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Research paper

Unveiling Complex Market Dynamics: A Wavelet Coherence Study of Turkish Stock Price and Volume Interactions

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Abstract:
This study investigates the dynamic relationship between stock prices and trading volumes in Borsa İstanbul using the wavelet coherence approach. Employing daily data from major sectoral indices, the analysis captures both time- and frequency-domain interactions between price and volume movements. The methodology enables detection of multi-scale dependencies and shifting lead–lag dynamics across different market phases. The results reveal significant coherence during high-volatility periods, suggesting strong information transmission between price and trading activity. Moreover, the findings indicate that short-term fluctuations are primarily driven by speculative behavior, while long-term linkages reflect fundamental market adjustments. These insights contribute to a deeper understanding of market efficiency and investor behavior in emerging markets. The study provides empirical evidence useful for policymakers, traders, and researchers seeking to interpret complex market structures within a time–frequency framework.

Keywords: Wavelet coherence analysis, Turkish stock market, time-frequency analysis, trading volume, price-volume nexus
Classification: JEL Classifications: C22

1 Introduction

Financial markets are inherently complex systems characterized by dynamic and evolving relationships among various indicators. The interplay between stock trading volume and closing price has long been of particular interest to investors, analysts, and researchers. However, traditional analytical methods often fail to capture the nuanced, time-varying nature of this relationship across different investment horizons. This limitation has prompted the adoption of more sophisticated approaches such as wavelet-based techniques. Wavelet analysis enables the decomposition of time-series data into multiple frequency components, thereby allowing for a detailed examination of market dynamics. Through this approach, researchers can uncover hidden patterns and correlations that traditional time-domain methods may overlook, thereby providing valuable insights for trading strategies and

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risk management.

In the Turkish market, analysts have observed that certain sectors, such as banking and manufacturing, exhibit more pronounced volume-price relationships. This tendency can be attributed to the heightened sensitivity of these sectors to macroeconomic indicators and their significant weight in the BIST index. Additionally, recent years have witnessed a notable rise in algorithmic and high-frequency trading (HFT), which has introduced new complexities into the market dynamics. These trading strategies can significantly influence volume patterns and trigger short-term price movements that do not necessarily align with the fundamental values.

Empirical evidence further supports the material impact of algorithmic and high-frequency trading on the Turkish financial markets. Ekinci and Ersan (2020) [9] demonstrate that even in a relatively lightly exposed market such as Borsa Istanbul, HFT contributes to liquidity provision and affects volatility, although it does not always increase. Similarly, Çelik (2024) [5] found that HFT activity plays an important role in the formation of speculative bubbles, primarily through elevated trading volumes and rapid execution speeds, which magnify short-term price fluctuations.

These findings suggest that the volume-price relationship extends beyond a broad market and is also evident in high-frequency trading environments. The widespread use of algorithmic strategies combined with the sensitivity of certain sectors to economic signals implies that price movements may exert a leading influence on trading activity over shorter time horizons. This observation underscores the importance of analyzing the lead-lag relationships between price and volume. This lead-lag dynamic indicates that price changes in the stock market can precede corresponding shifts in trading volume in the options market, reinforcing the need for time-frequency domain analysis.

To better understand this intricate relationship, this study employs wavelet coherence analysis to examine the dynamic interactions between stock trading volume and closing price. Wavelet coherence analysis is particularly well suited for this purpose, as it allows for the simultaneous investigation of time and frequency dependencies between two time series. This study aims to identify periods of strong correlation, lead-lag structures, and potential causal interactions by applying wavelet coherence analysis to Turkish stock market data. This approach offers the ability to capture both short- and long-term co-movements, revealing patterns and dependencies that remain hidden under conventional time-domain methods.

The advantages of wavelet-based approaches have been well-documented in the literature. For example, Balcilar and Kayacan (2004) [3] applied wavelet multiresolution decomposition to the Istanbul stock price and volume series. Their findings suggest that, in the short term, a feedback mechanism exists between stock prices and trading volume. Conversely, in the long term, trading volume Granger causes stock prices. Consequently, these results offer a resolution to the long-standing debate on the direction of causation between stock prices and trading volume.

The findings of this study reveal two distinct phases in market behavior: (i) a trending phase characterized by a strong and stable relationship between volume and price and (ii) a consolidation phase in which this relationship weakens, increasing market uncertainty. By utilizing wavelet analysis, this study provides deeper insights into the evolving nature of financial markets and contributes to the development of more informed investment strategies and improved market forecasting.

