



2024, 13 (3), 1256-1276 | Research Article

Analysis of BIST Gold Index Volatility With Autoregressive Conditional Heteroscedasticity Models

İpek M. Yurttagüler¹

Abstract

Gold is one of the most accepted and reliable investment instruments of all time. On the other hand, its importance in today's financial markets is indisputable. The increasing importance of precious metals, especially gold, which started with the mercantilist process, continues until today. The mercantilist process was a period in which the existence of gold and silver mines was accepted as a measure of wealth. In this period when protectionist economic policies were implemented, it was accepted that the more precious metals entered into the country with the economic policies implemented, the greater the wealth. The importance of gold continued after the end of the mercantilist process. Both the gold standard system and the Bretton Woods periods were also periods when gold was an important investment instrument. Today, gold appears as an asset that is frequently used in times of crisis, both because it is a safe investment instrument and because it is used as a store of value. In this context, empirically measuring and predicting volatility in gold prices is important due to its economic effects on key macroeconomic variables. However, although it lays the groundwork for a theoretical and empirical literature, it stands out that it has a relatively limited research area. This study estimates volatility using ARCH-GARCH-EGARCH and TGARCH modeling techniques with Türkiye gold price data between 2005-2023. These models are statistical models used to model volatility changes in time series. With these models, it is possible to understand and predict how volatility in time series changes over time. At this point, the study aims to contribute to the relatively small literature on gold market volatility. The findings of the study show that the most appropriate model to estimate the volatility in gold prices for Türkiye is GARCH(1,1).

Keywords: Volatility, Gold Price, BIST Gold Index, ARCH, GARCH

Yurttagüler, İpek M. (2024). Analysis of BIST Gold Index Volatility With Autoregressive Conditional Heteroscedasticity Models, *Journal of the Human and Social Science Researches*, 13 (3), 1256-1276.
<https://doi.org/itobiad.1390321>

Date of Submission	13.11.2023
Date of Acceptance	30.07.2024
Date of Publication	30.09.2024
*This is an open access article under the CC BY-NC license.	

¹ Assist. Prof. Dr., Istanbul University, Faculty of Economics, Department of Economics, İstanbul, Türkiye, ipeksa@istanbul.edu.tr, <https://orcid.org/0000-0003-3368-3787>



BİST Altın Endeksi Volatilitésinin Otoregresif Koşullu Heteroskedastisite Modelleriyle Analizi

İpek M. Yurttagüler¹

Öz

Altın tüm zamanların en çok kabul gören ve güvenilir yatırım araçlarından biridir. Hem asırlardır süren önemi hem de günümüzdeki popülaritesi göz önüne alındığında iktisat literatüründe çalışmalara konu olmuş bir varlıktır. Özellikle merkantilist süreçle birlikte altın başta olmak üzere değerli madenlerin artan önemi günümüze kadar devam etmiş ve günümüz finans piyasalarında oldukça önemli bir yer edinmiştir. Merkantilist süreç altın ve gümüş madenlerinin varlığının bir zenginlik ölçütü olarak kabul edildiği bir dönemdir. Korumacı iktisat politikalarının uygulandığı bu dönemde, uygulanan iktisat politikalarıyla birlikte ülke içerisine ne kadar çok değerli maden girerse zenginliğin o kadar fazla olduğu kabul edilmektedir. Merkantilist sürecin sona ermesinin ardından da altının önemi devam etmiştir. Gerek altın standardı sistemi, gerekse de Bretton Woods dönemleri yine altının önemli bir yatırım enstrümanı olduğu dönemlerdir. Günümüzde de altın, gerek güvenli bir yatırım enstrümanı olması gerekse de değer saklama aracı olarak kullanılması nedenleriyle kriz dönemlerinde sıklıkla başvuru alan bir varlık olarak karşımıza çıkmaktadır. Bu bağlamda, altın fiyatlarındaki oynaklığın ampirik olarak ölçülmesi ve tahmin edilmesi, temel makroekonomik değişkenler üzerindeki ekonomik etkileri nedeniyle önem taşımaktadır. Ancak, teorik ve ampirik bir literatüre zemin hazırlasa da görece olarak sınırlı bir araştırma alanı bulunduğu göze çarpmaktadır. Bu çalışma, 2005-2023 yılları arasında Türkiye altın fiyatı verileriyle ARCH-GARCH-EGARCH ve TGARCH modelleme tekniklerini kullanarak volatilitiyi tahmin etmektedir. Oynaklık kavramının modellenmesi noktasında, ARCH ve GARCH modelleri ailesine başvurulmasının önemli bir sebebi bulunmaktadır. Bu modeller, zaman serilerindeki oynaklık değişimlerini modellemek için kullanılan istatistiksel modellerdir. Bu modeller ile birlikte, zaman serilerindeki oynaklığın zaman içinde nasıl değiştiğini anlamak ve tahmin etmek mümkün olmaktadır. Bu çalışma, altın piyasası volatilitésine ilişkin sınırlı sayıdaki literatüre katkı sağlamayı amaçlamaktadır. Çalışmanın bulguları, Türkiye için altın fiyatlarındaki oynaklığı tahmin etmek için en uygun modelin GARCH(1,1) olduğunu göstermektedir.

Anahtar Kelimeler: Oynaklık, Altın Fiyatları, BIST Altın Endeksi, ARCH, GARCH

Yurttagüler, İpek M. (2024). BİST Altın Endeksi Volatilitésinin Otoregresif Koşullu Heteroskedastisite Modelleriyle Analizi, *İnsan ve Toplum Bilimleri Araştırmaları Dergisi*, 13 (3), 1256-1276.

<https://doi.org/itobiad.1390321>

Geliş Tarihi	13.11.2023
Kabul Tarihi	30.07.2024
Yayın Tarihi	30.09.2024
*Bu CC BY-NC lisansı altında açık erişimli bir makaledir.	

¹ Dr. Öğrt. Üyesi, İstanbul Üniversitesi, İktisat Fakültesi, İktisat Bölümü, İktisat Teorisi Anabilim Dalı, İstanbul, Türkiye, ipeksa@istanbul.edu.tr, <https://orcid.org/0000-0003-3368-3787>

Introduction

The concept of volatility is a recurring theme in economic literature, particularly in the realm of financial markets. It holds significant importance in the decision-making process of investors. At its core, volatility is concerned with measuring the deviation of an investment instrument from its average value. As such, it is a concept that is closely scrutinized in the analysis of macroeconomic stability. The concept of volatility is also frequently employed in other markets, including exchange rate markets, crypto markets, oil markets, and gold markets. In this context, the present study aims to examine the volatility of the gold market.

The Istanbul Gold Exchange operates under the "General Regulation on the Establishment and Working Principles of Precious Metals Exchanges," which was formulated by the Capital Markets Board (CMB) pursuant to Article 40/A of the Capital Markets Law No. 2499. This regulation was published in the Official Gazette No. 21541 on April 3, 1993, and subsequently came into effect. Although the Istanbul Gold Exchange officially commenced its operations on July 26, 1995, it is not limited to the trading of gold bullion, but also facilitates futures transactions. The establishment of this exchange has enabled the tracking of the gold market index, making the determination of market volatility a significant area of research.

