PERSISTENCE AND LONG RUN CO-MOVEMENTS BETWEEN GENDER EQUALITY AND GLOBAL PRICES

Juan Infante, University Villanueva, Madrid, Spain
juan.infante@villanueva.edu

Marta del Río, University Villanueva, Madrid, Spain
marta.delrio@villanueva.edu

and

Luis A. Gil-Alana, University of Navarra, Pamplona, Spain
alana@unav.es

ABSTRACT

This paper looks into the continuous trends, steadiness and associations of gender equality and global indices. We examine the level of integration of each group of information from a fractional standpoint for the years 2014-2021. The findings demonstrate that all the individual series are remarkably consistent, with levels of integration close to 1 and no evidence of mean reverting behaviour. Looking at potential cointegrating relationships among the two variables, if we use a classical method based on the two steps approach of Engle and Granger (1987) the order of integration of the estimated errors is very close to 1 showing no evidence of cointegration at all. However, using the more powerful fractional CVAR (FCVAR) approach, the results strongly support the hypothesis of cointegration, finding evidence of long run co-movements between the two series. Investment strategies and policy implications of these results are reported at the end of the manuscript.

Keywords: Stock market prices; fractional integration; co-movements; main reversion; long memory.

JEL Classification: C22; G12; G15.

Luis A. Gil-Alana gratefully acknowledges financial support from the MINEIC-AEI-FEDER ECO2017-85503-R project from 'Ministerio de Economía, Industria y Competitividad' (MINEIC), `Agencia Estatal de Investigación' (AEI) Spain and `Fondo Europeo de Desarrollo Regional' (FEDER).

1. Introduction

The Global Equality Index (GEI) is a adjusted market capitalization-weighted index that attempts to track the advancement of public companies dedicated to visibility in data reporting connected to gender. Standardized disclosure of gender-related data allows companies to attract capital and talent, empowers investors to make investment decisions through a social lens and enables employees and communities to hold companies accountable for progress. Together, these actions build the business case for gender equality. The structure involves 59 queries, pertaining to disclosing picked figures on subjects such as female command and career growth, gender remuneration and equal remuneration, comprehensive environment, sexual harassment rules, and pro-female notoriety. A firm's GEI rating is decided by its transparency and results (data exactness). The 380 companies listed in the 2021 list accomplished a base of 50% all out GEI score and have a market capitalization more than $1B USD. Focusing on five key pillars, the framework offers detailed information on how to measure and track data critical to achieving gender equality in the workplace. The MSCI World Index includes a wide array of both big and small-sized businesses from 23 countries with Developed Markets. It takes into account approximately 85% of the freely available market capitalization for each country, adding up to 1,585 entities altogether.

The objective of this research is to assess the resilience and long-term viability of the Bloomberg Gender Equality Index and the MSCI World Index in global financial markets. By tracking their trajectory over time, we aim to gauge the degree of integration between the data points from these indices, potentially revealing insights as a continuous value. This approach not only grants us increased flexibility in model specification but also enriches our understanding of potential market shocks and their implications.

Importantly, beyond the technical analysis, we intend to delve into the real-world significance of our findings. We posit the question: Why might these two time-series be cointegrated, and what does this tell us about the broader market dynamics? Such co-integration, if proven, could provide pivotal insights into the interconnectedness of gender equality initiatives and global market trends—a perspective of great interest to both investors seeking diversified portfolio strategies and policymakers aiming for sustainable market growth. To determine this potential long-term relationship between the two indices, we will employ both fractional integration and cointegration methodologies. Our hope is that the results will not only shed light on the statistical relationship but also underscore the economic rationale and implications of such a connection, ultimately guiding investment strategies and policy decisions.

The remaining part of this paper is organized in the following manner: Section 2 briefly reviews existing literature on forecasting stock market prices. Section 3 covers the methodological approach. The data utilised is outlined in Section 4, with the primary empirical findings in Section 5. Lastly, Section 6 contains the overall conclusions of this paper.

2. Literature review

For an investment to be considered Socially Responsible, it must meet environmental, social and governance criteria called ESG (Environment, Social and Governance). At the end of the 90s, the advancement of sustainable investment became a reality and it was decided to launch the Dow Jones Sustainability Index, the first global index to incorporate sustainability criteria. Soon after, the United Nations (UN) took a big step with the implementation of the principles for responsible investment. A sustainable product and behaviour is considered to reduce inefficiency, improve the use of resources and lead to an innovation that supposes cost reductions in the long term (Clark et al., 2015). These criteria are established as quality indicators of companies that add value to potential economic performance.

In recent years, the Social factor (The S of ESG) is gaining importance within the ESG criteria. In particular, the criterion of gender diversity is becoming very relevant, due to the fact that all organizational levels of a company have a favourable impact on financial performance and customer experience, in addition to improving the work environment and human capital management (Albuquerque et al., 2018). It is a growing trend worldwide to invest in companies that are leaders in promoting diversity and gender equality. The diversity criterion tries to make equality compatible with the recognition of the singularity on which the construction of subjectivity is installed. The balance between equality justice, on the one hand, and valuation of individual and intergroup variability, on the other, represent the two conceptual pillars on which the development of the diversity strategy is based (Barberá and Ramos, 2004). Implementing an effective diversity strategy has become increasingly important to organizations and will continue to be key for them. Increasingly, companies are addressing gender diversity criteria. This is reflected in the Sustainable Goals as defined by the United Nations, in which Gender Equality appears as number five.

