



A Two-Stage Analysis of Interaction Between Stock and Exchange Rate Markets: Evidence from Turkey

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Abstract

In this study, we use a novel approach to explore possible connections between foreign exchange and stock returns using Turkish financial data from 2005 to 2022. Our method involves a two-stage technique. The first stage begins by decomposing individual time series signals into separate intrinsic mode functions (IMFs) with a complete ensemble empirical mode decomposition with added noise algorithm. Extracted IMFs are then used to construct high and low-frequency components through a fine-to-coarse algorithm. In the second phase, we utilized a cross-quantilogram technique to analyze the dependence in quantiles of the original return series along with frequency components obtained in the previous stage. Results revealed several important insights. Firstly, a relatively higher effect ran from stock returns to exchange rate returns for the pertinent period. Secondly, tail dependence is apparent, as returns are discernibly linked. Thirdly, the tail dependence in the returns is more profound in the high-frequency composition than in the low-frequency component. Lastly, the structure of dependence has stayed mostly constant throughout the sample period analyzed.

Keywords CEEMDAN · Cross-quantilogram · Borsa Istanbul · Turkish Lira

JEL Classification C49 · F31 · G15

1 Introduction

Giudici [1] defines data science as 'an integrated process that consists of a series of activities that go from the definition of the objectives of the analysis, to the selection and processing of the data to be analyzed, to the statistical modelling and summary

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such data and, finally, to the interpretation and evaluation of the obtained statistical measures'. This definition highlights the broad scope of the term 'data science', which encompasses a wide range of components, the application of which depends on the objectives of the analysis. For instance, data mining, a key component of data science often lacks a systematic exploration from the mathematical perspective [2]. To investigate the foundations and components of data science, a multidisciplinary effort is required [3]. Therefore, while sophisticated analytical methods offer refined measures, effective insights are drawn through interdisciplinary applications. The financial market, particularly, stock investment is one of the typical cases where complete and accurate data availability allows for the application of advanced analytical techniques [4]. Stock prices constitute a critical component of financial and risk management [5]. Despite being difficult to forecast [6, 7], financial asset prices, including returns, are challenging to model. While this empirical study focuses on analyzing emerging financial market data, the scalability and robustness of our applied methods could underscore their relevance to different components of data science such as statistics, data analysis, and even big data. For example, [8] identified correlational analysis as one of the major categories of big data analytics.

Since the 2001 economic crisis, the Turkish financial markets have experienced prolonged growth periods. The economic growth increased the investor's confidence and eventually led to overall stability regarding interest rates and inflation. Low investment risk was a key feature in leading the financial boom. For example, [9, 10] showed that investment and trading in Turkey increased during this period due to steady rates of interest, inflation, and currency along with stock market liberalization. However, the recent devaluation of the currency demonstrated the vulnerability of the overall economic structure [11]. Currency and stock markets in Turkey are interlocked in a way that makes it an interesting case study, particularly when one asset is experiencing a volatile period. Understanding the depths of interaction among financial markets is imperative. After evaluating modern literature, we can observe that researchers place the utmost value on the links between foreign exchange and stock markets. One of the reasons for putting this much importance on analyzing this phenomenon could be due to the critical economic consequences of the relationship [12]. For instance, to offset the risk associated with hedging portfolios, investors must understand the braided dynamics of these markets. If an increase in currency value denotes loss, a positive correlation between both markets may neutralize risk, whereas a negative correlation might amplify the risk associated with both variables [13]. The implications of the nexus are multi-fold. It provides insights not only to investors and portfolio managers but also helps policymakers to understand the financial perspective [14].

Numerous empirical studies have demonstrated a clear linkage between the two assets and axiomatically in their respective returns. However, since most studies analyze asset returns in their nominal values, raising a question of whether there is a difference in correlation that can be attributed to separate frequencies such as short-term and long-term fluctuations. How much do we understand about the connectivity in the tails of returns? Many papers explored the direction and strength of causality and correlation, but evidence on which frequency provides better explanatory power for directional predictability is scarce. Furthermore, how does this relation evolve when these markets experience calm and crisis periods? Any insights we can obtain from

answering these questions can be of great significance, especially towards hedging tail risk, which is often the most challenging part of portfolio management. Our empirical investigation aims at answering these questions.

Two frameworks can explain the connection between forex and stock markets: flow-oriented and stock-oriented. The flow-oriented approach presents the idea that exchange rate fluctuations will impact export competitiveness and the balance of trade. Due to this, profits and income will be affected, thereby shifting stock prices [15]. Also, [16] proposed that because of the exchange rate, stock market innovations affect aggregate demand through liquidity and wealth effects, hence inducing money demand and exchange rates. Another way of understanding it is by explaining the effect of exchange rates on both, that is, the international and the domestic operations of a company. Regarding overseas operations, exchange rates influence exports, imports, and assessments of assets and liabilities, whereas domestic operations are affected by competition and input/output prices. It affects the cash flows and profitability of a company, thereby influencing investors' assessment of stocks and inducing a change in the prices of stocks.¹ The stock-oriented approach suggests an effect flowing from stock prices toward exchange rates. In literature, this approach has two explanations: monetary models and portfolio balance models. Under a monetary-based model, financial asset prices absorb exchange rate effects. Asset prices obtained through discounting expected future cash flows and common macroeconomic factors may affect stock prices and exchange rate dynamics [19, 20]. Portfolio balance models suggest a negative relation between stock prices and exchange rates.² The inverse relationship can be viewed through direct and indirect channels [25]. To account for direct channels, consider an increase in domestic stock prices. Hence, it will encourage foreign investors to sell foreign assets in their portfolios and buy more domestic assets with domestic currency. Increased demand will appreciate the local currency. Indirect channel considers that a rise in the stock market will attract foreign investment, increasing net worth and domestic wealth. As demand for domestic goods increases, interest rates will have to be synced. Subsequently, an increase in interest rates will lead to higher demand for local currency and therefore, the currency will appreciate.

Even though the relationship between exchange rates and stock markets possesses a theoretical foundation, there is a lack of sufficient advanced analytical methods applied to this area [26]. In this study, we attempt to fill the gap in the literature by introducing a unique two-step approach and testing it on the Turkish Lira's USD/TRY exchange rate (TL hereafter) and Borsa Istanbul 100 (BIST hereafter) returns. In the first stage, we decompose the nominal returns into separate IMFs and residuals using a novel decomposition technique, Complete Ensemble Empirical Mode Decomposition with Added Noise (CEEMDAN). This step allowed us to differentiate between short and long-term timeframes. There are a few advantages of using this method over its preliminary versions.³ Firstly, it solves the problem of mode mixing that might appear in its predecessors. Secondly, it reduces the construction error and is computationally more efficient. After extracting IMFs from CEEMDAN, we applied a fine-to-coarse

¹ For details, readers are referred to [17, 18].

² For details, readers are referred to [21–24].

³ such as empirical mode decomposition (EMD) and ensemble empirical mode decomposition (EEMD).

algorithm to construct high and low-frequency components for the original time series. In the next step, we applied the cross-quantilogram (CQ) method, testing for possible dependence in conditional quantiles of returns' series. CQ works on the premise of permitting the analysis of quantiles through a regression-like framework. The main difference between quantile regression and CQ is that in a regression framework, only the quantile of the dependent variable gets checked for predictability through independent variable(s); whereas CQ measures predictability in the quantiles of both, that is, dependent and independent variables [27]. Moreover, using CQ allows us to consider long lags in contrast to regression, which is crucial to our research questions. Our contribution holds in the difference of approach that we apply here, thereby supplementing the present literature. Our method to analyze the relationship relies on a two-stage process presented in the next section. The two-step approach enabled us to analyze markets when returns are in extreme quantiles, that is when markets are experiencing bearish and bullish phases. Moreover, we were able to infer additional economic insights, like how this connection changes concerning short and long-term periods.

Ordering of the paper is as follows: Sect. 2 provides a brief overview of the current studies. Section 3 sets forth the methodology used in the analysis. Section 4 describes the data used in the analysis. Section 5 lists the estimation results and their summary. Section 6 presents the discussion, policy implications, and conclusion of the study.

2 Literature Review

In one of the earliest empirical studies on the connection between stock prices and exchange rate changes, [28] found no significant pattern of interaction between forex and the stock market. Despite this, their work inspired researchers to explore the relationship under different conditions. However, empirical evidence has been opaque. Agarwal [29] proposed a positive correlation between US stock and exchange rate markets; however, the relation was coincidental rather than predictive. Ma and Kao [30] concluded that foreign exchange rates have financial and economic effects on stock prices. The financial effect suggests that stronger currencies are associated with favorable stock prices, whereas the economic effect marks that currency appreciation will have a two-way impact on the stock markets of export-dominant and import-dominant countries. Jorion [31] found that the exchange rate risk for investors in the US stock market varies by industry, however, it is diversifiable. It can be noted here that their methodology rested on a rather strict assumption that exchange risk is constant, which is at odds with some other findings in the literature, such as [32], which identified the presence of nonzero conditional risk premia. As discussed in the previous section, two main theoretical models, that is, stock and flow-oriented approaches, have been examined to explain these empirical findings (see e.g., [33–37] among others).

