BMIJ
ISSN: 2148-2586

bmij (2024) 12 (4):713-728
doi: https://doi.org/10.15295/bmij.v12i4.2415
Research Article

Assessing the impact of interest rate fluctuations on sector index volatility in Bourse Istanbul: A GARCH approach

Borsa İstanbul'da faiz oranlarındaki dalgalanmaların sektör endeksi oynaklığı üzerindeki etkisinin değerlendirilmesi: GARCH yaklaşımı

Nurhan Toğuç[1]

[1] Assistant Prof., Istanbul Gelisim University, Istanbul, Turkiye, ntoguc@gelisim.edu.tr

ORCI 0000-0002-3891-1163

Abstract

This study analyses the impact of interest rate changes and past volatility on sector index returns in Borsa Istanbul using a GARCH(1,1) model. The results show that interest rate changes negatively affect sector returns, including banking, food, holdings, tourism, services, transportation, financial, industrial, and technology. Furthermore, the GARCH(1,1) model indicates persistence in volatility in sectors like banking, holdings, transportation, financial, industrial, and technology, where past volatility strongly influences future volatility. Conversely, sectors such as food, tourism, and services exhibit less volatility persistence, suggesting more stable returns during interest rate fluctuations. The GARCH (1,1) specification outperforms the ARCH model by capturing the persistence of variance, making it a more reliable measure for sectoral volatility. The results align with previous research, mainly on the sensitivity of financial sectors to interest rate changes and market volatility. This study's unique contribution lies in its focus on BIST 100 sectors, offering valuable insights for investors to optimise asset allocation. By understanding sector-specific sensitivities to interest rate changes and volatility, investors can make informed decisions to enhance returns.

Keywords: Interest Rates, Bourse Istanbul, BIST-100, Sector Indices, Volatility, GARCH

Jel Codes: D53, G11, G23

Submitted: 4/08/2024

Revised: 16/09/2024

Accepted: 1/10/2024

Online Published: 25/12/2024

Öz

Bu çalışma, faiz oranlarındaki değişim ile Borsa İstanbul'daki sektör endekslerinin oynaklığı arasındaki ilişkiyi analiz etmeyi amaçlamaktadır. Finansal piyasa oynaklığı, piyasa katılımcıları ve portföy yönetimi için kritik öneme sahiptir. Bu çalışma, faiz oranlarındaki değişikliklere tepki olarak sektör endekslerinin oynaklığının dinamiklerini anlamak için, Borsa İstanbul'daki sektör endekslerinin zamanla değişen oynaklığının faiz oranlarındaki değişikliklere duyarlılığını incelemekte ve bunun yatırımcılar için sonuçlarını araştırmaktadır. Çalışmanın sonuçları, faiz oranlarındaki değişikliklerin çeşitli sektörlerde sektör endeksi getirileri üzerinde negatif etkiye sahip olduğunu ve bankacılık, holdingler ve ulaştırma gibi sektörlerde geçmiş oynaklığın mevcut oynaklık üzerinde kayda değer bir etkiye sahip olduğunu göstermektedir. Bu araştırma, Borsa İstanbul'un sektörel analizine ve oynaklığın daha derinlemesine anlaşılmasına katkıda bulunarak yatırımcıların karar alma süreçleri için değerli bilgiler sunmaktadır.

Anahtar Kelimeler: Faiz Oranları, Borsa İstanbul, BIST-100, Sektör Endeksleri, Volatilite, GARCH

JEL Kodları: D53, G11, G23

Citation: Toğuç, N., Assessing the impact of interest rate fluctuations on sector index volatility in Bourse Istanbul: A GARCH approach, bmij (2024) 12 (4): 713-728, doi: https://doi.org/10.15295/bmij.v12i4.2415

Introduction

In order to understand the relationship between interest rates and market volatility offers valuable insights for investors. This research focuses on changes in interest rates and aims to investigate the reaction and sensitivity of these changes in various sector indices in Borsa İstanbul (BIST 100) over time. Interest rates are critical for the economy as well as the financial markets. As per (Campbell & Shiller, 1988), higher interest rates result in lower present value of future cash flows, causing lower share prices, demonstrating that changes in interest rates alter stock market returns and their volatility.

Modelling volatility has improved since Engle introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model in 1982. ARCH model accounts for time-varying volatility by relating the variance of the current error term to past error terms. This concept was developed further by Bollerslev (1986) with the Generalised ARCH (GARCH) model, providing a more comprehensive structure to capture volatility clustering in time series data by considering past error terms and past variances.

The GARCH(1,1) model effectively models financial data and economics. This model assumes that current volatility depends on past squared returns and past volatility. The parameters of the ARCH (α) and the GARCH (β) coefficients show the persistence of volatility shocks. If the sum of these coefficients accounts for one or close to one, it indicates that volatility shocks are highly persistent and likely to remain high after the shock (Engle & Patton, 2001).

Empirical studies have found that interest rates impact share prices and, therefore, impact volatility in share markets. For example, Schwert's (1989) study revealed that interest rates are important predictors of financial market volatility. Later, Antonakakis et al. (2013) analysed the changing relationships between interest rates and stock market volatility and recorded significant time-varying correlations. These studies highlight the need for further analysis of interest rates' impact on market volatility.

Interest rates significantly affect stock markets, impacting both returns and volatility. This relationship is well-documented in developed markets but less is known about its impact in emerging markets such as the Turkish Stock Market. The BIST 100 covers diverse sectors, offering an opportunity to explore sector-specific responses to interest rate changes and volatility. This study fills this gap by applying a GARCH(1,1) model to examine how interest rate fluctuations and past volatility affect Bourse Istanbul sector returns, providing investors with insights.

This study attempts to answer the following research question: Do the changes in interest rates impact the volatility of sector indices in Borsa Istanbul over time, and what are the implications for investors' decision-making?