Companies have realized that gender diversity creates better organizations with greater creativity and innovation, better teamwork and flexibility. Corporate governance is not entirely effective if there is no true managerial diversity. Women on the board of directors give greater importance to CSR policies and have a greater sensitivity towards them (Williams, 2003; Bernardi et al., 2009). Kahreh et al. (2014) state that women directors are more oriented and pay higher attention towards social responsibility when compared to their male counterparts.

The literature on modelling financial data is very extensive. From the classical random walk model testing the Efficient Market hypothesis (Fama, 1970), there are thousands of articles investigating if stock market prices are stationary or not using unit root methods. Earlier studies include, among others, Groenewold and Kang (1993), Ayadi and Pyun (1994), Tabak (2007), Narayan (2008), Hasanov (2009), Gozbasi et al. (2014), Tiwari and Kyophilavong (2014), Wang et al., (2015), etc. though already in 1991, Cochrane (1991) demonstrated that standard unit root tests had arbitrarily low power in finite samples. Nowadays, it is well known that unit root testing methods also have very low power against different types of alternatives such as trend-stationarity models (DeJong et al., 1992), structural breaks (Perron, 1989; Campbell and Perron, 1991), regime switching (Nelson et al., 2001) and even fractional integration (Diebold and Rudebusch, 1991; Hassler and Wolters, 1994; Lee and Schmidt, 1996; etc.). In this regard, the unit root literature was later extended to the fractional case, allowing the number of differences to render the series stationary to be a fractional value. In doing so, persistence in the data can be examined in a more flexible way. Examples are the papers by Omay and Baleanu (2021) showing that not considering the structural break and fractional integration simultaneously in the testing process may lead to misleading results about the stochastic behaviour of the Covid-19 pandemic. In another paper, Omay (2015) proposed a Fractional Frequency Flexible Fourier Form DF-type unit root test, where the small sample properties of the proposed test were found to be better than that of the integer frequency counterpart. Other contributions of fractional integration in the context of stock market prices include the papers by Caporale and Gil-Alana (2002), Aloy et al. (2010), Afzal and Sibbertsen (2021), etc.

Beltratti and Morana (2006) investigated the idea that there is a continual, long-term association between stock markets across different countries. They applied models of fractional cointegration that contain shared, long-term components. Furthermore, they observed the bond between macroeconomic aspects and stock market volatility and established evidence of a double association between stock markets and macroeconomic unsteadiness. Previous investigations completed by Baur and Schulze (2005) have established that regular stock index returns demonstrate signs of "some" contagion (described as the crisis-specific co-exceedance not made clear by the variables for different quantiles), which can be anticipated within and between regions. Examinations into the link between financial markets and other elements, for example oil prices (Sahu et al., 2014; Guesmi et al., 2016; Hamdam and Hamdam, 2019; Mokni and Youssef, 2019; Hou et al., 2019; Sarwar et al., 2020; Ehouman, 2020; Salisu and Gupta, 2021; etc.) and macro fundamentals (Conrad and Loch, 2014; Otieno et al., 2019; etc.) have been highly essential, with the outcomes of cointegration suggesting the existence of a long-term balanced link.

Particularly concentrating on the associations between different indices, there have been considerable breakthroughs since Beltratti and Morana's (2006) pioneering exploration. Gil-Alana et al. (2014) inspected the repeating cycle of rises and drops seen in US, European and Asian markets utilizing GARCH models. Caporale et al. (2016) investigated the SP500 and EuroStoxx50 indices from 1986-2013 using fractional cointegration techniques and concluded that there was no distinct pattern of persistence, though it was more apparent in bullish markets. They determined that cointegration did not exist for the entire period, yet from 1996-2009, it did exist. Gagnon et al. (2016) proved the coherence and integration of five US and European stock indices with daily data from 2003-2013; during the 2007-2009 global crisis, they discovered an augment in endurance and the rate of adaptation, whereas outside that period, the cointegration association was more faded, primarily for higher-order instants.

3. Methodology

In the empirical section of the paper, a mix of partial differentiation and combination methods were used. We chose these techniques to demonstrate the level of resilience within the indices and how it has changed over time.