The following sections cover the literature review and methodology, detail the findings from the wavelet coherence and power spectrum analyses, and explore the implications for market participants and financial economists.

2 Interplay of Trading Volume and Price Changes in Stock Markets

In the literature on the relationship between stock prices (or returns) and trading volume, researchers have applied a wide range of econometric methods to capture both short- and long-run dynamics as well as to account for possible asymmetries in the causal structure. Many studies on emerging markets, particularly Turkeys Borsa Istanbul (formerly ISE/IMKB), have relied heavily on Granger causality tests, while others have incorporated VAR-based frameworks, frequency-domain approaches, and asymmetric causality methodologies to refine earlier findings.

One of the most widely used approaches in this area is the Granger causality (GC) test. Elmas and Yıldırım (2010) [10] investigated the relationship between price and volume for the IMKB-BANK index, using session-based data for 2001, 2006, and 2008. Their findings showed unidirectional causality running from stock returns to trading volume, providing evidence for the positive feedback hypothesis in the Turkish market, suggesting that investors tend to behave rationally in line with this hypothesis. Similarly, Umutlu (2008) [19] analyzed the daily closing prices and trading volumes of the ISE National All Index over the 2002-2007 period. The Granger causality results indicate a unidirectional causal link between price and volume changes. Additional VAR analyses show that the past four daily price and volume values significantly affected future trading volume changes. Variance decomposition and impulse-response functions confirmed that price shocks had dynamic effects on trading volumes in subsequent periods. In another study, Kayalıdere and Aktaş (2009) [14] focused on stocks continuously listed in the ISE-30 and ISE-50 indices between 2001 and 2008. Using daily data, this study's findings highlight the non-uniform relationship between price and volume, reinforcing the Mixture of Distribution Hypothesis. Consequently, this study confirms a positive correlation between returns and volume. Complementing these findings, Yılmaz and Yerdelen Kaygın (2018) [23] examined the relationship between the closing prices and trading volumes of the BIST 30 (XU030) and DAX (GDAXI) indices using daily data from 17.05.2010 to 03.08.2017. A Granger Causality Analysis was employed to assess whether a connection exists between the indices' closing prices and trading volumes, and if such a connection is present, to determine its direction. As a result of the analysis, causality was detected from trading volume to closing price in the BIST 30 index, and from closing price to trading volume in the DAX 30 index.

Complementing these causality-focused studies, Gallant et al. (1992) [11] provide a different perspective by applying a semi-nonparametric density estimation approach to long-term U.S. data from the New York Stock Exchange (1928–1987). After adjusting for calendar effects and long-run trends, they identified four main patterns: trading volume is positively related to volatility, large price movements are followed by high volume, lagged volume reduces the leverage effect, and controlling for lagged volume reveals a positive risk-return relationship. Their work is among the earliest to move beyond linear causality tests, offering deeper insights into price-volume co-movements in a developed market.

Beyond the standard Granger framework, several studies have adopted VAR-based and VECM-type models to analyze this nexus. Zor et al. (2016) [24] examined how different levels of information asymmetry affect the price-volume relationship by comparing the BIST National Market with the Second National Market. Their VAR results show that in the National Market, causality runs from prices to volume, whereas in the Second National Market, the direction is reversed. This implies that the direction of information flow, whether from price to volume or from volume to price, depends on the degree of asymmetric information in the market. In a broader context, Tripathy (2011) [18] studies the Indian stock market using VAR, VECM, impulse-response functions, and Johansens cointegration test. The results suggest bidirectional causality between trading volume and stock return volatility, along with evidence of a long-run equilibrium relationship between the two variables. Variance decomposition further confirms the influential role of trading volume in explaining the stock return dynamics in India. Adhikari (2020) [1]) focused on the Nepalese stock market and employed a bivariate VAR and Granger causality test on a sample of 49 stocks traded on the Nepal Stock Exchange from 2011 to 2018. The overall findings show no significant causal relationship at the market-wide level. However, sectoral analysis revealed unidirectional causality from volume to returns in commercial banks, while in the finance, hydropower, and insurance sectors, causality ran from returns to volume. No causality was observed in other sectors, such as development banks or hotels, and, importantly, no evidence of bidirectional causality emerged in any sector.