Considering the Turkish context, several studies provide valuable insights into the interaction between these two markets. Tiryaki et al. [38] used NARDL analysis to show that an appreciation in the real rate of TL causes a decrease in stock index returns, which is in line with the flow-oriented theory. Altin [39] applied the Johansen cointegration test on daily closing prices of exchange rates and stock index for the

period 2001–2013 and found that the effect runs from forex to stock index, providing evidence of a clear long-term relationship between the two markets; however, it varies depending on the denominations of TL. Aydemir and Demirhan [40] analyzed the relation between TL and individual indices (technology, industry, financial, services, and national index) and proposed a significant presence of a bi-directional effect between the two markets. Other studies that explored the impact of Turkish foreign exchange rate movements on the firm and sector levels include [18, 41, 42]. Some studies incorporated additional information into the framework to uncover specific directional predictability. Aydin and Cavdar [43] applied VAR and ANN to monthly series of exchange rates, gold prices, and stock index for the period 2000–2017. Econometric forecasting obtained with ANN produced better results in comparison to VAR for predicting fluctuations in variables for the period 2015–2017. Likewise, [44] used the ARDL Bounds test and error correction model on quarterly data that included stock index, interest rate, portfolio investment flows, FDI flows, GDP, and oil price. GDP, exchange rate, portfolio inflows, and FDI had a positive impact on the stock market, whereas oil and interest rates affected it negatively. Recent advancements in econometrical approaches also contributed to novel analysis applied to this problem. He et al. [26] used a wavelet coherence approach on monthly exchange rates and stock index. Their results showed that the direction and strength of causality are different for time and frequency domains. Literature suggests that asymmetries exist in the connections between these two markets concerning time. It will be interesting to explore whether there exists a difference in linkage concerning different quantiles. The advantages of using a quantile-based framework can aid us in extracting useful economic interpretations. For example, when returns are in extreme quantiles, it reflects the bearish or bullish period within a market. Some studies have used a quantile framework to get insights into this phenomenon. Tekin and Hatipoğlu [45] used quantile regression on the Turkish stock market to test the effect of exchange rate and oil prices. Gokmenoglu et al. [46] applied quantile-on-quantile regression to study the nexus between stock prices and exchange rates for the selected emerging economies, including Turkey. Their findings suggest that stock prices are not uniformly affected by exchange rates across all quantiles. Most variation exists in tail quantiles, whereas heterogeneity among countries could be due to the openness of the economies. When the stock market is in a bearish state, the exchange rate's effect is more pronounced.

Based on the literature review, we can observe that numerous scholars have evaluated this relationship through alternative perspectives, but evidence varies due to the employed statistical approach, data, and timeframe used. Additionally, most studies have employed a one-dimensional approach that allows one to check for a static relation between the two markets. Existing empirical evidence suggests that asymmetries and heterogeneity in the relationship between these two markets exist, however, a small number of papers have looked into the linkage through the application of nonlinear and dynamic techniques. Moreover, fewer studies have inspected the financial markets for an analysis that captures the extreme ends of tail returns. Our adopted approach would aid us in distinguishing between the short and long-term effects of extraordinary times in each market, which may be extremely useful in formulating sophisticated hedging strategies. The variables employed in our study have a well-established theoretical and empirical foundation in the literature. The presence of a dynamic relation is clear,

but the extent of the linkage is vague. Even studies that found no long-run relation between these two markets, argued that there exists some predictive ability in each market that may facilitate in explaining the movements of the other market [35]. We aim to supplement current literature and fill in the gaps identified. To the best of our knowledge, this is the first study that employs this methodology on Turkish financial data.

3 Methodology

3.1 Complete Ensemble Empirical Mode Decomposition with Added Noise (CEEMDAN)

3.1.1 Empirical Mode Decomposition (EMD)

Based on the spirit of fourier transform, EMD method introduced by [47] is a nucleus of Hilbert Huang Transform (HHT). It plainly is a signal processing technique that decomposes a complex signal into finite functions known as Intrinsic Mode Functions (IMFs). These contain signals at different time scales. Consider $X(t)$ to be a signal with the following representation:

$$X(t) = \sum_{i=1}^n IMF_i(t) + \varepsilon_n(t) \quad (1)$$

where $\varepsilon_n(t)$ is extracted residual of the signal. EMD can be defined in the following steps:

1. Considering the signal $X(t)$ and its local extrema, lower and upper envelopes are found by fitting a cubic spline function.
2. Let $fm(t)$ be the local mean of the lower and upper envelopes, curve of this local mean and the difference between original signal and local mean are the first residue (ε_1) and IMF_1 , respectively.
3. Above steps are repeated, until the residue $\varepsilon(t)$ becomes a constant or monotonic function.

3.1.2 Ensemble Empirical Mode Decomposition (EEMD)

To counter the issue of mode mixing, [48] proposed adding Gaussian white noise to the original series and then performing EMD.⁴ Steps are given below:

1. Add noise component $n_j(t)$ to the signal $X(t)$.
2. Perform EMD to get IMF component $K_{i,j}(t)$ which is j^{th} component at the i^{th} time.
3. Repeat above steps for N times, by adding different noise each time.

⁴ It refers to the situation where an IMF contains the signals of another IMF.

4. After decomposing IMFs N times, resulting mean value is considered to be the final IMF:

$$K_j(t) = \frac{1}{N} \sum_{i=1}^N K_{i,j} \quad (i = 1, 2, \dots, N_j = 1, 2, \dots, K) \quad (2)$$

3.1.3 Complete Ensemble Empirical Mode Decomposition with Added Noise (CEEMDAN)

Torres et al. [49] proposed that EEMD could not eliminate the white noise error after computation and therefore put forward another method CEEMDAN. It follows following steps:

1. First IMF and residue is obtained as in EMD, then second IMF and corresponding residue is given by:

$$\begin{aligned} \overline{IMF_2}(t) &= \frac{1}{N} \sum_{i=1}^N E_1(\varepsilon_i(t) + \tau_1 E_1(w_i(t))) \\ \varepsilon_2(t) &= \varepsilon_1(t) - \overline{IMF_2}(t) \end{aligned} \quad (3)$$

where E_1 is IMF₁ and τ_1 is signal-to-noise ratio.

2. Similarly k^{th} IMF and ε_n can be taken as:

$$\begin{aligned} \overline{IMF_k}(t) &= \frac{1}{N} \sum_{i=1}^N E_1(\varepsilon_{n-1}(t) + \tau_{k-1} E_{k-1}(w_i(t))) \\ \varepsilon_k(t) &= \varepsilon_{k-1}(t) - \overline{IMF_k}(t) \end{aligned} \quad (4)$$

3. Above process carries on until ending criterion is met by residual ε_n . Finally, original signal can be obtained as:

$$X(t) = \sum_{i=1}^M \overline{IMF_i}(t) + \varepsilon(t) \quad (5)$$

where $\varepsilon(t)$ is the residual signal.

EEMD solves mode mixing issue that may emerge in EMD during signal processing. It resolves it by adding a white noise to the signal, however, during signal reconstruction, it cannot entirely eliminate the Gaussian noise, which may lead to spurious signals. CEEMDAN, on the other hand, effectively deals with mode mixing, reduces reconstruction error, and provides efficiency in calculation costs [50].

3.2 Fine-to-Coarse Algorithm

We followed [51, 52], and [53], among others, and used a fine-to-coarse algorithm to construct different components from IMFs. This algorithm basically composes

three components, high-frequency, low-frequency, and a long term trend. It works on the premise that the sum of the IMFs before the change point will form short term component, the sum of IMFs after the change point will form long term component, and the residual will be the trend component.⁵ Our process can be summarized in the following steps:

1. Keep adding $IMF_1(t)$ to $IMF_i(t)$ for each component except residual.
2. Perform Jarque-Bera test on each step.
3. Perform Wilcoxon rank sum test and check for which i the median departs significantly from 0.
4. Set i identified in step 3 as break point.
5. All IMFs until point i are considered as high frequency components, whereas rest of the IMFs are taken as low frequency element of the original signal.

