FinTech as a Disruptive Technology for Financial Institutions

Abdul Rafay
University of Management and Technology, Pakistan

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Chapter 8
FinTech and Stock Market Behaviors:
The Case of Borsa Istanbul

Taner Sekmen
Eskisehir Osmangazi University, Turkey

Mercan Hatipoglu
Cankırı Karatekin University, Turkey

ABSTRACT

This chapter examines the effects of high-frequency trading (HFT) and algorithmic trading (AT) activities, which represent important technological developments in financial markets in the past two decades, on Borsa Istanbul in terms of volatility. To clarify stock market behaviors in terms of volatility, asymmetry, and risk return after the BISTECH transition, the GJR-GARCH-in-Mean and I-GARCH models were used. The dataset consists of the daily stock return series of the main and sub-sector indexes of Borsa Istanbul, covering the period from October 24, 2012 to June 1, 2018. Although there are mixed results for the sub-indexes, it is observed that in the post-BISTECH period, volatility increases significantly in the BIST 100 and BIST 30 indexes, where AT and HFT activities are used more frequently. In particular, the duration of volatility returns to average after shock increases about seven times for BIST 100 and about eight times for the BIST 30 in the post-BISTECH period. Overall, the results indicate that AC and HFT activities may have disruptive effects on financial markets.

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INTRODUCTION

In recent years, there has been a significant increase in both high-frequency trading (HFT) and algorithmic trading (AT) activity in financial markets. Most of the transaction volume in developed markets is created by HFT. Despite this rapid increase in AT and HFT activities, our knowledge about their effects on financial markets is limited. Some researchers say that these developments have benefits like price discovery efficiency, while others note that they may lead to an increase in volatility and adverse selection problems. Although these debates continue, this technological transformation, which began in the U.S. in the 1990s, has spread rapidly to developing countries in recent years. In parallel with these developments, Borsa Istanbul and NASDAQ signed a strategic cooperation agreement in 2014. The first stage of the "Technology Transformation Program" is called BISTECH, a stock market transaction system that was put into operation in 2015, along with Genium INET software and other technological components. The first stage of BISTECH, which consists of many large-scale and years-long programs, was put into practice on November 30, 2015. Borsa Istanbul and NASDAQ announced that Borsa Istanbul has started to use nine leading technologies, including transaction systems, data distribution, index calculation, market surveillance, reporting, and pre- and post-transaction risk management. With the BISTECH Project, Borsa Istanbul has increased the number of orders processed from 4,000 messages to 100,000 messages per second, and the transmission speed of orders has decreased from 1 millisecond to 100 microseconds with the FIX standard protocol. The second phase of the program, the Futures and Options Market (VIOP), began operating on the BISTECH system on March 6, 2017. According to policymakers, these transformations are expected to lead to a reliable, high-performance, fast and multi-instrumental structure in the VIOP. The VIOP, which complies with international standards in terms of technical features, is becoming an international market where investors can use the existing technological systems of foreign institutional investors, which operate by using a similar technological infrastructure.

Although these technological innovations can provide advantages such as increased liquidity, reduced transaction costs and increased competition, high-frequency trading and algorithmic trading may have some negative effects on other market participants. These effects could include the adverse selection problem, increased trading volume and market volatility. Since the introduction of AT strategies, the limit order submissions and cancellations as well as intraday price volatility have increased in some markets (Hagströmer and Norden, 2013). AT might also increase volatility because many algorithms are similar, and therefore their trades are highly correlated, as suggested by Chaboud et al. (2014) and Kalejian and Mukerji (2016). Another concern about HFT activities is that they may increase price movements in a stock market and thus disrupt stability in financial markets. Consequently, understanding the effects of HFT on stock volatility can provide information on controlling the activities of these traders.

According to Martinez and Rosu (2013), an increase in trading volume and market volatility is desirable as long as HFT boosts the efficiency of market pricing by using available information immediately. Brogaard et al. (2014) stress that the main concern about HFT is the possibility of creating market instability, but there is no evidence in their work regarding that point. In Brogaard's 2010 and 2012 studies, no evidence is obtained that HFT increases market volatility. Jones (2013), who reviews the theoretical and empirical literature, classifies the positive effects generated by HFT, while also emphasizing that the negative effects of HFT could not be determined in most of the prior studies. The author also adds that stock price instability may negatively occur during periods of unexpected volatility. However, Zhang (2010) finds some evidence that the stocks with higher HFT ratios increase volatility. Biais and Woolley (2011) list the potential negative effects of HFT as follows: (i) it may lead to manipulation in various forms; (ii) adverse selection can arise because non-HFT traders are slower and less informed than HFT traders; (iii) there can be imperfect competition resulting from the high fixed costs of the infrastructure of the HFT; (iv) there could be an increase in systemic risk resulting from HFT activities having similar strategies. Although there is more evidence in the literature supporting the positive effects of HTF, the concerns mentioned above have not yet been fully addressed.

Furthermore, almost all the studies discussed in the literature analyze developed markets. HFT and AC activities are a relatively new phenomenon for emerging markets. The relevant literature does not say anything about the effects of HFT and AC in those countries that have different economic and market foundations. Despite the fact that the studies on developed markets are generally presented as evidence of the advantages of HFT and AC, the impact of these activities on emerging markets may be quite different. Therefore, more evidence is needed on developing countries in order to understand the effects of HFT and AT activities more clearly. According to our observations on Turkey, which is an emerging market, stock market volatility has increased in the BIST 30 (the 30 largest companies listed on Borsa Istanbul) and BIST 100 indexes (the 100 largest companies listed on Borsa Istanbul), as well as some specific stocks after the transition to the BISTECH system. Abnormal movements, especially in the stock prices of companies in the BIST 30, which have had relatively low volatility levels for years, were observed during this period. Most traders and analysts say that these movements are largely caused by the newly introduced algorithms. All these observations make us skeptical concerning some findings in the literature. For this reason, this study is based on the idea that the technological developments that occurred in Borsa Istanbul may also have had some disruptive effects. In this sense, the study analyzes how stock market behaviors were affected by the introduction of HFT and AT transactions in Borsa Istanbul. More specifically, it focuses on comparing volatility, risk, return and asymmetry behaviors before and after the implementation of BISTECH. Unlike in other studies, a long-term and macro perspective is preferred. The risk, return and asymmetry issues have not been examined before by taking into account HFT in Borsa Istanbul. Therefore, this study allows for a deeper understanding of the effects of HFT on the stock market of a developing country, and a comparison of the results obtained from this developing country with developed countries.