More recent contributions have emphasized the need to capture the frequency domain and asymmetric causality dynamics, recognizing that the relationship between stock prices and trading volume may vary over different horizons or under different market conditions. Orhan and ltaş (2024) [16] investigated the BIST100 index for the period 2017–2021 using daily data. After confirming non-stationarity at levels with RALS-LM unit root tests, they applied Breitung and Candelons (2006) frequency-domain causality test. Their results revealed that stock prices Granger-cause trading volumes at the 1% and 5% significance levels in the medium and long term. Conversely, no causality was detected from volume to prices in the medium- or long-term, although a short-term causal effect from volume to price was found. Similarly, Yılancı and Bozoklu (2014) [22] highlight the importance of considering time-varying and asymmetric responses. Using a time-varying asymmetric causality test over the period 1990–2012, they demonstrated unidirectional causality running from components of trading volume to components of stock prices and further showed that this relationship changes over time, underscoring the dynamic nature of the price-volume nexus.

When comparing these different methodological strands, it becomes clear that while traditional Granger causality tests and VAR-based approaches have provided valuable insights into the direction and strength of the price-volume relationship, they are often limited in capturing the dynamic, nonlinear, and time-dependent nature of financial markets. Frequency-domain and asymmetric causality tests have moved the literature forward by recognizing that the direction and magnitude of causal effects may vary across horizons and market conditions. However, with the increasing availability of high-frequency financial data, wavelet coherence analysis has emerged as a powerful tool. Unlike conventional time-domain or frequency-domain tests, wavelet coherence allows for the simultaneous examination of both time and frequency dimensions, offering a localized view of how stock prices and trading volumes co-move and transmit information across different investment horizons. This is especially important in modern markets, where shocks can propagate quickly at high frequencies but may also have lingering effects at lower frequencies. Therefore, this research that incorporates wavelet-based methods is likely to offer a more comprehensive and nuanced understanding of the price-volume nexus, bridging the gap between short-term trading behavior and long-term market dynamics.

3 Methodology

3.1 Data

The total trading volume (ih) and XU100 closing prices (f) for the period from 02-01-1987 to 22-08-2025 were obtained from the Central Bank of the Republic of Turkey database. The historical trajectory of Turkey's stock exchange (XU100) from 1990 to 2025 is depicted in both price and trading volume charts (Figure 1 and 2). The most notable characteristic is the sustained long-term upward trend, with the index increasing from 1,000s to over 10,000. However, this overall upward trajectory was periodically disrupted by the significant fluctuations marked by profound crises. The abrupt decline in 1994, historic collapse during the 2000–2001 financial crises that eradicated nearly all previous gains, correction observed during the 2008 global crisis, and pronounced declines during the 2018 currency crisis represent the most significant turning points in this fluctuating trajectory. In particular, the massive, almost vertical rally that began after the sudden and alarming crash sparked by the 2020 pandemic has become one of the most turbulent periods in the stock markets history. Looking at the period after 2023, it is observed that the sharp rally has lost momentum and entered a consolidation (sideways movement) phase (Figure 1). The trading volume trajectory serves as an indicator

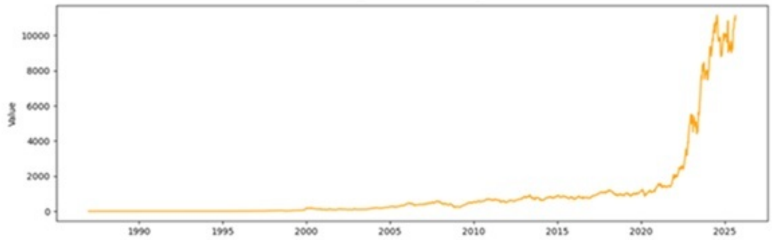

Figure 1: XU100 Closing Prices over Time

of the market's dynamics and the degree of investor enthusiasm. In contrast to price, volume exhibits a considerably more volatile pattern, and undergoes substantial fluctuations during pivotal market periods. Significant increases in trading volume are observed during the "panic selling" phases of the financial crises in 2001 and 2008, as well as during the expansion of the retail investor base in 2017-2018 and the periods of uncertainty induced by currency shocks. Notably, the most significant increase in volume was observed in the post-2020 period. This era represents a "quantitative leap," characterized by the influx of millions of new investors into the stock market driven by low interest rates. Consequently, market depth expanded, and trading volumes reached unprecedented levels. While the volume experienced a slight decline from these record levels during 2023-2025, it remains significantly above historical averages, suggesting that robust investor interest persists (Figure 2). Meaningful relationships emerged when we read these two graphs together. In