3.3 Cross Quantilogram (CQ)

Han et al. [54] developed a method that measures cross quantile dependence of two time series. Let $\{y_{i,t}, t \in \mathbb{Z}\}$, $i = 1, 2$ be a bidimensional time series.⁶ We define $y_{1,t}$ and $y_{2,t}$ as TL and BIST returns, respectively. Denoting $F_i(\cdot)$ as the distribution function of $y_{i,t}$ having density function $f_i(\cdot)$, corresponding conditional quantile function can be represented as $q_i(B_i) = \inf\{v : F_i(v) \geq \beta_i\}$ for $\beta_i \in (0, 1)$. Range of quantiles we require is denoted by $\tilde{\beta}$, assuming $\tilde{\beta}$ is a Cartesian product of closed intervals $(0, 1)$ such that $\tilde{\beta} \equiv \tilde{\beta}_1 \times \tilde{\beta}_2$, where $\tilde{\beta}_i = [\beta_i, \bar{\beta}_i]$ for some $0 \leq \beta_i \leq \bar{\beta}_i \leq 1$.

For an arbitrary pair of quantiles, we consider a measure of serial dependence between two events $\{y_{1,t} \leq q_{1,t}(\beta_1)\}$ & $\{y_{2,t-k} \leq q_{2,t-k}(\beta_2)\}$. According to [54], $\{1[y_{i,t} \leq q_{i,t}[\cdot]]\}$ is called the quantile exceedance process or quantile-hit for $i = 1, 2$. CQ is simply the cross correlation of such processes and can be defined as:

$$\rho_{\beta}(k) = \frac{E[\Phi_{\beta_1}(y_{1,t} - q_{1,t}(\beta_1))\Phi_{\beta_2}(y_{2,t-k} - q_{2,t-k}(\beta_2))]}{\sqrt{E[\Phi_{\beta_1}^2(y_{1,t} - q_{1,t}(\beta_1))]} \sqrt{E[\Phi_{\beta_2}^2(y_{2,t-k} - q_{2,t-k}(\beta_2))]}} \quad (6)$$

for $k = 0, \pm 1, \pm 2, \dots$, where $\Phi_{\beta}(\mu) \equiv 1[\mu \leq 0] - a$.⁷ Unconditional quantile functions can be estimated by minimizing two separate problems: $\hat{q}_1(\beta_1) = \arg \min_{v_1 \in R} \sum_{t=1}^T \pi_{\beta_1}(y_1 - v_1)$ and $\hat{q}_2(\beta_2) = \arg \min_{v_2 \in R} \sum_{t=1}^T \pi_{\beta_2}(y_2 - v_2)$ where $\pi_{\beta}(\mu) \equiv \mu(\alpha - 1[\mu \leq 0])$. Sample cross quantilogram is given as:

$$\hat{\rho}_{\beta}(k) = \frac{\sum_{t=k+1}^T \Phi_{\beta_1}(y_{1,t} - \hat{q}_{1,t}(\beta_1))\Phi_{\beta_2}(y_{2,t-k} - \hat{q}_{2,t-k}(\beta_2))}{\sqrt{\sum_{t=k+1}^T \Phi_{\beta_1}^2(y_{1,t} - \hat{q}_{1,t}(\beta_1))} \sqrt{\sum_{t=k+1}^T \Phi_{\beta_2}^2(y_{2,t-k} - \hat{q}_{2,t-k}(\beta_2))}} \quad (7)$$

⁵ To construct separate components, we preferred Wilcoxon rank sum test over t-test used by [51] to overcome misspecifying normal distribution assumption of IMF sums.

⁶ The process requires both time series to be strictly stationary.

⁷ CQ is defined for a bivariate process. For the analysis of a single series, the process is simply quantilogram of [55].

Table 1 Summary statistics of daily log returns

	Mean	Sd	Min	Max	Skew	Kurt	J.B	ADF	PP
TL	0.06	1.10	-20.90	20.54	0.41	66.32	817,706***	-15.65***	-3905.70***
BIST	0.06	1.64	-11.06	12.13	-0.48	4.26	3537.70***	-15.21***	-4418.20***

This table presents summary statistics of daily log returns of TRY for the period January 2005 to October 2022, including mean (Mean), standard deviation (Sd), minimum (Min), maximum (Max), skewness (Skew), and kurtosis (Kurt), JB is Jarque-Bera statistic. ADF and PP are Augmented Dickey-Fuller and Phillips-Perron unit root tests, respectively

*** Significant at 1% level

for $k = 0, \pm 1, \pm 2, \dots$, $\hat{\Phi}_\beta(k) \in [-1, 1]$. Here we are interested in testing null hypothesis: $\hat{\Phi}_\beta(k) = 0$ (indicates no directional predictability) against alternative $\hat{\Phi}_\beta(k) \neq 0$ (corresponding to the presence of directional predictability). Han et al. [54] proposed a stationary bootstrap procedure to construct confidence interval bands around estimated values. In this paper, we opt for a Box-Ljung portmanteau test $\hat{Q}_\beta^p = T(T+2) \sum_{k=1}^p \hat{\Phi}_\beta^2(k)/(T-k)$.⁸

4 Data

Our data sample comprises closing prices of the USD/TRY exchange rate (TL) and the Borsa Istanbul 100 (BIST) index taken over the period January 2005 and October 2022.⁹ We follow [26, 39–41, 57, 58], among others, while choosing our variables for foreign exchange and stock markets. These variables correspond to daily closing values of domestic currency units against the U.S. dollar and daily closing values of the stock market's main index. We use daily log differences of closing prices as returns R_t .¹⁰ Nominal returns represent trading returns which are reflected through adjustments in information transfer between prices. These returns capture information transmission between the stock market and exchange rates, hence providing an explanatory and instant measure for trading profits or losses. According to [32], nominal returns assume that the dollar denominates the investor's consumption basket, which is not subject to parity risk. We report summary statistics and unit root tests for both returns in Table 1. While both series are non-normally distributed, ADF and PP tests suggest the absence of unit roots within both financial returns at levels. The correlation between the asset returns is plotted in Fig. 1. The top right panel shows the Pearson correlation coefficient along with test significance. Both asset returns move in an opposite direction with a moderate correlation. We conducted all our analysis using open source [59, 60] programming languages.

⁸ In practice, the Box-Ljung version is preferred due to its superior performance for a small sample and a large p [56].

⁹ For creating a matching sample for the two series, we removed missing dates so that both returns are synced.

¹⁰ $R_t = 100 * \log(P_t/P_{t-1})$, where P_t is the price at time t .

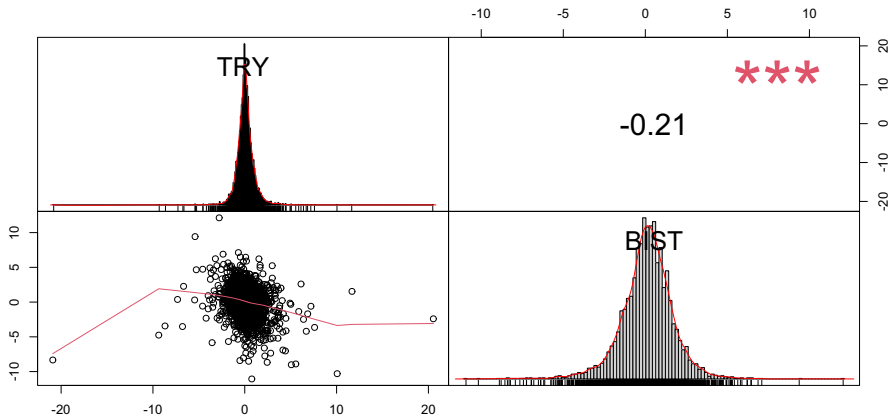


Fig. 1 This figure plots the correlation between TL returns and BIST returns for the period Jan, 2005 to Oct, 2022

5 Empirical Results

5.1 Decomposition Results

We first decomposed the original series using EMD, EEMD, and CEEMDAN. To compare the decomposition results among the three algorithms, we checked for correlation between log returns and individual IMFs. Results are reported in Table 2. While correlations between calculated and original signals are similar across the three methods, EEMD and CEEMDAN performed slightly better in comparison to EMD. One reason could be that the EMD is prone to mode mixing, that is, spurious signal generation in the presence of white noise. More specifically, estimates suggest that for most functions, CEEMDAN generated better results across both series. As can be observed, the correlations obtained using EEMD and CEEMDAN are close to each other. To further check for the aggregated effect, we computed the reconstruction error. According to this approach, the sum of all components is aggregated and then the difference between the aggregated sum and the original signal is computed. Mean values close to zero suggest better performance of the decomposition technique. For TL, the mean error of EEMD is -0.001 (standard deviation is 0.033 and the maximum value is 0.12), which is higher than CEEMDAN error of $7.9e-20$ (standard deviation is $1.7e-16$ and the maximum value is $1.8e-15$). For BIST returns, the mean error of EEMD is -0.0015 (standard deviation is 0.049 and the maximum value is 0.18), which is higher than CEEMDAN error of $-3.3e-19$ (standard deviation is $2.6e-16$ and the maximum value is $3.6e-15$).¹¹ Based on both diagnostic evaluations, we decided to proceed with our analysis using the CEEMDAN method.