In order to reveal how stock market behaviors changed in the post-BISTECH period, we use daily price data for the main and 15 sub-sector indexes in Borsa Istanbul. The dataset covers the period from October 24, 2012 to June 1, 2018. The study uses the GJR-GARCH-in-Mean approach to model further empirical investigation of volatility. GJR-GARCH-in-Mean makes it possible to simultaneously capture both the risk premium and asymmetry. In addition, we check the GJR-GARCH-in-Mean model's findings on volatility using the I-GARCH method.

Our results suggest that the impact of volatility of the previous period on current volatility increases for most of the indexes in the post-BISTECH period. The I-GARCH model does not reveal that the effects of shocks on volatility have changed significantly, but the GJR-GARCH-in-Mean model shows that there are significant changes in the impact of sudden shocks on volatility for sub-indexes in the post-BISTECH period. Also, the existence of asymmetries for most indexes is determined in both periods. We observe that the risk return relationship has changed for most indexes in the post-BISTECH. The findings on BIST 100 and BIST 30 show us that volatility increases significantly in these indexes for the post-BISTECH period. In particular, the duration of volatility returns to average after shock increases about 7 times for BIST 100 and about 8 times for BIST 30 after the BISTECH transition.

Although the findings from the GJR-GARCH-in-Mean model do not allow for a definite judgment, the volatility of the BIST 30 and BIST Banks indexes, which are considered to be more intensive in HFT and AT activities, seems to increase. However, the results are not very generalizable and need to be supported by further research. This study is designed as follows: Section II reviews the literature on HFT and AT activities in stock markets. Section III identifies the model and data. Section IV deals with the model estimates and the last section is the conclusion.

BACKGROUND ON HIGH-FREQUENCY TRADING AND ALGORITHMIC TRADING

Empirical studies on AT and HFT discuss their effects on different dimensions such as price discovery, adverse selection, price spreads, market quality, liquidity and the volatility of asset prices. In addition, most of these studies focus on the short-term consequences of AT and HFT, and the two concepts are often used interchangeably. However, HFT and AT are different concepts. AT is defined as "the use of computer algorithms to automatically make trading decisions, submit orders, and manage those orders after submission" (Hendershott and Riordan, 2009). Both HFT and AT use automatic decision mechanisms generated by computers, but these two concepts are different from one another in terms of the duration of the positions. Positions are preserved for a very short time in HFT and are usually closed at the end of the day. There is no such a restriction for AT, and so HFT is actually a type of AT (Brogaard, 2010). For this reason, the studies examining the effects of AT and HFT in the literature are categorized separately. In the last part of this section, the findings on studies that analyze the effects of AT and HFT on stock market and price volatility are evaluated.

Hendershott et al. (2011) assess the impact of algorithmic trading on market quality and especially on liquidity for NYSE stocks, using IV regressions and data from February 2001 to December 2005. They find that algorithmic trading improves liquidity for large-cap stocks. Statistically significant results cannot be obtained for small-cap stocks. Furthermore, AT narrows spreads, while also reducing price discovery and adverse selection. Hendershott and Riordan (2013) focus on the role of algorithmic traders on the liquidity supply and demand by using data from a total of 13 days, between January 1 and January 18, 2008, for 30 Deutscher Aktien Index stocks. Their findings are based on probit regression estimations. They conclude that algorithmic traders are likely to reduce liquidity volatility, as they provide liquidity when it is expensive, and algorithmic traders consume liquidity when it is cheap. Chaboud et al. (2014) examine the impact of algorithmic trading on price discovery for three currency pairs: euro-dollar, dollar-yen and euro-yen in the global foreign exchange market by using a structural VAR model and Granger causality tests. Using the three major currencies, and HFT data from 2003–2007, the authors find that AT reduces arbitrage opportunities and high-frequency excess volatility, thus improving price efficiency. However, high correlations between different traders' AT strategies lead to excess volatility. Frino et al. (2017a) investigate the effect of earnings announcements on trading activities. Their dataset is obtained from the Australian Securities Exchange (ASX) for the period October 27, 2008 to October 23, 2009. The authors calculate cumulative average returns and cumulative adjusted average returns to study asymmetries. They also use the (vector autoregressive model) VAR model to examine the relationship between AT and non-AT volume balances and returns. Analyses were conducted for both algorithmic and non-algorithmic trades in the periods immediately before and after corporate earnings announcements. As a result, they state that the algorithms react more quickly and accurately than non-algorithmic traders and thus increase market efficiency. Frino et al. (2017b) examine the effect of algorithmic trading on market liquidity during the high information asymmetry periods for Borsa Italiana. Their dataset covers the period from August 2, 2009 to November 20, 2012 for 35 FTSE MIB stocks. They first calculate different proxies for AT, then provide summary statistics and use the regression method. The authors highlight that market depth decreases and bid-ask spreads widen in the pre-AT period, while bid-ask spreads do not change and market depth does not decrease in the post-AT period. As a result, it is noted that AT increases market liquidity during periods of high information asymmetry.