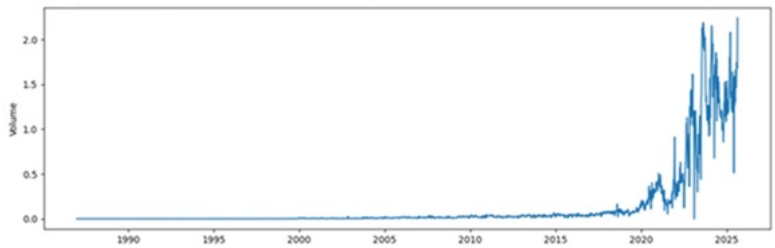

Figure 2: XU100 Trading Volume over Time

healthy upward trends (2003-2007 and 2020-2023), the increase in volume alongside the rise in price indicates broad participation in the upward trend and suggests that the trend is based on solid foundations. Conversely, when volume weakens when the price reaches new highs (as seen before 2018 and after 2023), it can be interpreted as a warning signal. Additionally, periods when prices fall rapidly and volume surges excessively (the lows of 2001 and 2020) usually indicate a ”panic selling” atmosphere and can signal that the market is approaching bottom levels. At this point, the importance of the unique perspective provided by wavelet coherence analysis becomes apparent. While traditional price and volume charts provide a historical account of market events, wavelet analysis offers insights into the cyclical forces operating at various time scales and assesses the statistical significance of these cycles. Therefore, in determining strategies for investors, it is crucial not only to consider price levels but also to understand which time period cycles are active and dominant, as this provides a significant advantage. Wavelet analysis is an indispensable tool for deciphering the complex structure of the market in its temporal and cyclical dimensions, allowing us to assess not only the direction of a trend, but also the strength and reliability of the underlying rhythms driving it. This makes it especially essential for timing opportunities and managing risk in markets such as the Turkish stock exchange, which exhibits both strong trends and high volatility.

3.2 Methodological process

This study employs a comprehensive and rigorous methodology to investigate the dynamics between the trading volume and closing prices in the Turkish stock market. The research process outlined in the flow chart above begins with the selection of variables and the collection of data on the total trading volume and the closing prices of the XU100 index (Figure 3). The subsequent data preprocessing stage is critical and involves operations such as handling missing values and standardizing the data using techniques such as standard scaler to ensure comparability. This process is essential because financial variables often operate at vastly different scales and magnitudes. Without standardization, a variable with a larger numerical range could disproportionately dominate the learning process of the model compared to a variable with a smaller range. This step is a fundamental prerequisite for building robust machine-learning models and conducting accurate multiscale signal processing. A key phase of the methodology is the suitability check for the time-series data. This involves applying unit root tests and the test of independence to assess nonlinear dependencies, which are essential prerequisites for a robust time-series analysis.

Financial time series often exhibit complex dynamics that cannot be adequately captured using conventional linear-detrending techniques. One of the main reasons is that the underlying relationships in financial and economic data are not stable over time; rather, they evolve due to structural changes, shocks, and varying market conditions. In other words, the dependencies embedded within such data shift across different time horizons, which requires a method capable of examining the dynamics at multiple scales. Wavelet analysis provides a natural framework for this purpose, as it allows for the decomposition of the original series into time-frequency components without losing temporal or spectral information. Using the

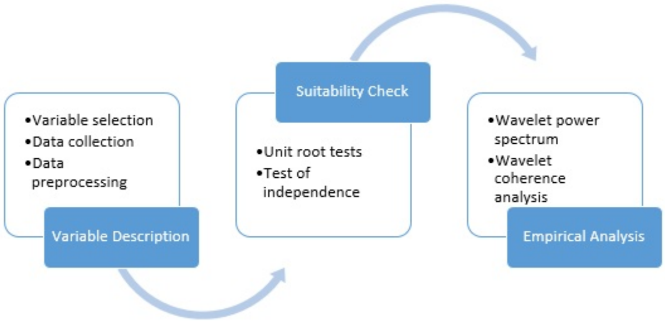

Figure 3: Research Process of The Study

scaling and translation properties of wavelet functions, the original series can be transformed into a sequence of components that represent long- and short-term fluctuations [13]. As emphasized by GenÇay et al. (2002) [12], the discrete wavelet transform (DWT) is particularly suitable for the analysis of economic and financial time series because it produces coefficients at all frequencies, making systematic statistical inference infeasible. In contrast, DWT provides an efficient multiscale decomposition that is computationally tractable and theoretically consistent with the properties of financial data. Let y_t denote the observed time series. Using the discrete wavelet transform (DWT) with a Daubechies-4 (db4) wavelet basis [6], the series can be expressed as in Equation(1):

$$y_t = \sum_k a_{J,k}\phi_{J,k}(t) + \sum_{j=1}^{J}\sum_k d_{j,k}\psi_{j,k}(t) \tag{1}$$