The power of gold and precious metals to be a measure of wealth and to determine the economic structures of countries, which began with the mercantilist period, continued over time as they took an important place in the international monetary system. Since the second half of the 19th century, it has emerged within the monetary system as the main factor of the international monetary system and as an investment instrument. Although its popularity has relatively decreased over time with the emergence of different financial instruments, it is observed that the demand for gold increases again, especially during economic crisis periods. In this context, gold can be considered as a safe haven to eliminate the risk and uncertainty environment in the markets (Bams et.al.2017: 270-271; Fang et.al.2018: 414).

The gold market exhibits distinct attributes in comparison to other financial markets owing to its unique structure. Distinguished by its status as a precious metal and its finite supply, gold is subject to varying tax and regulatory frameworks across different countries. Furthermore, aside from serving as a safe haven during periods of international tensions, political turmoil, or armed conflict, it is also susceptible to speculative influences. Consequently, it becomes evident that gold, akin to any other investment instrument, entails a range of risks. These risks can be enumerated as follows (Giannellis and Koukouritakis, 2019: 27-28; Qian et al., 2019: 1-2; Vengesai et.al., 2022: 34; Ding et.al., 2022: 2)

- ✓ Risk of price fluctuations: Gold prices may fluctuate constantly under the influence of many factors. Factors such as geopolitical events, economic indicators, central bank policies may affect gold prices.
- ✓ Risk of interest rate changes: Rising interest rates may increase the returns of alternative investment instruments and reduce the attractiveness of gold. High interest rates can make gold appear as a non-returning asset.

- ✓ Exchange rate risk: Gold is generally traded in dollars. While the depreciation of the dollar may increase gold prices, the appreciation of the dollar may suppress gold prices.
- ✓ Liquidity risk: The gold market may sometimes experience periods of low liquidity. In this case, trading gold may be more difficult and transaction costs may increase.
- ✓ Manipulation risk: As in financial markets, there may be a manipulation risk in the gold market. Players who try to artificially influence prices may cause misleading movements in the market.
- ✓ Taxes and regulations: Buying, selling and processing gold may be subject to taxation and regulations that vary by country and region. This may result in additional costs or transaction difficulties for investors.

Such risks regarding the gold market cause fluctuations in prices in this market. Volatility in gold prices causes it to affect many areas of the economy, especially financial markets.

Several crucial factors that influence volatility in the gold market can be enumerated as follows (Fang et al., 2018: 414; Beckmann et al., 2019: 663-664; Li et al., 2023: 1-2):

- ✓ Economic Uncertainty: During periods of economic uncertainty, investors frequently seek refuge in safe haven assets. Gold is often regarded as a preferred asset by investors seeking to safeguard their portfolios against economic crises, political instability, and financial turmoil. The heightened demand for gold resulting from such uncertainties can lead to an increase in its prices.
- ✓ Interest Rates: The relationship between interest rates and gold prices is inverse. Low interest rates can enhance the appeal of gold and stimulate demand by reducing the returns of alternative investment instruments. Conversely, high interest rates may render gold an unyielding asset, thereby reducing its demand.
- ✓ Exchange Rates: Since gold is usually traded in dollars, the value of the dollar affects gold prices. A depreciation of the dollar can increase the price of gold because it becomes more valuable against the dollar. Conversely, a strong dollar could suppress the price of gold.
- ✓ Geopolitical Factors: Political or geopolitical tensions, threats of war or tensions in international relations may increase gold demand. In such cases, investors may look for a safe haven and turn to gold.
- ✓ Supply and Demand Balance: One of the basic principles of the gold market is the supply and demand balance. While factors such as mine production, miners' activities, central banks' gold reserves and the jewelry industry affect the supply of gold, investor demand may vary.
- ✓ Speculation: Speculative transactions and investment funds can also affect gold prices. Interest in gold from large investors or speculators may increase market volatility.

This study aims to estimate volatility for the Turkish economy by using gold market closing data for the period 2005-2023. The main reason why volatility was chosen for the gold market is that measuring, researching and monitoring is a very important analysis subject and is important for many different stakeholders. It is important to detect this

volatility in making investment decisions, performing risk management, and analyzing the effects of monetary policies implemented by central banks. On the other hand, gold market volatility can also be considered an indicator of global economic uncertainties or crises. Economists and analysts try to predict economic trends by monitoring volatility levels in the gold market. For these reasons, the volatility of the gold series is investigated in the study.

The examination of volatility in the literature predominantly focuses on financial market variables, thus resulting in a relatively limited amount of research on the volatility of the gold market. Different studies in the existing body of literature have explored spot and forward gold markets, focusing on the spot gold variable. However, this particular study diverges from previous research by conducting an analysis on the return series of the gold index. Moreover, meticulous attention was given to ensuring that the time period under consideration was current and relevant. Consequently, this study aims to make a valuable contribution to the existing literature by addressing this research gap.

In the study, daily data set between 2005 and 2023 was used. In this way, it is aimed to make a clearer estimate of volatility. According to the findings, it was determined that there was volatility in gold prices within the time period considered and the effect of this volatility was eliminated with the GARCH (1,1) model.

In the study, after the introduction section where the general characteristics of the gold market and its relationship with volatility are included, the empirical literature is examined. After explaining the econometric method used in modeling the volatility of the variable considered, the data set and analysis results are included. In the conclusion section, the findings obtained from the analysis are evaluated.

Empirical Literature

Volatility in the gold market emerges as an important macroeconomic indicator. Gold market volatilities are examined in order to observe both the reactions to the policies implemented by central banks and the behavior of investors in case of uncertainty in the economy. For these reasons, there are many studies that evaluate volatility both theoretically and empirically. This section includes literature examples on measuring volatility in the gold market, which is extremely important for both policy makers and investors.

In the study, Şencan (2017) tried to determine the conditional heteroscedasticity model with the highest explanatory power in modeling the BIST gold index return volatility. In the study where daily data set was used between 01.08.2012 and 13.10.2015, index closing data were used and symmetric and asymmetric GARCH type models were examined. The study's findings led to the determination that the GARCH(1,1) model is the most suitable approach for elucidating the volatility of the gold index.

Kurt Cihangir and Uğurlu (2017) investigate the gold market volatility in Türkiye in their study. It was aimed to determine asymmetric effects in the study, where the date range 01.01.2010 - 28.10.2016 was taken and the daily data set was used. In this context, APARCH, TARCH and EGARCH models have also been used along with the GARCH model. According to the findings obtained in the study, the APARCH model was determined to be the most appropriate model in explaining the volatility of the gold

market. During the period under consideration, it was determined that in the case of Türkiye, volatility was significantly influenced by positive shocks rather than negative shocks.

Kayral (2017) conducted a study aimed at identifying the optimal model for explaining gold market volatility in Türkiye. The study analyzed data spanning from 27.07.1995 to 27.07.2016 and focused on conditional heteroscedasticity models. Among the models evaluated, the EGARCH (1,1) model was found to have the highest explanatory capacity. Furthermore, the study revealed that the impact of positive economic news on gold market volatility is more significant than that of negative news.