This action of subtracting d-differences of a time sequence to make it stationary I(0) is referred to as the I(d) technique. This approach can be employed with any real number d, granting the possibility of fractional levels of differentiation. In simpler terms, it states that x_t follows a process of integration of order d, i.e., $x_t \sim I(d)$ if it can be written as:

$$(1 - L)^d x_t = u_t, \qquad t = 1, 2, \ldots, \tag{1}$$

where L is the lag operator, i.e. $Lx_t = x_{t-1}$, and u_t is I(0). If d = 0 in (1), $x_t = u_t$, and x_t it is considered to be a short-memory as compared to the situation of long memory which is observed with d > 0. It is thought to have long memory due to the strong relationship between observations which are separated by a large amount of time, and the polynomial in L in (1) can be written as:

$$(1 - L)^d = 1 - dL + \frac{d(d-1)}{2} L^2 - \ldots .$$

Hence, d parameter can be seen as a sign of stability within the data, the bigger the figure, the stronger the dependence in the data. Furthermore, it allows us to discriminate between reverting to the average and not reverting in a more adjustable manner than the conventional techniques that simply make use of either 0 (for steady series) or 1 (for non-steady series). In the realm of genuine values of d, convergence to its long lasting projection will happen as long as d is less than one, and the nearer d is to zero, the quicker the return to equilibrium.

The estimation of d is conducted via the Whittle function in the frequency domain using a parametric approach developed in Robinson (1994) which is very convenient for our purposes, since it is valid for all range of values of d, including those in the nonstationary region ($d \geq 0.5$). Moreover, it has a standard N(0, 1) null limit distribution, which holds independently of the inclusion of deterministic terms in the model such as intercepts and/or linear trends.

We next look at the long run co-movements between the variables by looking at the cointegration relationship. However, once more, we use here fractional degrees of differentiation, testing if the long run equilibrium relationship follows a fractional process. We use here among other methods, the Fractional Cointegration VAR approach (FCVAR) developed in Johansen and Nielsen (2010, 2012) and which tests if the individual series are I(d) in its multivariate representation while the long run equilibrium relationship is I(d-b) with positive b, where d and b can be both fractional values.

4. Data

Bloomberg's ESG database, consisting of more than 11,500 publicly listed companies, is evaluated to establish if a security is valid to be included in the Global Equality index by examining the following conditions: i) the present market value must be a minimum of 1 billion USD (1,000,000,000); ii) the average day-to-day value traded in the past three months must be above 50,000 USD; iii) the 3-month average trading value must exceed 5,000 USD. This is especially useful for our purpose, since it covers all values of d, ranging from the stationary to the non-stationary range. If there is more than one firm that meets the criteria, the selection of the stock for the index will be based on its liquidity, with the average number of shares traded and the typical daily value traded taken into account, as well as the size of its market capitalization.

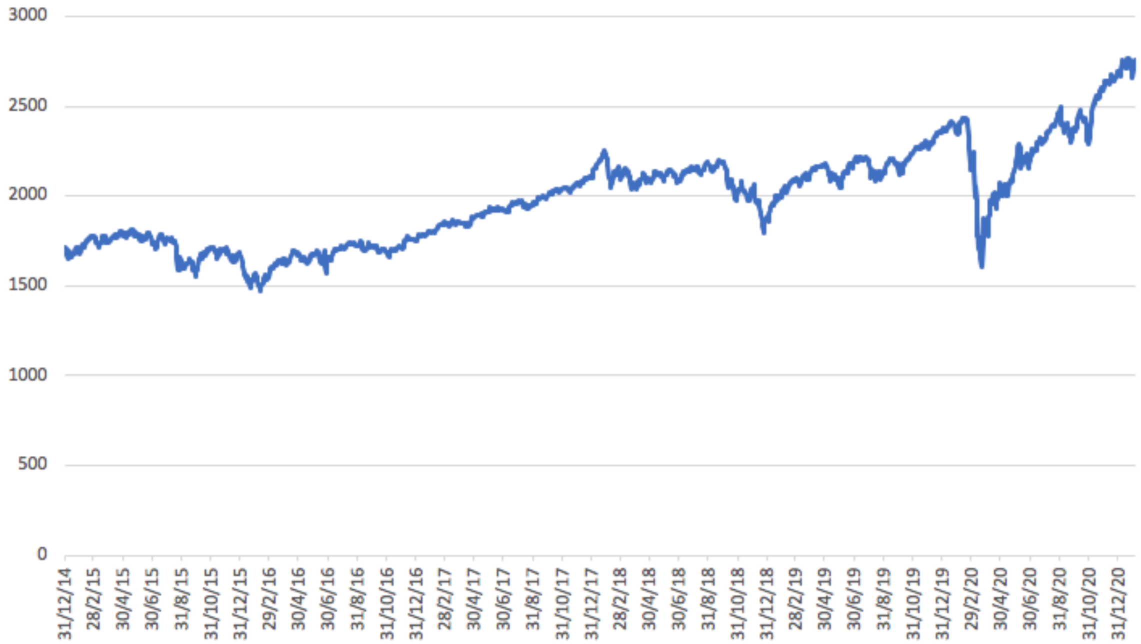
Publicly-traded equity on the stock market are taken into consideration for the index if they meet the universal criteria and have a GEI score higher than a benchmark that is set universally. The precise threshold for selection into the index is examined and modified yearly. GEI evaluations are determined yearly utilizing the data from the preceding fiscal year that is available in the Bloomberg Terminal Fundamental Analysis (FA). FA offers comprehensive financial details including environmental, social, and corporate governance (ESG) data for each company. It also provides a universal template that facilitates the comparison of firms that present records in different formats. The index uses a modified market capitalization-weighted system, which is calculated by multiplying each firm's current market cap and its own GEI score. The weightings of the GEI index are evaluated and possibly altered at the commence of each year, and then every quarter during the year when the New York Stock Exchange opens on the Monday after the third Friday of the month. The constituents of the index remain unchanged for the whole year, except for corporations that are delisted or taken over by related companies.