where $a_{J,k}$ are the approximation coefficients associated with the scaling functions $\phi_{J,k}(t)$ that capture the low-frequency trend and $d_{j,k}$ are detail coefficients associated with the wavelet functions $\psi_{j,k}(t)$ that capture short-run fluctuations [17]. The trend component is reconstructed from the approximation coefficients, and the residual process is obtained as in Equation(2):

$$\hat{\varepsilon}_t = y_t - \hat{T}_t \tag{2}$$

where $\hat{T}_t$ is the estimated low-frequency trend. Stationarity is then assessed by applying the augmented Dickey-Fuller (ADF) regression to the residuals in Equation(3) [8]:

$$\Delta\hat{\varepsilon}_t = \alpha + \gamma\hat{\varepsilon}_{t-1} + \sum_{i=1}^{p}\delta_i\Delta\hat{\varepsilon}_{t-i} + \hat{u}_t \tag{3}$$

where $\Delta\hat{\varepsilon}_t = \hat{\varepsilon}_t - \hat{\varepsilon}_{t-1}$, α is a constant, p denotes the chosen lag order, and $\hat{u}_t$ is a term of white noise error. The null hypothesis $H_0 : \gamma = 0$ corresponds to the presence of a unit root (non-stationarity), while the rejection of H_0 in favor of $H_1 : \gamma < 0$ implies the stationarity of the detrended series.

To complement unit root tests, the BDS test [4] was applied to residuals to detect non-linear dependencies that may persist, even after detrending and stationarity adjustments. The BDS statistic is constructed by comparing the empirical correlation integral of the series with that of an independently and identically distributed (i.i.d.) benchmark process. The rejection of the null hypothesis of i.i.d. behavior indicates the presence of a nonlinear structure in the data, which is especially relevant for financial and economic time series where complex dependence patterns are common.

The core of the empirical investigation utilized wavelet analysis techniques. Specifically, the wavelet power spectrum was used to identify the dominant cyclical patterns and evolution of variances within each series over time, while the wavelet coherence analysis was used to uncover the magnitude, phase and significance of the localized correlation between the two variables at different time frequencies. Let $\psi \in L^2(\mathbb{R})$; the wavelet is defined as in Equation (4). In this equation, τ represents the position parameter, which determines the wavelet's location, while s is the scale parameter that alters the wavelet's size. Additionally, the function $\psi(t)$, identified as the wavelet, must satisfy the zero-mean condition $\int_{-\infty}^{\infty} \psi(t)dt = 0$ and the unit energy condition $\int_{-\infty}^{\infty} \psi^2(t)dt = 1$.

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right) \tag{4}$$

The mother wavelet was defined as $\psi^*(\cdot)$ with time interval t, the continuous wavelet transform of $x(t) \in L^2(\mathbb{R})$ can be defined as in Equation (5). Here, $\psi^*(\cdot)$ is chosen from among wavelet functions with different properties depending on the intended use. In this study, the Morlet wavelet, defined as $\psi(t) = \pi^{-1/4}e^{-iw_0 t}e^{-w_0^2/2}$, which allows working on both amplitude and phase and is widely used in economic applications, was preferred [21]:

$$W_x(s,\tau) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{|s|}}\psi^*\left(\frac{t-\tau}{s}\right)dt \tag{5}$$

The energy conservation property of the continuous wavelet transform implies that the sum of the variances at each time scale is equal to the variance of the transformed original series [20]. The admissibility condition that allows for the reconstruction of the time series from its wavelet transform $\psi(f)$, is defined as $C_\psi = \int_0^\infty \frac{|\psi(f)|^2}{f}df < \infty$ where $\psi^*(\cdot)$ denotes the Fourier transform. With these conditions, the wavelet power spectrum, which shows the local variance of the series of interest in the time-frequency domain, is calculated as shown in Equation (6):

$$\|x\|^2 = \frac{1}{C_\psi}\int_0^\infty \left[\int_{-\infty}^{\infty} |W_x(s,\tau)|^2 du\right]\frac{ds}{s^2} \tag{6}$$

The wavelet power spectrum is a density map that shows how the energy distribution of a signal changes with time and frequency. Unlike the traditional Fourier spectrum, it reveals the local features of the signal owing to its ability to perform time-frequency analysis. The intensity on the color scale corresponds to the absolute squared values of the wavelet coefficients; red and white tones represent high power, while blue and dark tones indicate low power. The vertical axis displays the period (or frequency) values, and the horizontal axis represents time.