Brogaard et al. (2014) focus on the impact of HFT trading, as well as price discovery and price efficiency during days of high permananent volatility. The authors analyze 120 randomly selected stocks for 2008 and 2009 listed on NASDAQ and the NYSE. Their estimations are based on correlation analysis and the state space model. The findings of the study indicate that HTFs generally reduce temporary pricing errors while facilitating price efficiency. Despite the debate on whether HFTs may lead to market instability, there is no direct evidence in the study that HFTs contribute to market instability. In another study investigating the effects of high-frequency trading on the foreign exchange market, Manahov et al. (2014) analyze the effects of HTF in terms of technical analysis and market efficiency. They perform AR-GARCH model and K nearest neighbor model based on Strongly Typed Genetic Programming (STGP), using data from August 27, 2012 at 10 pm (GMT) to February 12, 2013 at 10:59 am (GMT). The authors, working with the currency pairs EUR/USD, USD/JPY, GBP/USD, AUD/USD, USD/CHF and USD/CAD, conclude that HFT improves market efficiency, and it is important in the price discovery process in terms of increasing information and reducing pricing errors. Aitken et al. (2015) examine the relationship between HFT and end-of-day price dislocation in 22 stock markets, including in Australia, Canada, China (Shanghai and Shenzhen), Germany, Hong Kong, India (Bombay and the National Stock Exchange of India), Japan, Korea (KOSDAQ and Korea Stock Exchange), Malaysia, New Zealand, Norway, Singapore, South Korea, Sweden, Switzerland, Taiwan, the U.K. and the U.S. (NASDAQ and NYSE) for the January 2003–June 2011 period. According to their panel data estimations, they suggest that the presence of HFT reduces the frequency and severity of end-of-day price dislocation. Conrad et al. (2015) investigate the relationship between high-frequency quotation and the behavior of stock prices for the 2009–2011 period in the U.S., and for the 300 largest stocks on the Tokyo Stock Exchange. They design unconditional tests to provide crosssectional evidence and use a reduced VAR model for different market types. They emphasize that the presence of high-frequency quotes reduces trading costs while improving liquidity and price efficiency. Jain et al. (2016) examine whether high-frequency quoting and trading (HFQ) increases systemic risks for 150 stocks on the Tokyo Stock Exchange. The Arrowhead high-speed trading platform was introduced in Tokyo on January 2010. The sample is divided into two sub-samples, covering the pre- and post-Arrowhead periods. The authors test the impact of the Arrowhead platform by using multiple regression models after they calculate systemic risk through the value at risk (VaR) and ΔCoVaR methods. It is observed that liquidity improves after the introduction of the Arrowhead high-speed trading platform. However, this platform increases shock propagation risk and quote-stuffing risk. The Arrowhead platform leads to systemic risk based on two different measures in study. Baron et al. (2017), meanwhile, use data on the 25 largest Swedish stocks from January 4, 2010 to December 30, 2014, focusing on the role of competition among high-frequency traders. They estimate regression models using ordinary least squares (OLS) and probit regressions. The study shows that faster HFT firms earn more trading revenues than others. Moreover, the faster HFTs capture more trading opportunities and obtain more risk-adjusted revenues.

When we look at the effects of AC and HFT on volatility, mixed and contradictory results are observed in the literature. Gsell (2008), one of the earliest studies investigating the effects of algorithmic trading on markets, focuses on price formation and price volatility through the simulation approach. The study implies that low latency leads to lower market volatility, and large volumes to execute by the algorithmic trader negatively affect market prices. Zhang (2010), examining the effects of high-frequency trading on stock price volatility and price discovery in the U.S. capital market, generally provides evidence on the potentially harmful effects of HFT. He estimates a fixed-effect model by using quarterly data containing 391,013 firm-quarter observations from 1985Q1 to 2009Q2. He finds a positive correlation between HFT and stock price volatility. This positive correlation is larger for stocks with high institutional holdings and for those among the top 3,000 stocks in market capitalization. When HFT volume is high, stock prices overreact to news about firm fundamentals. Therefore, it is suggested that HFT is weak when it comes to transferring information about firm fundamentals to asset prices. Brogaard (2010) analyzes the impact of high-frequency traders on the U.S. equity market. The dataset covers 2008 and 2009 years, as well as the period from February 22, 2010 to February 26, 2010 for 120 stocks. The findings, which come from OLS regressions and ordered logit regressions, point to HFTs contributing to the price discovery process and providing the best bid and offer quotes. In the study, it is also stated that HFTs do not increase volatility but in fact can reduce it. On days when volatility is high, HFT trading levels show little change. Kirilenko et al. (2011), examining the effects of HTFs in the Flash Crash event in E-mini S&P 500 stock index futures on May 6, 2010, emphasize that HFTs accelerated downward price movements during the Flash Crash. The regression estimates are based on data from May 3, 2010 through May 6, 2010. The authors also state that HFTs did not trigger the Flash Crash but increased market volatility. In another study analyzing whether algorithmic trading activities increase volatility, Groth (2011) presents evidence that algorithmic traders do not increase volatility more than normal traders in the stock market. The high-frequency dataset, which covers October 8, 2007 to October 12, 2007, used in study is obtained from the German Frankfurt Stock Exchange. The evidence is based on OLS regression and Two-Stage Least-Squares Regression (2SLS). In addition, it is argued that algorithmic trading participation does not increase volatility, and that algorithmic traders do not lead to a decrease in liquidity during periods of high volatility. Liu (2012) uses the difference-in-difference-in-differences (DDD) approach and data from 2006 and 2008 to investigate the impact of high-frequency trading on stock volatility in the Swedish stock market. According to the findings of the study, HFT reduces intraday volatility in the normal market environment. The removal of HFT activity leads to increased stock volatility for liquid stocks. Hagströmer and Norden (2013) use data on 30 Swedish large-cap stocks traded on the NASDAQ-OMX Stockholm and analyze only two months of data, from August 2011 and February 2012. The authors use the event study, as well as some descriptive statistics. They conclude that market-making HFTs take 63–72% of trading volume and 81–86% of limit order traffic. Moreover, market-making HFTs have lower latency and reduce intraday price volatility. Scholtus et al. (2014) assess the importance of speed for HTF strategies in responding to macroeconomic news. Their regression is based on data from the highly liquid S&P 500 ETF traded on NASDAQ from January 6, 2009 to December 12, 2011. The authors conclude that a delay of 300 milliseconds reduces the returns of trading strategies based on macroeconomic news. Moreover, this effect is greater on days with high volatility. The study also suggests that in the minute after the arrival of macroeconomic news, the best quota trading volume and depth increase, but algorithmic trading activities increase the volatility and reduce overall depth. Boehmer et al. (2015) analyze data from 42 stock markets for the 2001–2011 period to examine the effects of algorithmic trading on liquidity, short-term volatility and information efficiency. They use panel regressions and the instrumental variable (IV) approach. The findings show that AT improves liquidity and information efficiency, while also increasing volatility. The authors note, however, that this increase in volatility is not due to the faster price discovery or increased AT activity during periods of high volatility, as is often emphasized in previous studies. In addition, AT systematically affects the liquidity and volatility of small and low-priced stocks. Kalejian and Mukerji (2016) focus on the effects of high-frequency algorithmic trading on long-term volatility and non-AT investors. Their data includes 200 of the most frequently traded companies in the S&P 500 during the period from May 1, 1985 to May 31, 2012. Their estimations are based on a general spatial two-stage least squares model. The authors emphasize that HFT increases the volatility resulting from news, as well as volatility spillovers between industries. Since the introduction of AT, the variance and covariance of return volatility has increased in most industries. Hasbrouck (2018) focuses on the impact of high-frequency quoting on short-term volatility in bids and offers in U.S. equity market. The study uses a linear fixed effects panel regression model and U.S. equity data for April 2011. It indicates that bids and offers are more volatile than implied in the long term.