The MSCI World Index is built using the MSCI Global Investable Indexes (GIMI) System. This method is extensive and consistent, making it possible to compare global markets of all sizes, sectors, and investment styles. The index is updated four times a year—in February, May, August, and November—as a way to quickly respond to shifts in the stock market while limiting unnecessary changes. Twice a year, in May and November, the boundaries of the large and mid-cap stocks in the index are recalculated. The index is calculated -using the Laspeyres' concept of a weighted arithmetic average together with the concept of chain-linking- 5 days a week, from Monday to Friday.

The two indices under examination -the Bloomberg Gender Equality Index and the MSCI World Stock Market Index- are displayed in Figures 1 and 2 respectively. In the charts, Bloomberg Gender Equality Index shows a higher volatility than the MSCI World Stock Market Index, because the latter offers a broader and more uniform index for all market capitalization size, sector and style categories. The chart is drawn up with daily data series from December, 31st 2014 until February, 5th 2021 for both indexes.

Figure 1: Time series plot: Bloomberg Gender Equality Index

Figure 2: Time series plot: MSCI World Stock Market Index



5. Empirical results

We begin this section by estimating the fractional differencing parameter, d, of each series independently. To do this, we use the following model:

$$y_t = \beta_0 + \beta_1 t + x_t; \qquad (1 - L)^d x_t = u_t, \qquad t = 1, 2, \ldots, \qquad (1)$$

where y_t is the observed time series, and β_0 and β_1 refer respectively to a constant and a linear time trend; x_t is supposed to be I(d) so that u_t is I(0).

Table 1 displays the estimates of d in the model given by equation (1) along with the 95% confidence bands for the values of d, assuming first that u_t in (1) is a white noise process and then allowing for autocorrelation in the error term, in this case using the exponential spectral approach of Bloomfield (1973). This is a non-parametric method where the model for u_t is only implicitly determined by its spectral density function, whose log-form approximates the one of an autoregressive (AR) structure. We separately examine scenarios where there are no predetermined terms (in other words, $\beta_0 = \beta_1 = 0$ a priori in (1)); only involving an intercept (that is, $\beta_1 = 0$ a priori in (1)); and featuring an intercept and a linear time trend (which means β_0 and $\beta_1 = \neq 0$ initially in (1)), marking in bold in the table the selected model for each case.

This selection is based on the t-values of the estimated coefficients in the d-differenced processes, cognizant that the two equations in (1) can be collectively expressed as:

$$\tilde{y}_t \;=\; \beta_0 \tilde{1}_t + \beta_1 \tilde{t}_t + u_t, \qquad\qquad t \;=\; 1,\; 2, \ldots, \tag{2}$$

with $\tilde{y}_t = (1-L)^d y_t$; $\tilde{1}_t = (1-L)^d 1$ and $\tilde{t}_t = (1-L)^d t$. Then, noting that u_t is I(0) by construction, the t-values in Equation (2) remain valid. Table 2 displays the estimated coefficients for each series.

[Insert Tables 1 and 2 about here]

We observe in Table 1 (Panels i) and ii)) that the intercept is sufficient to describe the deterministic part of the model since the time trend coefficients are found to be statistically insignificant in all cases. The estimates of d are about 1 in all cases, and the unit root null hypothesis is not rejected under the assumption of white noise errors, but is rejected in favour of d > 1 if autocorrelation is permitted. In the case of the logged values (panels iii) and iv)), the estimates of d are slightly lower. This evidence of unit roots is not so clearly supported when using the spectral model of Bloomfield (1973) for the disturbance term (panel iv), since d is slightly higher than 1, and the unit root null is now rejected in favour of d > 1 in the two cases examined. Nevertheless, using standard methods that simply consider integer degrees of differentiation (i.e., 0 and 1), (e.g., Dickey and Fuller ADF, 1979; Phillips and Perron, PP, 1988; Kwiatkowski et al., KPSS, 1992; Elliot et al., ERS, 1996, and Ng and Perron, 2001; etc.), the I(1) hypothesis cannot be rejected in any single case.

Based on the evidence supporting the I(1) hypothesis, we next examine if the two series are related in the long run by using cointegration methods. However, instead of considering the classical case that impose an I(0) structure on the error term, we allow for the possibility of fractional cointegration. First, we use the approach developed in Engle and Granger (1987), further developed in Cheung and Lei (1993) and Gil-Alana (2003) for the fractional case. The idea is simple. First, we look at the order of integration of the individual series (already done in

Tables 1 and 2), and based on the fact that the two series display statistically the same degree of integration, we take next the residuals of the OLS regression of one of the variables over the other, testing now the degree of differentiation in the estimated residuals. The estimated regressions for both original data and logged values produced the following results:

$$MXWO_t = \underset{(17.56)}{562.717} + \underset{(44.94)}{12.834}\, BFGEI_t + x_t; \qquad t = 1, 2, \ldots,$$

and

$$\log(MXWO)_t = \underset{(62.54)}{4.2563} + \underset{(48.94)}{0.7084}\, \log(BFGEI)_t + x_t; \qquad t = 1, 2, \ldots,$$

(t-values) in parenthesis. Table 3 displays the estimates of d in (1) on these residuals, once more for the three cases of no terms, an intercept, and an intercept with a linear time trend, and now supposing again that u_t is a white noise process and autocorrelated using the model of Bloomfield (1973).

