LINEAR AND NONLINEAR GRANGER CAUSALITY RELATIONSHIP BETWEEN STOCK INDICES AND FINANCIAL VARIABLES

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Abstract

This paper examines the relationship between the daily observations of stock prices and the selected financial variables over the period September 20, 2010 to August 2, 2019. Our variables are found to be nonlinear at any reasonable significance level. Seven out of eleven stock indices and all financial factors are nonlinearly level stationary, while five stock indices are integrated of the first order. The findings of the linear causality test present evidence of a bidirectional causal association between the changes in bond yields and some equity returns, CDS fluctuations and BIST Sport index returns; and BIST Industrials index returns with copper prices in TRY. These results are supported by nonlinear causality tests at different lag levels. Besides, there seems to appear two-way nonlinear causal associations in mean and in the second moment between our variables, denoting the contribution of the short, medium, and long-run nonlinear causalities to the overall causal relationship. We also find a significantly negative linkage between the financial factor growths and equity returns, which is scale-dependent. Our findings have significant implications for risk and portfolio management and economic policy decisions.

JEL Codes: E44, G11, G12.

Keywords: Linear, Nonlinear, Causality, Wavelets, Stock Return.

BORSA ENDEKSLERI VE MAKRO EKONOMIK DEĞIŞKENLER ARASINDA DOĞRUSAL VE DOĞRUSAL DIŞI NEDENSELLİK İLİŞKİSİ*

Öz

Bu çalışmada borsa endeksleri ve makro değişkenlere ait 2010-09-20 ve 2019-08-02 arası günlük kapanış fiyatları kullanılarak bu değişkenler arasındaki olası doğrusal ve doğrusal dışı nedensellik ilişkisi incelenmiştir. Test sonuçlarına göre tüm değişkenlerin doğrusal dışılık özelliklerini taşıdıkları tespit edilmiştir. Yedi borsa endeksinin ve makroekonomik faktörlerin düzeyde, kalan beş endeksin ise birinci farkında durağan olduğu saptanmıştır. Doğrusal nedensellik testine göre tahvil faizi değişmeleri ile bazı borsa endeks getirileri arasında; CDS ile BIST Spor endeksi fiyat değişimleri arasında; bakır fiyatları ile BIST Sınaî endeks getirileri arasında çift yönlü nedensellik ilişkisi olduğu bulgusuna rastlanmıştır. Elde edilen bu sonuçlar, farklı seviyelerdeki doğrusal dışı nedensellik test sonuçlarıyla uyum sağlamaktadır. Ayrıca değişkenler arasında ortalamada ve varyansta kısa, orta ve uzun dönemde geçerli çift yönlü doğrusal dışı nedensellik ilişkisi olduğu belirlenmiştir. Bu sonuç, değişkenler arasındaki nedensellik ilişkisinin her bir frekanstan destek aldığını ortaya koymaktadır. Son olarak, borsa endeks getirileri ile makroekonomik değişkenlerin fiyat değişimleri arasında istatistiksel olarak anlamlı ve ölçeğe göre derecesi değişen zıt yönlü bir ilişki olduğu sonucuna ulaşılmıştır. Bu sonuçlar risk ve portföy yönetimi ve iktisadi kararlar için büyük önem arz etmektedir.

JEL Sınıflaması: E44, G11, G12.

Anahtar Kelimeler: Doğrusallık, Doğrusal Dışılık, Nedensellik, Dalgacıklar, Hisse Getirisi.

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1. Introduction

The association between the financial variables and stock prices has attracted a great deal of interest from economists and policy-makers. Using traditional approaches, they have tried to investigate the possibility of the existence, direction, and strength of the dependence of financial variables on equity prices. Given that the recent literature has produced ambiguous and contradictory results on this connection, this ambiguity encourages us to re-examine by using the linear and nonlinear causality tests and wavelets.

Given that bonds and stocks are being substituted for each other, the effects of interest rates on equity markets has been one of the most traditional topics in economics and finance theory. Since the standard theory posits that the value of any asset should be determined by its expected cash flows, any factor that could change its cash flows should have a major impact on their prices. Consequently, the initial literature mainly found a negative stock-bond relationship; see Flannery and James (1984) and Campbell (1987), pointing to the discount factor effect. Conversely, an illustrative list of papers includes Fama and French (1989), and Schwert (1989) report a negative relation between business condition and their expected nominal and real returns but a positive linkage between these markets. In a related paper, Stivers and Sun (2002) find that the direction of the comovement switches sign from positive to negative or loses its strength throughout high uncertainty in the stock market while Rankin and Idil (2014) detect a reverse switch for the linkage during the recent global financial crisis. In terms of causality tests, Gan et al. (2006), Tiwari (2012), and Çifter and Özün (2008) report causality from share returns to bond yields while the reverse causal linkage is detected by Acikalin et al. (2008) and Özer and Kamisli (2015). Among many empirical papers such as Wongbangpo and Sharma (2002), Alaganar and Bhar (2003), Aktaş and Akdağ (2013), and Moya-Martínez et al. (2015) highlight a causality in both directions for the underlying markets. For example, Alaganar and Bhar (2003) document bidirectional causalities in mean and variance at different lead/lags between the long-term interest rates and the equity returns of Bank, Insurance, and Financial sectors for G7 seven countries. Moya-Martínez et al. (2015), on the other hand, report scale-dependent causal linkages for Spain firms, i.e., there exists a feedback mechanism between the bond yield changes and the stock returns of Chemicals and Paper, Financial Services, Food and Beverages, Industrials, and Technology and Telecom industries at different time scales. On the other hand, Forson and Janrattanagul (2014) and Coşkun et al. (2016) detect causality in neither direction.

As discussed above, factors that have significant impacts on the discount rate also significantly affect stock prices. Among these factors, the stock-oil interaction has been a matter of great interest to academics and policy-makers, of which strength and direction of this relation may depend on the level of dependence of being a net oil importer or exporter for a country. In a pioneering work, Jones and Kaul (1996) detect a substantial detrimental impact of the oil prices on the aggregate equity market in the postwar period in G7 seven countries. Consistent with these findings, Faff and Brailsford (1999) report a significantly negative connection for Paper and Packaging and Transport and a significantly positive sensitiveness to the oil price changes for Oil and Gas and Diversified Resources industries during the sample period 1983-1996 in Australia. Similarly, Güler and Nalın (2013) detect a positive linkage for BIST Chemical Petrol Plastic and BIST Industrials sectoral indices and a negative connection for the aggregate index, BIST100, XU100, in Turkey. Recent findings by Şener et al. (2013) show a long-run relationship between the negative and the positive components of the oil and stock prices in Turkey and conclude that an increase in the oil prices would raise costs of production, therefore, result in a decrease in the equity prices in the absence of a perfect substitution among the production factors. In an influential paper, Kilian and Park (2009) find that the response of U.S. real equity returns to the shocks in oil prices varies considerably to the underlying cause of these stocks, namely approximately 22% of the long-run variation are explained by the demand and supply shocks driving the global oil markets. The shifts in precautionary demand, for example, driven by political disturbances in the Middle East, are found to be responsible for large declines in the equity prices while the positive shifts in oil prices driven by an unexpected expansion in the global economy cause a persistent affirmative impact on cumulative equity returns. In addition to the findings of Kilian and Park (2009), Wang et al. (2013) did not find any significant asymmetric impacts from the shocks in oil prices on the equity returns across all the exporting and importing countries, with the only exception of Korea. In a similar vein, they find that there is nonlinear causation impact from the changes in oil prices on the equity returns only in Japan (1 out of 9 oil-importing countries) at one lag, in Norway and Russia (2 out of 7 oil-exporting countries) at two lags. Abdioğlu and Değirmenci (2014), on the other hand, report a cointegration relationship between some nonfinancial indices, particularly for the industrial sector, and oil price in Turkey using daily observations over the sample period 2005-2013. Besides, they document a unidirectional causal linkage running from equity returns of BIST Services, BIST Telecommunication, BIST Financials, BIST Holding and Investment, BIST Insurance, BIST Industrials, BIST Chemical Petrol Plastic, BIST Basic Metal, BIST Metal Products Machinery, BIST Nonmetal Min. Product, and BIST Textile Leather indices and a two-way causality for BIST W. and Retail Trade index. Wen et al. (2019) investigate this relationship using the linear and nonlinear cointegration and causality test and document a linear and nonlinear cointegration relationship between the sectoral indices and WTI prices. Besides, they detect one-way linear causal linkages running from WTI prices to Agriculture, Social Services, and Media at different significance levels. The findings of the nonlinear causality test report bidirectional causality between the stock prices (including the aggregate stock indices of Shanghai Composite Index, Shenzhen Component Index (SZCI), and 13 subindices) and WTI oil prices, pointing to the key role of volatility persistence in these markets in China.

