate being lower than 1, implying that the series is mean-reverting, thus the series has the tendency to revert to its mean level after a period of time. For d = 1, it implies the non-rejection of the unit root in the series. For $d \geq 1$, it implies that the series is non-mean reverting and that the effects of shocks to the series will persist forever.

3.1 Homogeneity of the fractional order of integration

In a multivariate set-up, the natural generalization of fractional integration is the concept of fractional cointegration. However, the first step for cointegration in a bivariate context is that the two parent series must display the same degree of integration. The homogeneity test presented here is based on Robinson and Yajima (2002). The testing procedure sets out the following null hypothesis:

$$H_0 : d_x = d_y \tag{10}$$

where d_x and d_y are fractional integration orders of the two time series to be cointegrated. The test statistic is then given as

$$\hat{T}_{xy} = \frac{m^{1/2}\left(\hat{d}_x - \hat{d}_y\right)}{\left\{\frac{1}{2}\left[1 - \hat{G}_{xy}^2 \Big/ \left(\hat{G}_{xx}\hat{G}_{xy}\right)\right]\right\}^{1/2} + h(T)}, \tag{11}$$

where $h(T) > 0$ and $\hat{G}_{xy}$ is the (xy)th element of $\hat{\Lambda}\left(\lambda_j\right)^{-1} I\left(\lambda_j\right)\hat{\Lambda}\left(\lambda_j\right)$ with $\hat{\Lambda}\left(\lambda_j\right) = diag\left\{e^{i\pi\hat{d}_x/2}\lambda^{-\hat{d}_x}, e^{i\pi\hat{d}_y/2}\lambda^{-\hat{d}_y}\right\}$ and $I\left(\lambda_j\right)$ is the periodogram with Fourier frequency $\lambda_j = 2\pi j/N$, and periodogram points, $j = 1,...,m < N/s$.

3.2 Hausman test of no cointegration versus fractional cointegration

Once the equality of fractional orders is established, we carried out an Hausman-type test of no cointegration in a fractional unit root framework, as given in Marinucci and Robinson (2001). The test relies on estimates $\hat{d}_*$ obtained based on the semiparametric approach of Robinson (1995b) which uses the information $\hat{d}_x = \hat{d}_y = d_*$, while $\hat{d}_*$ is a restricted estimate obtained in the bivariate context in the case of Robinson and Yajima (2002), under the assumption that $\hat{d}_x = \hat{d}_y$, that is,

$$\hat{d}_* = \frac{-\sum_{j=1}^{m} 1_2' \hat{\Omega}^{-1} Y_j v_j}{2 \times 1_2' \hat{\Omega}^{-1} 1_2 \sum_{j=1}^{m} v_j^2}, \tag{12}$$

with 1_2 indicating a (2×1) vector of 1s, $\hat{\Omega}$ is the variance-covariance matrix of $Y_j = (Y_{11}, Y_{2j})' = \left[\log I_{xx}(\lambda_j), \log I_{xx}(\lambda_j)\right]'$ and $v_j = \log j - \frac{1}{m}\sum_{j=1}^{m} \log j$. The statistic in (12) is normally distributed with mean d_* and variance $\frac{\left(1_2' \hat{\Omega}^{-1} 1_2\right)^{-1}}{4m}$.

4. Data

The datasets used in this paper are the daily closing indices of Chicago Board Options Exchange volatility for global stock and commodity market fear gauges as well as other US market equities, sourced from the St Louis Federal Reserve Bank database at https://fred.stlouisfed.org. The variables are described in Table 2 with the data ranging from 16/03/2011 to 06/05/2020. Our analysis cuts across 11 fear gauges for the US and global commodities, Eurocurrency, stocks, technology, and energy sector equities, in addition to the global fear index. As noted during the peak of the COVID-19 pandemic when businesses were shut down, many people were laid off from their jobs while others continue to work from home using technology. This technology is majorly of any of Amazon, Google, Apple, IBM, while energy demand had been shifted from industries to homes due to lockdown. Due to that, we also include oil and energy sector stocks with EuroCurrency stocks. Gold and silver are two important global commodities and these two are closed substitutes.