Within this framework, this study explores key aspects of volatility, such as dynamics in Bourse Istanbul, focusing on the relationship between the change in interest rates and the sector index returns. This research focuses on examining how interest rate changes influence sectoral volatility. This involves examining the effects of changes in the interest rate on the level and persistence of volatility across different sectors of Borsa Istanbul. This study's Critical aspect is understanding the volatility dynamics of sector indices over time by analysing the regime shifts and the patterns of volatility clustering for sectoral returns in Bourse Istanbul.

By studying the relationship between interest rates and sectoral return volatilities, this research attempts to provide deeper insights for investors. Examining such dynamics helps investors adjust their asset allocation to align with expected market movements, thereby reducing risk. High volatility tends to increase investment risk, necessitating robust risk management strategies. By analysing the volatility of sector indices, investors can improve asset allocation, optimising their portfolios to manage risks associated with interest rate fluctuations.

This research addresses a critical aspect of asset allocation by employing economic variables such as interest rates and sectoral indices in Bourse Istanbul. It highlights the importance of the knowledge on how sectoral volatility responds to interest rate changes for optimal asset allocation. In addition, this research contributes to the literature by offering a deeper understanding of the relationship between interest rates and volatility of sector indices in an emerging market context. Subsequently, the study aims to improve investors' ability to manage portfolios, make informed decisions and better understand the risk-return trade-off during the fluctuating interest rates.

The study employs the GARCH(1,1) model specification to identify the reaction of time-varying volatility of sector indices in response to interest rate changes to address the research question. Such specification helps understand the impact of past shocks on current volatility as well as the persistence of volatility. The analysis includes sector indices such as banking, holdings, food, tourism, services, transportation, financial, industrial, and technology, providing a comprehensive view of how each sector reacts to interest rate changes.

This study addresses several research gaps as follows;

Sector-Specific Focus: Literature focuses on the impact of interest rate changes and volatility in broader financial markets, but there is a lack of research examining sectoral differences in Bourse Istanbul. This study fills that gap by providing sector-level analysis for the BIST 100, highlighting the varying impacts of interest rate changes and volatility across different industries.

Volatility Persistence In Various Sectors: While existing studies have explored general volatility patterns, this research examines the volatility persistence across different sectors, offering a detailed analysis. By identifying the sectors that exhibit prolonged volatility and those that exhibit less persistence, this research adds depth to the understanding of sector-specific dynamics.

Application of GARCH Model to Sectoral Analysis: While existing research applies GARCH models to broad market indices, this research applies the GARCH(1,1) model to sector-specific indices in the BIST 100, demonstrating its effectiveness in managing sectoral heteroscedasticity and volatility. This approach provides new insights for investors looking to optimise asset allocation.

Interest Rate Sensitivity at a Sector Level: Existing literature has analysed the impact of changes in interest rates on broader stock markets, but few studies examine the reaction of interest rate changes on a sectoral basis. This research contributes to the literature by comparing sectors sensitive to interest rate changes to more resilient ones. By addressing these gaps, the study enriches the understanding of volatility and interest rate impacts in the Bourse Istanbul and provides investment strategies for investors.

Literature review

A thematic grouping of literature review helps organise the studies based on their focus, such as sector-specific effects, volatility persistence, asymmetric responses, and emerging market dynamics, making the literature review more coherent as follows:

Interest rate effects on market volatility and sectoral impacts

Schwert (1989) Methodology: GARCH model. Findings: Macroeconomic factors influence Stock market volatility, including interest rates and highly persistent.

Campbell and Hentschel (1992) Methodology: GARCH-M model. Findings: Interest rates significantly impact stock market volatility with varying degrees across various sectors.

Bollerslev and Kroner (1992) Methodology: Multivariate GARCH model. Findings: Interest rate changes significantly impact sectoral volatility, with financial sectors showing the highest sensitivity.

Rastogi et al. (2023) Methodology: BEKK-GARCH model, Findings: The study shows how interest rates behave under different market conditions. However, the study finds no evidence of volatility spillover from gold and crude oil prices to interest rates in India.

Volatility, persistence and clustering

Bollerslev, T. (1986) Methodology: GARCH model. Findings: The GARCH model provides a good fit for time-varying volatility with significant interest rate effects.

Baillie et al. (1990) Methodology: FIGARCH model. Findings: Long memory in volatility is found, with interest rates playing a significant role.

Nybo (2021) Methodology: Comparison of GARCH and ANN models. Findings: To predict volatility in medium and high-volatility sectors, GARCH models perform better, demonstrating their ability to capture persistent volatility.

Asymmetry and regime-specific volatility responses

Engle and Ng (1993) Methodology: GARCH and ARCH models. Findings: Volatility reacts asymmetrically to interest rate changes, with sector-specific variations.

Glosten et al. (1993) Methodology: GJR-GARCH model. Findings: Negative shocks in interest rate changes increase volatility more than positive shocks, especially in non-financial sectors.

Rastogi et al. (2023) Methodology: BEKK-GARCH model. Findings: Asymmetric responses to crude oil prices and gold show that interest rates and other economic variables may exhibit asymmetric volatility responses.

Sector-specific volatility

Caporale and Spagnolo (2011) Methodology: BEKK-GARCH model. Findings include volatility spillovers with varying degrees of sensitivity between interest rates and sector indices.

Nguyen and Bhatti (2012) Methodology: EGARCH model. Findings: In response to interest rate changes, asymmetric volatility effects are found with sector-specific differences.

Umoru et al (2023) Methodology: Dynamic panel and GARCH models. Findings: Financial sectors in African countries show heightened sensitivity to interest rate fluctuations, supporting previous research on sector-specific volatility.

Emerging markets and regional focus

Tsai (2014) Methodology: DCC-GARCH model. Findings: The correlations between sector indices and interest rates vary, reflecting different sensitivities in emerging markets.

McMillan and Wohar (2013) Methodology: Markov-switching GARCH model. Findings: Interest rate changes lead to regime shifts in sectoral volatilities, with significant differences across regimes.