In theory, the majority of studies have shown that credit default swaps (CDS) and stock prices are negatively correlated (see Fung et al., 2008; Sadeghzadeh, 2019; Norden and Weber, 2009; Dupuis et al., 2009; and Eren and Başar, 2016). For instance, Norden and Weber (2009) investigate the association between daily, weekly, and monthly observations of CDS, bond, and stock prices over a sample period of 2000-2002. The findings of the paper show that the fluctuation of CDS had a significantly stronger adverse impact on stock returns than bond yields. The strength of the correlation is higher for the US than EU firms, for telecommunication firms than for other firms, and financial firms than for non-financial firms. Hancı (2014), on the other hand, detect a significantly negative relationship between the underlying variables regarding GARCH(2,1) model results and conclude that the mean reverse is very resistant (0.98) for a sample period between January 2008 and December 2012 in Turkey. Conversely, Narayan (2015) documents that the shock in CDS returns had a heterogeneous effect on the return and volatility of the sectoral stocks and are most dominant over the 2007-2008 financial crisis and time-varying shock spillovers, are a major factor in explaining the association between share and CDS returns. In term of causality tests, however, some studies provide strong evidence in favor of the one-way causality, such as Byström (2005), Fung et al. (2008), and Forte and Peña (2009), while others find bidirectional causal linkages, see for example Başarır and Keten (2016), Sadeghzadeh (2019), Şahin and Özkan (2018), Yenice et al. (2019). In a pioneering work, Longstaff et al. (2003) investigate the lead-lag connection between stock, bond, and CDS markets and report bidirectional causal linkages between CDS and stock returns. The CDS spread, for example, is found to be a useful predictor of future stock prices for 10 out of 67 individual stocks while the reverse causality holds for 12 out of 67 firms. Besides, Fung et al. (2008) examine the market-wide linkages between the underlying markets using daily observations between 2001:01 and 2007:12 and detect a bidirectional causal linkage between the high-yield CDS and stock markets which emerges with deteriorating but is absent in case of improving in stock market conditions. Similarly, they find a unidirectional causality running from the volatility of both the high-yield and investment-grade CDS indices to the volatility in stock markets and a two-way causality between the stock market volatility and the high-yield CDS market, pointing to the key role of the CDS market in determining of volatility spillover and the stock market in determining of information transmission in the pricing progress.

The question of whether fluctuations in copper prices play a major role in determining and predicting equity prices is of great interest to investors and regulatory authorities; however, this relationship has not yet sufficiently well-developed by academicians and researchers. For instance, Eyüboğlu and Eyüboğlu (2016), using cointegration and causality test, find a long-run relationship between stock prices of mining sectors and a set of precious metals including gold, silver, and copper over the sample period 2003:03-2014:12. Also, they detect a significantly negative relationship for only one out of four stock prices.

Boyacioglu et al. (2016), on the other hand, find a unidirectional causal linkage from copper prices to two out of four individual stock prices in Turkey. Conversely, the papers of Choi and Hammoudeh (2010) and Sadorsky (2014) demonstrate the existence of a positive connection between the underlying variables. They also state that copper is an important precious metal since it moves with the business cycles, therefore, the author states that it is often regarded as Dr. Copper because of the ability to predict economic activity. It is also observed that the dynamic conditional correlation between the copper and stock prices increased since 2002. Regarding the DCC-AGARCH model, according to Sadorsky (2014) findings, the average value of the hedge ratios between stock and copper prices is found to be $26, i.e., a $100.0 long position in the stock market could be hedged for $26 in the copper market. The average weight for the stock-copper portfolio, which should be updated regularly, is found to be 0.80, namely, for a $100 portfolio, $20 and $80 should be invested in copper and stocks, respectively.

Previous studies investigating the stock-gold relationship in terms of the direction and structure of causality obtain ambiguous and contradictory findings. Of the studies that have found significantly negative linkage are Ciner et al. (2013) for the US; Aksoy and Topcu (2013) for Turkey; Le and Chang (2016) for Japan, and Chkili (2016) for BRICS countries. Ciner et al. (2013), for example, detect a significant adverse relationship between gold and share prices in the US and conclude that gold acts as a safe-haven for stocks during periods of financial turmoil. This result reinforces the findings of Chkili (2016), who employs the A-DCC model and uses the weekly observations of stock indices of BRICS countries, and gold prices suggest that investors are recommended to buy gold to reduce their portfolios' total risk. Besides, Arouri et al. (2015) also claim that gold is a safe-haven for Chinese market investors and plays a crucial role in explaining the market return and volatility. By using the GARCH approach, on the other hand, Akel and Gazel (2015) conclude that the investors in Turkey did not consider gold as a safe-haven instrument during the financial turmoil period. On the other hand, several researchers such as Ciner et al. (2013) and Eyüboğlu and Eyüboğlu (2016) have concurred that gold prices had significantly positive impacts on stock prices. In the related paper, Eyüboğlu and Eyüboğlu (2016) investigate the relationship between a set of commodities and stock prices of the mining sector in Turkey and highlight that gold prices have significantly positive impacts on two out of four stock prices. Based on the Granger causality, however, there is a unidirectional causal linkage from stock prices to gold prices obtained by Smith (2001) and Gilmore et al. (2009) for the US, Fahami et al. (2014) for Thailand, Büyüksalvarci and Abdioglu (2010), Özer et al. (2011), Aksoy and Topcu (2013), and Acikalin and Basci (2016) for Turkey. Büyüksalvarci and Abdioglu (2010), for example, investigate the relationship between financial factors and stock market index, XU100, for the period 2001:03-2010:06 and detect one-way causal linkages running from the stock prices to the exchange rate, gold prices, money supply, industrial production, and inflation rate. They conclude that the stock market could be used as a useful predictor for the future growth of these variables in Turkey. An illustrative list of papers that report a unilateral causality from gold prices to stock prices contains Patel (2013), Coronado et al. (2015), and Gazel (2016). In her paper, Gazel (2016) studies cointegration and causal linkages between stock index and gold prices and finds out that both variables are cointegrated over the sample period between January 2, 2006 and February 29, 2016. The results of the paper also show a one-way causality, and the author interprets the non-rejection of the null hypothesis from stock prices to gold prices due to the risk conception of investors and insufficient financial deepening in the Turkish market. Furthermore, there is also a bidirectional causal association between the underlying variables, as reported by Mishra (2014), Coronado et al. (2015), and Jain and Biswal (2016). By employing symmetric and asymmetric nonlinear causality tests, Jain and Biswal (2016) discover a bidirectional asymmetric causality between the negative components gold prices and SENSEX index and interpret this finding as a result of shifting between these two investment asset classes to optimize their risk-return tradeoff. However, some researchers did not find any significant outcome between stock and gold prices. This list includes the paper of Fahami et al. (2014) for Malaysia and Indonesia; Tiwari and Gupta (2015) for India and Coskun et al. (2016) for Turkey.

This paper undertakes an empirical attempt to study the relationship between the stock prices and the selected financial variables, including bond, CDS, copper, gold, and WTI in TRY prices. Our data set includes the daily prices in Turkey over the period September 20, 2010, to August 2, 2019, for a total of 2107 observations for each variable. Based on the nonlinearity test, the variables are found to be nonlinear at any reasonable significance level. Seven out of eleven stock indices and all financial factors are nonlinearly level stationary, while five indices are integrated of the first order. The findings of the linear causality test provide evidence of a bidirectional causal association between the changes in bond yields and some equity returns, CDS fluctuations and BIST Sport index returns; and BIST Industrials index returns with copper prices in TRY. These results are supported by nonlinear causality tests at different lag levels. Besides, there seems to appear two-way nonlinear causal associations in mean and in the second moment between our variables, denoting the contribution of the short, medium, and long-run nonlinear causalities to the overall causal relationship. We also find a significantly negative linkage between the financial factor growths and equity returns, which is scale-dependent. Our findings recommend that the fluctuations in financial factors could be used to predict equity price changes in all investment horizons, while the causal relationship also does run in the opposite direction in the short, medium, and long-run.