Karabacak et. al. (2014) investigate the BIST100 index return and gold return volatility in their study. The aim of the study, in which the daily data set between January 3, 2003 and September 11, 2013 is used, is to determine the most appropriate model explaining volatility. For the period considered, it has been determined that the explanatory power of the TARARCH (1,1) model is more than the others in terms of BIST100 index return and the GARCH (1,1) model is more explanatory power than the others in terms of gold return.

Tokat (2013) conducted a study to examine the volatility in gold, foreign exchange, and stock markets using the MGARCH model, a multivariate GARCH model. The study utilized a daily dataset spanning from January 3, 2000, to June 8, 2012. The findings indicated that all the variables under consideration exhibited heteroskedasticity, implying that they were influenced by their own past shocks. Additionally, the study identified changes in the dollar exchange rate as one of the factors influencing volatility in the gold market.

In the study conducted by Kutan and Aksoy (2004), a daily data set between 02.01.1996 and 14.02.2001 is used and it is investigated to what extent the CPI index affects the volatility in the gold market return in Türkiye, which is an example of a country experiencing high inflation. According to the findings obtained from the study in which the GARCH (1,1) model was used, it was determined that the gold stock market did not react significantly to the CPI news. Therefore, it has been concluded that it is not a good protection tool against inflation. On the other hand, it has been found that the gold market reacts to the information announced about GNP and trade balance. In other words, it has been determined that real sector news has a greater impact on gold market volatility.

In their study, Hasana et. al. (2019) modeled the volatility of gold returns for Indonesia using a daily data set between January 1, 2014 and September 23, 2016. In the study, they aim to solve the heteroscedasticity problem by using GARCH models. After analyzing the period under consideration, it has been determined that the GARCH (1,1) model is the most suitable model for volatility analysis and exhibits the highest level of explanatory capability.

In the study, Şengül (2023) compares the predictive powers of the models by using Support Vector Regression-GARCH hybrid models combined with the traditional volatility models, as well as traditional volatility models regarding gold market return volatility. GARCH, EGARCH, GJR-GARCH, SVR-GARCH models were analyzed in the study using the daily data set between 01/01/2010–01/04/2023. According to the

findings, it was concluded that the SVR-GARCH model makes more effective predictions.

In their study, Ejap et. al. (2022) aim to model the volatility in the gold market through GARCH(1,1), EGARCH(1,1) and TGARCH(1,1) models. The evaluation of model performance in the study involved the utilization of a daily data set spanning from January 4, 2016 to October 29, 2021. This assessment was conducted by comparing information criteria. Accordingly, the model with the lowest value in the information criterion is considered the best model. According to the findings, it has been observed that the TGARCH(1,1) model has a better ability to reflect the good or bad news in the economy and it has been concluded that it performs better than other models.

In their study, Swain and Samal (2017) analyze the price volatility in the gold market in the Indian economy. GARCH models were used in the study where the daily data set between 01.01.2011 - 30.06.2016 was examined. According to the findings, the result of the GARCH(1,1) model indicates that approximately 85% of the volatility in the gold market is derived from the previous day's forecasts. According to the result of the EGARCH model, it was observed that a higher volatility occurred after the downward movement of the gold market return. According to the TGARCH (1, 1) model, it was concluded that both positive and negative shocks are equally effective on the volatility that will occur in the future period.

In the study, Bentes (2015) examined the volatility of gold returns using GARCH family models. GARCH(1,1), IGARCH(1,1) and FIGARCH(1,1) models were discussed in the study using daily data between 02.08.1976 - 06.02.2015. According to the findings, it has been determined that the FIGARCH(1,1) model is the model with the highest explanatory power in predicting the volatility in gold returns.

In their study, Akel and Gazel (2015) used a daily data set between 03.07.2000 and 03.11.2014 to investigate whether gold is a good alternative to avoid risk against stock investments. In this context, models belonging to the GARCH family were used. TARARCH and EGARCH models, which take into account asymmetric effects, were used. Based on the results, it was determined that the TARARCH(1,1) model was the optimal choice. It has been disclosed that a positive correlation exists between the returns of stocks and the returns of gold.

In their investigation, Sopipan et. al. (2012) conducted an analysis on the volatility of gold returns using a daily dataset spanning from 04.01.2007 to 31.08.2011. The study employed the MSGARCH model and compared its findings with those of the GARCH(1,1), EGARCH(1,1), and GJR-GARCH(1,1) models. While each model yielded significant results individually, the evaluation of goodness of fit statistics and loss functions revealed distinct outcomes for all models.

In their study, Gencer and Musoğlu (2014) examined the volatility of the Istanbul Gold Exchange by applying various GARCH models. In the study using the daily data set between 04.01.2006 and 20.11.2013, they concluded that the explanatory powers of the EGARCH and CGARCH models were higher.

Econometric Method

Autoregressive Conditional Heteroskedasticity (ARCH) Model

The ARCH model, which stands for Autoregressive Conditional Heteroskedasticity, is a statistical model used in econometrics and time series analysis to model and forecast volatility in financial markets and other time series data. It was developed by Robert F. Engle in the early 1980s and earned him the Nobel Prize in Economics in 2003.

The primary concept underlying the ARCH model is to encompass the dynamic nature of volatility or variance in a time series. In numerous financial and economic time series, the presumption of a consistent variance (homoskedasticity) is invalid, indicating that the volatility of the data fluctuates over time. The ARCH model tackles this concern by formulating the conditional variance of a time series as a function of previous observations.

The ARCH model was initially introduced by Engle in 1982 with the aim of explaining the inflationary environment in England. However, over time, it has been applied to various other variables. Engle's study in 1982 revealed that the variance of the error term was not constant and was dependent on past values, indicating the presence of autocorrelation between the error term variances in the UK inflation variable. Based on this finding, Engle proposed the development of the ARCH model, which was constructed to account for this autocorrelation (Engle, 1982: 987).

According to conventional time series models, it is postulated that the error term variance remains constant. When analyzed within the context of these models, it is recognized that in the presence of heteroskedasticity, the least squares estimator retains its unbiased and consistent properties, but it yields statistically insignificant outcomes in parameter estimation. Consequently, it becomes imperative to address the issue of heteroskedasticity or develop models that accommodate this variability in variance (Songül, 2010: 4).

The ARCH model is predicated on the fundamental premise that the variance of the error term in a given period t , denoted as $(=\sigma_t^2)$, is contingent upon the square of the error term in the preceding period $(t-1)$, represented as (u_{t-1}^2) . This implies that autocorrelation is not solely confined to the interdependencies between present and past error terms, but is also linked to the present and past variances of the error terms (Gujarati, 2009: 449-450).