The co-movement of two series, $x(t)$ and $y(t)$ in the time-frequency domain was measured by wavelet coherence analysis. For wavelet coherence analysis, it is first necessary to calculate the cross-wavelet transform and power. The aforementioned cross-wavelet transform is calculated as in Equation (7). where $W_x(u,s)$ and $W_y^*(u,s)$ represent the continuous wavelet transforms of $x(t)$ and $y(t)$, respectively:

$$W_{xy}(u,s) = W_x(u,s)W_y^*(u,s) \tag{7}$$

The cross-wavelet transform, which can be defined as the local covariance in the time-frequency domain between two series, is calculated as $|W_{xy}(u,s)|$. In addition to the correlation between the two series in both the time and frequency dimensions, the measure of their co-movement is examined using the squared wavelet coherence ($R_n^2(s)$). Similar to the Pearson correlation coefficient, which ranges between 0 and 1. Because the theoretical distribution of wavelet coherence has not been derived, its statistical significance can be tested through Monte Carlo simulations [21]:

$$R_n^2(s) = \frac{|s(s^{-1}W_n^{xy}(s))|^2}{s|s^{-1}|W_n^x(s)|^2|s|s^{-1}|W_n^y(s)|^2|} \tag{8}$$

In wavelet coherence graphs, the phase difference, represented by arrows, conveys crucial information about the lag or synchronicity in the oscillations between the two time series. The phase itself is defined as a series position within its pseudo-cycle, and acts as a function of frequency. The color spectrum, which ranges from dark purple/blue (low coherence) to green and light yellow to bright yellow (high coherence), indicates the strength of the correlation, with bright yellow areas signifying a stronger relationship. The direction of the arrows provides a detailed interpretation of this relationship: arrows pointing to the right ($\rightarrow$ or $\nearrow$) signify a positive correlation, while arrows pointing to the left ($\leftarrow$ or $\nwarrow$) indicate a negative correlation. Furthermore, the vertical component of the arrow reveals a lead–lag structure. Specifically, an arrow pointing diagonally right and up ($\nearrow$) means that the first variable leads the second in a positive correlation (in-phase), whereas an arrow pointing diagonally right and down ($\searrow$) shows the second variable leading the first, also with a positive correlation. Conversely, an arrow pointing diagonally left and down ($\swarrow$) indicates the first variable leads the second in a negative correlation (anti-phase), and an arrow pointing left and up ($\nwarrow$) shows the second variable leading the first under a negative correlation. Arrows pointing purely to the left, right, up, or down suggest no clear causal relationship between the two variables at that specific time and frequency.

Finally, the empirical analysis synthesizes these findings to draw meaningful conclusions about the multiscale relationship between trading volumes and stock prices.

4 Data and Empirical Analysis

To investigate the stationarity properties of the series, unit root tests including the Augmented Dickey-Fuller (ADF), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Wavelet-Detrended ADF tests were applied (Table 1).

Table 1: Unit Root Test Results

Test	**Variable**	**Test Statistic**
ADF	ih	2.9444
ADF	f	4.6112
KPSS	ih	2.6141
KPSS	f	2.7715
Wavelet-Detrended ADF	ih	-8.1533***
Wavelet-Detrended ADF	f	-3.6966***

Note: *** indicates significance at the 1% level.

The results of unit root tests indicate that both the trading volume (ih) and closing price (f) series are non-stationary in their raw forms, as evidenced by the insignificant ADF statistics and significant KPSS values. However, when the series are detrended using the Wavelet-Detrended ADF approach, both become stationary at conventional significance levels. This finding suggests that the non-stationarity observed in the original series primarily stems from smooth structural components or long-term trends rather than stochastic unit roots.

Finally, the Brock-Dechert-Scheinkman (BDS) test was employed to examine independence and linearity. The BDS test results, which are shown in Table 2, reject the null hypothesis of i.i.d. behavior, implying the presence of nonlinearity and dependence structures in both trading volume and index returns. Overall, the evidence shows that while the raw series are nonstationary, wavelet detrending reveals stationarity, and nonlinear dynamics appear to characterize both variables (Table 2).

Table 2: BDS Test Results

Dimension (m)	**2**	**3**	**4**	**5**	**6**
ih	48.1199***	47.5718***	46.2983***	45.6380***	45.5849***
f	51.9078***	49.9020***	48.0952***	47.1534***	46.9181***

Note: *** indicates significance at the 1% level.