This paper proceeds as follows. Section 2 describes the tests of nonlinearity, unit root, and causality, respectively, and wavelets. In Section 3, we present the summary statistics for our variables and the empirical findings for Turkey. Section 4 contains concluding remarks for investors and policymakers and recommendations on future studies.

2. Methodology

To test the null of linearity against the alternative of a nonlinear model in this paper, we apply the W_λ linearity test statistic of Harvey et al. (2008). On the other hand, for stationarity of the time series, we employ the Kruse (2011) nonlinear unit root test. Given the outcome of the Kruse (2011) test, we present the linear causality of Hacker and Hatemi-J (2012) test and the nonlinear causality test results of Nishiyama et al. (2011).

2.1. Wavelets

In wavelet literature, there exist two basic wavelet genders: mother (wavelet function) and father wavelets (scaling function). They integrate to 0 and 1 and represent the smooth/trend part and the detailed, i.e. deviation from trend, part of the signal, respectively. Theorists and practitioners use the basic function of the mother wavelet by translating and dilating it to capture simultaneously time and frequency information from the data, therefore, overcoming the limitations of the Fourier transform which its basis functions are localized only in frequency. As indicated in the paper of Ramsey (2014), wavelets seen as a refinement of Fourier analysis are an ideal tool for analyzing both stationary and long-term nonstationary variables and their relationships.

$$\phi_{j,k}(t) = \frac{1}{\sqrt{2^j}}\phi\left(\frac{t-2^j k}{2^j}\right) \tag{1}$$

$$\psi_{j,k}(t) = \frac{1}{\sqrt{2^j}}\psi\left(\frac{t-2^j k}{2^j}\right) \tag{2}$$

where j indexes the scale, therefore, 2^j is the scale/dilation factor and $2^j k$ is the translation parameter since k indexes translation.

Given a time series, $x(t)$ with N observations, the wavelet coefficients are given by the following integrals

$$d_{j,k} = \int \psi_{j,k}\, x(t)\,dt \tag{3}$$

$$s_{j,k} = \int \phi_{j,k}\, x(t)\,dt \tag{4}$$

where $j = 1,2,\dots,J$ is the maximum number of scale sustainable with the underlying data and the wavelet transform coefficients, $d_{j,k}$ and $s_{j,k}$, are defined as the detail and the smooth coefficients. Further, they capture the higher and lower frequency oscillations at the finer and coarser scale 2^j, respectively.

Given these both wavelet transform coefficients, a multiresolution representation (MRA) of $x(t)$ from the coarsest scale downwards up to scale J is can be mathematically depicted using Eq. (5)

$$x(t) = \sum_{k} s_{J,k}\phi_{j,k}(t) + \sum_{k=1}^{j} d_{j,k}\psi_{j,k}(t) \tag{5}$$

J	d_1	d_2	d_3	d_4	d_5	d_6	d_7	s_J
2	0.00294979	-0.00072004					[s_2]	-0.00105176
3	0.00294979	-0.00072004	-0.00182575				[s_3]	0.00077399
4	0.00294979	-0.00072004	-0.00182575	-0.0011589			[s_4]	0.00193288
5	0.00294979	-0.00072004	-0.00182575	-0.0011589	-0.00013675		[s_5]	0.00206963
6	0.00294979	-0.00072004	-0.00182575	-0.0011589	-0.00013675	0.00091154	[s_6]	0.00115809
7	0.00294979	-0.00072004	-0.00182575	-0.0011589	-0.00013675	0.00091154	0.00010809	0.00105

Figure 1 Multiresolution Decomposition (MRD) with J=7 Resolution Levels
Source: Gök (2019, 119).

The number of MRA coefficients at each scale, j, generated by the maximal overlap discrete transform (MODWT) is equal to sample size, N. Further, the detail coefficients d1, d2, d3, d4, d5, d6, and d7 correspond to [2-4), [4-8), [8-16), [16-32), [32-64), [64-128), and [128-256) days, respectively. The smooth coefficients, on the other hand, is equal to [256<) days.

In a similar vein but with different MODWT function, it is possible to obtain wavelet variance, covariance, correlation, and cross-correlation estimations through (1, .., *J*) wavelet coefficients and one scaling coefficients. It is worth noting that the number of coefficients at each scale is not equal to sample size, N due to boundary problems. That is, the number of coefficients uninfluenced by the boundary conditions would be $N_j = N - L_j + 1$ where L_j is $(L-1)*(2^j-1)+1$ and L represents the wavelet filter. After calculating wavelet variance and covariance of two time series, the dilatation equation of wavelet correlation can be expressed as follows

$$\hat{\rho}_{X,Y}(\lambda_i) = \frac{\sigma_{XY}(\lambda_i)}{\sigma_X(\lambda_i)*\sigma_Y(\lambda_i)} \tag{6}$$

where $\sigma_X(\lambda_i)$ denotes wavelet variance of X and wavelet covariance between X and Y is $\sigma_{XY}(\lambda_i) = \frac{1}{\hat{N}_j}\sum_{t=L_j-1}^{N-1} \widehat{W}_{j,t,X}\widehat{W}_{j,t,Y}$.

2.2. Nonlinearity Tests

The first step for our analysis is the testing for linearity against STAR nonlinearity by using the Harvey et al. (2008) nonlinearity test. According to the W^* linearity test statistics of Harvey and Leybourne (2007), testing for linearity is performed by the following regression

$$y_t = \theta_0 + \theta_1 y_{t-1} + \theta_2 y_{t-2}^2 + \theta_3 y_{t-3}^3 + \sum_{i=1}^{m} \theta_{4,i} \Delta y_{t-i} + \epsilon_t \tag{7}$$

To test the null hypothesis of linearity, $H_0: \theta_2 = \theta_3 = 0$ against the alternative hypothesis of nonlinearity, $H_1: \theta_2 \neq 0 \text{ or } \theta_3 \neq 0$, of a nonlinear model, they (2007) propose using the following model

$$W_T = \frac{RSS_1 - RSS_0}{RSS_0/T} \sim \chi^2(2). \tag{8}$$

It should be remarked that both the null and alternative hypothesis does not specify whether the underlying time series, y_t, is linear $I(0)$ or $I(1)$ and the nonlinearity is of an $I(0)$ or $I(1)$ form, respectively. Differently speaking, this test does not require a priori assumption for the integration order.

Harvey et al. (2008), on the other hand, propose a linearity test which also does not depend on the integration order, i.e., it can be applied either $I(0)$ or $I(1)$ processes. The test actually consists of a simple data-dependent weighted average of two Wald test statistics, which becomes efficient when the time series $I(0)$ for the first component and $I(1)$ for the second component. The weighted average Wald test statistic can be constructed as

$$W_\lambda = (1-\lambda)W_0 + \lambda W_1 \underset{d}{\rightarrow} \chi^2(2) \tag{9}$$

where W_0 and W_1 signify the Wald test statistics when the underlying series is stationary at the level and first difference. In Eq. (9), λ is some function that converges in probability to zero for a stationary variable at the level and to one for the series with a unit root at the level. To choose a suitable function for λ Harvey et al. (2008) suggest this functional form

$$\lambda(R,M) = exp\left(-k\left(\frac{R}{M}\right)^2\right) \tag{10}$$

where k is some finite positive constant while R and M represent properly chosen unit root and stationarity statistics. When the underlying data is stationary, as dictated by the authors (2008), $(R/M)^2$ diverges and λ converges to zero, and when the series $I(1)$, it converges to zero and λ converges to one, ensuring that both W_0 and W_1 chosen by W_λ are appropriate for the integration order.

The authors (2008) consider the possibility of more general autoregressive structures and offer using the DGP in the equation below

$$\Delta y_t = \lambda_1 \Delta y_{t-1} + \lambda_2 (\Delta y_{t-1})^2 + \lambda_3 (\Delta y_{t-1})^3 + \sum_{i=2}^{m} \lambda_{4,i} \Delta y_{t-i} + \epsilon_t \tag{11}$$

The corresponding Wald tests for $I(0)$ and $I(1)$ situations are given as

$$I(0) \rightarrow W_0 = T\left(\frac{RSS_0^r}{RSS_0^u} - 1\right) \quad \& \quad I(1) \rightarrow W_1 = T\left(\frac{RSS_1^r}{RSS_1^u} - 1\right) \tag{12}$$

where W_0 and W_1 follow an asymptotic $\chi^2(2)$ distribution under the null hypothesis.