¹¹ To conserve space, plots for reconstruction errors are not reported, however, they are available upon request from the corresponding author.

Table 2 Correlation results

	TL			BIST		
	EMD	EEMD	CEEMDAN	EMD	EEMD	CEEMDAN
IMF1	0.63	0.66	0.66	0.71	0.73	0.73
IMF2	0.46	0.54	0.48	0.41	0.5	0.44
IMF3	0.35	0.44	0.47	0.37	0.43	0.45
IMF4	0.24	0.31	0.36	0.23	0.31	0.39
IMF5	0.17	0.19	0.25	0.17	0.22	0.27
IMF6	0.14	0.16	0.18	0.13	0.17	0.20
IMF7	0.10	0.12	0.15	0.08	0.11	0.15
IMF8	0.06	0.07	0.10	0.06	0.09	0.10
IMF9	0.05	0.06	0.05	0.04	0.07	0.09
IMF10	0.04	0.01	0.04	0.02	0.03	0.06
IMF11	-0.01	0.02	0.02	0	-0.01	0.04
Residual	0.04	0.04	0.03	0.03	0.03	0.04

This table presents correlation coefficient estimates between decomposed components and returns of TL and BIST obtained through EMD, EEMD, and CEEMDAN techniques. Bold values show highest correlation among three techniques

With an ensemble size of 100, each member estimated contained additional white noise with a standard deviation of 0.3.¹² In Figs. 2 and 3, we plot IMFs extracted through signal processing. Frequencies with sharp fluctuations are apparent in initial functions but gradually smoothed into low amplitudes. The last frequency carries residue, which we have considered to be the long-term trend for financial returns. Statistics for IMFs of TL and BIST returns are given in Tables 3 and 4, respectively. We report the correlation between the original series and obtained IMFs with: Pearson's and Kendall's coefficients. Let us first consider FX returns. A highly significant correlation exists between IMFs and returns, with decreasing magnitude as we move towards higher IMFs. Variance as a sum of IMFs & residual reported in the last column is suggestive that the first three IMFs account for over 81% of the total variance. It highlights the importance of short-term fluctuations. If we observe stock returns, a similar pattern is clear. Correlation is gradually declining, from IMF 1 to IMF 11 though almost all values are significant. Like FX returns, the sum of the variance of the first 3 IMFs explains around 80% of the total variance. Hence, short-term fluctuations are crucial for stock returns as well. The shortest mean period for both assets is around 2.7 days.

5.2 Component Reconstruction Results

Following [52, 53], and [51], and as detailed in subsection 3.2, we use the fine-to-coarse algorithm to reconstruct high-frequency and low-frequency components from IMFs obtained previously. Table 5 reports estimation results. Jarque-Bera test results find

¹² In their original paper, [47] defined two conditions that an IMF must satisfy, our obtained functions fulfill both the conditions. For details, readers are referred to section 4 of their paper.

Table 3 IMF statistics for TL returns

	Mean period (days)	Pearson correlation	Kendall correlation	Variance as % of observed	Variance as % of (\sum IMFs + residual)
IMF1	2.71	0.66***	0.54***	51.13	56.34
IMF2	4.18	0.48***	0.33***	11.97	13.19
IMF3	5.51	0.47***	0.31***	10.77	11.87
IMF4	9.15	0.36***	0.25***	6.65	7.33
IMF5	17.21	0.25***	0.18***	4.10	4.52
IMF6	31.39	0.18***	0.12***	1.95	2.15
IMF7	57.88	0.15***	0.09***	1.85	2.04
IMF8	117.29	0.10***	0.08***	1.17	1.29
IMF9	247.61	0.05***	0.02**	0.51	0.56
IMF10	495.22	0.04**	0.03***	0.35	0.38
IMF11	891.40	0.02	0.02	0.15	0.17
Residual		0.03*	0.02**	0.14	0.15
Sum				90.74	100

This table presents IMF statistics of daily log returns of TRY for the period January 2005 to October 2022

***, **, * Significant at 1%, 5%, and 10% levels, respectively

Table 4 IMF statistics for BIST returns

	Mean period (days)	Pearson correlation	Kendall correlation	Variance as % of observed	Variance as % of (\sum IMFs + residual)
IMF1	2.74	0.73***	0.55***	53.44	63.09
IMF2	4.37	0.44***	0.31***	6.38	7.53
IMF3	5.91	0.45***	0.30***	7.36	8.68
IMF4	9.82	0.39***	0.25***	6.93	8.18
IMF5	18.12	0.27***	0.17***	4.12	4.87
IMF6	33.51	0.20***	0.12***	2.64	3.12
IMF7	65.54	0.15***	0.09***	1.94	2.29
IMF8	135.06	0.10***	0.06***	1.01	1.19
IMF9	278.56	0.09***	0.06***	0.59	0.70
IMF10	557.12	0.06***	0.04***	0.13	0.16
IMF11	1485.67	0.04***	0.03***	0.03	0.03
Residual		0.04***	0.03***	0.12	0.14
Sum				84.69	100

This table presents IMF statistics of daily log returns of BIST for the period January 2005 to October 2022

*** Significant at 1% level

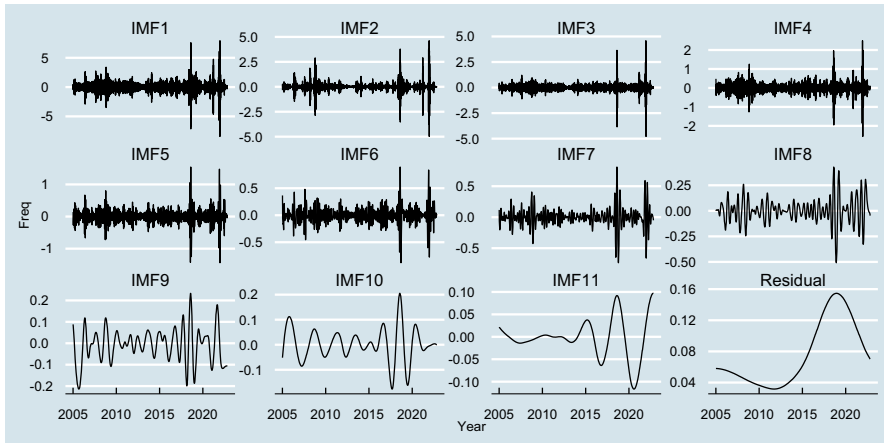


Fig. 2 This figure plots the TL returns decomposition with CEEMDAN for the period Jan, 2005 to Oct, 2022. Estimation is done by using an ensemble size of 100 and 0.3 standard deviation

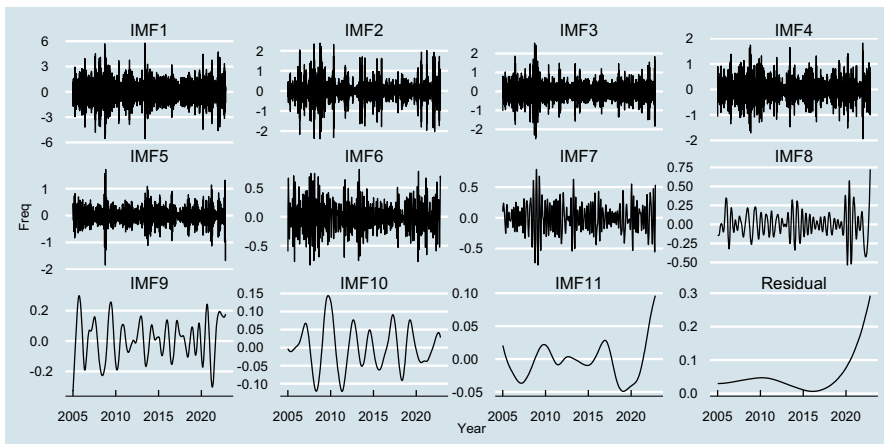


Fig. 3 This figure plots the BIST returns decomposition with CEEMDAN for the period Jan, 2005 to Oct, 2022. Estimation is done by using an ensemble size of 100 and 0.3 standard deviation

significant non-normality in IMFs of both asset returns. Then, we use the Wilcoxon rank sum test to identify the median departing significantly from zero. Test statistics for FX returns started to be statistically significant at acceptable levels from IMF 5 and onwards, whereas, in the case of stock returns, IMF 7 is the index i . Therefore, as high-frequency components, we use the sum of IMFs 1–4 for the exchange rate, and the sum of IMFs 1–6 for stock index returns. The sum of all remaining IMFs is used as a low-frequency component whereas, the residual is the long-term trend for both series. To show the phenomenon visually, we plot only last year's values containing the original series and estimated components in Figs. 4 and 5.