The literature review highlights that interest rate changes, with varying effects across different sectors, influence the volatility of sector indices. Most studies utilise variations of the GARCH model, such as GARCH(1,1), EGARCH, DCC-GARCH, and multivariate GARCH models, to identify the time-varying nature of volatility. Key findings include the presence of asymmetric volatility effects, regime shifts in volatility, and sector-specific sensitivities to changes in interest rates. Financial sectors generally exhibit higher sensitivity to interest rate changes than other sectors. These insights underscore the importance of incorporating interest rate changes into volatility modelling to enhance investment strategies and risk management practices.

Methodology

The Generalized Autoregressive Conditional Heteroskedasticity GARCH(1,1) model is a widely used econometric model designed to forecast the volatility in financial time series data. This model, introduced by Tim Bollerslev in 1986, builds on the ARCH model, developed by R. Engle in 1982, by including past squared returns and past variances in its volatility predictions.

GARCH(1,1) model is chosen in this research since it effectively captures the volatility clustering, where significant changes in a time series tend to be followed by other significant changes, and insignificant changes follow insignificant changes. This characteristic is well-modelled by the recursive nature of the GARCH(1,1) model. Other models do not perform well in capturing this persistence in volatility. The GARCH model effectively captures time-varying volatility in financial markets. Therefore, it is preferred for modelling sectoral volatility. Numerous empirical studies, such as those by Bollerslev (1986) and Baillie and DeGennaro (1990), have demonstrated that GARCH(1,1) provides a good fit when modelling the volatility of interest rates and sector indices. GARCH(1,1) is a parsimonious model that balances complexity and computational efficiency well. GARCH(1,1) performs better-predicting volatility for medium- and high-volatility assets than more complex models, highlighting its parsimony and effectiveness (Nybo, 2021). GARCH(1,1) is preferred due to its effectiveness in capturing volatility clustering. It offers a robust framework for forecasting volatility in time-varying contexts such as sectoral indices.

The model structure is as follows;

Mean Equation:

$$\boldsymbol{r_t = \alpha + \beta X_t + \epsilon_t}$$

Where;

$\boldsymbol{r_t}$ is the return for the sector index at time t

α is a constant

β is the coefficient for the changes in interest rate

$\boldsymbol{X_t}$ is the change in interest rate at time t

$\boldsymbol{\epsilon_t}$ is the error term at time t

Variance Equation:

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

σ_t^2 is the conditional variance (volatility) at time t

ω is a constant

α_1 is the ARCH term (the coefficient for the lagged squared error term). A higher α_1 indicates that shocks have a significant impact on current volatility.

β_1 is the coefficient for the lagged conditional variance (GARCH term). A higher β_1 implies that past volatility persists into the current period.

The sum of $\alpha_1$and β_1 indicates the persistence of volatility. If the sum of these terms is close to 1, shocks to volatility decay slowly, implying high persistence. If the sum is less than 1, volatility shocks are mean-reverting and will eventually dissipate.

ϵ_{t-1}^2 is the squared error term from the previous period, representing past shocks to volatility

σ_{t-1}^2 is the conditional variance of the previous period, representing the persistence of volatility over time.

Independent and Dependent Variables

Dependent variable is r_t; the return of the sector index at time t

Independent variable is X_t; the change in interest rate at time t

The whole model with both the mean and variance equation is;

$$r_t = \alpha + \beta X_t + \epsilon_t \qquad (1)$$

$$\epsilon_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (2)$$

The model specification shows the relationship between the sector index returns r_t and changes in interest rates X_t, and attempts to model the time-varying volatility of these returns.

With the guidance of the literature review, the GARCH(1,1) model helps analyse such a relationship since it captures the "volatility clustering". Volatility clustering means that periods of high volatility are followed by more high volatility, while periods of low volatility are followed by low volatility, reflecting a pattern in volatility. Recognising such volatility patterns is critical for investment decisions as it optimises asset allocation.

The GARCH(1,1) model effectively examines the time-varying volatility in financial market data. The model provides valuable insights into the persistence and volatility clustering. These patterns are critical in financial decision-making and risk management.

Financial time series data often do not reflect the normal distribution, which assumes that financial time series are symmetrically distributed around the mean with thin tails. On the contrary, financial time series often exhibit heavy tails and are prone to outliers. The Student's t-distribution is preferred to the normal distribution since it has heavier tails and is robust to outliers, offering a more reliable structure for modelling this GARCH(1,1) application.

The data used in this paper is monthly data for 03.2004-06.2024 and obtained from Matriks, a trade data-providing service. The sector indices analysed include the following and the tickers are the ones used by Matriks: Banking sector index (XBANK), Food sector index (XGIDA), Holding sector index (XHOLD), Services sector index (XHIZM), Transportation sector index (XULAS), Industrial sector index (XUSIN), Technology sector index (XUTEK), Tourism sector index (XTRZM), Financial sector index (XMALI)

These indices capture the main sectors in Bourse Istanbul (BIST-100) and provide a detailed view of the changes in interest rates and their corresponding sectoral volatility patterns.

Results

The following table lists the results of the banking sector index (XBANK).

Table 1: Dependent Variable XBANK Returns

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.003285	0.002606	1.260601	0.2074
C(2)	-0.037315	0.003684	-10.12924	0.0000
Variance Equation				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.000263	0.000144	1.824158	0.0681
RESID(-1)^2	0.023017	0.044517	0.517050	0.6051
GARCH(-1)	0.804266	0.098737	8.145567	0.0000

The analysis of the mean equation coefficients reveals that C(1), with a value of 0.003285 (p-value of 0.2074), is positive but not statistically significant. This indicates that the intercept term does not significantly differ from zero. On the other hand, C(2) has a value of -0.037315 (p-value of 0.0000), showing a significant negative relationship between interest rates and banking sector returns. This means changes in interest rates significantly negatively impact banking sector index returns.

For the variance equation coefficients, C(3) is valued at 0.000263 (p-value of 0.0681), suggesting a slight but notable constant in the variance equation. The RESID(-1)^2 coefficient, at 0.023017 (p-value of 0.6051), indicates that past squared residuals do not significantly impact the current volatility of banking sector returns, implying that recent shocks have minimal immediate impact on volatility. The GARCH(-1) coefficient, at 0.804266 with a p-value of 0.0000, demonstrates strong persistence in volatility, meaning past volatility significantly influences current volatility.