2.3. Unit Root Test

In their most popular paper, Kapetanios et al. (2003) demonstrate that the exponential smooth transition autoregressive (ESTAR) model is given as

$$\Delta y_t = \Theta y_{t-1}(1 - exp\{-\varphi(y_{t-1} - \kappa)^2\}) + \varepsilon_t \tag{13}$$

where φ and κ are the smoothness and the location parameter, respectively. It should be noted that the location parameter, κ, presumed to be zero for their (2003) nonlinear unit root test, however, Kruse (2011) relaxes this restrictive assumption and considers the following modified ADF regression

$$\Delta y_t = \Theta y_{t-1}(1 - exp\{-\varphi(y_{t-1} - \kappa)^2\}) + \varepsilon_t \tag{14}$$

Following Kapetanios et al. (2003)'s definition, the author (2011) apply a first-order Taylor approximation $G(y_{t-1}; \varphi, \kappa) = (1 - exp\{-\varphi(y_{t-1} - \kappa)^2\})$ around $\varphi = 0$ and obtains the following regression

$$\Delta y_t = \alpha_3 y_{t-1} + \alpha_2 y_{t-1}^2 + \alpha_1 y_{t-1}^3 + u_t \tag{15}$$

The author (2011) imposes a zero restriction, i.e. $\alpha_3 = 0$, to improve the power of the test and suggest the following model

$$\Delta y_t = \alpha_2 y_{t-1}^2 + \alpha_1 y_{t-1}^3 + u_t \tag{16}$$

where $\alpha_2 = -2\kappa\varphi$ and $\alpha_1 = \Theta\varphi$. Kruse (2011) proposes a modified Wald type test based on the Hessian matrix for the unit root hypothesis $H_0: \alpha_1 = \alpha_2 = 0$ against globally stationary ESTAR process $H_1: \alpha_1 < 0, \alpha_2 \neq 0$

$$\tau = t^2_{\alpha_{\frac{1}{2}}} + 1(\hat{\alpha}_1 < 0)t^2_{\alpha_{1=0}} \tag{17}$$

It should be pointed out that the first summand is the squared t-statistic for the hypothesis $a_{1/2} = a_2 - a_1 v_{21}/v_{11} = 0$ with $a_{1/2}$ being orthogonal to a_1 while the second summand is the squared t-ratio for the hypothesis $a_1 = 0$.

2.4. Nishiyama et al. (2011) Nonlinear Causality Test

Nishiyama et al. (2011) suggest a nonparametric test that has power even when the observations are nonlinearly dependent. Their nonlinear causality test is restricted to the case when the underlying time series follows a stationary nonlinear AR process under the null hypothesis. For high-order nonlinear causality, they (2011) consider the following nonlinear dependence between time series

$$x_t = \theta(y_{t-1})\varepsilon_t + \delta(x_{t-1}) \tag{18}$$

where $\{y_t\}$ represents a stationary data, $\theta(\cdot)$ and $\delta(\cdot)$ denote unknown functions satisfying certain conditions for stationarity. Generally, y_{t-1} could be used to predict x_t^K where $K > 0$. The possible nonlinear causal linkage in the Kth moment is tested through the null hypothesis written in Eq. (19) against the alternative hypothesis given in Eq. (20).

$$E(x_t^K | x_{t-1}, \dots, x_1, y_{t-1}, \dots, y_1) = E(x_t^K | x_{t-1}, \dots, x_1)\, w.p.1 \tag{19}$$

$$E[x_t^K - E(x_t^K | x_{t-1}, \dots, x_1)]^2 > E[x_t^K - E(x_t^K | x_{t-1}, \dots, x_1, y_{t-1}, \dots, y_1)]^2 \tag{20}$$

where $w.p.1$ abbreviates to with probability one. For a nonlinear causality up to Kth moment is tested with the following null hypothesis

$$E(x_t^k | x_{t-1}, \dots, x_1, y_{t-1}, \dots, y_1) = E(x_t^k | x_{t-1}, \dots, x_1)\, w.p.1 \textit{ for all } k = 1, \dots, K. \tag{21}$$

With this definition, as denoted by the authors, a nonlinear causality up to the second moment relationship emerges for Eq. (18). When K is equal to 1, the test turns to be a noncausality test in mean. The authors (2011) assert that the test statistics can be straightforwardly constructed given the abovementioned definition. For our analysis, however, we employ the test for $k = 1$ and $k = 2$ to determine whether there exists nonlinear causality-in-mean and in the second moment, respectively.

3. Empirical Results and Discussion

Our empirical sample is composed of a set of financial variables including the two-year government bond yields, Bond, the 5-year credit default swaps for Turkey, CDS, Copper, Gold, and oil prices WTI and eleven sectoral indices including BIST100 (XU100), BIST30 (XU030), BIST Inf. Technology (XBLSM), BIST Leasing & Factoring (XFINK), BIST Food Beverage (XGIDA), BIST Corporate Governance (XKURY), BIST Sports (XSPOR), BIST Tourism (XTRZM), BIST Services (XUHIZ), BIST Industrials (XUSIN), and BIST Technology (XUTEK). The data covering the sample period September 20, 2010 and August 2, 2019 with a total of 2107 daily observations is derived from Energy Information Administration (EIA), the CBRT Bloomberg Terminal, and various websites. In the following empirical analysis, both the natural logarithms and compounded return of series are used.

Table 1 Harvey et al. (2008) Nonlinearity Test Results

Variable	W_λ	10%	5%	1%
LN_XU100	9.9999***	4.60	5.99	9.21
LN_XU030	7.8973**	4.60	5.99	9.21
LN_XBLSM	30.3592***	4.60	5.99	9.21
LN_XFINK	35.2724***	4.60	5.99	9.21
LN_XGIDA	11.0347***	4.60	5.99	9.21
LN_XKURY	5.7697*	4.60	5.99	9.21
LN_XSPOR	12.0998***	4.60	5.99	9.21
LN_XTRZM	6.5404**	4.60	5.99	9.21
LN_XUHIZ	14.2713***	4.60	5.99	9.21
LN_XUSIN	16.7972***	4.60	5.99	9.21
LN_XUTEK	9.9037***	4.60	5.99	9.21
LN_GOLD	30.7223***	4.60	5.99	9.21
LN_COPPER	17.5486***	4.60	5.99	9.21
LN_CDS	10.7195***	4.60	5.99	9.21
LN_BOND	8.069**	4.60	5.99	9.21
LN_WTI	20.2755***	4.60	5.99	9.21

Note: *, **, or *** indicate significant nonlinear dependencies at the 10%, 5%, or 1% significance levels, respectively.

Table 1 presents the findings of the W_λ linearity test statistic of Harvey et al. (2008). The results of W_λ linearity test reveal evidence against the null of linearity at different significance levels for all individual series, indicating that the null of linearity is strongly rejected in all cases, i.e. all variables are non-linear. We should, therefore, proceed by employing a nonlinear unit root test such as the Kruse (2011) for all variables since a linear unit root test may lack power if the true process is nonlinear.

Table 2 Kruse (2011) Nonlinear Unit Root Test Results

Variables	Lag	Case 1 (Raw)	Case 2 (Demeaned)	Case 3 (Detrended)
LN_XU100	[8, 8, 11]	2.9670	3.4620	14.092**
LN_XU030	[8, 8, 8]	2.7585	3.6348	13.6728**
LN_XBLSM	[21, 21, 21]	3.5016	2.9850	6.7860
LN_XFINK	[23, 23, 23]	1.8912	9.6995*	10.1230
LN_XGIDA	[11, 11, 11]	6.6699	11.3865**	15.3844**
LN_XKURY	[11, 11, 11]	3.3516	4.0149	15.6174**
LN_XSPOR	[24, 24, 24]	4.0951	2.3059	6.2368
LN_XTRZM	[18, 18, 18]	6.5233	9.519*	9.3282
LN_XUHIZ	[1, 1, 1]	2.8294	2.3368	6.5162
LN_XUSIN	[9, 9, 17]	3.5105	4.4679	13.9831**
LN_XUTEK	[23, 23, 23]	4.6878	5.3044	4.8850
LN_GOLD	[24, 24, 22]	7.4966	13.5664**	16.6769**
LN_COPPER	[24, 24, 24]	2.5215	20.3541***	11.9791*
LN_CDS	[22, 22, 22]	6.3370	9.3312*	16.3805**
LN_BOND	[23, 23, 23]	2.6042	7.5740	12.1858*
LN_WTI	[18, 16, 16]	3.1805	12.0786**	10.8547

Note: *, **, or *** indicate the rejection of the null hypothesis of unit root at the 10%, 5%, or 1% significance levels, respectively. The relevant critical values are 7.85 (10%), 9.53 (5%), 13.15 (1%) for Case 1; 8.60 (10%), 10.17 (5%), 13.75 (1%) for Case 2; 11.10 (1%), 12.82 (5%), and 17.10 (10%) for Case 3. Shaded area represents nonstationarity result.