An approach evaluated within the scope of variance models such as the ARCH model clearly reveals an independent variable that helps estimate the volatility of the time series under consideration. This situation can be expressed in its most general form with the following equation: (Enders, 2004: 112-113)

$$y_{t+1} = \varepsilon_{t+1}x_t \quad (1)$$

Equation (1) features the variable ε_{t+1} , which denotes an error term with a variance of σ^2 , while x_t is an independent variable. In the event that the independent variable remains constant in preceding periods, it can be inferred that the y_t series is subject to a white noise process with a constant variance. Conversely, if the independent variable assumes variable values instead of constants, the variance of the y_{t+1} variable is expressed as follows (Enders, 2004; Songül, 2010):

$$\text{Var}(y_{t+1}|x_t) = x_t^2 \sigma^2 \quad (2)$$

In accordance with equation (2), it can be inferred that there exists a relationship between the actual value of the independent variable x_t and the conditional variance of the dependent variable y_{t+1} . This implies that a positive correlation exists between the value of x_t and the conditional variance of y_{t+1} . Consequently, the determination of the x_t variable enables the estimation of the volatility of the y_t series (Enders, 2004: 113).

When departing from the assumption of constant variance, the conditional variance is characterized as an autoregressive process of order q (AR(q)). Equation (3) is defined as a general autoregressive conditional heteroscedasticity (ARCH) model.

$$\hat{\varepsilon}_t^2 = \alpha_0 + \alpha_1 \hat{\varepsilon}_{t-1}^2 + \alpha_2 \hat{\varepsilon}_{t-2}^2 + \dots + \alpha_q \hat{\varepsilon}_{t-q}^2 + v_t \quad (3)$$

Upon evaluating the estimation process of equation (3) as an autoregressive (AR(q)) model in conjunction with the Lagrangian multipliers test, an investigation into the presence of the autoregressive conditional heteroscedasticity (ARCH) effect is conducted. The statistical value of the ARCH LM test is computed using the formula $LM = (T - q)R^2$ and follows a χ^2 distribution with q degrees of freedom.

$$H_0 = \alpha_1 = \alpha_2 = \dots = \alpha_q = 0$$

$$H_1 = \alpha_1 \neq \alpha_2 \neq \dots \neq \alpha_q \neq 0 \quad (4)$$

The hypotheses are subjected to empirical testing, and based on the results, if the value of LM_{ARCH} is less than the critical value χ_q^2 from the table, the null hypothesis (H_0) is rejected, thereby accepting the presence of the ARCH effect. This conclusion is indicated by previous studies conducted by Gürsakal (2009) and Özden (2008).

Several notable features of the ARCH model have been identified by scholars such as Nargeleçekenler (2011) and Songül (2010). The conditional variance parameter is required to have a positive value. Similarly, the parameters $\alpha_0, \alpha_1, \alpha_2, \dots, \alpha_n$ must all be positive. Specifically, it is necessary that $\alpha_i \geq 0$, where $\alpha_0 > 0$ and $i=1,2,\dots,p$. In the event that $\alpha_1, \alpha_2, \dots, \alpha_n=0$ are all equal to zero, the variance will be equal to α_0 . Furthermore, it is essential that each individual α_n or the sum of all α_n 's is less than 1. This constraint ensures the stability of the ARCH process.

The ARCH model has been extended and refined over the years, leading to variations like GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models, which also incorporate a moving average component. These models find extensive application in the field of finance to simulate and predict volatility, a critical factor in risk management, option valuation, and portfolio optimization, among various other uses.

Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

Model

The ARCH model is a conditional heteroskedasticity model predicated on the supposition that error terms conform to an autoregressive (AR) process. The GARCH model, which was introduced by Bollerslev in 1986, posits that error terms adhere to the autoregressive moving average (ARMA) process. This assumption underpins the development of the GARCH model.

GARCH models, apart from incorporating the ARCH component, incorporate an additional conditional variance component that is influenced by both previous squared returns and previous conditional variances. This feature enables GARCH models to effectively capture the phenomenon of volatility clustering, wherein periods characterized by heightened volatility are observed to occur consecutively. GARCH models involve estimating model parameters, including coefficients for the autoregressive terms (p), the conditional variances (q), and potentially other parameters to capture specific characteristics of the time series.

GARCH models are typically denoted as GARCH(p, q), where ' p ' represents the order of the ARCH component (the number of lags of squared returns included), and ' q ' represents the order of the GARCH component (the number of lags of past conditional variances included).

The most comprehensive depiction of the GARCH(p, q) model is presented by Bollerslev (Bollerslev, 1986: 308-309).

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t), \quad (5)$$

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^p \beta_i h_{t-i} = \alpha_0 + A(L)\varepsilon_t^2 + B(L)h_t \quad (6)$$

This type of GARCH model must satisfy several conditions. These conditions:

$$\begin{aligned} p &\geq 0, \quad q > 0 \\ \alpha_0 &> 0, \alpha_i \geq 0, \quad i = 1, \dots, q, \\ \beta_i &\geq 0, \quad i = 1, \dots, p. \end{aligned}$$

In contrast, the GARCH(1,1) model, a commonly encountered model in the literature, exhibits a condition whereby $\alpha_1 + \beta_1 < 1$ (Bollerslev, 1986: 311).

The GARCH model can be used for various purposes in finance, such as risk management, portfolio optimization, and option pricing. Analysts and traders often use GARCH models to forecast future volatility, which can be valuable for making investment decisions, risk assessment, and setting hedging strategies.

It's worth noting that there are extensions and variations of the basic GARCH model, such as EGARCH (Exponential GARCH) and IGARCH (Integrated GARCH), which account for different aspects of volatility dynamics. Additionally, there are more complex models like GJR-GARCH that incorporate sudden jumps in volatility.

EGARCH

GARCH models are widely utilized for measuring volatility, but they have been found to possess certain deficiencies. The most significant of these limitations is their assumption of a symmetrical response to shocks in the economy, irrespective of the nature of the shock. However, it is well-established that asymmetric reactions can occur in response to positive or negative shocks in the economy. Consequently, there is a need for asymmetric models. These models are constructed by allowing the impact of negative shocks in the economy to differ from that of positive shocks. In order to address the inadequacy of GARCH models in capturing the leverage effect in financial time series, Nelson (1991) developed EGARCH (Exponential GARCH) models.

This model, developed by Nelson (1991), is modeled in its most general form as follows:

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^q \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^p \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^r \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \quad (7)$$

The EGARCH model employs the logarithm of conditional heteroscedasticity, thereby eliminating the constraint on GARCH parameters to not take negative values. This is due to the fact that, even if the parameters assume negative values, the logarithmic transformation ensures that h_t remains positive. Moreover, the EGARCH model provides valuable insights into the magnitude and persistence of economic shocks. The model also incorporates the asymmetry effect, which is determined by the volatility parameter α_i . Finally, the presence of the leverage effect is indicated if the estimated parameter α_i is statistically significant (Korkmaz and Çevik, 2009: 29. Özden, 2008: 344).

TGARCH

The TGARCH (Threshold GARCH) model is a variation of the more widely known GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model used in econometrics and financial time series analysis. In a standard GARCH model, the volatility of a financial time series is assumed to depend on its past volatility, and the model incorporates lagged squared returns and lagged squared volatility terms. Financial returns frequently display volatility clustering, wherein phases of elevated volatility are succeeded by similar phases, and conversely.