[Insert Table 3 about here]

The first thing we observe in Table 3 is that according to this approach there is no evidence of cointegration of any degree between the two variables since the order of integration of the residuals (and log-residuals) are about 1 in all cases. Thus, though the values are now smaller than those presented in Tables 1 and 2 the reduction in the degree of differentiation is minimal and the unit root null cannot be rejected in any single case. Note, however, that these results might be biased, first because the estimation is now conducted on estimated rather than on observed values. Also, the OLS approach may not necessarily be the best approach in this context of potential cointegration (Robinson and Hualde, 2003). Thus, in what follows, we use the multivariate FCVAR approach developed by Johansen and Nielsen (2010, 2012) widely used in recent years in the analysis of cointegration.

The results are displayed in Table 4 and we observe that the two series (original and logged) display a similar pattern, finding support for cointegration. In fact, the order of integration in the bivariate representation of the two series is equal to 0.969 with the original data, and 0.975 with the logged transformed values, while the reductions in the orders of integration in the cointegration relationships are precisely the same values (0.969 and 0.975) suggesting that the errors in the long run equilibrium relationships are I(0) or short memory. This result is not in line with the one based on the two step approach previously used, and this can clearly be a consequence of the bias produced in the former method when using estimated rather than observed errors.

6. Concluding comments

This research delved into the relationship between Gender Equality and the MSCI World index, evaluating them independently and then analyzing the correlations between the data over the period from 2014 to 2021 on a daily basis.

The results of fractional integration techniques show that both series are very consistent and the integration orders in both tend to be close to 1, particularly when the autocorrelation is taken into account. There were no signs of mean reverting. This absence of mean reverting is in agreement with the findings of prior research (DePenya and Gil-Alana, 2004; Tabak, 2007; Narayan, 2008; Hasanov, 2009; Gozbasi et al., 2014; Tiwary and Kyophilavon, 2014; etc.). Our discoveries for the single series vary from those of Adekoya (2020) and Caporale et al. (2020). Adekoya (2020) revealed mean-reversion and long-term memory in 18 OECD countries, with samples that were longer than ours, starting from January 1973 to August 2018. Conversely, Caporale et al. (2020) claimed that the Russian market had no-persistence and mean-reversion characteristics with daily examples from 2010 to 2018. These distinctions may be due to the different periods of sampling and the degree of shock exposure.

While examining long-term equilibrium relationships, our research revealed evidence of cointegration using the multivariate approach proposed by Johansen and Nielsen (2010, 2012) via the FCVAR models. However, this cointegration was not observed when employing the two-step approach, which estimates the order of integration in the regression errors between the variables. This inconsistency suggests a need to further prove into alternative methods for estimating the relationship's coefficients and the differencing parameter's estimation techniques. Given the broader scope of the MSCI in comparison to the Gender Equality Index, it is plausible that the two series may not be co-integrated. However, the rising demand for gender diversity criteria by investors during security selection indicates a shifting dynamic. Companies, aiming to be featured in the general MSCI index, may increasingly strive to align with these gender diversity benchmarks. This potential alignment could result in an increasing co-movement between the two series over time. Thus, future research might benefit from exploring this dynamic interplay, further validating the findings observed with the multivariate approach of Johansen and Nielsen (2010, 2012).

References Remove the names and keep only initial in all references. DONE

Adekoya, O. B. (2020). Persistence and efficiency of OECD stock markets: linear and nonlinear fractional integration approaches. Empirical Economics. https://doi.org/10.1007/s00181-020-01913-4.

Afzal, A., and Sibbertsen, P. (2021). Modelling fractional cointegration between high and low stock prices in Asian countries, Empirical Economics 60, 661-681.

Albuquerque, R. A., Koskinen, Yrjo J., and Zhang, C. Corporate Social Responsibility and Firm Risk: Theory and Empirical Evidence (January 15, 2018). European Corporate Governance Institute (ECGI) - Finance Working Paper No. 359/2013, Available at SSRN: https://ssrn.com/abstract=1961971 or http://dx.doi.org/10.2139/ssrn.1961971

Aloy M., Boutahar, M., Gente, K., and Péguin-Feissolle, A. (2010). "Fractional integration and cointegration in stock prices and exchange rates," Economics Bulletin 30(1), 115-129.

Ayadi, O.F., and Pyun, C.S. (1994). An application of variance ratio test to the Korean securities market, Journal of Banking and Finance 18, 643-658.

Barberá, E., and Ramos, A. (2004). Liderazgo y discriminación de género. Revista de Psicología General y Aplicada 57, 2 147-160.