INSERT TABLE 2 ABOUT HERE

5. Empirical results

We start by computing the estimates of the fractional differencing parameter, *d*, for all the markets. For robustness, we employ both semiparametric and parametric approaches. For both the LW and GPH estimators under the semiparametric method, across the three periodogram points, we only find clear evidence in favour of mean reversion in the fear index for Amazon stocks. While, in other markets, the decision is inconclusive as both mean reversion and I(1) evidence exists (see Table 3). Based only on the GPH estimator, we found clear evidence of mean reversion in the fear indices of Global, Amazon, Apple, and Goldman Sachs stocks, while the LW estimator gave clear evidence of mean reversion for Oil and Amazon stock fear indices. The results, based on the Robinson (1994) approach are presented in Table 4. We found mean reversion in the majority of the cases, with the exception of oil, silver, and energy sector stocks. Mean reversion in the remaining indices such as global, gold, S&P100, EuroCurrency, technology, and energy stocks imply that stocks quickly revert back to their mean level if there are external shocks, and this will last for a short period.

INSERT TABLE 3 ABOUT HERE

INSERT TABLE 4 ABOUT HERE

Testing for the homogeneity condition, the results are reported across Table 5. If the bandwidth number is $T^{0.6}$, we find evidence of equal orders of integration in all except one case: Amazon versus Global; if $j = T^{0.7}$, the two cases displaying disparity in the degree of integration are Energy sector versus Global, and Silver versus Oil; and, if $j = T^{0.8}$, we observe more rejections of the null hypothesis of no homogeneity of the fractional order, d, especially when the homogeneity test is directed towards Oil. In particular, for the homogeneity of the fractional order of the fear indices with the oil fear index, the homogeneity null hypothesis is rejected for eight of the fear indices considered at the extreme bandwidth number, excluding Gold and Apple.

INSERT TABLE 5 ABOUT HERE

Tables 6 and 7 focus on the Hausman test for fractional cointegration of the fear indices with each of the global fear index and oil fear index, respectively. The results of testing the null hypothesis of no cointegration against the alternative of fractional cointegration using the procedure in Marinucci and Robinson (2001) are presented in the tables. The first two values in each cell of the result tables are the estimates of the test statistics given relative to each individual series forming the pair, while the lowest value (in parenthesis) is the bivariate estimate of the fractional parameter d obtained under the assumption of equal orders of integration.

INSERT TABLE 6 ABOUT HERE

INSERT TABLE 7 ABOUT HERE

Starting with the evidence against the global fear index (VIX) (Table 6), our first observation is that there is a presence of a long-run relationship among virtually all of the variables following the evidence of a fractional cointegration relationship in the majority of the cases. In fact, this evidence is supported by the three bandwidth numbers in the cases of Oil, Gold, S&P100; IBM, Goldman Sachs, and Energy Sector. For the rest of the cases, the evidence is supported in at least one of the bandwidth numbers proposed. Interestingly, we observe that the order of integration of the cointegrating relations is still large, being in all cases within the interval (0.5, 1). This implies a nonstationary mean-reverting pattern in the long-run equilibrium relationship. Thus, if any crisis occurs that induces global fear, shocks triggered by the index on other indices are temporal. The effect of the shocks tends to be temporary on the cointegrating relationship of the indices, although it only dies out rather slowly due to the nonstationary mean-reverting behaviour in the long-run equilibrium relationships. In other words, even in the absence of any government policy geared towards the recovering of initial trends, the effects of the shocks will still automatically die out, although not rapidly. On the other hand, similar results are revealed for the cointegration analysis of the Oil fear index with other indices (see Table 7). In what appears to be a strong mirroring of the results in Table 6, evidence of fractional cointegration for the three bandwidths proposed in the same series is also observed, except for the IBM index. To be clear, the only exception to the nonstationary mean reversion in the long-run equilibrium relationships of Oil fear index with other indices in Table 7 relates to the Energy Sector whose *d*-value is 0.467 for the $T^{0.6}$ bandwidth, thus potentially suggesting stationary mean reversion, though close to the nonstationary region. Notwithstanding, they all still indicate mean-reverting long-run behaviour.