Table 5 Reconstruction results

	TL		BIST	
	J.B	W.R.S	J.B	W.R.S
IMF1	56,601 ^{***}	4,908,358	235.3 ^{***}	4,934,614
IMF2	213,397 ^{***}	4,911,613	1092.2 ^{***}	4,942,127
IMF3	369,735 ^{***}	4,865,335	1597.2 ^{***}	4,951,016
IMF4	469,496 ^{***}	4,872,272	2228.5 ^{***}	4,977,141
IMF5	553,915 ^{***}	4,818,902 [*]	2861 ^{***}	5,012,193
IMF6	628,932 ^{***}	4,783,081 ^{**}	3308.3 ^{***}	5,082,068
IMF7	720,730 ^{***}	4,745,892 ^{***}	3434.4 ^{***}	5,111,140 [*]
IMF8	765,083 ^{***}	4,756,035 ^{**}	3618.3 ^{***}	5,121,411 [*]
IMF9	784,430 ^{***}	4,644,915 ^{***}	3669.9 ^{***}	5,188,583 ^{**}
IMF10	805,114 ^{***}	4,647,780 ^{***}	3669.3 ^{***}	5,197,518 ^{***}
IMF11	811,537 ^{***}	4,620,697 ^{***}	3649.8 ^{***}	5,181,104 ^{**}

This table presents estimates for Jarque-Bera normality test (J.B.), and Wilcoxon Rank Sum test (W.R.S.) of TL and BIST returns. These values are used to reconstruct time series into short term and long term components

^{***}, ^{**}, ^{*} Significant at 1%, 5%, and 10% levels, respectively



Fig. 4 This figure graphs the TL return and components obtained after reconstruction of IMFs. This plot contains only last year of the complete data so to provide a 'zoomed in' version of the total sample

5.3 Directional Connectivity Results

For better comprehension, we present our results through CQ plots and heat maps. We subdivide this section into two parts. First, we present predictability directed from TL returns toward BIST returns for all components. In the second part, we provide the possible linkage moving in the opposite direction, i.e., from BIST to TL returns. We provide sample CQ $\hat{\rho}_\beta(k)$ and portmanteau test \hat{Q}_β^p for possible dependence in tails of both returns so that we'll be able to infer how extreme events impact returns

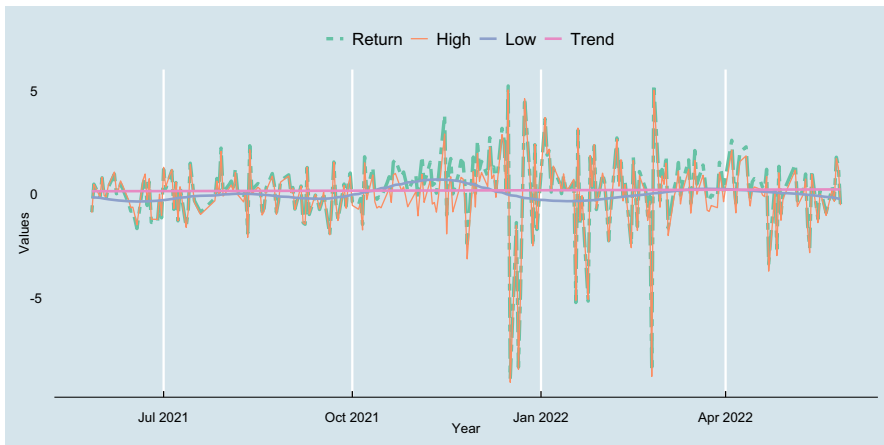


Fig. 5 This figure graphs the BIST return and components obtained after reconstruction of IMFs. This plot contains only last year of the complete data so to provide a 'zoomed in' version of the total sample

in the other market. Precisely, we consider $\beta_1 = 0.1, 0.9$ and $\beta_2 = 0.1, 0.9$ for the quantiles. We also checked for an effect on the median quantile, i.e., when $\beta = 0.5$ but, for brevity, results are not reported.¹³ To summarize the effect in median returns, significant directional predictability in both directions exists only in the first few lags of the low-frequency component.

5.3.1 Exchange Rate to Stock Index

In Fig. 6a-c, we plot predictability from the exchange rate to the stock index. We also show 95% confidence interval bootstrap values based on 1000 replicates testing the null hypothesis of no directional predictability. Consider the case when β_2 and $\beta_1 = 0.1$, CQ is not significant for many lags given through the portmanteau test for 60 lags. It means that high loss in TL failed to predict greater negative returns in BIST. When $\beta_1 = 0.9$, CQ is negative but mostly insignificant. This result suggests that high losses in TL returns do not facilitate significant prediction in tail returns of BIST. Figure 6b presents CQ when $\beta_2 = 0.9$. It shows significance but only in the initial lags. The implication is that when TL is higher than its 0.9 quantiles, there is a likelihood of a large loss in BIST returns within the first few days. For $\beta_1 = 0.9$, CQ is positive and significant for the initial lags implying that there is a chance of a high positive return in BIST when TL is in a high quantile. However, the magnitude of the correlation is not too strong. Figure 6c plots the CQ heatmap of directional predictability with one day lag for all quantiles. A star in the box means the significance of the portmanteau test. As noted before, even though there is some correlation, it may not be considered evidence of strong directional predictability.

In Fig. 7a-c, we plot the high-frequency component of the returns. The outcomes are very close to the results of the original series. There exists some dependence but

¹³ Results can be shared upon request from the corresponding author.

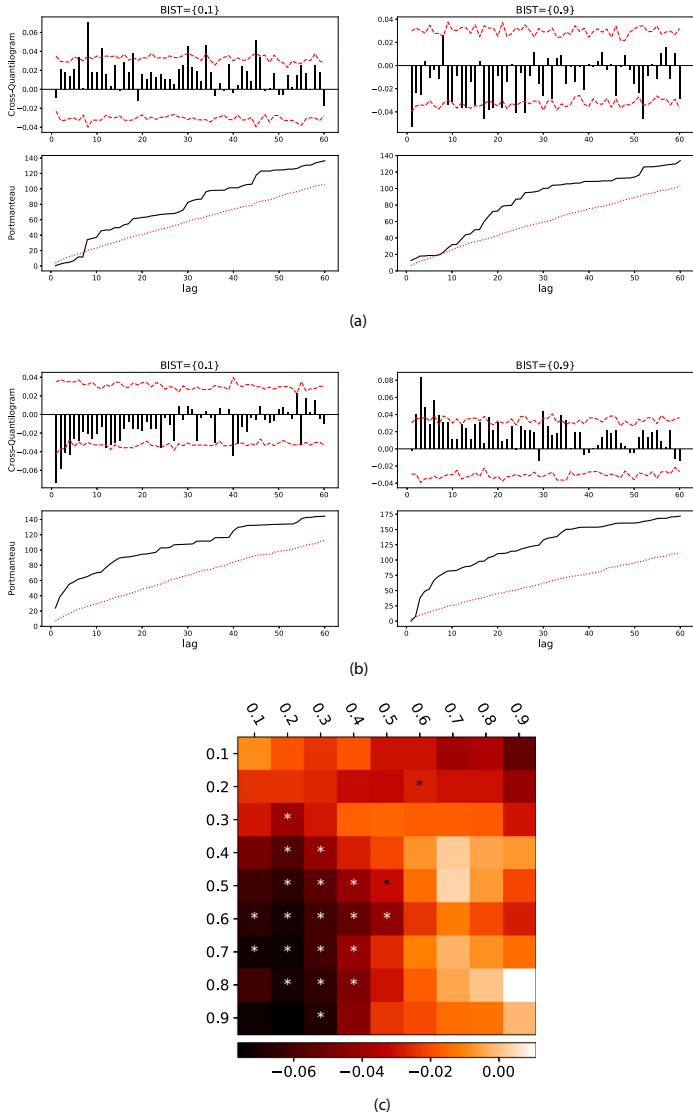


Fig. 6 Directional predictability from TL to BIST. **a** This subfigure presents the directional predictability from TL returns to BIST returns when $\hat{\rho}_\beta(k)$ for $\beta_2 = 0.1$. In first row plots, bars are sample cross quantilogram whereas \hat{Q}_β^P values are given in second row. Red lines are bootstrap values with 95% confidence interval centered at zero. **b** This subfigure presents the directional predictability from TL returns to BIST returns when $\hat{\rho}_\beta(k)$ for $\beta_2 = 0.9$. In first row plots, bars are sample cross quantilogram whereas \hat{Q}_β^P values are given in second row. Red lines are bootstrap values with 95% confidence interval centered at zero. **c** Heatmap of spillover from TL to BIST: This subfigure presents the heatmap for sample cross quantilogram at $(\beta_2, \beta_1) | (\beta_2, \beta_1) \in 0.1, \dots, 0.9$ and $k = 1$. It gives magnitude of spillover from TL returns to BIST returns with lag 1. The star means significance in test. Quantiles for BIST and TL are given in x-axis and y-axis, respectively. (Color figure online)

only in the first few lags and when TL is in a high quantile. It shows weak evidence of directional predictability. It is expected since the results obtained in the previous section showed that initial IMFs explain most of the variance present in the original series. When TL is lower than its 0.1 quantiles, the CQ is insignificant for the low-frequency component plotted in Fig. 8a–c. In addition to that, most of the lags are not significant when TL is in its quantile 0.9. It suggests that the tail returns of TL's low-frequency component do not help predict the tail returns of BIST's low-frequency component.