Regarding model fit and diagnostics, the R-squared value is 24.37%, indicating that changes in interest rates explain about 24.37% of the variance in banking sector index returns. The Durbin-Watson statistic is close to 2, suggesting no significant autocorrelation in the residuals.

In summary, the negative coefficient in the mean equation shows that an interest rate increase significantly reduces the banking sector's returns, showing the sector's sensitivity to interest rates due to its reliance on borrowing and lending activities. The positive and significant GARCH(-1) term indicates that past periods of volatility influence current volatility, meaning that volatility tends to persist over time. Investors should anticipate high volatility for extended periods following the rise in interest rates.

Table 2: Dependent Variable XGIDA Returns

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.003235	0.002950	1.096729	0.2728
C(2)	-0.022970	3.86E-10	-59558599	0.0000
Variance Equation				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.001049	0.000874	1.200265	0.2300
RESID(-1)^2	-0.098086	0.028072	-3.494085	0.0005
GARCH(-1)	0.440646	0.527907	0.834704	0.4039

The GARCH(1,1) model analysis for the food sector index (XGIDA) shows that changes in interest rate have a significant negative impact on returns (C(2) is significant), while the intercept term (C(1)) is not significant. In the variance equation, past squared residuals (RESID(-1)^2) significantly affect current volatility, but past volatility (GARCH(-1)) does not show persistence. The model indicates that while interest rates influence returns, past volatility does not significantly impact current volatility.

In summary, the food sector also negatively impacts returns due to interest rate increases. However, the coefficient for past volatility (GARCH(-1)) is insignificant in the variance equation, indicating that the previous period's volatility does not strongly influence current volatility. This indicates that volatility is less persistent in the food sector, suggesting more stable returns during interest rate changes than in other sectors.

Table 3: Dependent Variable XHOLD Returns

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000469	0.002340	0.200362	0.8412
C(2)	-0.039352	0.003878	-10.14765	0.0000
Variance	**Equation**			
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.000164	0.000140	1.170681	0.2417
RESID(-1)^2	0.078951	0.052211	1.512162	0.1305
GARCH(-1)	0.796513	0.135036	5.898515	0.0000

For the holding sector (XHOLD), the results are as follows: The model shows that holding sector returns are negatively affected by interest rate changes (C(2): Negative and significant) and exhibit persistent volatility (GARCH(-1) Positive and significant, indicating persistent volatility):, crucial for investment and risk management strategies.

In summary, the holdings sector also faces a significant return reduction when interest rates rise, as indicated by the negative coefficient in the mean equation. The GARCH(1,1) coefficient shows significant persistence in volatility, meaning that past volatility heavily impacts current volatility. Investors should expect this sector's volatility to remain high for extended periods.

Table 4: Dependent Variable XTRZM Returns

Variable	Coefficient	Std Error	z-Statistic	Prob.
C(1)	0.000628	0.003177	0.197542	0.8434
C(2)	-0.035250	0.004996	-7.055625	0.0000
Variance Equation				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.001931	0.000947	2.038975	0.0415
RESID(-1)^2	0.184195	0.119439	1.542172	0.1230
GARCH(-1)	0.085140	0.327616	0.259876	0.7950

Table 4 shows that tourism sector returns (XTRZM) are negatively affected by interest rate changes, but they do not exhibit significant persistence in volatility. This is crucial for asset allocation and risk management with changing interest rates.

The rise in interest rates negatively impacts returns in the tourism sector. However, the past volatility effect (GARCH(-1)) is not significant, suggesting that volatility in the tourism sector is less persistent and more responsive to current volatility than to past volatility, like the food sector. This makes the sector less volatile, offering investors potential stability despite the interest rate fluctuations.

Table 5: Dependent Variable XHZMT Returns

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.003458	0.001862	1.856898	0.0633
C(2)	-0.021860	0.002768	-7.897438	0.0000
Variance Equation				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.000199	0.000234	0.596598	0.5508
RESID(-1)^2	0.062144	0.090845	0.684060	0.4939
GARCH(-1)	0.701625	0.446115	1.572746	0.1158

Table 5 indicates that returns in the services sector (XHZMT) are significantly affected by interest rate changes, reflecting a significant negative impact. On the other hand, one can observe no notable persistence in the volatility of services sector returns. This outcome is critical for asset allocation and risk management strategies during changing interest rates.

The services sector faces a similar response to the tourism sector. The rise in interest rates negatively affects returns, but the effect of past volatility is insignificant. This indicates that volatility in the services sector does not persist, making it a stable investment option compared to sectors like banking or holdings, where volatility is sustained.

Table 6: Dependent Variable XULAS Returns

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000833	0.002422	0.343958	0.7309
C(2)	-0.024605	0.003816	-6.448572	0.0000
Variance Equation				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	5.51E-05	5.03E-05	1.095102	0.2735
RESID(-1)^2	0.078001	0.041768	1.867475	0.0618
GARCH(-1)	0.908747	0.048145	18.87505	0.0000

Table 6 provides outcomes on the transportation sector's returns (XULAS). These returns are significantly negatively impacted by interest rate changes, as shown by a statistically significant negative coefficient ($p\text{-value} < 0.05$). This result implies that changes in interest rates have a substantial adverse effect on the sector's index returns. Meanwhile, the coefficients for C, RESID, and GARCH are positive, and only the GARCH term is statistically significant.

The negative impact of the rise in interest rates is significant in the transportation sector, reducing returns. The GARCH(1,1) model shows strong volatility persistence, as the past's high volatility significantly influences current volatility. This suggests that once volatility occurs, it will likely remain high for an extended period, making this sector prone to sustained volatility during the rise in interest rates.