In sum, the fact that Silver, EuroCurrency, and technology stocks (Amazon, Google, Apple, and IBM) do not cointegrate with Global and Oil fear indices in all the three periodogram points implies weak evidence of cointegration, while Oil, Gold, S$P100, Goldman Sachs and Energy Sector fear indices indicate strong evidence of cointegration since cointegration occurs at the three periodogram points. A few studies have also reached similar conclusions in terms of the relationship between fear indices. For example, Bouri et al. (2017) disclose that the stock market fear of the BRICS countries can be predicted by both global and within-the-group stock market fear. Tsai (2014) also establishes significant spillover of stock market fear among five developed countries. On the other hand, the recent news report of CNN (2020) on May 12 gives credence to our discovery of the weak long-run relationship between each of the global and oil fear indices and the technology stocks. The news report reveals that despite the stay-at-home orders, as well as financial depression caused by the COVID-19 to financial markets which further induces fear, technology giants among other firms have been able to push forward. It thus seems that technology stocks are often less affected by global and oil market fear.

6. Conclusions

The present paper investigates the level of fear of the US and global stocks and commodities over the years with respect to the global stock movement. The global stock fear index was estimated from the US S&P500 index by the CBOE, and the index has since been used to determine the global stock implied volatility movement. Similarly, in this paper, CBOE fear indices for Oil, Gold, Silver, S&P100, EuroCurrency, Amazon, Google, Apple, IBM, Goldman Sachs, and Energy Sector's stocks were used. Each fear index was used in a fractional cointegration framework with global stock and oil fear indices. The results obtained indicated: (i) mean reversion of fear indices in the nonstationarity region implying that the indices slowly revert to their mean levels once triggered by financial or any other exogenous crisis; (ii) evidence of cointegration of global stock and Oil with each of the other stocks or commodity fear indices; (iii) weak cointegration of global stock and Oil with technology stocks.

Practical policy inferences can be drawn from these findings. Investors in the U.S. stocks and commodities need to closely monitor the movement in the global stock and oil implied volatilities, as they are significant transmitters of fear. Even in the presence of shocks, the long-run relationship between the indices will still not be altered, except that the effect of the shocks (such as disrupting the co-movement) will be transitory. In addition to this, the weak correlation of the technology stock with the global stock indices suggests that the former can suitably hedge investors against the risks from the latter. In other words, in the presence of heightened risks associated with the global stock and crude oil markets, technology stocks can serve as a safe haven for investors.

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Table 1: Summary of Fear indices during the two global crisis periods

	2007/2008 financial crisis period		Covid-19 health crisis period	
Fear Gauge	**Index**	**Date of maximum value**	**Index**	**Date of maximum value**
Global	80.86	2008-11-20	82.69	2020-03-16
Oil	100.42	2008-12-11	325.15	2020-04-21
Gold	64.53	2008-10-10	48.98	2020-03-18
Silver	80.64	2011-09-28	100.66	2020-03-18
SP100	87.24	2008-11-20	93.85	2020-03-18
EuroCurrency	30.66	1998-08-26	19.31	1998-08-26
Amazon	66.06	2011-10-03	72.66	2020-03-16
Google	55.60	2011-10-03	78.07	2020-03-16
Apple	62.60	2011-10-04	101.69	2020-03-16
IBM	50.03	2018-12-26	96.65	2020-03-18
Goldman sachs	87.47	2011-10-03	123.83	2020-03-18
Energy Sector	57.47	2011-10-03	130.61	2020-03-18

* Compilation of CBOE fear gauges for Silver and Energy sector stocks and US Equities such as Amazon, Google, IBM, Apple, IBM, and Goldman Sachs commenced after the 2007/08 crisis, so in order not to leave the record blank, we reported their first crisis value.

Table 2: Variable Description and samples

Fear gauge	Ticker	Description
Global	VIX	The CBOE fear gauge index is computed on S&P 500 index. This stock index presents the overall stock performance in the US and the market gauge obtained is taken as a global fear gauge.
Oil	OVX	The CBOE fear index is computed using crude oil stock performance
Gold	GVZ	Gold stock market performance
Silver	VXSLV	Silver stock market performance
S&P100	VXO	Best 100 highly traded stocks in the Standards & Poor stock index
EuroCurrency	EVZ	Euro/U.S. dollar exchange rate with the CBOE ETF Volatility Index
Amazon	VXAZN	One of the five highly active equity stocks in the US which is a technology stock
Google	VXGOG	One of the five highly active equity stocks in the US which is a technology stock
Apple	VXAPL	One of the five highly active equity stocks in the US which is a technology stock
IBM	VXIBM	One of the five highly active equity stocks in the US which is a technology stock
Goldman Sachs	VXGS	One of the five highly active equity stocks in the US
Energy Sector	VXXLE	US energy sector stocks components