The TGARCH model introduces a threshold element to account for the fact that volatility dynamics may change under certain conditions or regimes. Specifically, it assumes that there are different volatility regimes, and the transition between these regimes is governed by a threshold. When the financial series crosses this threshold, the volatility dynamics change.

The leverage effect is tried to be determined with the TGARCH model developed by Zakoian in 1994. In other words, the TGARCH model was created by adding the leverage variable to the GARCH model. At this point, its difference from the GARCH model is that it tries to explain the asymmetry in the variance of the error terms (Arduç, 2006: 25).

The TGARCH(p,q) model is shown as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^r \gamma_k \varepsilon_{t-k}^2 I_{t-k}^- + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 \quad (8)$$

$$I_{t-k}^- = \begin{cases} 1, & \varepsilon_{t-i} < 0 \\ 0, & \varepsilon_{t-i} \geq 0 \end{cases}$$

In the context of TGARCH models, the value of $\varepsilon_{t-i} = 0$ is regarded as a threshold value. It is postulated that the impact of positive shocks ($\varepsilon_{t-i} > 0$) on the conditional variance is greater than that of negative shocks ($\varepsilon_{t-i} < 0$) on the conditional variance. This effect is incorporated into the model through the I_{t-k}^- parameter. The TGARCH model posits that the impact of positive news is represented by α_i , while the impact of negative news is represented by $\alpha_i + \gamma_i$. It follows that a positive value of γ_i implies a greater effect of negative news. Conversely, a γ_i value of zero indicates that the TGARCH and GARCH models are equivalent (Hossain et al., 2005:419-425. Mapa, 2004:3-5. Özden, 2008: 344-345).

Data Set and Analysis Results

In the field of volatility modeling, it is widely acknowledged in academic literature that daily or weekly data sets are commonly employed. For the purposes of this study, the daily closing data of the BIST gold index, spanning from January 3, 2005 to August 21, 2023, was utilized. The data series was sourced from the official website of Borsa Istanbul and was subjected to modeling using the ARCH-GARCH technique.

While examining the volatility of the BIST gold index closing series discussed in the study, logarithmic transformation was first performed. The main reason for this is that the real size of the fluctuation in the series can be determined by performing the logarithmic transformation. The dimensions of the movement in index values are very different from each other. This difference is observed more clearly in logarithmically transformed series. In this way, the effects of shocks and crises are analyzed more clearly.

The initial stage of time series analysis is widely acknowledged to be the assessment of stationarity. Consequently, the first step undertaken was to investigate the stationarity of the series under consideration.

Table 1: Results of unit root tests

	Gold Index	
	Test Statistics	5% Critical Value
ADF unit root test	-67.97329	-2.862031
PP unit root test	-68.20283	-2.862031
KPSS unit root test	0.289432	0.463000

Based on the outcomes of the ADF, Phillips Perron, and KPSS unit root tests, as presented in Table 1, it can be inferred that the BIST gold index series exhibits stationarity at a significance level of 5%.

In this study, ARCH-GARCH models were employed to ascertain the volatility of the series under investigation. To this end, lagged conditional variances were incorporated into the model. As a preliminary step in estimating the models, it is imperative to establish the average equation based on the ARMA models that align with the structure of the variable in question. In this context, upon examining the significance of the parameters and employing model selection criteria, it was determined that the ARMA(1,1) model was the most appropriate choice for the gold series.

Table 2: ARMA(1,1) Model Forecast Results for BIST Gold Index

	Coefficients	Standard Error	t Value	Probability Value
Constant	0.001072	0.000222	4.836667	0.0000
AR(1)	0.562226	0.073395	7.660297	0.0000
MA(1)	-0.618580	0.070380	-8.789097	0.0000
AIC	-5.495376			
SC	-5.489343			
Log. L.	11563.52			

For the series considered, the presence of the ARCH effect in the error terms of the estimated ARMA(1,1) model is determined by the ARCH-LM test. The results of this test are given in Table 3.

Table 3: ARCH-LM test results for the ARMA(1,1) model

F-statistic:	61.02825	Prob. F(3,4200)			0.0000
Obs*R-squared:	175.6042	Prob. Chi-Square(3):			0.0000
Variable	Coefficient	Standard Error	t Value	Probability Value	
c	0.000171	2.51E-05	6.811911	0.0000	
RESID^2(-1)	0.076496	0.015419	4.961132	0.0000	
RESID^2(-2)	0.171595	0.015236	11.26251	0.0000	
RESID^2(-3)	0.038052	0.015419	2.467813	0.0136	

Table 3 examines the presence of the ARCH effect in the error term of the ARMA(1,1) model. The null hypothesis, which suggests the absence of an ARCH effect, is rejected based on the findings. Specifically, the ARCH-LM test results for the BIST gold series indicate the existence of three ARCH effects, as the probability values are below the significance level of 0.05. Consequently, an ARCH (3) model is established in light of these observations.

Table 4: Test results of ARCH(3) model

Variable	Coefficient	Standard Error	z Value	Probability Value
c	0.000910	0.000134	6.810327	0.0000
AR(1)	0.286632	0.106610	2.688609	0.0072
MA(1)	-0.378418	0.102347	-3.697389	0.0002
VARIANCE EQUATION				
C	8.33E-05	2.42E-06	34.46652	0.0000
RESID(-1)^2	0.281640	0.015408	18.27909	0.0000
RESID(-2)^2	0.214125	0.012970	16.50928	0.0000
RESID(-3)^2	0.216025	0.013043	16.56198	0.0000

Consequently, the equations that constitute the ARCH(3) model can be formulated in the following manner:

$$Gold_t = 0.000910 + 0.286632 Gold_t - 0.378418 \epsilon_{t-1} \tag{9}$$

The variance equation can be defined as:

$$h_t = 0.0000833 + 0.281640 h_{t-1}^2 + 0.214125 h_{t-2}^2 + 0.216025 h_{t-3}^2 \tag{10}$$

Equation (8) represents the variance equation, wherein all coefficients possess positive values. In this respect, it provides the necessary condition. Furthermore, the sum of coefficients in the equation (0.0000833+0.281640+0.214125+0.216025=0.7118733) is less than 1. The sum of coefficients in this equation is a crucial indicator. It is concluded that as the sum of the coefficients approaches 1, the volatility increases relatively. This value obtained in the study indicates that the volatility inertia is relatively above average.

ARCH-LM test is applied to detect the existence of the ARCH effect of the resulting ARCH(3) model. According to the ARCH-LM test, the null hypothesis tests that there is no ARCH effect, and the alternative hypothesis tests that there is an ARCH effect.

Therefore, rejecting the null hypothesis indicates the existence of the ARCH effect. Table 5 shows the ARCH-LM test results with 1, 4, 8 and 12 delays.