MAIN FOCUS OF THE CHAPTER

Econometric Models

The Gjr-Garch model developed by Glosten et al. (1993) captures volatility asymmetry with an additional leverage parameter. The model, which only considers negative shocks, can be seen in Equation (1):

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \lambda 1_{\{\varepsilon_{t-1}<0\}}\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{1}$$

In this equation, if $\varepsilon_t < 0$, the indicator function $\lambda 1_{\{\varepsilon_{t<0}\}} = 1$; otherwise, it is 0. The effect of negative shocks or positive shocks is therefore determined.

In the literature on volatility, the expected return of stocks depends on their volatility. A riskier investor, therefore, will endure higher risk for higher returns. Engle et al. (1987) developed the GARCH-in-Mean model to test this phenomenon.

The model can be explained with the help of the following Equations (2) and (3):

$$r_t = u + \delta\sigma_t^2 + a_t, \qquad a_t = \sigma_t \in_t \tag{2}$$

$$\sigma_t^2 = \omega + \theta a_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{3}$$

In Equation (2), the parameters u and δ are constant, and the parameter δ is called the risk premium. The positive parameter δ indicates a linear relationship between expected return and risk. Furthermore, the significance of the δ coefficient is also considered to be the reason for the autocorrelation observed among past observations of the return series. The reason for the negative relationship between risk and return is that investors see the future as riskier than the present (Alexander, 2001).

This study uses the GJR-GARCH-in-Mean approach to model a further empirical investigation of volatility. In order to capture both the risk premium and asymmetry simultaneously, we combine the two models by integrating the risk premium parameter in the mean equation. The GJR-GARCH-in-Mean (p,q) model can be represented by the following equation as presented by Hamzaoui and Regaieg (2016):

$$r_t = u + \delta\sigma_t^2 + a_t \tag{4}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \lambda 1_{\{\varepsilon_{t-1<0}\}}\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{5}$$

In addition, we can calculate the half-life of volatility, which measures the persistence of volatility in the GJR-GARCH-in-Mean model. It can be calculated in the model with the following equation (Alexander, 2008):

$$\sigma^2 = \frac{\omega}{1-\left(\alpha+\beta+\frac{1}{2}\lambda\right)} \tag{6}$$

When analyzing the financial time series with ARCH models, the sum of the coefficients α and β, depending on the number of observations, does not provide the stability condition of these models. For such cases, Engle and Bollerslev (1986) developed the Integrated GARCH model to provide the stability of the process. The following model was developed to get rid of the effect caused by permanent autocorrelation in the absolute value of the yield series (Rachev, 2007, p. 302):

$$\sigma^2 = \omega + \alpha\varepsilon_{t-1}^2 + \left(1-\alpha\right)\sigma_{t-1}^2 \tag{7}$$

In this model, parameters α and β satisfy the condition that $\alpha + \beta = 1$, and the process is stable.

Data Description

The daily stock return series are used to analyze the effects of AT and HFT activities on stock market volatility. The data covers the period from October 24, 2012 to June 1, 2018 and includes 15 sub-sector indexes, as well as the BIST 100 and BIST 30 indexes. These sub-sectors are BIST Bank; BIST Basic Materials; BIST Chem., Petrol, Plastic; BIST Corporate Governance; BIST Electricity; BIST Food, Beverage; BIST Hold. and Investment; BIST Technology; BIST Insurance; BIST Leasing, Factoring; BIST Metal Products, Mach.; BIST Real Estate; BIST Sports; BIST W. and Retail Trade and BIST Wood, Paper, Printing. All data was obtained from Datastream. The analyses are carried out by dividing the period into two sub-periods, before and after the BISTECH transition.

The stock return series are calculated as follows:

$$R_t = lnP_t - lnP_{t-1} \tag{8}$$

where R_t represents the stock return at time t, and ln indicates the natural logarithm. P_t is the stock market index at time t, and P_{t-1} is the stock market index at time $t-1$. According to this formula for computing the returns, the prices of the stocks and indexes are adjusted by the stock exchange for corporate events such as dividends and share capital increases.

SOLUTIONS AND RECOMMENDATIONS

In this section, we present the estimates for the GJR-GARCH-in-Mean model and I-GARCH model with the Gauss distribution, the Student's t-distribution and the Generalized Error Distribution (GED). The estimates of the GJR-GARCH-in-Mean model and I-GARCH model of Borsa Istanbul's main and sub-indexes are given in Table 1 through Table 17. The tables show estimates for the periods before and after the BISTECH transition. The ARCH-LM statistics in the tables help us to determine whether the returns series contain the ARCH effect. The values in the tables show the ARCH-LM statistic and probability values. The probability values for the ARCH-LM statistics indicate that there are no ARCH effects in most of the estimated models before and after BISTECH transition. Thus, the variance equations are correctly specified in most of our models. We also investigated the autocorrelation in our models. Lag(5) values in the tables represent weighted Ljung-Box test statistics on standardized residuals until the 5th lag. Insignificant Ljung-Box statistics show that there is no autocorrelation of the standardized residuals. The model comparison is done by evaluating the Akaike (AIC), Bayesian (BIC) and Hannan-Quinn (HQ) information criteria. The lowest values for the AIC, BIC and HQ statistics represent the best model. As a result, when the information criteria and residuals tests are examined, there are at least one appropriate estimated model for each sub-sector.