Table 3: Estimates of Fractional integration based on LW and GPH methods for three bandwidths

		LW estimator			GPH estimator		
Fear gauge	**Ticker**	**$j = N^{0.6}$**	**$j = N^{0.7}$**	**$j = N^{0.8}$**	**$j = N^{0.6}$**	**$j = N^{0.7}$**	**$j = N^{0.8}$**
Global	VIX	0.8346 (0.0486)	0.9203 (0.0329)	0.8884 (0.0223)	0.8682 (0.0673)	**0.9203 (0.0442)**	0.8966 (0.0295)
Oil	OVX	0.8243 (0.0486)	0.7741 (0.0329)	**0.9721 (0.0223)**	0.8239 (0.0673)	0.7150 (0.0442)	0.9154 (0.0295)
Gold	GVZ	**0.9483 (0.0486)**	**0.9399 (0.0329)**	0.8981 (0.0223)	**0.9810 (0.0673)**	**0.9575 (0.0442)**	0.8927 (0.0295)
Silver	VXSLV	**0.9718 (0.0486)**	0.8789 (0.0329)	0.8691 (0.0223)	**0.9323 (0.0673)**	0.8800 (0.0442)	0.8735 (0.0295)
S&P100	VXO	0.8077 (0.0486)	**0.9413 (0.0329)**	0.9108 (0.0223)	0.8027 (0.0673)	**0.9203 (0.0442)**	0.9146 (0.0295)
EuroCurrency	EVZ	**0.9302 (0.0486)**	0.9181 (0.0329)	0.9367 (0.0223)	**0.9901 (0.0673)**	**0.9422 (0.0442)**	**0.9489 (0.0295)**
Amazon	VXAZN	0.7452 (0.0486)	0.8662 (0.0329)	0.9074 (0.0223)	0.8955 (0.0673)	0.8638 (0.0442)	0.8555 (0.0295)
Google	VXGOG	0.7433 (0.0486)	**0.9358 (0.0329)**	0.9227 (0.0223)	0.8242 (0.0673)	**0.9251 (0.0442)**	0.9061 (0.0295)
Apple	VXAPL	0.8155 (0.0486)	0.8804 (0.0329)	0.8801 (0.0223)	0.8813 (0.0673)	**0.9356 (0.0442)**	0.8980 (0.0295)
IBM	VXIBM	0.7686 (0.0486)	**0.9549 (0.0329)**	0.9219 (0.0223)	0.8978 (0.0673)	**0.9570 (0.0442)**	0.9058 (0.0295)
Goldman sachs	VXGS	0.8264 (0.0486)	0.9022 (0.0329)	0.9267 (0.0223)	0.8364 (0.0673)	0.9120 (0.0442)	**0.9526 (0.0295)**
Energy Sector	VXXLE	0.8887 (0.0486)	**0.9931 (0.0329)**	**0.9843 (0.0223)**	0.8846 (0.0673)	**0.9553 (0.0442)**	**0.9548 (0.0295)**

Note, N = 2386, the total number of observations. The number of periodogram points N^k correspond to 106, 231 and 503.Standard errors of fractional integration parameter, d are in parenthesis. Evidences of I(1) hypothesisare in bold.

Table 4: Estimates of Fractional integration based on Robinson (1994) approach

	No regressors	An intercept	A linear time trend
Global	0.85 (0.82, 0.88)	**0.86 (0.83, 0.89)**	0.86 (0.83, 0.89)
Oil	0.97 (0.94, 1.00)	**0.99 (0.96, 1.02)**	0.99 (0.96, 1.02)
Gold	0.92 (0.88, 0.95)	**0.92 (0.88, 0.96)**	0.92 (0.88, 0.96)
Silver	1.01 (0.97, 1.05)	**1.02 (0.98, 1.06)**	1.02 (0.98, 1.06)
SP100	0.80 (0.78, 0.83)	**0.80 (0.78, 0.83)**	0.80 (0.78, 0.83)
EuroCurrency	0.91 (0.88, 0.91)	**0.91 (0.88, 0.95)**	0.91 (0.88, 0.95)
Amazon	0.91 (0.88, 0.95)	**0.90 (0.87, 0.94)**	0.90 (0.87, 0.94)
Google	0.87 (0.84, 0.90)	**0.87 (0.84, 0.90)**	0.87 (0.84, 0.90)
Apple	0.86 (0.83, 0.90)	**0.87 (0.84, 0.91)**	0.87 (0.84, 0.91)
IBM	0.84 (0.81, 0.87)	**0.84 (0.80, 0.87)**	0.84 (0.80, 0.87)
Goldman sachs	0.88 (0.85, 0.91)	**0.88 (0.85, 0.91)**	0.88 (0.85, 0.91)
Energy Sector	0.96 (0.93, 0.99)	**0.98 (0.95, 1.01)**	0.98 (0.95, 1.01)

In bold, results of the selected deterministic term based on the significance of the constant and intercept in the Robins (1994) fractional integration framework.