5.3.2 Stock Index to exchange rate

In Fig. 9a–c, we show estimation results of directional predictability of returns from BIST to TL. Figure 9a presents $q_1(\beta_1) = 0.1$, which is when BIST returns are in low quantile. When $\beta_2=0.1$, the CQ plot is positive and significant for most lags, implying that when BIST returns are negative, it is likely to have a high negative return in the TL market. Similarly, when $\beta_2 = 0.9$, CQ is negative and significant in most lags suggesting a large gain in TL returns. The portmanteau test confirms this relation. Figure 9b presents a scenario when $q_1(\beta_1) = 0.9$, which is when BIST returns are within a high quantile. Considering $\beta_2 = 0.1$, sample CQ is mainly negative and significant for some lags, providing evidence that there is a chance of having a high loss in TL returns. Likewise, when $\beta_2 = 0.9$, CQ bars are positive but mostly insignificant for almost all lags, suggesting a low likelihood of having a high positive gain. The heatmap given in Fig. 9c shows strong directional predictability in the returns from BIST to TL in almost all quantiles with one day lag. Another observation to note here is that, compared to the effect from TL to BIST, the correlation is relatively higher in most quantiles. Like the case with high-frequency dependability from TL to BIST, here we notice a similar pattern plotted in Fig. 10a–c. High-frequency component results are akin to the return series results. It implies that BIST tail returns in high frequency provide significant predictability for the tail returns of TL. However, the effect is not significantly strong for all lags. As far as low-frequency dependence is concerned, it does not provide significant connectivity from BIST to TL plotted in Fig. 11a–c.

5.4 Rolling Window Analysis

Based on the results that we obtained in the previous sections, it is quite evident that directional predictability is stronger from BIST to TL returns, and within components, the high-frequency component reveals more information compared to the low-frequency component. We decided to explore how this relationship has evolved over the period under analysis. For this purpose, we used a one-year rolling window analysis to check if any irregular movements may provide us with some further insights. Here we plot dependence in tails that is $\beta_1 = \beta_2 = 0.1, 0.9$ and $k = 1$ for the years 2005, ..., 2022. Considering returns in the lower tail, Fig. 12 shows that dependence was significantly high until around 2009, after which it mostly stayed constant throughout the whole sample under analysis. Moving towards the opposite direction, i.e., on the other side of the tail, we see that it has remained rather calm

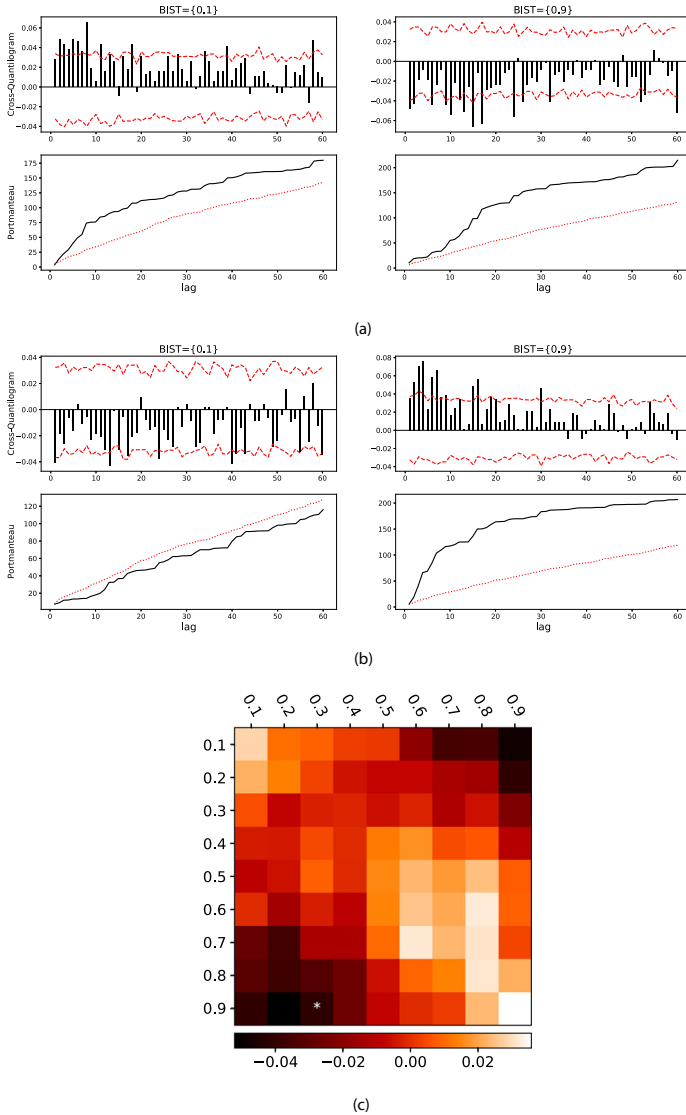


Fig. 7 Directional predictability from TL (high frequency) to BIST (high frequency). **a** Directional predictability from TL (high frequency) to BIST (high frequency) when $\hat{\rho}_\beta(k)$ for $\beta_2 = 0.1$: This subfigure presents the directional predictability from high frequency TL returns to high frequency BIST returns when $\hat{\rho}_\beta(k)$ for $\beta_2 = 0.1$. In first row plots, bars are sample cross quantilogram whereas \hat{Q}_β^p values are given in second row. Red lines are bootstrap values with 95% confidence interval centered at zero. **b** Directional predictability from TL (high frequency) to BIST (high frequency) when $\hat{\rho}_\beta(k)$ for $\beta_2 = 0.9$: This subfigure presents the directional predictability from high frequency TL returns to high frequency BIST returns when $\hat{\rho}_\beta(k)$ for $\beta_2 = 0.9$. In first row plots, bars are sample cross quantilogram whereas \hat{Q}_β^p values are given in second row. Red lines are bootstrap values with 95% confidence interval centered at zero. **c** Heatmap of spillover from TL (high frequency) to BIST (high frequency): This subfigure presents the heatmap for sample cross quantilogram at $(\beta_2, \beta_1) | (\beta_2, \beta_1) \in 0.1, \dots, 0.9$ and $k = 1$. It gives magnitude of spillover from high frequency TL returns to high frequency BIST returns with lag 1. The star means significance in test. Quantiles for BIST and TL are given in x-axis and y-axis, respectively. (Color figure online)