According to the AIC, BIC and HQ criteria, the normal distribution is the most appropriate distribution for all estimated models regardless of model type and period. Therefore, the findings of the normal distribution are used when interpreting the results. However, in the models where the diagnostic tests for the normal distribution estimates are not consistent, the second-best model is preferred according to the information criteria. In addition, the I-GARCH model is better than the GJR-GARCH-in-Mean model for modeling volatility in the pre-BISTECH period; however, the I-GARCH model for the BIST Basic Materials and BIST Real Estate indexes has autocorrelation and an ARCH effect. The results of the GJR-GARCH-in-Mean model are interpreted for these indexes. In the post-BISTECH period, the GJR-GARCH-in-Mean model is the best fit model for the BIST 100; BIST 30; BIST Bank; BIST Chem., Petrol, Plastic; BIST Corporate Governance; BIST Hold. and Investment; BIST Metal Products, Mach.; BIST Sports; BIST W. and Retail Trade; BIST Technology and BIST Insurance indexes.

The α parameter shows the effect of unexpected shocks to the return series on volatility. This parameter appears to be insignificant for the BIST 100 and BIST 30 in the GJR-GARCH-in-Mean model pre- and post-BISTECH. Thus, it is not possible to argue for the impact of sudden shocks on the volatility of the main indexes. When the other sub-sectors are examined, unexpected shocks have a significant impact on the volatility of BIST Chem., Petrol, Plastic; BIST Electricity; BIST Food, Beverage; BIST Leasing, Factoring; BIST Metal Products, Mach.; BIST Real Estate and BIST W. and Retail Trade indexes for post-BISTECH period, while they are insignificant in the pre-BISTECH period. On the other hand, the BIST Technology; and BIST Wood, Paper, Printing indexes are insignificant in the post-BISTECH period. The sudden shocks have a significant impact for BIST Insurance and BIST Sports in both periods.

We check the robustness of the GJR-GARCH-in-Mean model estimates by running the I-GARCH model. The results of the two models are substantially different from each other, especially for the pre-BISTECH period. The I-GARCH model predicts that the α parameter is statistically significant in all models in the pre- and post-BISTECH period except for the BIST Hold. and Investment and BIST Insurance indexes. The impact of unexpected shocks on volatility for these indexes is statistically significant just for the post-BISTECH period. The I-GARCH model does not reveal that the effects of shocks on volatility have changed significantly. However, the results of both models are evaluated together; our findings for the alpha parameter based on the estimates of the GJR-GARCH-in-Mean model and I-GARCH model provide

Table 1. BIST 100

	Model	Dist.	Parameters						In-Sample Criteria			Residuals Tests		
			c	ω	α	β	δ	λ	AIC	BIC	HQ	Lag(5)	ARCH-LM(5)	Half-Life
Pre-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	0.003** (0.001)	0.000*** (0.000)	0.000 (0.012)	0.850*** (0.016)	-0.214* (0.113)	0.168*** (0.033)	5.670	5.635	5.657	3.309 (0.35)	0.950 (0.74)	10.31
		Student	0.002** (0.001)	0.000*** (0.000)	0.000 (0.012)	0.879*** (0.016)	-0.148 (0.017)	0.127*** (0.035)	5.755	5.714	5.739	3.685 (0.29)	1.32 (0.63)	11.97
		GED	0.002 (0.001)	0.000*** (0.000)	0.000 (0.006)	0.865*** (0.017)	-0.123 (0.122)	0.141*** (0.036)	5.750	5.710	5.735	3.76 (0.28)	1.16 (0.68)	10.53
	I-GARCH (1,1)	**Gauss**	0.000* (0.000)	0.000** (0.000)	0.111*** (0.025)	0.888			5.620	5.602	5.613	3.788 (0.28)	1.315 (0.64)	
		Student	0.000** (0.000)	0.000 (0.000)	0.061*** (0.017)	0.938			5.736	5.713	5.727	4.382 (0.20)	3.128 (0.27)	
		GED	0.000** (0.000)	0.000 (0.000)	0.084* (0.050)	0.915			5.728	5.705	5.719	4.104 (0.24)	1.801 (0.51)	
Post-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	0.003* (0.001)	0.000 (0.000)	0.004 (0.010)	0.968*** (0.007)	-0.285* (0.173)	0.036*** (0.014)	6.065	6.025	6.050	2.810 (0.44)	4.228 (0.15)	75.23
		Student	-0.002 (0.002)	0.000* (0.000)	0.025 (0.044)	0.702*** (0.144)	0.248 (0.243)	0.176* (0.100)	6.125	6.077	6.106	3.154 (0.37)	1.217 (0.66)	3.40
		GED	0.001 (0.001)	0.000*** (0.000)	0.000 (0.008)	0.955*** (0.007)	-0.072 (0.099)	0.048** (0.022)	6.119	6.071	6.100	2.861 (0.43)	3.754 (0.19)	34.78
	I-GARCH (1,1)	**Gauss**	0.000* (0.000)	0.000 (0.000)	0.031*** (0.007)	0.968			6.062	6.042	6.054	2.048 (0.60)	5.480 (0.08)	
		Student	0.000 (0.000)	0.000 (0.000)	0.046*** (0.008)	0.953			6.117	6.089	6.106	2.129 (0.58)	2.983 (0.29)	
		GED	0.000 (0.000)	0.000 (0.000)	0.037*** (0.007)	0.962			6.118	6.090	6.107	2.037 (0.60)	4.044 (0.16)	

Note: *** denotes significance at the 1% level, and ** at the 5% level and * at the %10 level. The standard deviations of coefficients are in parenthesis and the probability values of the residuals tests are also reported in parenthesis.