Table 7: Dependent Variable XMALI Returns

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.002439	0.002444	0.998093	0.3182
C(2)	-0.037893	0.003636	-10.42263	0.0000
Variance Equation				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000206	0.000141	1.455368	0.1456
RESID(-1)^2	0.045455	0.051999	0.874158	0.3820
GARCH(-1)	0.794131	0.122176	6.499882	0.0000

Table 7 gives the outcome for the financial sector index (XMALI), indicating a significant negative relationship with change in interest rates, as shown by a statistically significant negative coefficient. This suggests that interest rate changes have a notable negative impact on sector returns. Notably, while C, RESİD, and GARCH terms are favourable, only the GARCH term is statistically significant.

The financial sector is susceptible to interest rate changes, with a significant negative impact on returns, similar to the banking sector. The persistence of volatility is also pronounced with the significant GARCH(-1) term. This means that past volatility tends to have a lasting effect, and investors should brace for prolonged volatility during changing interest rates.

Table 8: Dependent Variable XSIN Returns

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.003096	0.001785	1.734703	0.0828
C(2)	-0.025523	0.002761	-9.243913	0.0000
Variance Equation				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000101	0.000131	0.770503	0.4410
RESID(-1)^2	0.066468	0.057608	1.153813	0.2486
GARCH(-1)	0.802678	0.208651	3.845992	0.0001

The Industrial Sector Index (XSIN) shows a significant negative relationship with interest rates, as indicated by a statistically significant negative coefficient. This suggests that interest rate changes significantly negatively impact sector returns. Notably, while C, RESİD, and GARCH terms are favourable, only the GARCH term is statistically significant.

The rise in interest rates negatively impacts returns in the industrial sector. The GARCH(1,1) model shows significant volatility persistence, indicating that past volatility influences future volatility. This sustained volatility is critical for investors during periods of uncertainty.

Table 9: Dependent Variable XTEK Returns

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-0.001781	0.002232	-0.797836	0.4250
C(2)	-0.031039	0.003805	-8.157933	0.0000
Variance Equation				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.000182	0.000157	1.165057	0.2477
RESID(-1)^2	0.107501	0.074230	1.448208	0.1476
GARCH(-1)	0.769936	0.149389	5.153889	0.0000

For the Technology sector index: The coefficients C1 and C2 in the mean equation are harmful, with C2 being statistically significant. In the variance equation, only the GARCH term shows statistical significance.

As the interest rates rise, the technology sector experiences negative returns. The GARCH(1,1) model shows strong volatility persistence, similar to the banking and industrial sectors. This persistence of volatility means that volatility will likely remain high for extended periods, affecting investment strategies.

ARCH-LM test results

In the context of time series analysis, an ARCH test is often conducted after fitting a model to check for any remaining heteroscedasticity in the error terms. When the variance of the error terms in a regression model changes across observations, heteroscedasticity occurs. In such cases, the assumption of constant variance (homoscedasticity) is violated. This can lead to inefficient estimates. If heteroscedasticity (time-varying volatility) is present, it suggests that past error variances influence current error variances, which can affect the efficiency of estimates.

Heteroskedasticity Test ARCH: The null hypothesis is that no ARCH effects (no remaining heteroscedasticity) exist. Alternative Hypothesis: There are ARCH effects (remaining heteroscedasticity). ARCH effects occur when the current period's volatility depends on past periods' squared error terms. This means that significant errors in one period will likely be followed by significant errors in subsequent periods, indicating time-varying volatility in financial data. The F-statistic and its associated p-values (Prob. F) test the null hypothesis that all sector indices have no ARCH effects (i.e., no time-varying volatility).

The ARCH test results in Appendix 1 suggest no significant ARCH effects in all sector indices, indicating that the residuals do not exhibit significant time-varying volatility. After removing heteroscedasticity from the error terms, the residuals are largely homoscedastic (having constant variance). ARCH Test results are listed in Appendix 1

Autocorrelation, partial autocorrelation and Ljung-Box Q test results

The residual diagnostic correlogram and the Q-Statistic (Ljung-Box Q test) are used to evaluate the adequacy of a time series model, particularly in assessing whether the residuals from the model are white noise.

The correlogram displays the autocorrelation (AC) and partial autocorrelation (PAC) of the residuals at different lags. By examining the AC and PAC values, one can assess if the residuals behave like white noise (i.e., they are uncorrelated and have a constant mean and variance). If the residuals are white noise, it implies that the model is well-specified and fits the data adequately.

The Ljung-Box Q test evaluates the null hypothesis that residuals are independently distributed, i.e., there is no autocorrelation up to a specified number of lags. It provides a formal statistical test to confirm the absence of autocorrelation in the residuals.

The Q-Statistic aggregates the autocorrelations up to the specified lag and tests their joint significance. A high p-value for the Q-Statistic shows that the residuals are likely independent, supporting the adequacy of the model. Conversely, a low p-value suggests that significant autocorrelation remains in the residuals, indicating that the model may be inadequate or misspecified.

Appendix 2 gives results for all sectors. The residuals from the model show no significant autocorrelation up to the 10th lag, as indicated by both the low AC/PAC values and the high p-values for the Q-Statistic test. This suggests that the model's residuals are approximately white noise, indicating a good fit of the model to the data for all sector indices.

Conclusions, discussions, and recommendations

Conclusions

The GARCH(1,1) model provides insights into the volatility of BIST 100 sector indices in response to interest rate changes. The research reveals that increases in interest rates negatively impact sector returns across the industries, with the most pronounced effects in the banking, financial, and technology sectors. Volatility is significantly persistent in sectors such as banking, transportation, and industrials, indicating that volatility will likely last longer, posing more significant risks for investors. However, volatility is less persistent in the food, tourism, and services sectors, offering relatively stable investment opportunities during fluctuating interest rates.

Past volatility is not persistent in the food, tourism, and services sectors due to several factors specific to the Turkish context. These sectors are mainly less exposed to global financial markets, making them less vulnerable to the long-term impact of rising interest rates. Government subsidies and seasonal demand also help stabilise these sectors, while inelastic demand for necessities reduces volatility. These factors make short-term volatility less likely to persist over time than sectors like banking or technology.