The continuous wavelet transform (CWT) power spectrum of the variables was examined, and the results are shown in Figure 4. In the case of trading volume (ih), the spectrum reveals a pronounced concentration of power between 1994 and 2008 (approximately between 500 and 1500 time units). This period corresponds to an era of high inflation, financial liberalization, and structural changes in the Turkish banking sector. The 1994 financial crisis, 2000–2001 banking crisis, and 2008 global financial crisis are visible as sudden increases in trading activity, represented by red/yellow bands in the spectrum. After 2010, the power distribution shifted toward lower periods and became more homogeneous, indicating a relatively stable phase in the market.

For closing prices (f), the spectrum shows a different pattern compared to the trading volume. In the early 2000s (around time units 1000–1200), short-period, high-volatility dynamics dominated, whereas in the 2010–2020 period, longer-period power concentration became more evident. This suggests that during the era of abundant global liquidity, BIST displayed more trend-following behavior. In the post-2020 period (1800–2000), increasing power across both short and long periods reflects heightened uncertainty and volatility following the COVID-19 pandemic. In both spectra, the structural breaks caused by the 2001 and 2008 crises were clearly identifiable as vertical energy bands. Wavelet coherence analysis was conducted following the CWT power spectrum, and the results are presented in Figure 5.This analysis reveals a dynamic and shifting relationship between trading volume and price that can be broadly divided into three distinct market regimes. In the first period, spanning approximately time index 0–200, the immediate aftermath of the 1994 Banking Crisis is characterized by a pronounced dark red band at 4–8 day periods, indicating exceptionally strong short- and medium-term synchronizations between trading volume and price. Arrows pointing primarily to the right (→)signify a positive correlation, whereas a slight downward tilt (↓) suggests that volume leads to price. This environment, marked by high uncertainty but emerging directional consensus, saw elevated trading volumes reinforcing price movements, reflecting typical trend market behavior.

In the second period, from a time index of 200 onward, coherence decreases noticeably, particularly in short- and medium-term periods (0.2–0.6), as indicated by the prevalence of blue regions in the plot. This interval coincides with multiple systemic and political shocks, including the 2001 Financial Crisis, 2008 Global

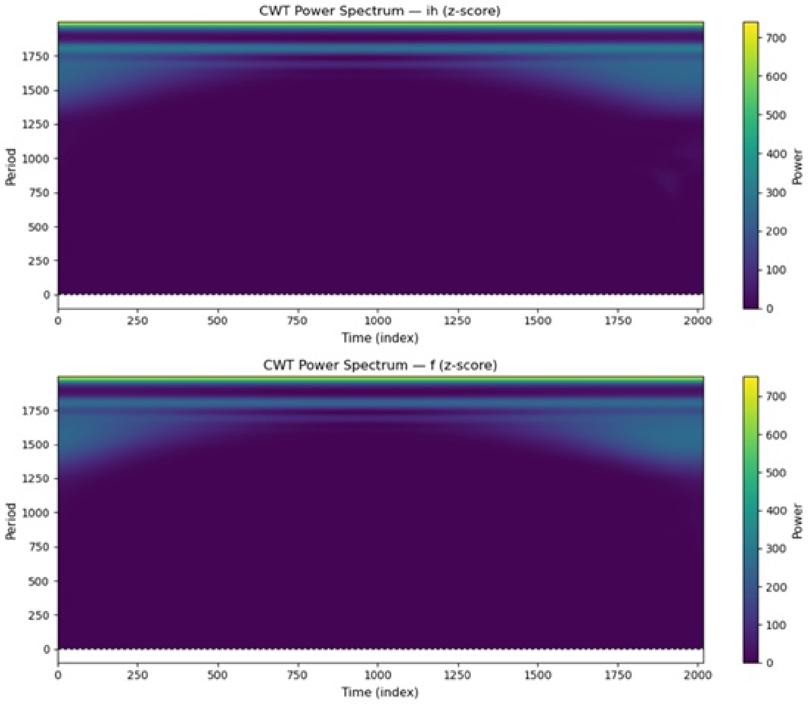

Figure 4: Continuous Wavelet Transform (CWT) Power Spectrum of Trading Volume and Closing Prices.

Note. Warmer colors (yellow/red) indicate higher power and stronger volatility concentrations at the corresponding time and period scales.