Table 2. BIST 30

	Model	Dist.	Parameters						In-Sample Criteria			Residuals Tests		
			c	ω	α	β	δ	λ	AIC	BIC	HQ	Lag(5)	ARCH-LM(5)	Half-Life
Pre-BISTECH Period	GJR-GARCH-in-Mean (1,1)	Gauss	0.003** (0.001)	0.000*** (0.000)	0.000 (0.011)	0.867*** (0.015)	-0.213* (0.125)	0.141*** (0.028)	5.544	5.509	5.531	3.307 (0.35)	1.029 (0.72)	10.92
		Student	0.002 (0.001)	0.000*** (0.000)	0.000 (0.011)	0.886*** (0.015)	-0.150 (0.127)	0.117*** (0.032)	5.612	5.571	5.596	3.525 (0.31)	1.300 (0.64)	12.46
		GED	0.002*** (0.000)	0.000*** (0.000)	0.002 (0.011)	0.874*** (0.017)	-0.113** (0.052)	0.125*** (0.036)	5.611	5.571	5.596	3.562 (0.31)	1.172 (0.68)	11.29
	I-GARCH (1,1)	Gauss	0.000 (0.000)	0.000 (0.000)	0.093*** (0.034)	0.906			5.502	5.485	5.495	3.603 (0.30)	1.439 (0.60)	
		Student	0.000** (0.000)	0.000 (0.000)	0.050*** (0.011)	0.949			5.594	5.570	5.585	4.283 (0.22)	3.681 (0.20)	
		GED	0.000 (0.000)	0.000 (0.000)	0.073*** (0.028)	0.926			5.592	5.569	5.583	3.848 (0.27)	1.986 (0.47)	
Post-BISTECH Period	GJR-GARCH-in-Mean (1,1)	Gauss	0.004 (0.002)	0.000*** (0.000)	0.002 (0.009)	0.971*** (0.003)	-0.311 (0.221)	0.035*** (0.013)	5.979	5.938	5.963	3.525 (0.31)	5.914 (0.06)	85.42
		Student	0.001 (0.002)	0.000*** (0.000)	0.004 (0.012)	0.947*** (0.011)	-0.052 (0.252)	0.051** (0.024)	6.024	5.977	6.006	3.634 (0.30)	4.284 (0.14)	29.86
		GED	0.000 (0.001)	0.000*** (0.000)	0.000 (0.007)	0.959*** (0.007)	-0.028 (0.128)	0.045** (0.020)	6.026	5.978	6.007	3.371 (0.34)	5.398 (0.08)	40.40
	I-GARCH (1,1)	Gauss	0.000* (0.000)	0.000 (0.000)	0.028*** (0.006)	0.971			5.975	5.955	5.967	2.604 (0.48)	6.938 (0.03)	
		Student	0.000 (0.000)	0.000 (0.000)	0.042*** (0.007)	0.957			6.023	5.996	6.013	2.661 (0.47)	3.817 (0.19)	
		GED	0.000 (0.000)	0.000 (0.000)	0.033*** (0.006)	0.966			6.025	5.998	6.015	2.569 (0.49)	4.998 (0.10)	

Note: *** denotes significance at the 1% level, and ** at the 5% level and * at the %10 level. The standard deviations of coefficients are in parenthesis and the probability values of the residuals tests are also reported in parenthesis.

Table 3. BIST bank

	Model	Dist.	Parameters						In-Sample Criteria			Residuals Tests		
			c	ω	α	β	δ	λ	AIC	BIC	HQ	Lag(5)	ARCH-LM(5)	Half-Life
Pre-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	0.004 (0.004)	0.000*** (0.000)	0.009 (0.015)	0.846*** (0.046)	-0.253 (0.245)	0.104*** (0.034)	4.970	4.935	4.957	0.603 (0.94)	0.624 (0.84)	7.21
		Student	0.003 (0.004)	0.000** (0.000)	0.005 (0.016)	0.849*** (0.058)	-0.166 (0.223)	0.121** (0.047)	5.024	4.983	5.008	4.410 (0.20)	0.681 (0.82)	7.87
		GED	0.002 (0.006)	0.000** (0.000)	0.008 (0.016)	0.840*** (0.058)	-0.108 (0.349)	0.116** (0.046)	5.020	4.980	5.005	4.355 (0.21)	0.672 (0.73)	7.09
	I-GARCH (1,1)	**Gauss**	0.000 (0.000)	0.000 (0.000)	0.036*** (0.008)	0.963			4.939	4.921	4.932	3.973 (0.25)	1.260 (0.65)	
		Student	0.000 (0.000)	0.000 (0.000)	0.034*** (0.008)	0.965			5.006	4.983	4.997	4.072 (0.24)	1.568 (0.57)	
		GED	0.000 (0.000)	0.000 (0.000)	0.034*** (0.008)	0.965			5.003	4.979	4.994	4.055 (0.24)	1.412 (0.61)	
Post-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	0.004 (0.009)	0.000 (0.000)	0.000 (0.022)	0.976*** (0.013)	-0.290 (0.575)	0.027* (0.013)	5.380	5.332	5.361	5.426 (0.08)	2.013 (0.46)	66.20
		Student	0.000 (0.003)	0.000*** (0.000)	0.010 (0.009)	0.942*** (0.010)	0.008 (0.249)	0.046** (0.022)	5.433	5.379	5.412	5.746 (0.06)	0.916 (0.75)	24.00
		GED	-0.000 (0.001)	0.000*** (0.000)	0.000 (0.005)	0.967*** (0.005)	0.038 (0.126)	0.036** (0.015)	5.424	5.369	5.402	5.293 (0.08)	1.837 (0.50)	40.62
	I-GARCH (1,1)	**Gauss**	0.000 (0.000)	0.000 (0.000)	0.020*** (0.004)	0.979			5.374	5.346	5.363	4.656 (0.14)	1.969 (0.47)	
		Student	0.000 (0.000)	0.000 (0.000)	0.042*** (0.010)	0.957			5.434	5.400	5.420	4.769 (0.12)	0.362 (0.92)	
		GED	-0.000 (0.000)	0.000 (0.000)	0.031*** (0.007)	0.968			5.424	5.389	5.410	4.651 (0.14)	0.802 (0.79)	

Note: *** denotes significance at the 1% level, and ** at the 5% level and * at the %10 level. The standard deviations of coefficients are in parenthesis and the probability values of the residuals tests are also reported in parenthesis.