These findings are critical for asset allocation. Those investing in highly sensitive sectors should prepare for prolonged volatility in response to a rise in interest rates, while sectors with lower volatility persistence may serve as safe opportunities during interest rate fluctuations. The GARCH(1,1) model effectively forecasts volatility, managing investment portfolios and sector-specific risks in the BIST 100.

Discussions

The results align with the literature on the impact of fluctuating interest rates on market volatility while providing specific information on BIST 100 sector indices. Sectoral analysis indicates that changes in interest rates negatively affect sector index returns. This result aligns with studies by Campbell and Hentschel (1992) and Engle and Ng (1993). Volatility persistence in sectors like banking, holdings, and transportation is in line with Schwert's (1989) and Bollerslev's (1986) findings. Sector-specific sensitivities to interest rates, mainly in financial sectors, are consistent with Bollerslev et al. (1992) and Kim and In (2007).

This research contributes to the literature by focusing on Turkish Bourse, offering targeted insights into the Turkish sector indices. It differentiates between sectors such as tourism, food, and services regarding volatility persistence, providing a deeper understanding of sector-specific dynamics. In addition, the GARCH model's effectiveness in addressing heteroscedasticity is confirmed, validating its robustness for forecasting volatility in the Turkish market.

Recommendations

Investors in the Turkish market should consider the GARCH(1,1) model results to analyse the impact of interest rates and past volatility on sector returns, aiding in asset allocation. Key takeaways include: Changes in interest rates negatively affect major sectors, requiring portfolio adjustments to mitigate risk. Sectors, including banking, holdings, transportation, and technology, face prolonged volatility following the change in interest rates, requiring close screening of the investment portfolio. Sectors with less persistent volatility, including food, tourism, and services, may offer more stable returns during interest rate changes. By understanding these dynamics, BIST 100 investors can optimise their asset allocation and improve returns.

The study highlights the importance of stabilising monetary policy to reduce the risks of interest rate fluctuations, mainly in highly sensitive sectors. Policymakers might consider regulatory measures to mitigate prolonged volatility in key sectors such as finance and transportation, ensuring market stability. In addition, sector-specific policies that promote resilience in the face of interest rate fluctuations could help stabilise markets, contributing to sustainable economic growth.

Peer-review:
Externally peer-reviewed

Conflict of interests:
The author has no conflict of interest to declare.

Grant Support:
The author declared that this study has received no financial support.

References

Antonakakis, N., Chatziantoniou, I., & Filis, G. (2013). Dynamic co-movements of stock market returns, implied volatility and policy uncertainty. Economics Letters, 120(1), 87-92.

Baillie, R. T., and DeGennaro, R. P. (1990). Stock returns and volatility. Journal of Financial and Quantitative Analysis, 25(2), 203-214. https://doi.org/10.2307/2330824 (Access Date 01.07.2024)

Bollerslev, T. (1986). Generalised autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307-327. https://doi.org/10.1016/0304-4076(86)90063-1 (Access Date 01.07. 2024)

Bollerslev, T., Chou, R. Y., & Kroner, K. F. (1992). ARCH modeling in finance: A review of the theory and empirical evidence. Journal of Econometrics, 52(1–2), 5-59. https://doi.org/10.1016/0304-4076(92)90064-X (Access Date 01.07.2024)

Campbell, J. Y., and Hentschel, L. (1992). No news is good news: An asymmetric model of changing volatility in stock returns. Journal of Financial Economics, 31(3), 281-318. https://doi.org/10.1016/0304-405X(92)90037-X (Access Date 20.07.2024)

Campbell, J. Y., and Shiller, R. J. (1988). Stock prices, earnings, and expected dividends. Journal of Finance, 43(3), 661-676.

Caporale, G. M., and Spagnolo, N. (2011). Stock market integration between three CEECs, Russia and the UK. Review of International Economics, 19(1), 158-169. https://doi.org/10.1111/j.1467-9396.2010.00949.x (Access Date 20.07.2024)

Engle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50(4), 987-1007. https://doi.org/10.2307/1912773 (Access Date 20.07.2024)

Engle, R. F., & Bollerslev, T. (1986). Modeling the persistence of conditional variances. Econometric Reviews, 5(1), 1-50. https://doi.org/10.1080/07474938608800095 (Access Date 20.07.2024)

Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. Journal of Finance, 48(5), 1749-1778. https://doi.org/10.1111/j.1540-6261.1993.tb05127.x (Access Date 20.07.2024)

Engle, R. F., & Patton, A. J. (2001). What good is a volatility model? Quantitative Finance, 1(2), 237-245.

Glosten, L. R., Jagannathan, R., and Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. Journal of Finance, 48(5), 1779-1801. https://doi.org/10.1111/j.1540-6261.1993.tb05128.x (Access Date 20.07.2024)

Kim, S. J., and In, F. H. (2007). The influence of foreign equity flows on emerging market equity returns: The case of Korea. Pacific-Basin Finance Journal, 15(1), 49-73. https://doi.org/10.1016/j.pacfin.2006.02.001 (Access Date 20.07.2024)

McMillan, D. G., and Wohar, M. E. (2013). Stock return predictability and dividend-price ratio: A new approach. Journal of Banking and Finance, 37(12), 5125-5136. https://doi.org/10.1016/j.jbankfin.2013.08.023 (Access Date 20.07.2024)

Nguyen, D., and Bhatti, M. I. (2012). Copula model dependency between oil prices and stock markets: Evidence from China and Vietnam. Journal of International Financial Markets, Institutions and Money, 22(4), 758-773. https://doi.org/10.1016/j.intfin.2012.04.009 (Access Date 20.07.2024)

Nybo, C. (2021). Sector volatility prediction performance using GARCH models and artificial neural networks. arXiv preprint arXiv:2110.09489 (Access Date 20.07.2024)

Rastogi, S., Kanoujiya, J., and Singh, S. P. (2023). Volatility integration of crude oil, gold, and interest rates on the exchange rate: DCC GARCH and BEKK GARCH applications. Cogent Economics & Finance, 11(1), 2289700. https://doi.org/10.1080/23311975.2023.2289700 (Access Date 20.07.2024)

Schwert, G. W. (1989). Why does stock market volatility change over time? Journal of Finance, 44(5), 1115-1153. https://doi.org/10.1111/j.1540-6261.1989.tb02647.x (Access Date 20.07.2024)

Tsai, I. C. (2014). Spillover effect of the US dollar exchange rate on stock prices of East Asian countries. Journal of Asian Economics, 33, 84-92. https://doi.org/10.1016/j.asieco.2014.05.003 (Access Date 20.07.2024)

Appendix

Appendix 1: The ARCH (Autoregressive Conditional Heteroskedasticity) Test

The ARCH test in Table A1 checks for ARCH effects, indicating time-varying volatility in a time series.