Table 5: ARCH-LM test results for the ARCH(3) model

F-statistic	0.313247	Prob. F (1,4203)	0.5757
Obs*R-squared	0.313373	Prob. Chi-Square (1)	0.5756
F-statistic	0.760732	Prob. F (4,4197)	0.5507
Obs*R-squared	3.044348	Prob. Chi-Square (4)	0.5504
F-statistic	1.857525	Prob. F (8,4189)	0.0622
Obs*R-squared	14.83948	Prob. Chi-Square (8)	0.0623
F-statistic	3.136685	Prob. F (12,4181)	0.0002
Obs*R-squared	37.42037	Prob. Chi-Square (12)	0.0002

According to the ARCH-LM test results used to determine the volatility of the series subject to the research, while the existence of volatility is not mentioned in the 1st, 4th and 8th lags, the presence of volatility is noticeable in the 12th lag. Since not all existing lags indicate that there is no ARCH effect, GARCH models were used. In this way, it is aimed to determine a model in which volatility is eliminated.

At this stage of the study, GARCH models were established in order to eliminate the ARCH effect and to determine which of the ARCH (3) - GARCH (1,1) - EGARCH(1,1) - TGARCH(1,1) models is more appropriate for the variable under consideration.

Table 6: Test results for the GARCH(1,1) model

Variable	Coefficient	Standard Error	z Value	Probability Value
c	0.000663	0.000137	4.827350	0.0000
AR(1)	0.377537	0.167712	2.251100	0.0244
MA(1)	-0.453958	0.159292	-2.849849	0.0044
VARIANCE EQUATION				
C	9.72E-06	6.45E-07	15.05681	0.0000
RESID(-1)^2	0.182347	0.007821	23.31385	0.0000
GARCH(-1)	0.787664	0.007235	108.8614	0.0000

According to the findings in Table 6, it was determined that the GARCH variable gave significant results. At this point, the study aimed to determine the most appropriate model by investigating other GARCH models. In this regard, EGARCH and TGARCH models were also used.

Table 7 presents the estimation outcomes for the EGARCH(1,1) model. As a preliminary measure, the statistical significance of the EGARCH(1,1) model's constant terms and coefficients is examined. Hypotheses are formed separately for ω , α_1 , β_1 , γ_1 . Null hypotheses test that the coefficients ω , α_1 , β_1 , γ_1 are not statistically significant, respectively, and alternative hypotheses test that these terms are statistically significant.

Table 7: Test results for the EGARCH(1,1) model

Variable	Coefficient	Standard Error	z Value	Probability Value
c	0.000924	0.000191	4.840001	0.0000
AR(1)	-0.994939	0.000619	-1606.202	0.0000
MA(1)	0.999537	3.84E-05	26050.29	0.0000
VARIANCE EQUATION				

C(4)	-8.515743	0.063122	-134.9084	0.0000
C(5)	0.314138	0.014869	21.12659	0.0000
C(6)	-0.055942	0.008011	-6.983384	0.0000
C(7)	0.044740	0.007579	5.903339	0.0000
Prob. Chi-Square(2)				0.0000

The equation system of the EGARCH(1,1) model is created as follows:

$$\log(\sigma_t^2) = -8.515743 + 0.314138 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - 0.055942 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + 0.044740(\sigma_{t-1}^2) \tag{11}$$

The presence of a negative γ_1 value in the equation suggests the existence of a leverage effect. This implies that a decrease in the value of the series under consideration results in greater volatility compared to an equivalent increase in value.

For the adequacy of the model, the ARCH-LM test is applied to the squares of the error terms of the EGARCH(1,1) model. In this way, it is investigated whether the ARCH effect disappears with the established model. According to the results of the ARCH-LM test applied to the squares of the error terms in the EGARCH(1,1) model, it is observed that there is an ARCH effect since the Probability Chi-Square (2) value is less than 0.05. Therefore, the ARCH effect could not be eliminated with the EGARCH model. Therefore, the EGARCH(1,1) model is not a suitable model for the series considered.

At this point, the TGARCH(1,1) model is also examined to determine which model is more suitable.

Table 8: Test results for the TGARCH(1,1) model

Variable	Coefficient	Standard Error	z Value	Probability Value
c	0.000852	0.000162	5.260313	0.0000
AR(1)	0.355377	0.169568	2.095781	0.0361
MA(1)	-0.434282	0.161789	-2.684252	0.0073
VARIANCE EQUATION				
C	9.03E-06	6.14E-07	14.69975	0.0000
RESID(-1)^2	0.197311	0.009549	20.66228	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.085242	0.010867	-7.844223	0.0000
GARCH(-1)	0.810894	0.007224	112.2503	0.0000
Prob. Chi-Square(1)				0.4007
Prob. Chi-Square(12)				0.4896

Table 8 presents the estimation outcomes for the TGARCH(1,1) model. As a preliminary measure, the statistical significance of the TGARCH(1,1) model's constant terms and coefficients is examined. Hypotheses are formed separately for ω , α_1 , β_1 , γ_1 . Null hypotheses test that the coefficients ω , α_1 , β_1 , γ_1 are not statistically significant, respectively, and alternative hypotheses test that these terms are statistically significant.

The equation system of the TGARCH(1,1) model is created as follows:

$$\sigma_t^2 = 0.00000903 + 0.197311\varepsilon_{t-1}^2 - 0.085242\varepsilon_{t-1}^2 I_{t-1}^- + 0.810894(\sigma_{t-1}^2) \quad (12)$$

As in previous conditional variance models, the existence of the ARCH effect is investigated for the TGARCH(1,1) model. Therefore, Chi-Square probability values are examined and they are seen to be greater than 0.05. Accordingly, "H₀ : There is no ARCH effect on the squares of the error terms." hypothesis cannot be rejected. Since the γ_1 coefficient determined in the model has a value other than zero, the existence of an asymmetry effect is mentioned. However, the TGARCH(1,1) model includes the condition that the parameters in the variance equation are positive. For this reason, although it has a statistically significant value and is a suitable model according to the model selection criteria, the TGARCH(1,1) model is not determined as the most appropriate model.

At this point, it is necessary to determine which model is more appropriate between the ARCH(3), GARCH(1,1), EGARCH(1,1) and TGARCH(1,1) models. For this reason, the selection criteria for the models are compared.

Table 9: Model Selection Criteria

Criteria	MODEL SELECTION CRITERIA			
	ARCH(3)	GARCH(1,1)	EGARCH(1,1)	TGARCH(1,1)
Loglikelihood	12257.11	12357.79	11760.02	12368.85
Akaike	-5.825062	-5.873415	-5.588691	-5.878198
Schwarz	-5.814504	-5.864365	-5.578132	-5.867640
Hannan-Quinn	-5.821329	-5.870215	-5.584958	-5.874465

Table 9 shows the selection criteria for the ARCH(3), GARCH(1,1), EGARCH(1,1) and TGARCH(1,1) models. According to the findings, it is determined that the GARCH(1,1) model is a more suitable model. At this point, when deciding between models in terms of suitability, the model with greater Log likelihood values is preferred. On the other hand, the model with a larger absolute value in terms of Akaike, Schwarz and Hannan-Quinn values is considered to be a more appropriate model. Under these conditions, it was concluded that the GARCH(1,1) model is a more appropriate model in terms of the BIST gold index variable that is the subject of the research.

At this point, since the variance equation coefficients of the TGARCH(1,1) model have negative values and the EGARCH(1,1) model cannot eliminate the ARCH effect, they are not considered as an appropriate model to explain volatility, although they meet other criteria.