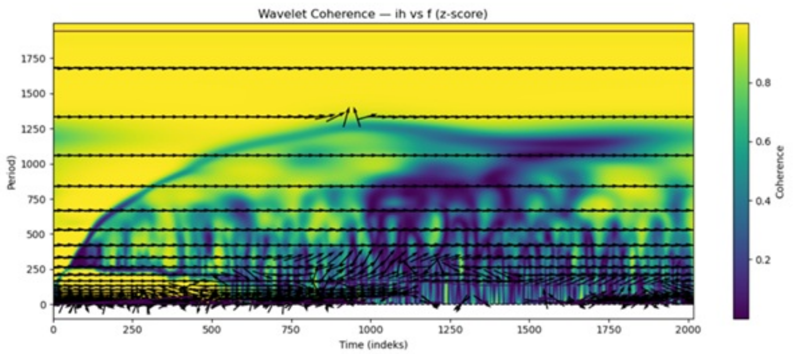

Figure 5: Wavelet Coherence Analysis Between Trading Volume and Closing Prices.

Note. The color scale (0–1) measures coherence strength, where warm colors denote strong correlation. Arrows represent the phase relationship: rightward (→) arrows indicate positive co-movement, while downward (↓) arrows imply that volume leads price.

Crisis, 2013 Gezi Protests, 2016 Coup Attempt, and 2018 Currency Shock. These events fragmented market expectations, weakening the volume-price relationship so that volume fluctuations no longer consistently influenced prices, and markets often exhibited sideways consolidation or directional ambiguity. Wavelet coherence effectively captures periods of instability in the frequency domain.

Finally, across the entire timeframe, weak but persistent coherence is observable at the longest periods, indicating a stable yet modest long-term association between volume and price. This long-term relationship appears to be relatively resilient to short-term shocks, reflecting enduring fundamental trends that persist despite periods of high volatility and market disruption.

The wavelet coherence analysis between Borsa Istanbuls closing prices and trading volume from January 1987 to August 2025 shows that price-volume dynamics become highly synchronized during major crises and political shocks. The coherence was relatively low and fragmented during stable periods, but sharp increases were observed during turbulent periods. The 1994 banking crisis and the 2001 financial crisis display strong coherence at the short- and medium-term horizons, while the 2008 global crisis produces a large, sustained coherence region at longer horizons, reflecting prolonged stress in financial markets. The 2013 Gezi protests and the 2016 coup attempt were associated with short-lived spikes in coherence, whereas the 2018 currency crisis and the 2020 COVID-19 shock triggered widespread coherence across multiple frequencies, indicating intensified linkages between trading activity and price fluctuations. Finally, the 2023 elections also generated localized increases in coherence, suggesting short-term political effects. Overall, the results imply that during episodes of economic or political instability, trading volume and prices in the Turkish stock market move closer together, signaling herding behavior and heightened market stress.

5 Conclusion

This study used advanced techniques in the time-frequency domain, specifically wavelet coherence analysis, to investigate the dynamic interactions between stock trading volumes and closing prices in the Turkish stock market. The analysis reveals complex and evolving relationships across different investment horizons, providing valuable insights into market dynamics.

The findings suggest that the volume of the trade and the closing price exhibit varying degrees of coherence and lead-lag relationships on different timescales. Short-term investors may benefit from understanding these patterns to optimize their trading strategies, whereas long-term investors can gain insight into broader market trends.

Two distinct phases in market behavior were identified: (i) a trending phase characterized by a strong and stable relationship between volume and price and (ii) a consolidation phase in which this relationship weakens, increasing market uncertainty. The wavelet coherence analysis demonstrated that price-volume dynamics become highly synchronized during major crises and political shocks, while coherence is relatively low and fragmented during stable periods.

Events such as the 1994 banking crisis, the 2001 financial crisis, the 2008 global crisis, the 2013 Gezi protests, the 2016 coup attempt, the 2018 currency shock, and the 2020 COVID-19 pandemic triggered widespread coherence across multiple frequencies, indicating intensified links between trading activity and price fluctuations. These findings align with previous studies [2, 7, 15], which highlight the synchronization of financial variables under stress.

This study contributes to the development of more informed investment strategies and improved market forecasting by providing a nuanced understanding of the evolving nature of financial markets. The wavelet-based approach used in this research offers a more comprehensive understanding of market dynamics than traditional analytical methods. By simultaneously examining both the time and frequency dimensions, this technique provides a localized view of the comovement between stock prices and trading volumes across different investment horizons. This nuanced perspective enables researchers and investors to identify how market behaviors evolve over time and across different scales, potentially leading to more sophisticated investment strategies and improved market forecasting models. Future research could extend this analysis to other emerging markets or specific sectors within the Turkish market to further elucidate the complex interaction between trading volumes and price changes. In addition, incorporating other relevant variables, such as volatility or macroeconomic indicators, could provide a more comprehensive understanding of market dynamics.

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