Baur, D., and Schulze, N. (2005). Coexceedances in financial markets—a quantile regression analysis of contagion. Emerging Markets Review, 6 (1): 21-43, https://doi.org/10.1016/j.ememar.2004.10.001.

Beltratti, A., and Morana, C. (2006). Breaks and persistency: macroeconomic causes of stock market volatility. Journal of Econometrics 131 (1–2): 151-177,

Beran, J. (1995). Maximum Likelihood Estimation of the Differencing Parameter for Invertible Short and Long Memory Autoregressive Integrated Moving Average Models, Journal of the Royal Statistical Society, Series B, 57, 4, 659-672.

Bernardi, R. A., Bosco, S. M., and Columb, V. L. (2009). Does Female Representation on Boards of Directors Associate with the 'Most Ethical Companies' List&quest. Corporate Reputation Review, 12(3), 270-280

Bloomfield, P. 1973. An exponential model in the spectrum of a scalar time series, Biometrika 60, 217-226.

Campbell, J.Y., and Perron, P. (1991). Pitfalls and opportunities. What macroeconomists should know about unit roots, NBER Macroeconomic annual, pp. 1141-1201.

Caporale, G. M., and Gil-Alana, L.A. (2002). Fractional integration and mean reversion in stock prices, The Quarterly Review of Economics and Finance 42, 3, 599-609.

Caporal, G.M., Gil-Alana, L.A., and Orlando, J.C. (2016). Linkages between the US and European stock markets: a fractional cointegration approach. International Journal of Finance & Economics 21: 143–153. DOI: 10.1002/ijfe.1537

Caporale, G.M., Gil-Alana, L.A., and Poza , C. (2020). Persistence, non-linearities and structural breaks in European stock market indices. The Quarterly Review of Economics and Finance 77, 50-61. https://doi.org/10.1016/j.qref.2020.01.007

Caporale, G. M., Gil-Alana L. A., and Tripathy, T. (2020). Volatility persistence in the Russian stock market. Finance Research Letters 32. https://doi.org/10.1016/j.frl.2019.06.014.

Cheung, Y-W., and Lai, K.S. (1993). A fractional cointegration analysis of purchasing power parity, Journal of Business and Economic Statistics 11, 1, 103-112.

Chuang, H. (2015). Volatility persistence in stock market. Economics Letters 133, 64-67. https://doi.org/10.1016/j.econlet.2015.05.018

Clark, G.L., Feiner, A., and Viehs, M. (2015). From the Stockholder to the Stakeholder: How Sustainability Can Drive Financial Outperformance. University of Oxford, Business Organizations & Markets: Formal & Informal Structures eJournal**.**

Conrad, C., and Loch, K. (2014). Anticipating Long-Term Stock Market Volatility. Journal of Applied Econometrics 30 (7), 1090-1114. https://doi.org/10.1002/jae.2404

Cochrane, J.H (1991). A critique of the application of unit root tests,. Journal of Economic Dynamics and Control. Volume 15, Issue 2. Pages 275-284. ISSN 0165-1889, https://doi.org/10.1016/0165 1889(91)90013(https://www.sciencedirect.com/science/article/pii/016518899190013Q)

DeJong, D., Nankervis, J., Savin, N.E., and Whiteman, C.H. (1992). Integration versus trend stationarity in time series, Econometrica 60, 423-433.

DePenya, J. R., and Gil-Alana, L.A. (2004). Do Spanish stock market prices follow a random walk, European Review of Economics and Finance 3, 3-13.

Dickey, D.A., and Fuller, W. A. (1979). Distributions of the Estimators for Autoregressive Time Series with a Unit Root*, Journal of American Statistical Association*, 74(366), pp.427-481.

Diebold, F.X., and Rudebusch, G.D. (1991). On the power of Dickey-Fuller test against fractional alternatives. Econ. Lett. 35, 155–160.

Ehouman, Y. E. (2020). Volatility transmission between oil prices and banks' stock prices as a new source of instability: Lessons from the United States experience, Economic Modelling 91, 198-217. https://doi.org/10.1016/j.econmod.2020.06.009

Elliot, G., Rothenberg, T.J., and Stock, J.H. (1996). Efficient Tests for an Autoregressive Unit Root, *Econometrica*, 64, 813-836.

Engle, R., and Granger, C.W.J. (1987). Cointegration and error correction. Representation, estimation and testing, Econometrica 55, 251-276.

Fama, E. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. The Journal of Finance, 25, 383-417.
http://dx.doi.org/10.2307/2325486

Gagnon, M. H., Power J., and Toupin, D. (2016). International stock market cointegration under the risk-neutral measure. International Review of Financial Analysis, 47: 243-255. https://doi.org/10.1016/j.irfa.2016.08.002

Gil-Alana, L.A. (2003). Testing of fractional cointegration in macroeconomic time series, Oxford Bulletin of Economics and Statistics 65, 4, 517-529.