Table 4. BIST basic materials

	Model	Dist.	Parameters						In-Sample Criteria			Residuals Tests		
			c	ω	α	β	δ	λ	AIC	BIC	HQ	Lag(5)	ARCH-LM(5)	Half-Life
Pre-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	-0.000 (0.004)	0.000** (0.000)	0.000 (0.029)	0.723*** (0.102)	0.072 (0.263)	0.141** (0.055)	5.440	5.405	5.426	1.156 (0.82)	0.699 (0.82)	3.01
		Student	0.000 (0.002)	0.000** (0.000)	0.050 (0.041)	0.790*** (0.066)	0.029 (0.171)	0.109* (0.059)	5.572	5.532	5.557	1.041 (0.85)	0.591 (0.85)	6.23
		GED	0.000* (0.000)	0.000** (0.000)	0.021 (0.035)	0.767*** (0.080)	0.010 (0.011)	0.131** (0.061)	5.556	5.516	5.541	1.015 (0.85)	0.578 (0.86)	4.42
	I-GARCH (1,1)	**Gauss**	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	1.000			5.379	5.362	5.372	1.534 (0.73)	19.45 (0.00)	
		Student	0.001*** (0.000)	0.000* (0.000)	0.167*** (0.050)	0.832			5.569	5.546	5.560	1.124 (0.83)	0.455 (0.89)	
		GED	0.000*** (0.000)	0.000*** (0.000)	0.151*** (0.031)	0.848			5.540	5.517	5.532	1.264 (0.79)	0.041 (0.90)	
Post-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	-0.003 (0.007)	0.000** (0.000)	0.005 (0.028)	0.798*** (0.092)	0.267 (0.411)	0.093* (0.052)	5.207	5.166	5.191	2.083 (0.59)	0.047 (0.89)	4.26
		Student	-0.005 (0.006)	0.000 (0.000)	0.011 (0.028)	0.826*** (0.097)	0.399 (0.371)	0.068 (0.051)	5.214	5.166	5.195	2.054 (0.60)	0.053 (0.87)	5.06
		GED	-0.005 (0.003)	0.000* (0.000)	0.010 (0.027)	0.820*** (0.097)	0.378* (0.207)	0.074 (0.051)	5.219	5.171	5.200	2.082 (0.59)	0.509 (0.88)	4.92
	I-GARCH (1,1)	**Gauss**	0.001** (0.000)	0.000 (0.000)	0.016*** (0.003)	0.983			5.195	5.175	5.187	1.483 (0.74)	2.964 (0.29)	
		Student	0.001** (0.000)	0.000 (0.000)	0.023*** (0.004)	0.976			5.210	5.182	5.199	1.438 (0.75)	1.919 (0.48)	
		GED	0.001** (0.000)	0.000 (0.000)	0.020*** (0.003)	0.979			5.213	5.186	5.203	1.450 (0.75)	2.222 (0.42)	

Note: *** denotes significance at the 1% level, and ** at the 5% level and * at the %10 level. The standard deviations of coefficients are in parenthesis and the probability values of the residuals tests are also reported in parenthesis.

Table 5. BIST Chem., petrol, plastic

	Model	Dist.	Parameters						In-Sample Criteria			Residuals Tests		
			c	ω	α	β	δ	λ	AIC	BIC	HQ	Lag(5)	ARCH-LM(5)	Half-Life
Pre-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	0.000 (0.002)	0.000*** (0.000)	0.000 (0.040)	0.808*** (0.048)	0.037 (0.204)	0.162*** (0.044)	5.691	5.656	5.678	1.611 (0.71)	1.052 (0.71)	5.92
		Student	0.001 (0.002)	0.000*** (0.000)	0.016 (0.051)	0.830*** (0.037)	0.011 (0.194)	0.147*** (0.054)	5.794	5.753	5.778	1.521 (0.73)	1.150 (0.68)	8.39
		GED	0.000 (0.000)	0.000*** (0.000)	0.000 (0.013)	0.826*** (0.043)	0.038 (0.027)	0.160*** (0.047)	5.793	5.752	5.777	1.613 (0.71)	1.168 (0.68)	7.03
	I-GARCH (1,1)	**Gauss**	0.000* (0.000)	0.000 (0.000)	0.029*** (0.007)	0.970			5.635	5.618	5.628	1.263 (0.79)	3.427 (0.23)	
		Student	0.001*** (0.000)	0.000*** (0.000)	0.193*** (0.037)	0.806			5.790	5.766	5.781	1.677 (0.69)	0.931 (0.75)	
		GED	0.001 (0.000)	0.000*** (0.000)	0.190*** (0.039)	0.809			5.779	5.756	5.770	1.770 (0.67)	0.889 (0.76)	
Post-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	0.009*** (0.001)	0.000 (0.000)	0.011* (0.006)	0.977*** (0.000)	-0.717*** (0.091)	0.002 (0.013)	5.884	5.843	5.868	2.473 (0.51)	0.485 (0.88)	68.84
		Student	0.010*** (0.002)	0.000** (0.000)	0.000 (0.006)	0.973*** (0.001)	-0.759*** (0.247)	0.025* (0.013)	5.989	5.941	5.970	2.551 (0.49)	0.286 (0.94)	51.39
		GED	0.009*** (0.003)	0.000* (0.000)	0.000 (0.011)	0.976*** (0.001)	-0.671** (0.289)	0.021 (0.021)	5.974	5.926	5.956	2.461 (0.51)	0.391 (0.91)	52.43
	I-GARCH (1,1)	**Gauss**	0.000* (0.000)	0.000 (0.000)	0.016*** (0.003)	0.983			5.879	5.858	5.871	1.731 (0.68)	0.820 (0.78)	
		Student	0.001*** (0.000)	0.000 (0.000)	0.023*** (0.004)	0.976			5.985	5.958	5.975	1.691 (0.69)	0.543 (0.87)	
		GED	0.001** (0.000)	0.000 (0.000)	0.020*** (0.003)	0.979			5.973	5.946	5.962	1.689 (0.69)	0.642 (0.84)	

Note: *** denotes significance at the 1% level, and ** at the 5% level and * at the %10 level. The standard deviations of coefficients are in parenthesis and the probability values of the residuals tests are also reported in parenthesis.