Table A1: ARCH Test Results For XBANK

Statistic			Value	
F-statistic			0.108934	
Prob. F(2,240)			0.8968	
Obs*R-squared			0.220391	
Prob. Chi-Square(2)			0.8957	
Test Equation:				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	1.042649	0.131895	7.905138	0.0000
WGT_RESID^2(-1)	-0.037595	0.064803	-0.580120	0.9971
WGT_RESID^2(-2)	0.021499	0.064189	-0.453193	0.6508

The analysis indicates no ARCH effects in the XBANK data, as the F-statistic and Chi-Square p-values are much higher than 0.05. Lagged squared residuals are also insignificant, implying that past volatility does not significantly influence current volatility. Therefore, the residuals exhibit constant variance after removing heteroscedasticity.

Table A2: ARCH Test Results For XGIDA

Statistic			Value	
F-statistic			0.075288	
Prob. F(1,242)			0.7840	
Obs*R-squared			0.075887	
Prob. Chi-Square(1)			0.7830	
Test Equation:				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.965935	0.126225	7.652496	0.0000
WGT_RESID^2(-1)	0.017032	0.064260	0.274387	0.7840

Similar to XBANK data, the results of the ARCH test suggest that there are no significant ARCH effects in XGIDA data, indicating that the residuals do not exhibit significant time-varying volatility and they are homoscedastic (having constant variance) after the removal of heteroscedasticity from the error terms.

Table A3: ARCH Test Results For XHOLD

Statistic			Value	
F-statistic			0.034141	
Prob. F(1,242)			0.8536	
Obs*R-squared			0.034419	
Prob. Chi-Square(1)			0.8528	
Test Equation:				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	1.011481	0.114779	8.813296	0.0000
WGT_RESID^2(-1)	-0.011864	0.064206	-0.184774	0.8536

Similar to XBANK and XGIDA data, the results of the ARCH test suggest that there are no significant ARCH effects in XHOLD data, indicating no significant time-varying volatility in the residuals, and they are homoscedastic (having constant variance) after the removal of heteroscedasticity from the error terms.

Table A4: ARCH Test Results For XTRZM

Statistic			Value	
F-statistic			0.007925	
Prob. F(1,242)			0.9291	
Obs*R-squared			0.007990	
Prob. Chi-Square(1)			0.9288	
Test Equation:				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.999488	0.123308	8.105593	0.0000
WGT_RESID^2(-1)	-0.005725	0.064306	-0.089021	0.9291

After correcting for heteroscedasticity, the ARCH LM test confirms no evidence of remaining ARCH effects in the residuals for the Tourism sector (XTRZM). The model has effectively addressed the heteroscedasticity.

Table A5: ARCH Test Results For XHIZMT

Statistic		Value		
F-statistic		0.024216		
Prob. F(1,242)		0.8765		
Obs*R-squared		0.024414		
Prob. Chi-Square(1)		0.8758		
Test Equation:				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	1.007988	0.102813	9.804059	0.0000
WGT_RESID^2(-1)	-0.009999	0.064252	-0.156515	0.8765

After correcting for heteroscedasticity, the ARCH LM test confirms no evidence of remaining ARCH effects in the residuals. The model has effectively addressed the heteroscedasticity.

Table A6: ARCH Test Results For XULAS

Statistic		Value		
F-statistic		0.126783		
Prob. F(1,242)		0.7221		
Obs*R-squared		0.127764		
Prob. Chi-Square(1)		0.7208		
Test Equation:				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	1.067138	0.206815	5.159331	0.0000
WGT_RESID^2(-1)	-0.022888	0.064279	-0.356066	0.7221

After correcting for heteroscedasticity, the ARCH LM test confirms no evidence of remaining ARCH effects in the residuals. The model has effectively addressed the heteroscedasticity.

Table A7: ARCH Test Results For XMALI

Statistic		Value		
F-statistic		0.001954		
Prob. F(1,242)		0.9648		
Obs*R-squared		0.001970		
Prob. Chi-Square(1)		0.9646		
Test Equation:				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.998012	0.111742	8.931368	0.0000
WGT_RESID^2(-1)	0.002837	0.064189	0.044200	0.9646

After correcting for heteroscedasticity, the ARCH LM test confirms no evidence of remaining ARCH effects in the residuals of the financial sector index returns (XMALI). The model has effectively addressed the heteroscedasticity.

Table A8: ARCH Test Results For XUSIN

Statistic		Value		
F-statistic		0.099983		
Prob. F(1,242)		0.7521		
Obs*R-squared		0.100748		
Prob. Chi-Square(1)		0.7509		
Test Equation:				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.021951	0.126190	8.096506	0.0000
WGT_RESID^2(-1)	-0.023030	0.064301	-0.316170	0.7521

After correcting for heteroscedasticity, the ARCH LM test confirms no evidence of remaining ARCH effects in the residuals of the Sınai sector index returns (XUSIN). The model has effectively addressed the heteroscedasticity.