Table 2 displays the results of the Kruse (2011) nonlinear unit root test for all variables applied on the raw data (case 1), the demeaned (case 2), and the detrended (case 3) series. Evidently, the null hypothesis of nonstationarity on the demeaned or detrended series could be rejected for all variables. However, a perusal of Table 2 reveals that the null hypothesis of a nonlinear unit root in all stock indices cannot be rejected for raw series. For the demeaned and detrended series, the null also cannot be rejected in favor of the alternative for nine out of eleven and seven out of eleven indices. Overall, our findings present empirical supports of nonstationarity for LN_XBLSM, LN_XSPOR, LN_XUHIZ, and LN_XUTEK, indicating that these indices are integrated of the first order[2].

[2] Results of the Kruse (2011) test for the first-difference of LN_XBLSM, LN_XSPOR, LN_XUHIZ, and LN_XUTEK are not reported here in order to conserve space.

Given that our variables are found to be stationary at the level or integrated of the first order, we should proceed by employing linear and nonlinear VAR causality modeling for the return series. The first test employed is the Hacker and Hatemi-J (2012) symmetric causality test, where the findings are reported in Table 3. It should be noted that the left side shows the causality results running from the index returns to the changes in financial variables while the reverse causality results are given on the right side. Using Hacker and Hatemi-J's (2012) test on the first differenced data as in Li et al. (2016, 679), we identify a bidirectional causal link between DL_Bond and DL_XU100, DL_XU030, DL_XKURY, DL_XUHIZ, and DL_XUSIN; between DL_CDS and DL_XSPOR; between DL_Copper and DL_XUSIN. A noteworthy finding of this study is that unidirectional causalities exist from DL_CDS and DL_Copper to DL_XKURY, indicating that lagged values of the differenced CDS and copper prices are useful for prediction in BIST Corporate Governance index returns. As expected and in common with most existing research for the emerging countries, DL_WTI is found to exert significant lagged impacts on the returns of DL_XGIDA and DL_XUSIN, whereas there seems to be no evidence for the reverse causal relationship. Furthermore, there is a strong one-way causal relationship running from DL_Gold to DL_XUHIZ at a 5% significance level and running from DL_XELKT to DL_Bond at a 1% significance level. Our results are consistent with the findings of Wongbangpo and Sharma (2002), who study the relationship in five ASEAN countries, and Aktaş and Akdağ (2013), who detect a two-way causal linkage between LN_XU100 and the deposit rates in Turkey.

Table 3 Hacker and Hatemi-J (2012) Symmetrical Causality Test Results

→Dependent.	DL_BOND		DL_CDS		DL_COPPER		DL_GOLD		DL_WTI	
↓Indpndt	W-Stat	Pval	W-Stat	Pval	W-Stat	Pval	W-Stat	Pval	W-Stat	Pval
DL_XU100	17.345 [1]	0	2.112 [1]	0.146	1.319 [1]	0.251	2.66 [2]	0.264	0.395 [1]	0.53
DL_XU030	19.087 [1]	0	2.684 [1]	0.101	1.102 [1]	0.294	2.783 [2]	0.249	0.433 [1]	0.511
DL_XBLSM	3.112 [2]	0.211	0.211 [1]	0.646	0.599 [1]	0.439	0.831 [2]	0.66	0.55 [1]	0.458
DL_XFINK	0.442 [1]	0.506	0.507 [1]	0.476	0.531 [1]	0.466	3.901 [2]	0.142	0.402 [1]	0.526
DL_XGIDA	0.844 [1]	0.358	1.517 [1]	0.218	0.872 [1]	0.35	1.261 [2]	0.532	0.28 [1]	0.596
DL_XKURY	13.701 [1]	0	1.519 [1]	0.218	1.311 [1]	0.252	2.901 [2]	0.234	0.058 [1]	0.81
DL_XSPOR	1.222 [2]	0.543	3.48 [1]	0.062	0.006 [1]	0.937	0.375 [2]	0.829	0.236 [1]	0.627
DL_XTRZM	0.92 [1]	0.338	0.001 [1]	0.97	0.249 [1]	0.617	1.116 [2]	0.572	0.014 [1]	0.906
DL_XUHIZ	8.337 [1]	0.004	0.802 [1]	0.371	0.314 [1]	0.575	2.39 [2]	0.303	0.396 [1]	0.529
DL_XUSIN	4.763 [1]	0.029	0.039 [1]	0.844	2.867 [1]	0.09	3.63 [2]	0.163	0.07 [1]	0.792
DL_XUTEK	3.394 [1]	0.065	0.003 [1]	0.96	0.116 [1]	0.734	3.077 [2]	0.215	1.192 [1]	0.275
→ Indpndt	DL_BOND		DL_CDS		DL_COPPER		DL_GOLD		DL_WTI	
↓Dependent	W-Stat	Pval	W-Stat	Pval	W-Stat	Pval	W-Stat	Pval	W-Stat	Pval
DL_XU100	9.006 [1]	0.003	17.488 [1]	0	1.636 [1]	0.201	0.924 [2]	0.63	0.631 [1]	0.427
DL_XU030	8.88 [1]	0.003	17.585 [1]	0	1.214 [1]	0.271	1.084 [2]	0.581	0.437 [1]	0.509
DL_XBLSM	8.566 [2]	0.014	0.298 [1]	0.585	0.079 [1]	0.779	3.687 [2]	0.158	0.002 [1]	0.962
DL_XFINK	0.024 [1]	0.878	0.592 [1]	0.442	3.547 [1]	0.06	3.261 [2]	0.196	0.452 [1]	0.501
DL_XGIDA	2.797 [1]	0.094	24.447 [1]	0	5.803 [1]	0.016	1.544 [2]	0.462	4.113 [1]	0.043
DL_XKURY	8.101 [1]	0.004	17.037 [1]	0	4.968 [1]	0.026	0.186 [2]	0.911	1.565 [1]	0.211
DL_XSPOR	5.924 [2]	0.052	3.999 [1]	0.046	0.774 [1]	0.379	2.587 [2]	0.274	0.741 [1]	0.389
DL_XTRZM	2.863 [1]	0.091	7.365 [1]	0.007	0.022 [1]	0.882	1.983 [2]	0.371	0.933 [1]	0.334
DL_XUHIZ	5.546 [1]	0.019	16.06 [1]	0	0.048 [1]	0.827	9.057 [2]	0.011	0.128 [1]	0.72
DL_XUSIN	2.977 [1]	0.084	12.659 [1]	0	18.411 [1]	0	0.297 [2]	0.862	7.764 [1]	0.005
DL_XUTEK	1.748 [1]	0.186	0.258 [1]	0.611	0.047 [1]	0.828	1.048 [2]	0.592	0.05 [1]	0.823

Note: Optimal lag length is provided in brackets [] and "Pval" denotes asymptotic Chi-Square p-value for each model. The relevant parameters are constructed as follows: kmax = 12*((2106/100)^0.25), bootsimmax = 5000, infocrit = 5 (HJC), maxlag = kmax, intorder = 0 (stationary variables).