Table 5: Test of Homogeneity of fractional integration orders

Global (VIX)				
Fear gauge	**Ticker**	**Test statistic**		
		j = N$^{0.6}$	**j = N$^{0.7}$**	**j = N$^{0.8}$**
Oil	OVX	1.2428	0.2563	**3.6166**
Gold	GVZ	0.1395	0.6136	**2.2174**
Silver	VXSLV	0.9376	1.7473	0.8827
S&P100	VXO	0.4578	0.6071	0.4125
EuroCurrency	EVZ	0.0622	0.1718	1.2431
Amazon	VXAZN	**2.1599**	0.7472	0.4963
Google	VXGOG	1.6824	0.2093	0.4962
Apple	VXAPL	1.6582	1.4436	1.9320
IBM	VXIBM	0.5406	0.2927	1.6698
Goldman Sachs	VXGS	0.8549	0.5291	0.1026
Energy Sector	VXXLE	0.3337	**2.2006**	**2.8905**
Oil (OVX)				
Fear gauge	**Ticker**	**Test statistic**		
		j = N$^{0.6}$	**j = N$^{0.7}$**	**j = N$^{0.8}$**
Gold	GVZ	1.3435	0.8347	1.5122
Silver	VXSLV	0.2905	**1.9615**	**2.7363**
S&P100	VXO	1.4605	0.0457	**3.8307**
EuroCurrency	EVZ	1.1758	0.4109	**2.3727**
Amazon	VXAZN	0.9057	0.9353	**3.0940**
Google	VXGOG	0.3277	0.0658	**3.1283**
Apple	VXAPL	0.2505	1.4958	1.9376
IBM	VXIBM	1.6500	0.4905	**2.1118**
Goldman Sachs	VXGS	0.6616	0.1220	**3.7046**
Energy Sector	VXXLE	1.6071	1.2699	**5.8212**

Note, significant test statistics are in bold. Critical value for the three periodogram points is 1.9600.

Table 6: Hausman test of no cointegration versus fractional cointegration: Global (VIX)

Global (VIX)			
	$j = N^{0.6}$	**$j = N^{0.7}$**	**$j = N^{0.8}$**
Oil	**H_{1o}: 12.211 H_{2o}: 14.331 (0.703)**	**H_{1o}: 26.611 H_{2o}: 134.711 (0.657)**	**H_{1o}: 247.984 H_{2o}: 100.651 (0.722)**
Gold	**H_{1o}: 34.945 H_{2o}: 7.334 (0.737)**	**H_{1o}: 48.798 H_{2o}: 37.525 (0.775)**	**H_{1o}: 21.486 H_{2o}: 16.003 (0.817)**
Silver	H_{1o}: 37.041 H_{2o}: 3.037 (0.761)	**H_{1o}: 10.119 H_{2o}: 28.414 (0.796)**	**H_{1o}: 0.487 H_{2o}: 0.326 (0.871)**
S&P100	**H_{1o}: 63.200 H_{2o}: 77.854 (0.527)**	**H_{1o}: 306.19 H_{2o}: 276.773 (0.533)**	**H_{1o}: 707.862 H_{2o}: 610.162 (0.491)**
EuroCurrency	H_{1o}: 13.893 H_{2o}: 0.664 (0.802)	**H_{1o}: 7.334 H_{2o}: 9.847 (0.847)**	H_{1o}: 6.451 H_{2o}: 0.431 (0.890)
Amazon	**H_{1o}: 12.621 H_{2o}: 38.112 (0.618)**	H_{1o}: 0.046 H_{2o}: 7.807 (0.855)	H_{1o}: 0.174 H_{2o}: 2.196 (0.884)
Google	**H_{1o}: 24.219 H_{2o}: 56.884 (0.571)**	**H_{1o}: 33.679 H_{2o}: 28.875 (0.795)**	H_{1o}: 4.145 H_{2o}: 0.259 (0.888)
Apple	**H_{1o}: 16.149 H_{2o}: 21.169 (0.672)**	**H_{1o}: 22.360 H_{2o}: 41.558 (0.770)**	H_{1o}: 1.455 H_{2o}: 1.455 (0.861)
IBM	**H_{1o}: 49.622 H_{2o}: 82.547 (0.518)**	**H_{1o}: 48.498 H_{2o}: 32.199 (0.788)**	**H_{1o}: 105.815 H_{2o}: 60.012 (0.758)**
Goldman Sachs	**H_{1o}: 28.089 H_{2o}: 31.260 (0.638)**	**H_{1o}: 112.744 H_{2o}: 131.742 (0.653)**	**H_{1o}: 249.988 H_{2o}: 176.122 (0.671)**
Energy Sector	**H_{1o}: 28.089 H_{2o}: 14.775 (0.698)**	**H_{1o}: 138.740 H_{2o}: 76.906 (0.716)**	**H_{1o}: 278.889 H_{2o}: 107.126 (0.717)**