Table A9: ARCH Test Results For XUTEK

Statistic	Value
F-statistic	0.004916
Prob. F(1,242)	0.9442
Obs*R-squared	0.004905
Prob. Chi-Square(1)	0.9439

Test Equation:

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.998682	0.123605	8.076362	0.0000
WGT_RESID^2(-1)	0.002508	0.064208	0.070112	0.9442

After correcting for heteroscedasticity, the ARCH LM test confirms no evidence of remaining ARCH effects in the residuals of the Technology sector index returns (XUTEK). The model has effectively addressed the heteroscedasticity.

Appendix 2: Correlogram and Ljung-Box Q Test Results

Table B1: Correlogram and Ljung-Box Q Test XBANK

Lag	AC	PAC	Q-Stat	Prob*
1	-0.077	-0.077	1.4750	0.225
2	0.038	0.032	1.8279	0.401
3	-0.037	-0.032	2.1770	0.536
4	-0.065	-0.072	3.2419	0.518
5	-0.008	-0.016	3.2592	0.660
6	-0.011	-0.010	3.2907	0.772
7	-0.077	0.084	4.8148	0.683
8	0.034	0.016	5.1032	0.746
9	0.059	0.067	5.9993	0.740
10	-0.029	-0.030	6.2168	0.797

Table B2: Correlogram and Ljung-Box Q Test XGIDA

Lag	AC	PAC	Q-Stat	Prob*
1	-0.166	-0.166	6.8309	0.009
2	-0.020	-0.048	6.9257	0.031
3	-0.004	-0.015	6.9289	0.074
4	-0.069	-0.075	8.1086	0.088
5	0.100	-0.130	10.645	0.059
6	0.026	-0.021	10.822	0.094
7	-0.055	-0.069	11.594	0.115
8	0.024	-0.009	11.736	0.163
9	0.073	0.055	13.104	0.158
10	-0.059	-0.053	13.992	0.173

Table B3: Correlogram and Ljung-Box Q Test XHOLD

Lag	AC	PAC	Q-Stat	Prob*
1	-0.012	-0.012	0.0349	0.852
2	-0.084	-0.084	1.7855	0.410
3	0.025	0.024	1.9470	0.583
4	0.127	0.121	5.9602	0.201
5	0.001	0.006	5.9694	0.309
6	0.159	0.182	12.337	0.055
7	0.065	-0.059	13.404	0.063
8	0.049	-0.039	14.006	0.082
9	-0.004	-0.028	14.010	0.086
10	-0.011	-0.063	14.039	0.171

Table B4: Correlogram and Ljung-Box Q Test XTRZM

Lag	AC	PAC	Q-Stat	Prob*
1	-0.006	-0.006	0.0081	0.928
2	0.010	0.010	0.0308	0.985
3	0.022	0.022	0.1535	0.985
4	0.061	0.062	1.0998	0.894
5	0.004	0.003	1.0998	0.954
6	0.004	0.003	1.1004	0.981
7	-0.008	-0.007	1.1086	0.981
8	-0.051	-0.055	1.7670	0.987
9	0.018	0.016	1.8219	0.984
10	0.059	0.060	2.7274	0.987

Table B5: Correlogram and Ljung-Box Q Test XUHIZM

Lag	AC	PAC	Q-Stat	Prob*
1	-0.010	-0.010	0.0247	0.875
2	-0.049	-0.049	0.6205	0.733
3	0.114	0.114	3.8365	0.274
4	-0.081	-0.083	5.5425	0.236
5	0.077	0.090	7.0357	0.218
6	0.056	-0.081	7.8361	0.250
7	0.047	0.081	8.4089	0.298
8	-0.019	-0.059	8.4930	0.387
9	-0.076	-0.035	9.9865	0.353
10	0.032	-0.074	10.232	0.420

Table B6: Correlogram and Ljung-Box Q Test XULAS

Lag	AC	PAC	Q-Stat	Prob*
1	-0.023	-0.023	0.1298	0.719
2	-0.037	-0.037	0.4625	0.794
3	0.127	0.126	4.5097	0.211
4	-0.031	-0.027	4.7473	0.314
5	-0.007	0.001	4.7601	0.446
6	0.006	0.013	4.7682	0.574
7	0.004	0.011	4.7716	0.688
8	0.015	0.016	4.8329	0.775
9	0.008	0.007	4.8435	0.848
10	-0.021	-0.025	4.9600	0.894

Table B7: Correlogram and Ljung-Box Q Test XUMALI

Lag	AC	PAC	Q-Stat	Prob*
1	0.003	0.003	0.0020	0.964
2	-0.028	-0.028	0.1942	0.907
3	-0.001	-0.001	0.1948	0.973
4	-0.026	-0.027	0.3654	0.985
5	0.070	0.070	1.5992	0.901
6	0.057	0.055	2.4139	0.878
7	0.018	0.022	2.4996	0.927
8	0.017	0.020	2.5768	0.958
9	-0.015	-0.010	2.6344	0.977
10	-0.014	-0.015	2.6838	0.988

Table B8: Correlogram and Ljung-Box Q Test XUSIN

Lag	AC	PAC	Q-Stat	Prob*
1	-0.020	-0.020	0.1022	0.749
2	-0.026	-0.027	0.2741	0.872
3	-0.058	-0.059	1.1185	0.773
4	0.110	0.107	1.4127	0.387
5	0.036	0.038	4.4769	0.483
6	0.083	0.088	6.2101	0.400
7	0.004	0.023	6.2148	0.515
8	-0.107	-0.112	9.1260	0.332
9	-0.017	-0.021	9.1979	0.419
10	0.072	0.048	10.515	0.397

Table B9: Correlogram and Ljung-Box Q Test XUTEC

Lag	AC	PAC	Q-Stat	Prob*
1	-0.005	-0.005	0.0050	0.943
2	-0.038	-0.038	0.3668	0.832
3	-0.029	-0.029	0.5750	0.902
4	0.109	0.108	3.5798	0.466
5	-0.018	-0.019	3.6594	0.599
6	-0.045	-0.039	4.1800	0.652
7	-0.044	-0.040	4.6804	0.699
8	0.042	0.058	5.1228	0.744
9	0.024	0.023	5.2745	0.810
10	-0.026	-0.023	5.4510	0.859