Table 4 Nishiyama et al. (2011) Nonlinear Granger Causality Results for Raw Return Series

Dependent	DL_BOND		DL_CDS		DL_COPPER		DL_GOLD		DL_WTI	
Independent	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
DL_XU100	3.137	5.482	7.710	1.965	4.824	7.667	2.680	3.879	5.276	3.342
DL_XU030	3.108	5.416	7.429	2.054	5.543	6.607	3.158	4.609	3.647	2.979
DL_XBLSM	3.979	7.584	11.982	3.690	2.695	3.380	5.288	4.757	7.044	4.675
DL_XFINK	5.443	3.826	6.777	8.733	4.190	4.597	2.797	11.820	8.689	5.125
DL_XGIDA	5.818	7.602	6.580	1.955	3.485	2.628	9.217	5.197	6.371	0.963
DL_XKURY	4.666	5.512	5.285	5.196	7.066	4.656	2.240	3.600	5.220	7.720
DL_XSPOR	3.513	4.828	6.864	2.801	2.891	2.895	5.753	4.296	6.912	7.440
DL_XTRZM	2.167	7.025	9.840	7.062	5.732	6.216	5.807	2.077	6.743	3.750
DL_XUHIZ	2.974	6.027	9.004	1.686	2.721	9.381	4.655	1.847	5.911	8.149
DL_XUSIN	4.134	9.637	6.653	6.743	1.567	3.396	1.789	5.315	5.519	3.604
DL_XUTEK	4.525	5.625	6.431	8.944	3.258	3.052	7.344	6.825	5.419	9.188

Independent	DL_BOND		DL_CDS		DL_COPPER		DL_GOLD		DL_WTI	
Dependent	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
DL_XU100	19.393**	8.328	5.887	7.182	4.709	10.819	9.621	6.663	3.593	5.370
DL_XU030	17.534**	6.334	5.247	7.336	4.252	10.501	6.781	6.526	4.686	5.524
DL_XBLSM	11.294	11.75	9.777	5.441	5.949	8.987	4.541	2.205	1.384	3.346
DL_XFINK	8.634	9.913	1.955	5.889	5.812	11.636	2.794	6.317	5.272	1.816
DL_XGIDA	10.902	5.410	1.591	4.398	5.662	4.673	1.055	2.134	3.403	4.203
DL_XKURY	19.393**	2.960	6.787	9.835	7.909	10.569	7.582	6.521	4.472	6.076
DL_XSPOR	5.378	7.013	7.065	3.069	2.487	2.464	2.811	6.805	2.640	3.786
DL_XTRZM	6.947	6.402	8.722	5.145	2.235	4.181	7.940	3.104	2.143	3.920
DL_XUHIZ	11.788	9.575	5.073	6.208	2.443	6.310	5.389	8.312	5.375	8.610
DL_XUSIN	14.616**	7.979	5.242	11.504	5.639	12.096	6.238	5.930	3.856	8.492
DL_XUTEK	12.245	5.338	8.300	6.304	3.787	6.670	8.568	2.542	2.850	4.957

Note: ** denotes that the null hypothesis is rejected at the 5% significance level, in which the upper 5% critical value of 14.38 is calculated by a Monte Carlo simulation (Nishiyama et al., 2011). The shaded area represents insignificant causality. The upper panel reports causality-in-mean while the bottom panel presents causality-in-variance.

The empirical results of the Nishiyama et al. (2011) nonlinear causality results for raw series are shown in Table 4. It should be noted that the upper panel includes the causality results from index returns to changes in financial variables, whereas the reverse causality is reported in the bottom panel. Our test statistics in the upper panel are lower than the critical value of 14.38, leading to accepting the null of non-causality in the first and second moments at a 5% significance level for all variables. As documented in the bottom panel, on the other hand, we also fail to reject the null hypothesis of non-causality in the second moment for all cases; however, we identify bidirectional causality-in-mean from DL_Bond to DL_XU100, DL_XU030, DL_XKURY, and DL_XUSIN at 5% significance level. The results for the DL_Bond case are broadly in agreement with the findings documented by Alaganar and Bhar (2003) who find bidirectional causalities in mean and variance between Bank, Insurance, and Financial sectors and stock prices in G7 seven countries.

Tables 5 and 6 reports the results for the nonlinear Granger causality test proposed by Nishiyama et al. (2011) for the wavelet decomposed series. Each variable is decomposed into ten wavelet scales applying the MODWT with the Daubechies [LA(8)] wavelet filter through the R package waveslim introduced by Whitcher (2005). The sum of the first four scales, d1, d2, d3, and d4 corresponding to [2-32) daily period, signify the short-run; the scales of d5, d6, and d7 corresponding to [32-256) daily period, denote the medium-run and the last three levels, d8, d9, and d10 corresponding to [256-2048) daily period, represents the long-run. Combining the findings of the two tables, we observe a bidirectional nonlinear causality-in-mean and in the second moment between variables that suggest some form of feedback mechanism in the medium and long-run. Also, the results of the paper support the presence of unilateral nonlinear causality-in-mean from DL_Bond to DL_XU100, DL_XU030, and DL_XUSIN; from DL_Gold to DL_XU100 and one-way causality in the second moment from DL_XUTEK to DL_WTI in the short-run, indicating the contribution of the short, medium, and long-run nonlinear causalities to the overall causal relationship for variables as mentioned earlier. It can be concluded that the equity returns are a good indicator for predicting future movements in interest rates, CDS, copper, gold, and WTI prices while the reverse causality also holds in the short, medium, and long-run. Our wavelet-based findings are in line with the papers of Tiwari (2012) for India; Çifter and Özün (2008) for Turkey; and Moya-Martínez et al. (2015) for Spain who report bidirectional causal linkages for both the aggregate and industry levels. Further, the evidence reinforces the conclusion drawn by Wen et al. (2019), who report a linear and nonlinear significant relationship between the sectoral indices and WTI prices. The findings related to the DL_CDS case obtained by Şahin and Özkan (2018) and Yenice et al. (2019) and pertinent to the DL_Gold case reported by Jain and Biswal (2016) who employ both symmetric and asymmetric tests parallel our results.

According to the wavelet-based correlation results which not tabulated but available from the author on request, the correlation of the equity returns with the changes in bond yields DL_Bond is, as expected and in common in theory, significantly negative at all wavelet scales for all stock indices, except for the 8th scale for DL_XGIDA (insignificant) and DL_XTRZM (insignificant). Virtually similar estimations that are in common with existing theory and evidence are observed when DL_CDS is used instead of DL_Bond. Additionally, there seems to be an inverse relationship between DL_Gold and the equity returns at the coarsest scales. For example, the gold price fluctuations exhibit significantly negative impacts on DL_XFINK and DL_XSPOR at the first three levels of decomposition; on DL_XU100, DL_XU030, DL_XUHIZ, and DL_XUSIN at scales of d1, d2, d3, d4, and d5; on DL_XBLSM, DL_XKURY, DL_XTRZM, and DL_XUTEK in the short- and medium-term corresponding to [2-128) daily period. At the highest scales, however, the relationship is negative for all stock returns, albeit not significant. On the other hand, we find evidence of the effect of commodity prices, DL_Copper, being negative and statistically insignificant on DL_XU030 and DL_XUSIN at all levels of decomposition. Similarly, the movements in oil prices, DL_WTI, appear to be negatively and positively but statistically insignificant related to DL_XU100, DL_XU030, DL_XKURY, DL_XTRZM, and DL_XUSIN at all scales. We also find that the correlation between DL_XGIDA and DL_WTI is scale-dependent, indicating that the strength and direction of the relationship depend on the level of decomposition. At scale d1, the linkage between DL_WTI and DL_XGIDA is negatively weak and statistically insignificant, but it displays coefficient sign reversal from negative to positive beyond the first scale; however, it becomes statistically significant only at the lowest frequency, d8, from 1024 days to 2048 days. The findings of the wavelet-based correlation association confirm the fundamental and theoretical correlation between financial factors and stock prices. Our findings are corroborated by Flannery and James (1984) for the stock-bond relationship; by Faff and Brailsford (1999) for stock-oil connection; by Norden and Weber (2009) for stock-CDS linkage; by Eyüboğlu and Eyüboğlu (2016) for the stock-copper association and by Chkili (2016) for the stock-gold connection.

Likewise, the contemporaneous and wavelet correlation estimations among the financial variable growth rates are given in Figure **2**. The findings of the contemporaneous correlations show that all growth rates are significantly and positively related to each other at the strongest significance level of 1% (see the coefficients with the probability values at the left and bottom of each plot)[3].

[3] The findings of the unconditional correlation estimations, not presented for space consideration but available on request, showed that all financial variables are significantly (at the 1% significance level) positively related to each other.