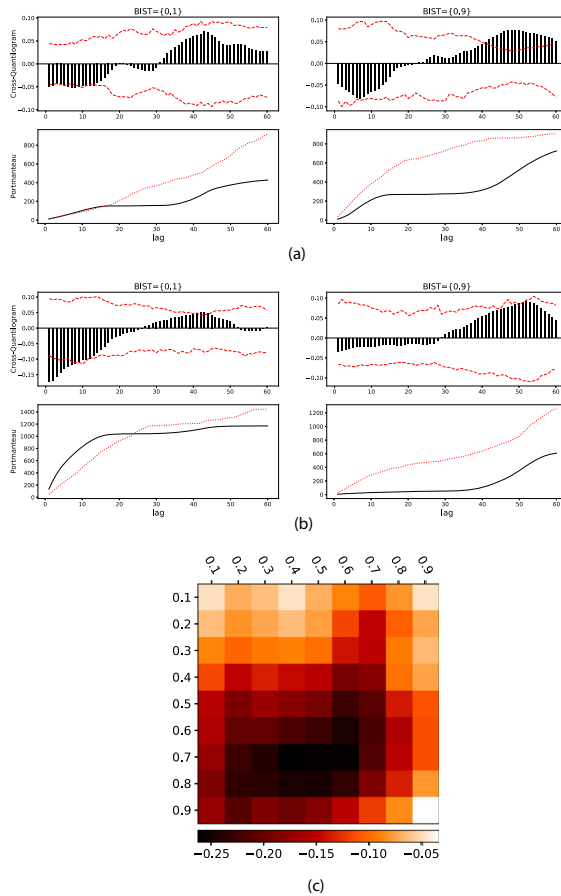


Fig. 8 Directional predictability from TL (low frequency) to BIST (low frequency). **a** Directional predictability from TL (low frequency) to BIST (low frequency) when $\hat{\rho}_\beta(k)$ for $\beta_2 = 0.1$: This subfigure presents the directional predictability from low frequency TL returns to low frequency BIST returns when $\hat{\rho}_\beta(k)$ for $\beta_2 = 0.1$. In first row plots, bars are sample cross quantilogram whereas \hat{Q}_β^P values are given in second row. Red lines are bootstrap values with 95% confidence interval centered at zero. **b** Directional predictability from TL (low frequency) to BIST (low frequency) when $\hat{\rho}_\beta(k)$ for $\beta_2 = 0.9$: This subfigure presents the directional predictability from low frequency TL returns to low frequency BIST returns when $\hat{\rho}_\beta(k)$ for $\beta_2 = 0.9$. In first row plots, bars are sample cross quantilogram whereas \hat{Q}_β^P values are given in second row. Red lines are bootstrap values with 95% confidence interval centered at zero. **c** Heatmap of spillover from TL (low frequency) to BIST (low frequency): This subfigure presents the heatmap for sample cross quantilogram at $(\beta_2, \beta_1) | (\beta_2, \beta_1) \in 0.1, \dots, 0.9$ and $k = 1$. It gives magnitude of spillover from low frequency TL returns to low frequency BIST returns with lag 1. The star means significance in test. Quantiles for BIST and TL are given in x-axis and y-axis, respectively. (Color figure online)

with no significant peaks and troughs; however, post-2020, it slightly increased but reverted towards its mean trajectory. This behavior can be accredited to the extreme jump in TL's nominal rate, gesturing to a weakening of the currency. A similar pattern is obvious for the high-frequency component of the returns plotted in Fig. 13.

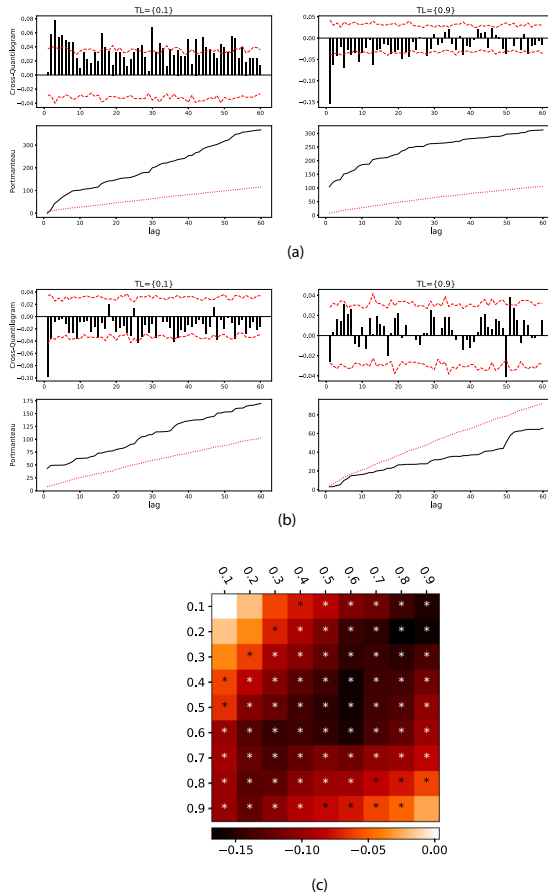


Fig. 9 Directional predictability from BIST to TL. **a** Directional predictability from BIST to TL when $\hat{\rho}_\beta(k)$ for $\beta_1 = 0.1$: This subfigure presents the directional predictability from BIST returns to TL returns when $\hat{\rho}_\beta(k)$ for $\beta_1 = 0.1$. In first row plots, bars are sample cross quantilogram whereas \hat{Q}_β^p values are given in second row. Red lines are bootstrap values with 95% confidence interval centered at zero. **b** Directional predictability from BIST to TL when $\hat{\rho}_\beta(k)$ for $\beta_1 = 0.9$: This subfigure presents the directional predictability from BIST returns to TL returns when $\hat{\rho}_\beta(k)$ for $\beta_1 = 0.9$. In first row plots, bars are sample cross quantilogram whereas \hat{Q}_β^p values are given in second row. Red lines are bootstrap values with 95% confidence interval centered at zero. **c** Heatmap of spillover from BIST to TL: This subfigure presents the heatmap for sample cross quantilogram at $(\beta_2, \beta_1) | (\beta_2, \beta_1) \in (0.1, \dots, 0.9)$ and $k = 1$. It gives magnitude of spillover from BIST returns to TL returns with lag 1. The star means significance in test. Quantiles for TL and BIST are given in x-axis and y-axis, respectively. (Color figure online)

5.5 Summary of the Empirical Evidence

Based on the empirical analysis, we can extract key insights into the questions raised earlier. The correlation between components varied noticeably, with the short-term frequency having a more profound effect. Tail connectivity is compelling in one direction, from stock returns to exchange rate returns. It could be considered as evidence

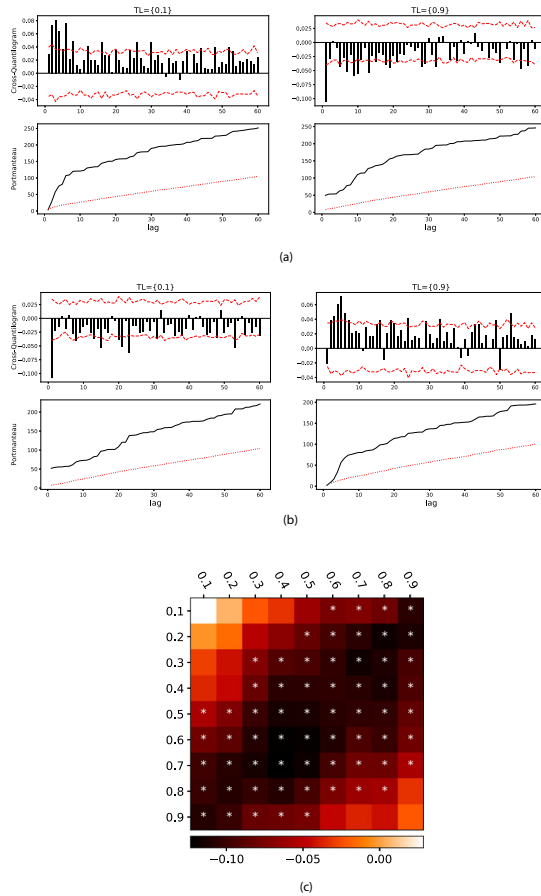


Fig. 10 Directional predictability from BIST (high frequency) to TL (high frequency). **a** Directional predictability from BIST (high frequency) to TL (high frequency) when $\hat{\rho}_\beta(k)$ for $\beta_1 = 0.1$: This subfigure presents the directional predictability from high frequency BIST returns to high frequency TL returns when $\hat{\rho}_\beta(k)$ for $\beta_1 = 0.1$. In first row plots, bars are sample cross quantilogram whereas \hat{Q}_β^p values are given in second row. Red lines are bootstrap values with 95% confidence interval centered at zero. **b** Directional predictability from BIST (high frequency) to TL (high frequency) when $\hat{\rho}_\beta(k)$ for $\beta_1 = 0.9$: This subfigure presents the directional predictability from high frequency BIST returns to high frequency TL returns when $\hat{\rho}_\beta(k)$ for $\beta_1 = 0.9$. In first row plots, bars are sample cross quantilogram whereas \hat{Q}_β^p values are given in second row. Red lines are bootstrap values with 95% confidence interval centered at zero. **c** Heatmap of spillover from BIST (high frequency) to TL (high frequency): This subfigure presents the heatmap for sample cross quantilogram at $(\beta_2, \beta_1) | (\beta_2, \beta_1) \in 0.1, \dots, 0.9$ and $k = 1$. It gives magnitude of spillover from high frequency BIST returns to high frequency TL returns with lag 1. The star means significance in test. Quantiles for TL and BIST are given in x-axis and y-axis, respectively. (Color figure online)

of asymmetry, heterogeneity, and to some extent, support for a stock-oriented effect highlighted in theoretical and empirical literature. Short-term frequency is crucial, especially if the purpose is to hedge tail risk between the Turkish stock returns and exchange rate returns. Connectivity became slightly higher during turbulent phases while the overall pattern of linkage stayed more or less constant. Our findings pro-