Conclusion And Recommendations

Gold appears as a precious metal that has fulfilled the functions of money for centuries. Notably, gold holds the dual role of being both a reliable store of value and a widely accepted medium of exchange. Additionally, gold possesses the advantageous characteristic of serving as a secure refuge for investors seeking stability and protection for their assets.

Gold began to play an important role in shaping economic and political policies, especially during the mercantilist period between the 16th and 18th centuries. The prevailing belief was that to accumulate gold and silver, a country would need to export more than it imported, resulting in a positive balance of trade. For this reason, the

mercantilist period was one of the driving forces behind the search for gold and Europe's effort to find colonies.

This mercantilist period, in which the importance of gold increased considerably, also revealed the necessity of maintaining a stable money supply in order to prevent the possible loss of value in coins. Therefore, it should be noted that the basic elements of monetary policy were developed through gold.

Although mercantilist policies were replaced over time by classical economics and new economic theories and practices such as the adoption of the gold standard that shaped the modern global economy, the importance of gold continued to exist.

Gold prices, like every commodity, are determined primarily by supply and demand dynamics. However, the supply-demand balance is insufficient to explain the fluctuations in gold prices, especially today. The main reason for this is that gold exhibits downward or upward mobility depending on economic instability, the existence of inflationary processes, changes in interest rates, geopolitical and political events. In summary, gold is a volatile asset. It may experience significant price fluctuations in the short and long term. These factors need to be closely monitored for investors to make informed decisions about buying, selling or holding gold.

Due to this important position of the gold market in terms of economies, the study made an analysis covering the period from January 3, 2005 to August 21, 2023 and tried to evaluate the economic dimensions of the volatility in gold prices.

The estimation of volatility in gold prices was conducted by considering the stationarity of the series. In order to ensure stationarity, the constancy of the error term variance was assessed through the implementation of the ARCH-LM test. The analysis encompassed an examination of the stationarity of the series, as well as an evaluation of the autocorrelation function and Cartesian graph. Furthermore, a unit root test was executed, and if the series was found to be non-stationary at the level, differencing was applied to achieve stationarity. The determination of the most suitable ARMA model was based on the analysis of the partial and autocorrelation functions. Subsequently, the ARCH effect was explored in the error squares of the identified ARMA model to ascertain the volatility of the gold price series. To model volatility, asymmetric models such as GARCH, EGARCH, and TGARCH were employed. The analysis indicated that the GARCH(1,1) model was the most appropriate. To evaluate the reliability of the model, the ARCH-LM test was repeated, revealing the disappearance of volatility in the model. Consequently, it was concluded that the GARCH(1,1) model effectively mitigates the impact of gold price volatility.

The objective of this study is to identify the optimal conditional heteroscedasticity models based on the daily return series data of the BIST 100 index. The volatility in the BIST 100 index return series was measured by considering the closing prices. Hence, it was determined that the GARCH(1,1) model is the most suitable model for elucidating the volatility of gold prices.

The research findings indicate that the volatility of the gold return series is not influenced by the leverage effect. This is evident from the asymmetry parameters derived from the TARARCH and EGARCH models, which consider the asymmetry in volatility but fail to impose the required constraints. Nevertheless, the significance of the asymmetry parameters suggests the presence of asymmetric effects in the models.

The GARCH(1,1) model is deemed the most suitable for measuring the volatility of the gold return series.

Additionally, comparable findings can be found in other scholarly works. Şencan (2017) and Karabacak et al. (2014) conducted research on the gold return index within the context of the Turkish economy, employing various conditional heteroscedasticity models. Their investigations yielded a congruent outcome.

Both the Turkish economy and the global gold markets are in a critical economic parameter category in many respects. Gold markets are markets that are affected by global and national political and geopolitical events, and where the reflections of the decisions taken by both political authorities and economic policy makers can be followed very closely. The stability of the fluctuation in gold prices depends on many parameters, both nationally and globally. Additionally, considering gold as a safe investment alternative shows that the behavior of economic actors will also have an impact on the stability of gold prices.

It also has an impact on the expectations and decision-making processes of economic actors. Therefore, it is crucial to establish stable economic policies within the country to mitigate the effects of global political and geopolitical events. A stable market is essential in determining investor preferences and constructing a portfolio. This approach is expected to have a positive impact on the Turkish economy, which is highly sensitive and fragile, by reducing fluctuations in gold prices.

The relationship between volatility and risk perception is widely acknowledged. High volatility in economies leads to decreased confidence and creates a risky environment for investors. This is particularly evident in developing countries where fragility is high, resulting in reduced confidence in the economy and affecting investors' risk perception. The cycle of fragility and volatility deepens, leading to increased market fragility. As a result, volatility plays a crucial role in shaping investors' decision-making processes. In economies such as Türkiye, where gold markets are heavily influenced by political and economic decisions, it is imperative to develop policies that reduce market fluctuations and implement them. Therefore, studies aimed at comprehending volatility in gold markets are essential in guiding policy decisions.

Peer-Review	Double anonymized - Two External
Ethical Statement	It is declared that scientific and ethical principles have been followed while carrying out and writing this study and that all the sources used have been properly cited.
Plagiarism Checks	Yes - Ithenticate
Conflicts of Interest	The author(s) has no conflict of interest to declare.
Complaints	itobiad@itobiad.com
Grant Support	The author(s) acknowledge that they received no external funding in support of this research.
Değerlendirme	İki Dış Hakem / Çift Taraflı Körleme
Etik Beyan	Bu çalışmanın hazırlanma sürecinde bilimsel ve etik ilkelere uyulduğu ve yararlanılan tüm çalışmaların kaynakçada belirtildiği beyan olunur.
Benzerlik Taraması	Yapıldı - Ithenticate
Etik Bildirim	itobiad@itobiad.com
Çıkar Çatışması	Çıkar çatışması beyan edilmemiştir.
Finansman	Bu araştırmayı desteklemek için dış fon kullanılmamıştır.