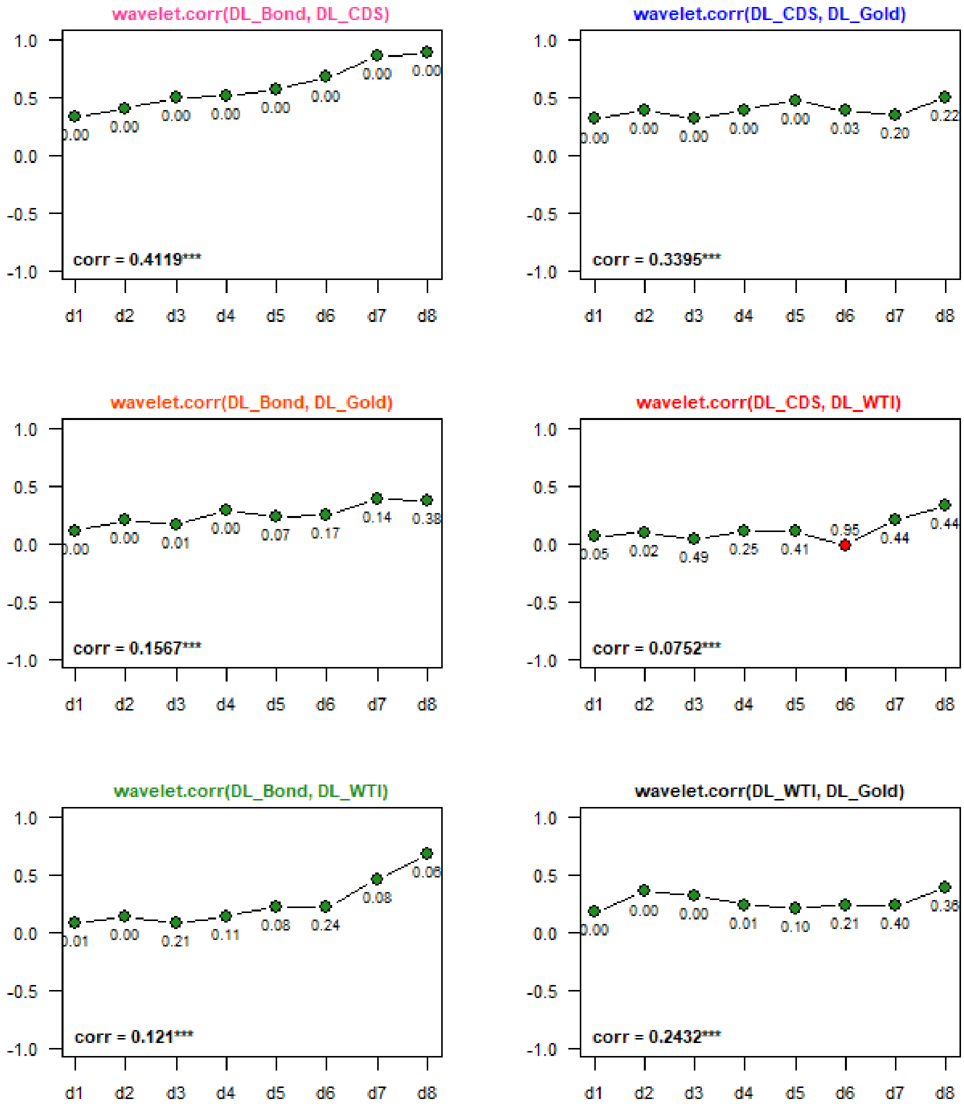

Figure 2 Wavelet Correlation Estimations

Not: Circles with green and with red indicate positive and negative correlation relationships, respectively. Further, the figures represent the probability values. The significance tests of wavelet correlations are performed with the Brainwaver R package (Achard, 2012).

Evidently, the findings of wavelet correlation estimations concur with the results from the contemporaneous correlations, suggesting that all associations among financial variables are positive but not significant at all time-scales, except for the pair of DL_Bond-DL_CDS. The strength of the return comovement between DL_Bond and DL_CDS, for example, is scale-dependent, that is, the correlation coefficient significantly increases from the finest (shortest) time scale (d1) corresponding to [2–4) daily periods to the coarsest (longest) time scale (d8) corresponding to [256–512) daily periods. Additionally, the results reveal a positive but significantly varying relationship among the other financial variables at all scales from 2 days to 512 days. For instance, DL_CDS has the lowest correlation with DL_WTI (7.5%) among financial variables, in which it is significantly positive at the lower [2–8 days) scales but stabilizes and becomes insignificant at the medium [8–64 days) scales, turn into a negative, albeit insignificant at scale d6 [8–64 days) and increases again insignificant at scales d7 and d8.

Table 5 Nishiyama et al. (2011) Nonlinear Granger Causality Results from Index Returns to Financial Variable Growth Rates by Wavelet Scale

	DL_Bond			DL_CDS			DL_COPPER			DL_GOLD			DL_WTI		
Mean	**Short**	**Medium**	**Long**	**Short**	**Medium**	**Long**	**Short**	**Medium**	**Long**	**Short**	**Medium**	**Long**	**Short**	**Medium**	**Long**
DL_XU100	3.520	610.031**	742.149**	8.625	623.476**	765.818**	6.190	600.734**	781.223**	4.530	615.767**	685.016**	5.623	594.294**	720.375**
DL_XU030	3.048	613.174**	738.513**	9.062	621.920**	749.102**	7.340	608.958**	818.441**	4.931	623.225**	683.809**	5.457	601.298**	717.153**
DL_XBLSM	3.453	638.990**	704.646**	7.089	665.577**	752.949**	4.958	635.753**	721.431**	3.642	640.047**	757.198**	11.921	619.724**	797.387**
DL_XFINK	3.002	605.339**	546.620**	9.807	601.078**	631.068**	3.691	607.148**	392.527**	4.071	610.816**	428.267**	4.484	576.624**	421.153**
DL_XGIDA	5.987	546.756**	722.346**	7.219	523.285**	722.811**	0.943	536.081**	669.643**	5.625	546.625**	692.390**	4.771	547.677**	509.976**
DL_XKURY	5.936	610.587**	733.995**	8.795	596.851**	786.688**	7.812	597.714**	702.863**	2.497	622.839**	684.587**	7.382	595.484**	702.727**
DL_XSPOR	5.952	662.188**	612.891**	3.229	654.466**	682.704**	7.456	677.894**	481.320**	5.408	678.560**	504.444**	6.031	659.015**	458.388**
DL_XTRZM	1.493	679.068**	532.514**	11.205	688.487**	574.970**	5.418	679.866**	615.039**	5.180	672.12**	574.497**	2.233	647.217**	458.956**
DL_XUHIZ	3.400	598.121**	763.115**	10.873	620.978**	784.222**	4.509	581.089**	685.739**	3.876	601.554**	720.561**	6.490	577.319**	633.210**
DL_XUSIN	2.539	619.695**	779.181**	8.154	602.724**	799.437**	2.213	597.805**	680.829**	2.025	617.451**	752.365**	5.832	587.140**	733.503**
DL_XUTEK	2.377	612.972**	731.052**	3.468	610.961**	692.000**	6.577	597.373**	663.052**	3.781	600.091**	737.401**	5.733	580.089**	752.886**

Variance	**Short**	**Medium**	**Long**	**Short**	**Medium**	**Long**	**Short**	**Medium**	**Long**	**Short**	**Medium**	**Long**	**Short**	**Medium**	**Long**
DL_XU100	3.024	371.309**	554.938**	6.770	367.844**	519.169**	4.029	289.554**	539.800**	6.964	284.178**	534.924**	5.392	294.731**	509.242**
DL_XU030	4.034	384.684**	594.69**	7.854	389.383**	513.387**	4.368	307.928**	490.327**	5.539	300.096**	572.96**	4.406	314.284**	455.226**
DL_XBLSM	5.459	440.509**	573.533**	4.037	509.669**	530.369**	7.206	400.062**	515.577**	6.171	388.724**	521.054**	3.810	401.639**	416.881**
DL_XFINK	4.753	355.172**	219.527**	3.192	391.853**	400.728**	5.316	326.482**	297.173**	8.620	334.591**	194.856**	5.603	355.175**	233.348**
DL_XGIDA	4.532	310.838**	367.829**	5.018	340.756**	261.764**	5.425	281.312**	257.343**	4.060	299.007**	247.742**	3.553	286.890**	282.170**
DL_XKURY	4.169	356.614**	499.093**	2.768	335.631**	511.857**	2.998	261.890**	492.423**	3.821	271.032**	474.923**	3.675	266.329**	506.135**
DL_XSPOR	1.492	461.989**	303.163**	6.899	530.100**	321.919**	5.001	460.428**	394.049**	3.626	460.619**	354.386**	6.055	463.771**	356.626**
DL_XTRZM	4.254	431.179**	349.191**	3.010	521.929**	291.816**	7.034	405.962**	369.283**	7.045	420.139**	202.375**	4.524	404.807**	347.390**
DL_XUHIZ	5.708	431.268**	452.695**	5.540	454.696**	537.678**	5.130	345.111**	393.076**	2.970	338.909**	407.723**	6.464	354.080**	427.614**
DL_XUSIN	5.179	345.442**	508.095**	2.809	383.599**	529.236**	3.538	245.023**	466.866**	1.815	287.703**	479.253**	4.670	279.122**	667.950**
DL_XUTEK	8.265	373.904**	504.891**	6.202	430.522**	481.832**	2.649	359.493**	580.288**	5.547	341.638**	463.582**	14.971**	329.456**	590.431**

Note: ** denotes that the null hypothesis is rejected at the 5% significance level, in which the upper 5% critical value of 14.38 is calculated by a Monte Carlo simulation. The shaded area represents insignificant causality results. The upper panel reports causality-in-mean while the bottom panel presents causality-in-variance.