Gil-Alana, L. A., Shittu O. I., and Yaya, O. S. (2014). On the persistence and volatility in European, American and Asian stocks bull and bear markets. Journal of International Money and Finance, 40: 149-162. https://doi.org/10.1016/j.jimonfin.2012.12.002

Gozbasi, O., Kucukkaplan I., and Nazlioglu, S. (2014). Re-exmaining the Turikish stock market efficiency. Evidence from nonlinear unit root tests, Economic Modelling 38, 381-384.

Groenewold, N., and Kang, K.C. (1993). The semi-strong efficiency of the Australian share market, Economic Record 69, 405-410.

Guesmi, K., Boubaker, H., and Son Lai, V. (2016). From Oil to Stock Markets
Journal of Economic Integration 31(1),103-133. https://doi.org/10.11130/jei.2016.31.1.103.

Hamdam R. K., and Hamdam A. M. (2019). Linear and nonlinear sectoral response of stock markets to oil price movements: The case of Saudi Arabia. International Journal of Finance and Economics 25 (3), 336-348.

Hasanov, M. (2009). Is South Korea's sotck market efficient? Evidence from a nonlinear unit root test, Applied Economics Letters 16, 2, 163-167.

Hassler, U., and Wolters, J., (1994). On the power of unit root tests against fractional alternatives. Economic Letters 45, 1–5.

Hou, Y., L. S., and Wen, F. (2019). Time-varying volatility spillover between Chinese fuel oil and stock index futures markets based on a DCC-GARCH model with a semi-nonparametric approach. Energy Economics 83, 119-143. https://doi.org/10.1016/j.eneco.2019.06.020

Jin, X. (2017). Time-varying return-volatility relation in international stock markets. International Review of Economics and Finance 51, 157-173. https://doi.org/10.1016/j.iref.2017.05.015

Johansen, S., and Nielsen, M.O. (2010). Likelihood inference for a nonstationary fractional autoregressive model. Journal of Econometrics 158, 51-66.

Johansen, S., and Nielsen, M.O. (2012). Likelihood inference for a fractionally cointegrated vector autoregressive model. Econometrica 80, 2667-2732.

Kahreh, M. S., Babania, A., Tive, M., and Mirmehdi, S. M. (2014). An examination to effects of Gender Differences on the Corporate Social Responsibility (CSR). Procedia-Social and Behavioral Sciences, 109, 664-668.

Kwiatkowski, D., Phillips, P.C.D., Schmidt, P., and Shin, Y.(1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?, Journal of Econometrics 54, 159–178.

Lee, D., and Schmidt, P. (1996). On the power of the KPSS test of stationary against fractionally integrated alternatives, Journal of Econometrics 73, 285-302.

Mokni, K., and Youssef, M. (2019). Measuring persistence of dependence between crude oil prices and GCC stock markets: A copula approach. The Quarterly Review of Economics and Finance 72, 14-33. https://doi.org/10.1016/j.qref.2019.03.003.

Narayan, P.K. (2008). Do shocks to G7 stock prices have a permanent effect? Evidence from panel unit root tests with structural change, Mathematics and Computers in Simulation 77, 4, 369-373.

Nelson, C.R., Piger, J., and Zivot, E. (2001). Markov regime switching and unit root tests, Journal of Business and Economic Statistics 19, 404-415.

Ng, S., and Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power, Econometrica 69, 519-1554

Omay, T. (2015). Fractional Frequency Flexible Fourier Form to approximate smooth breaks in unit root testing. Economics Letters 134, 123-126, ISSN 0165-1765, https://doi.org/10.1016/j.econlet.2015.07.010.

Omay, T., and Baleanu, D. (2021). Fractional unit-root tests allowing for a fractional frequency flexible Fourier form trend: predictability of Covid-19. Advances in Differences Equations 2021, 167 (2021). https://doi.org/10.1186/s13662-021-03317-9

Otieno, D.A., Ngugi, R.W., and Muriu, P.W. (2019). The impact of inflation rate on stock market returns: evidence from Kenya. Journal of Economics and Finance 43, 73–90. https://doi.org/10.1007/s12197-018-9430-5

Perron, P.(1989). The great crash, the oil price shock and the unit root hypothesis, Econometrica 57, 1361-1401.

Phillips, P.C., and Perron, P. (1988). Testing for a unit root in time series regression', *Biometrika* 75, 2, 335–346.

Robinson, P. M. (1994). Efficient tests of nonstationary hypotheses, Journal of the American Statistical Association 89, 1420-1437..

Robinson, P.M. and Hualde, J. (2003). Cointegration in fractional, systems with unknown integration orders, Econometrica 71, 6, 1727-1766.

Sahu, T. N., Bandopadhyay, K., and Mondal, D. (2014). An empirical study on the dynamic relationship between oil prices and Indian stock market. Managerial Finance 40 (2), 200-215. https://doi.org/10.1108/MF-06-2013-0131.

Salisu, A. A., and Gupta, R. (2021). Oil shocks and stock market volatility of the BRICS: A GARCH-MIDAS approach. Global Finance Journal, 48. https://doi.org/10.1016/j.gfj.2020.100546

Sarwar, S., Tiwari A. K., and Tingqiu C. (2020). Analyzing volatility spillovers between oil market and Asian stock markets. Resources Policy, 66. https://doi.org/10.1016/j.resourpol.2020.101608

Tabak, B.M. (2007). Testing for unit root bilinearity in the Brazilian stock market, Physica A: Statistical Mechanics and Its Applications 385, 1, 261-269.