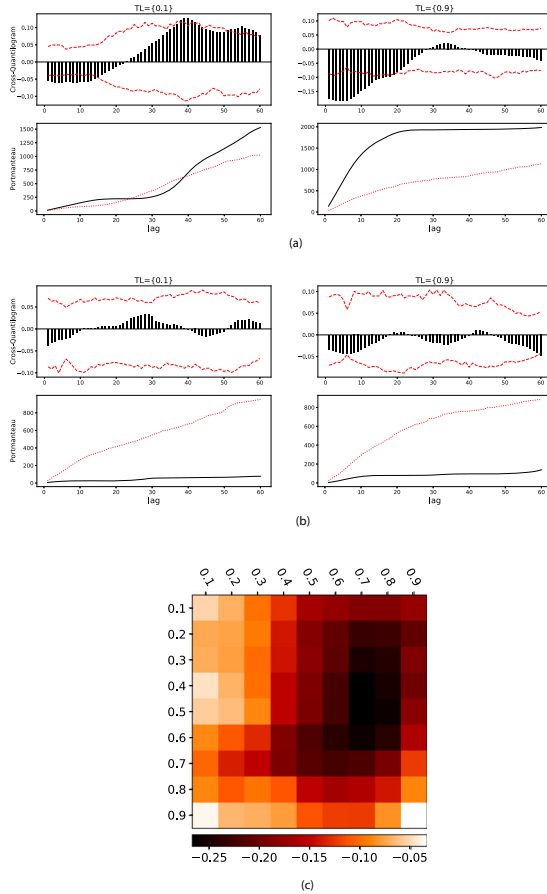


Fig. 11 Directional predictability from BIST (low frequency) to TL (low frequency). **a** Directional predictability from BIST (low frequency) to TL (low frequency) when $\hat{\rho}_\beta(k)$ for $\beta_1 = 0.1$: This subfigure presents the directional predictability from low frequency BIST returns to low frequency TL returns when $\hat{\rho}_\beta(k)$ for $\beta_1 = 0.1$. In first row plots, bars are sample cross quantilogram whereas \hat{Q}_β^P values are given in second row. Red lines are bootstrap values with 95% confidence interval centered at zero. **b** Directional predictability from BIST (low frequency) to TL (low frequency) when $\hat{\rho}_\beta(k)$ for $\beta_1 = 0.9$: This subfigure presents the directional predictability from low frequency BIST returns to low frequency TL returns when $\hat{\rho}_\beta(k)$ for $\beta_1 = 0.9$. In first row plots, bars are sample cross quantilogram whereas \hat{Q}_β^P values are given in second row. Red lines are bootstrap values with 95% confidence interval centered at zero. **c** Heatmap of spillover from BIST (low frequency) to TL (low frequency): This subfigure presents the heatmap for sample cross quantilogram at $(\beta_2, \beta_1) | (\beta_2, \beta_1) \in 0.1, \dots, 0.9$ and $k = 1$. It gives magnitude of spillover from low frequency TL returns to low frequency BIST returns with lag 1. The star means significance in test. Quantiles for BIST and TL are given in x-axis and y-axis, respectively. (Color figure online)

vide a unique perspective of information. It has meaningful economic interpretations critical to investors, hedgers, policymakers, practitioners, and market analysts.

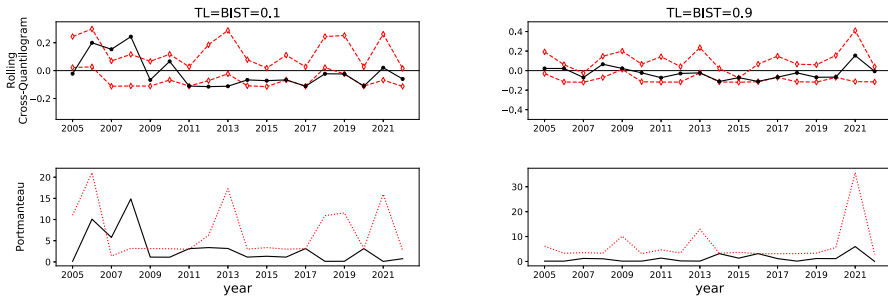


Fig. 12 This figure plots rolling window analysis for the effect from BIST returns to TL returns. In first row plots, black line is sample cross quantilegram over one year window with $k = 1$ whereas \hat{Q}_β^p values are given in second row. Red lines are bootstrap values with 95% confidence interval centered at zero. (Color figure online)

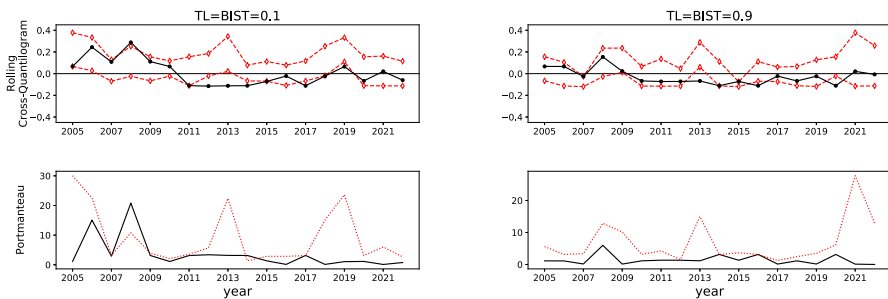


Fig. 13 This figure plots rolling window analysis for the effect from high frequency BIST returns to high frequency TL returns. In first row plots, black line is sample cross quantilegram over one year window with $k = 1$ whereas \hat{Q}_β^p values are given in second row. Red lines are bootstrap values with 95% confidence interval centered at zero. (Color figure online)

6 Discussions, Policy Implications, and Conclusion

In this study, we delved into the returns of the Turkish exchange rate and the stock market's main index through a two-stage process. In the first phase, we used the CEEMDAN algorithm to decompose individual nominal returns into separate IMFs and a residual. Then, we applied a fine-to-coarse algorithm aided by the Wilcoxon rank sum test to obtain high and low-frequency components of returns. Both these components could be interpreted as short-term and long-term fluctuations, respectively. In the second stage, we investigated tail connectivity between exchange rate and stock returns through a quantilegram, shedding light on market behavior during phases of significant gains or losses. Results suggest that in both markets, short-term fluctuations are comparatively more significant than long-term movements, having a mean period of almost three days. High loss in the currency market does not necessarily translate to a loss in the stock market. However, a high gain for investors in exchange rate returns may affect the stock returns for a short-term period. Alternatively, major losses or gains in the stock market will likely affect returns in the TL market for a shorter period. The low-frequency component (long-term dependence), shows little

significance in both directions. Rolling window analysis revealed that under turbulent phases such as 2008 and 2020, the correlation seemed to peak. This result is in line with [26], who suggested that during market distress, interaction becomes stronger.

Our analysis confirmed a few assertions in the literature while extending the line of empirical evidence. For example, [46] argued that exchange rates will not affect stock markets unless certain conditions are fulfilled. [37] and [40] proposed a bidirectional long-run causality between two markets which we could not confirm since our results provide evidence of a strong unidirectional link. A possible explanation for this result could be the difference in the approach employed. Our method specifically looked for connectivity within tail returns. While we found a strong correlation effect between returns, we argue that this effect varies concerning frequency and direction, similar to the findings of [26], who advocated the use of nonlinear and dynamic econometrical techniques. We also extend the notion put forward by [61] that between the stock and exchange rate markets of Turkey, an asymmetry exists in both, the short and long run. Our results also suggested different behavior of short-term and long-term components. As indicated by [52], the short-term component's attribution may be due to investor sentiments, and the long-term movements could be due to fundamentals such as supply and demand, interest rates, inflation, economic growth, and current account, among other variables. To some extent, we can conclude that our results partially support stock-oriented theory in the case of Turkish markets, as far as linkage in tail returns is concerned.

These results could be of great importance not only to policymakers but also to other market participants. For instance, our inference based on tail dependence existing between two return series could provide further insights into hedging behavior. It becomes critical, especially when markets are in their bearish or bullish state. Another implication from observing individual components is that market sentiment is of greater importance in determining the market prices than long-term fundamentals since it explains most of the variance out of the total variance observed. Even though low-frequency fluctuations moved in opposite directions, confirming the theoretical relation, we did not find it to be highly significant in the explanation of tail dependence. Finally, as far as directional predictability is concerned, BIST returns have relatively more influence on TL returns than the other way around.

Future work could incorporate additional causality methods to provide further evidence of dependence. In addition, since the technique employed in this paper only allows for a bi-directional relationship, which constrains the use of other economic variables, econometricians and data scientists could extend this method into higher domains, hence allowing the inclusion of additional market information into the analysis.

Author Contributions All authors contributed to the study conception and design.

Funding No funding was received for this study.

Data Availability We can provide the dataset upon reasonable request.

Code Availability We can provide the code upon reasonable request.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no Conflict of interest.

Ethics approval Not applicable

Consent to participate Not applicable

Consent for publication Not applicable

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