Note, in bold signifies the rejection of the null of no cointegration.

Table 7: Hausman test of no cointegration versus fractional cointegration: Oil (OVX)

Oil (OVX)			
	$j = N^{0.6}$	**$j = N^{0.7}$**	**$j = N^{0.8}$**
Global	**H_{1o}: 13.677** **H_{2o}: 11.608** **(0.703)**	**H_{1o}: 43.827** **H_{2o}: 170.781** **(0.616)**	**H_{1o}: 452.491** **H_{2o}: 242.022** **(0.635)**
Gold	**H_{1o}: 44.859** **H_{2o}: 10.260** **(0.710)**	**H_{1o}: 102.055** **H_{2o}: 7.807** **(0.705)**	**H_{1o}: 224.566** **H_{2o}: 402.619** **(0.654)**
Silver	H_{1o}: 35.985 H_{2o}: 2.659 (0.764)	**H_{1o}: 54.671** **H_{2o}: 9.580** **(0.698)**	**H_{1o}: 147.091** **H_{2o}: 365.303** **(0.669)**
S&P100	**H_{1o}: 6.418** **H_{2o}: 9.708** **(0.713)**	**H_{1o}: 184.343** **H_{2o}: 39.392** **(0.624)**	**H_{1o}: 309.371** **H_{2o}: 457.911** **(0.633)**
EuroCurrency	H_{1o}: 21.2981 H_{2o}: 2.205 (0.769)	H_{1o}: 52.157 H_{2o}: 1.448 (0.742)	**H_{1o}: 213.292** **H_{2o}: 293.932** **(0.700)**
Amazon	H_{1o}: 0.102 H_{2o}: 4.037 (0.751)	**H_{1o}: 41.580** **H_{2o}: 6.652** **(0.710)**	**H_{1o}: 154.893** **H_{2o}: 285.288** **(0.704)**
Google	H_{1o}: 0.013 H_{2o}: 4.898 (0.744)	**H_{1o}: 88.632** **H_{2o}: 6.432** **(0.711)**	**H_{1o}: 224.566** **H_{2o}: 32.980** **(0.684)**
Apple	H_{1o}: 0.980 H_{2o}: 1.641 (0.776)	**H_{1o}: 62.565** **H_{2o}: 10.119** **(0.696)**	**H_{1o}: 147.091** **H_{2o}: 318.370** **(0.689)**
IBM	H_{1o}: 2.205 H_{2o}: 10.448 (0.709)	**H_{1o}: 186.877** **H_{2o}: 35.193** **(0.632)**	**H_{1o}: 320.640** **H_{2o}: 444.423** **(0.638)**
Goldman Sachs	**H_{1o}: 11.214** **H_{2o}: 11.214** **(0.705)**	**H_{1o}: 126.854** **H_{2o}: 32.199** **(0.638)**	**H_{1o}: 318.370** **H_{2o}: 441.750** **(0.639)**
Energy Sector	**H_{1o}: 144.642** **H_{2o}: 105.668** **(0.467)**	**H_{1o}: 415.201** **H_{2o}: 119.225** **(0.516)**	**H_{1o}: 677.779** **H_{2o}: 645.120** **(0.570)**

Note, in bold signifies the rejection of the null of no cointegration.