Table 6 Nishiyama et al. (2011) Nonlinear Granger Causality Results from Financial Variable Growth Rates to Index Returns by Wavelet Scale

	DL_Bond			DL_CDS			DL_Copper			DL_Gold			DL_WTI		
Mean	**Short**	**Medium**	**Long**	**Short**	**Medium**	**Long**	**Short**	**Medium**	**Long**	**Short**	**Medium**	**Long**	**Short**	**Medium**	**Long**
DL_XU100	17.415**	661.807**	746.591**	9.664	728.447**	727.416**	9.217	630.715**	472.727**	15.965**	552.655**	633.62**	5.121	729.948**	667.376**
DL_XU030	14.893**	659.859**	757.509**	10.104	728.295**	735.254**	7.485	629.965**	469.943**	13.874	551.882**	650.256**	5.533	728.727**	667.873**
DL_XBLSM	6.758	667.861**	783.322**	11.191	740.190**	740.023**	2.247	638.358**	584.695**	1.701	565.643**	480.782**	1.787	724.306**	668.530**
DL_XFINK	12.636	614.151**	633.206**	10.536	689.383**	782.447**	2.381	590.269**	431.400**	5.917	530.324**	542.447**	6.093	645.580**	651.672**
DL_XGIDA	11.228	679.891**	700.395**	3.106	748.707**	719.195**	2.632	629.430**	558.994**	2.355	553.554**	614.556**	6.313	734.846**	614.707**
DL_XKURY	18.747**	665.289**	728.034**	7.475	730.454**	723.738**	13.741	634.113**	471.150**	10.772	550.927**	587.24**	4.839	729.846**	659.103**
DL_XSPOR	6.168	619.377**	670.240**	4.634	711.891**	731.288**	4.192	604.294**	592.289**	3.703	522.892**	525.061**	5.419	673.057**	612.023**
DL_XTRZM	6.614	660.888**	737.140**	6.671	741.318**	734.948**	3.883	620.830**	509.770**	7.315	547.406**	527.693**	3.136	716.135**	607.410**
DL_XUHIZ	13.519	668.333**	716.489**	9.719	734.978**	746.963**	5.617	624.565**	539.607**	10.074	555.261**	669.456**	5.861	732.080**	626.578**
DL_XUSIN	13.381	675.365**	719.775**	6.232	739.281**	738.606**	8.335	631.824**	438.496**	9.347	552.396**	535.298**	2.691	733.145**	623.476**
DL_XUTEK	6.609	660.949**	758.751**	9.951	723.643**	738.715**	4.525	622.600**	580.052**	11.013	546.955**	513.623**	6.025	719.471**	727.011**
Variance	**Short**	**Medium**	**Long**	**Short**	**Medium**	**Long**	**Short**	**Medium**	**Long**	**Short**	**Medium**	**Long**	**Short**	**Medium**	**Long**
DL_XU100	5.513	412.073**	474.551**	4.077	546.200**	501.953**	8.233	292.218**	210.439**	5.782	248.345**	261.54**	2.175	458.521**	311.183**
DL_XU030	3.637	413.992**	522.785**	4.172	547.822**	519.545**	8.365	292.210**	191.642**	5.528	246.836**	296.591**	2.351	455.927**	299.817**
DL_XBLSM	7.224	423.830**	597.663**	3.346	548.188**	683.146**	6.153	298.100**	197.002**	2.391	259.604**	348.180**	8.111	474.533**	416.366**
DL_XFINK	9.658	483.623**	439.775**	6.017	702.681**	464.181**	5.997	399.801**	285.317**	6.627	371.385**	201.033**	6.303	519.431**	306.513**
DL_XGIDA	3.589	406.063**	427.080**	4.016	551.067**	437.082**	3.142	298.850**	164.389**	3.967	253.935**	372.627**	3.805	459.933**	332.016**
DL_XKURY	6.027	410.092**	442.433**	3.503	551.749**	405.084**	6.174	292.333**	257.221**	6.088	256.048**	218.866**	3.920	466.011**	295.595**
DL_XSPOR	3.605	425.668**	506.467**	4.994	543.413**	528.781**	4.705	316.111**	193.293**	10.186	264.160**	440.199**	12.805	459.043**	294.639**
DL_XTRZM	4.729	422.371**	431.768**	2.152	569.092**	486.803**	2.593	301.026**	377.459**	3.091	256.396**	252.351**	6.501	458.955**	269.179**
DL_XUHIZ	6.375	410.815**	496.619**	5.955	552.083**	481.640**	8.551	295.036**	239.770**	9.058	245.717**	376.638**	5.478	463.589**	372.058**
DL_XUSIN	5.894	410.066**	435.554**	3.410	552.223**	449.516**	4.623	298.436**	213.152**	5.306	267.002**	252.973**	11.541	477.159**	337.583**
DL_XUTEK	6.231	400.995**	478.101**	2.622	545.982**	654.060**	1.353	308.221**	410.547**	1.555	252.644**	312.171**	4.960	456.342**	405.980**

Note: ** denotes that the null hypothesis is rejected at the 5% significance level, in which the upper 5% critical value of 14.38 is calculated by a Monte Carlo simulation. The shaded area represents an insignificant result. The upper panel reports causality-in-mean while the bottom panel presents causality-in-variance.

4. Conclusion

This paper undertakes an empirical effort to investigate the linear and nonlinear causal relationship between stock indices (BIST100, BIST30, BIST Inf. Technology, BIST Leasing Factoring, BIST Food Beverage, BIST Corporate Governance, BIST Sports, BIST Tourism, BIST Services, BIST Industrials, and BIST Technology) and financial variables (interest rates, CDS, copper, gold, and WTI) using daily closing prices over the 2010.09.20–2019.08.02 sample period. Since most of the time series may exhibit nonlinearity characteristics and, therefore, the results obtained by linear would be biased, we employ both the linear and nonlinear tests for the study.

The findings of Harvey et al. (2008) test statistics reject the null of linearity at any reasonable significance level. The results of the Kruse (2011) unit root test suggest that seven out of eleven financial variables are nonlinearly level stationary, whereas five out of eleven variables are integrated of the first order. Further, the null hypothesis is strongly rejected in favor of stationarity for all financial variables. Our findings of the Hacker and Hatemi-J (2012) test reveal bidirectional linear causalities between interest rate changes and BIST100, BIST30, BIST Corporate Governance, BIST Services, and BIST Industrials index returns; CDS changes and BIST Sports returns; copper prices in TRY and BIST Industrials index returns. The empirical findings of Nishiyama et al. (2011) suggest the rejection of non-causality-in-mean between interest rate changes and BIST100, BIST30, BIST Corporate Governance, and BIST Industrials index returns. Considering the investor's heterogeneities on investment periods, we also conduct a frequency-based causality test by wavelets. The nonlinear model supports a unidirectional causality-in-mean from the interest changes to the returns of BIST100, BIST30, and BIST Corporate Governance indices in the short, medium, and long-term, from 2 to 2048 days, whereas both bidirectional causalities in mean and in the second moments are detected for all cases in the medium [32-256 days) and long-term [256-2048 days). Lastly, the wavelet-based correlation results reveal that the financial variables are, in general, significantly positive at all wavelet scales but significantly negative related to the stock returns. Thus, our findings, overall, may provide significant implications for decision making by investors and policymakers.

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