References

- Akel, V. and Gazel, S. (2015). Finansal Piyasa Riski Ve Altın Yatırımı: Türkiye Örneği. *Çukurova Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, 24 (1) , 335-350.
- Arduç, Ü. (2006). Bankacılık Sektöründeki Dalgalanmaların Otoregresif Koşullu Değişen Varyans Modelleri ile İncelenmesi. (Yayımlanmamış yüksek lisans tezi), Marmara Üniversitesi.
- Bams, W. F. M., Blanchard, G., Honarvar Gheysary, I., and Lehnert, T. (2017). Does oil and gold price uncertainty matter for the stock market?. *Journal of Empirical Finance*, 44, 270-285. <https://doi.org/10.1016/j.jempfin.2017.07.003>
- Beckmann J.,Berger T. and Czudaj R., (2019). Gold price dynamics and the role of uncertainty. *Quantitative Finance, Taylor & Francis Journals*, vol. 19(4), 663-681.
- Bentes, Sonia R. (2015). Forecasting volatility in gold returns under the GARCH, IGARCH and FIGARCH frameworks: New evidence. *Physica A: Statistical Mechanics and its Applications, Elsevier*, vol. 438(C), 355-364.
- Bollerslev, T. (1986). Generalized auto regressive conditional heteroskedasticity. *Journal of Econometrics*, 31, 307-327. [https://doi.org/10.1016/0304-4076\(86\)90063-1](https://doi.org/10.1016/0304-4076(86)90063-1)
- Ding, Q., Huang, J., Gao, W., and Zhang, H. (2022). Does Political Risk Matter for Gold Market Fluctuations? A Structural VAR Analysis. *Research in International Business and Finance*, 60, Article ID: 101618, 1-15.
- Ejap, I.N.N., Azmi, N.N.K., Ariff, N.H.M. and Abdullah, N.H.A. (2022). Modelling and Forecasting Gold Price Return and Its Volatility. *Applied Mathematics and Computational Intelligence*, Volume 11, No.1, 399-411.
- Enders, W. (2004). *Applied econometric time series (Second ed.)*. John Wiley, New York.
- Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50(4), 987-1007. <https://doi.org/10.2307/1912773>
- Fang, L., Chen, B., Yu, H., and Qian, Y. (2018). The Importance Of Global Economic Policy Uncertainty in Predicting Gold Futures Market Volatility: A Garch-Midas Approach. *Journal of Future Markets*, 38 (3), 413-422.
- Gencer, Gaye H. and Musoglu, Z. (2014). Volatility Modeling and Forecasting of Istanbul Gold Exchange (IGE). *International Journal of Financial Research*, Vol. 5, No. 2; 2014, <http://dx.doi.org/10.5430/ijfr.v5n2p87>
- Giannellis, N., and Koukouritakis, M. (2019). Gold price and exchange rates: A panel smooth transition regression model for the G7 countries. *The North American Journal of Economics and Finance*, 49, 27-46.
- Gujarati, D.N. (2009). *Basic econometrics (Fifth ed.)*. New York: McGraw-Hill/Irwin.
- Gürsakal, S. (2009). Varyans kırılması gözlemlenen serilerde garch modelleri: döviz kuru oynaklığı örneği. *Erciyes Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 0 (32) , 319-337.

Hasanah, P., Nasir, S.Q. and Subchan (2019). Gold Return Volatility Modeling Using Garch. *Indonesian Journal of Mathematics Education*, Vol. 2, No. 1, 20-26.

Hossain, N., Troskie, C. G. and Guo, R., (2005). *Comparisons of The Ex Post Efficient Portfolios Under GARCH(1,1) Modeling and GARCH Model Extensions*. Proceedings of the 10th Annual International Conference on Industrial Engineering– Theory, Applications and Practice Clearwater, Florida, 419-425.

Karabacak, M. , Meçik, O. and Genç, E. (2014). Koşullu değişen varyans modelleri ile BİST 100 endeks getirisi ve altın getiri serisi volatilitésinin tahmini. *Uluslararası Alanya İşletme Fakültesi Dergisi*, 6 (1) , 79-90.

Kayral, İ. E. (2017). Estimating The Volatility of Turkey's Gold Market Index With Conditional Heteroscedasticity Models. *Journal of Management and Economics Research*, 15 (2) , 163-181. DOI: 10.11611/yead.264024

Korkmaz, T. and Çevik, E. (2009). Reel Kesim Güven Endeksi ile İMKB 100 Endeksi arasındaki dinamik nedensellik ilişkisi. *İstanbul Üniversitesi İşletme Fakültesi Dergisi*, 38 (1) , 24-37.

Kurt Cihangir, Çiğdem, and Uğurlu, E. (2017). Altın Piyasasında Asimetrik Oynaklık: Türkiye İçin Model Önerisi. *İşletme Araştırmaları Dergisi*, 9(3), 284–299.

Kutan, A. M. and T. Aksoy, (2004). Public Information Arrival and Gold Market Returns in Emerging Markets: Evidence from the Istanbul Gold Exchange. *Scientific Journal of Administrative Development*,2/1.

Li, X., Guo, Q., Liang, C. and Umar, M., (2023). Forecasting gold volatility with geopolitical risk indices. *Research in International Business and Finance*, vol. 64, 1-16.

Mapa, Dennis S., (2004), A Forecast Comparison of Financial Volatility Models: GARCH (1,1) is not Enough. *The Philippine Statistician*, Vol. 53, Nos. 1-4, 1-10.

Nargeleçekenler, M. (2011). Euro kuru satış değerindeki volatilitésinin arch ve garch modelleri ile tahmini. *İstanbul Üniversitesi İktisat Fakültesi Mecmuası*, 54 (2), 153-179.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: a new approach. *Econometrica*, 59(2), 347-370. <https://doi.org/10.2307/2938260>

Özden, Ü. H. (2008). İMKB bileşik 100 endeksi getiri volatilitésinin analizi. *İstanbul Ticaret Üniversitesi Sosyal Bilimler Dergisi*, 7(13), 339-350.

Qian, Y., Ralescu, D. A. and Zhang, B., (2019). The analysis of factors affecting global gold price. *Resources Policy, Elsevier*, vol. 64, 1-9.

Sermaye Piyasası Kanunu, (1993). https://borsaistanbul.com/files/Kiyimli_Madenler_Borsalarinin_Kurulus_ve_Calisma_Esasleri_Hakkinda.pdf.

Songül, H. (2010). Otoresif Koşullu Değişen Varyans Modelleri: Döviz Kurları Üzerine Uygulama. (Uzmanlık Yeterlilik Tezi.) Türkiye Cumhuriyet Merkez Bankası Araştırma ve Para Politikası Genel Müdürlüğü, Ankara.

Sopipan, N., Sattayatham, P. and Premanode, B. (2012). Forecasting volatility of gold price using markov regime switching and trading strategy. *Journal of Mathematical Finance*, 2, 121-131.

Swain Anil Kumar and Samal Gouri Prava. (2017). Price Volatility In The Indian Gold Spot Market: An Econometric Analysis. *International Journal of Advanced Research*, 5 (Jan). 1932-1947. DOI: <http://dx.doi.org/10.21474/IJAR01/2963>

Şencan, İ. (2017). BİST Altın Endeksi Oynaklığı Analizi ve Performans Ölçümü. *Maliye ve Finans Yazıları*, 1 (107) , 10-24 . DOI: 10.33203/mfy.307170

Şengül, Z. (2023). Comparison of GARCH and SVRGARCH models: Example of gold return. *Journal Of Applied Microeconometrics*, 3(1), 23–35. <https://doi.org/10.53753/jame.2068>

Tokat, H. (2013). Altın, Döviz ve Hisse Senedi Piyasalarında Oynaklık Etkileşimi Mekanizmasının Analizi. *İstanbul Üniversitesi Siyasal Bilgiler Fakültesi Dergisi*, 0 (48) , 151-162.

Vengesai E., Rupande L., Tinotenda Muguto H. and Muzindutsi P. F., (2022). Country risk and the interaction between gold price and gold stock index return volatilities: evidence from the South African market. *International Journal of Trade and Global Markets*, vol. 15(1), 32-41.

Zakoian, J. (1994). Threshold Heteroskedastic Models. *Journal of Economic Dynamics and Control*, 18, 931-955.