Tiwari, A.K., and Kyophilavong, P.(2014). New evidence from the random walk hypothesis for BRICS stock indices. A wavelet unit root test approach, Economic Modelling 43, 38-41.

Wang, J., Zhang, D., and Zhang J. (2015). Mean reversion in stock prices of seven Asian stock markets: Unit root test and stationary test with Fourier functions. International Review of Economics & Finance. Volume 37, Pages 157-164, ISSN 1059-0560. https://doi.org/10.1016/j.iref.2014.11.020.

Williams, R. J. (2003). Women on corporate boards of directors and their influence on corporate philanthropy. Journal of Business Ethics 42(1), 1-10.

Yavas, B. F., and Dedi, L. (2016). An investigation of return and volatility linkages among equity markets: A study of selected European and emerging countries. Research in International Business and Finance 37, 583-596. https://doi.org/10.1016/j.ribaf.2016.01.025

Table 1: Estimates of the differencing parameter on the individual series.

Series	No terms	An intercept	An intercept and a linear time trend
i) White noise errors			
MXWO	1.006 (0.975, 1.041)	**1.029 (1.000, 1.063)**	1.029 (1.000, 1.063)
BFGEI	1.002 (0.971, 1.037)	**1.014 (0.984, 1.048)**	1.014 (0.984, 1.048)
ii) Autocorrelated (Bloomfield) errors			
MXWO	1.011 (0.966, 1.093)	**1.103 (1.043, 1.162)**	1.103 (1.043, 1.162)
BFGEI	1.029 (0.974, 1.074)	**1.118 (1.044, 1.184)**	1.120 (1.044, 1.185)
iii) White noise errors			
Log of MXWO	0.997 (0.964, 1.032)	**1.013 (0.983, 1.046)**	1.013 (0.983, 1.046)
Log of BFGEI	0.997 (0.966, 1.032)	**1.001 (0.971, 1.035)**	1.001 (0.971, 1.035)
iv) Autocorrelated (Bloomfield) errors			
Log of MXWO	0.996 (0.941, 1.055)	**1.073 (1.019, 1.153)**	1.073 (1.019, 1.153)
Log of BFGEI	0.997 (0.941, 1.053)	**1.101 (1.029, 1.171)**	1.101 (1.029, 1.171)

The values in parenthesis are the 95% confidence intervals for the differencing parameter. In bold, the selected cases according to the deterministic terms.

Table 2: Estimated coefficients based on Table 1

Series	No terms	Intercept (t-value)	Time trend (t-value=
i) White noise errors			
MXWO	1.029 (1.000, 1.063)	4.606 (334.70)	---
BFGEI	1.014 (0.984, 1.048)	7.444 (759.47)	---
ii) Autocorrelated (Bloomfield) errors			
MXWO	1.103 (1.043, 1.162)	200.207 (72.57)	---
BFGEI	1.118 (1.044, 1.184)	1710.533 (91.01)	---
iii) White noise errors			
Log of MXWO	1.013 (0.983, 1.046)	1.527 (509.06)	---
Log of BFGEI	1.001 (0.971, 1.035)	2.007 (1547.09)	---
iv) Autocorrelated (Bloomfield) errors			
Log of MXWO	1.073 (1.019, 1.153)	4.606 (336.57)	---
Log of BFGEI	1.101 (1.029, 1.171)	7.444 (767.77)	---

Table 3: Estimates of the differencing parameter on the individual series.

Series: RESIDUALS	No terms	An intercept	An intercept and a linear time trend
White noise	0.97 (0.94, 1.01)	**0.97 (0.94, 1.01)**	0.97 (0.94, 1.01)
Bloomfield autocorr.	0.99 (0.94, 1.06)	**1.00 (0.95, 1.05)**	1.00 (0.95, 1.05)
Seasonal MA(1)	0.98 (0.94, 1.01)	**0.98 (0.94, 1.01)**	0.98 (0.94, 1.01)
Series: LOG RESIDUALS	No terms	An intercept	An intercept and a linear time trend
White noise	0.99 (0.96, 1.03)	**0.99 (0.96, 1.03)**	0.99 (0.96, 1.03)
Bloomfield autocorr.	1.00 (0.94, 1.06)	**1.00 (0.95, 1.06)**	1.00 (0.95, 1.06)
Seasonal MA(1)	0.99 (0.96, 1.03)	**0.99 (0.96, 1.03)**	0.99 (0.96, 1.03)

The values in parenthesis are the 95% confidence intervals for the differencing parameter. In bold, the selected cases according to the deterministic terms.

Table 4: Estimated values in the FCVAR approach

Series	d (Standard Error)	b (Standad Error)
Original series	0.969 (0.036)	0.969 (0.122)
Logged values	0.975 (0.035)	0.975 (0.127)

d represents the joint order of integration of the series in its bivariate representation while d is the reduction in the long run cointegration relationship.