Table 6. BIST corporate governance

	Model	Dist.	Parameters						In-Sample Criteria			Residuals Tests		
			c	ω	α	β	δ	λ	AIC	BIC	HQ	Lag(5)	ARCH-LM(5)	Half-Life
Pre-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	0.002* (0.001)	0.000*** (0.000)	0.000 (0.017)	0.812*** (0.023)	-0.206 (0.146)	0.232*** (0.049)	5.757	5.722	5.744	3.036 (0.40)	1.241 (0.66)	9.41
		Student	0.002* (0.001)	0.000*** (0.000)	0.016 (0.016)	0.838*** (0.022)	-0.130 (0.104)	0.183*** (0.053)	5.855	5.815	5.840	3.245 (0.36)	1.506 (0.59)	12.79
		GED	0.001*** (0.000)	0.000*** (0.000)	0.008 (0.012)	0.823*** (0.023)	- 0.087*** (0.027)	0.196*** (0.055)	5.851	5.810	5.835	3.608 (0.30)	1.427 (0.61)	9.67
	I-GARCH (1,1)	**Gauss**	0.001** (0.000)	0.000*** (0.000)	0.175*** (0.041)	0.824			5.703	5.686	5.697	4.321 (0.21)	1.448 (0.60)	
		Student	0.001*** (0.000)	0.000** (0.000)	0.136*** (0.029)	0.863			5.842	5.818	5.833	4.461 (0.20)	2.056 (0.45)	
		GED	0.000*** (0.000)	0.000** (0.000)	0.146*** (0.036)	0.853			5.832	5.809	5.823	4.675 (0.18)	1.610 (0.56)	
Post-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	0.003 (0.005)	0.000 (0.000)	0.004 (0.012)	0.964*** (0.011)	-0.296 (0.461)	0.038*** (0.008)	6.055	6.014	6.039	2.951 (0.41)	2.734 (0.33)	59.17
		Student	0.000 (0.002)	0.000*** (0.000)	0.004 (0.013)	0.924*** (0.012)	0.000 (0.248)	0.065** (0.029)	6.109	6.061	6.090	2.931 (0.41)	1.560 (0.57)	17.61
		GED	0.002 (0.001)	0.000*** (0.000)	0.000 (0.005)	0.954*** (0.006)	-0.142 (0.167)	0.047** (0.021)	6.103	6.055	6.084	2.936 (0.41)	2.630 (0.34)	32.65
	I-GARCH (1,1)	**Gauss**	0.000* (0.000)	0.000 (0.000)	0.034*** (0.007)	0.965			6.050	6.030	6.042	2.147 (0.58)	2.949 (0.29)	
		Student	0.000 (0.000)	0.000 (0.000)	0.047*** (0.009)	0.952			6.106	6.078	6.095	2.185 (0.57)	1.561 (0.57)	
		GED	0.000 (0.000)	0.000 (0.000)	0.039*** (0.007)	0.960			6.101	6.074	6.090	2.120 (0.59)	2.009 (0.46)	

Note: *** denotes significance at the 1% level, and ** at the 5% level and * at the %10 level. The standard deviations of coefficients are in parenthesis and the probability values of the residuals tests are also reported in parenthesis.

Table 7. BIST electricity

	Model	Dist.	Parameters						In-Sample Criteria			Residuals Tests		
			c	ω	α	β	δ	λ	AIC	BIC	HQ	Lag(5)	ARCH-LM(5)	Half-Life
Pre-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	0.000 (0.003)	0.000*** (0.000)	0.030 (0.027)	0.692*** (0.066)	-0.020 (0.181)	0.218*** (0.069)	5.285	5.250	5.271	2.703 (0.46)	0.277 (0.94)	3.77
		Student	-0.000 (0.002)	0.000** (0.000)	0.081* (0.047)	0.816*** (0.056)	0.043 (0.134)	0.087 (0.067)	5.489	5.449	5.474	3.090 (0.39)	0.301 (0.93)	11.53
		GED	0.000 (0.000)	0.000** (0.000)	0.057 (0.039)	0.787*** (0.065)	0.000 (0.000)	0.117* (0.068)	5.487	5.446	5.471	3.005 (0.40)	0.322 (0.93)	6.86
	I-GARCH (1,1)	**Gauss**	0.001** (0.000)	0.000*** (0.000)	0.249*** (0.053)	0.750			5.244	5.226	5.237	3.494 (0.32)	0.428 (0.90)	
		Student	0.000 (0.000)	0.000** (0.000)	0.157*** (0.045)	0.842			5.493	5.470	5.484	2.804 (0.44)	0.238 (0.95)	
		GED	0.000 (0.000)	0.000*** (0.000)	0.161*** (0.033)	0.838			5.483	5.460	5.474	3.472 (0.32)	0.273 (0.94)	
Post-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	-0.001 (0.004)	0.000** (0.000)	0.080* (0.049)	0.535*** (0.141)	0.306 (0.281)	0.202* (0.121)	5.773	5.725	5.754	2.609 (0.53)	0.776 (0.80)	1.92
		Student	-0.002 (0.003)	0.000* (0.000)	0.071 (0.058)	0.614*** (0.160)	0.260 (0.240)	0.188* (0.102)	5.868	5.813	5.847	3.450 (0.32)	0.481 (0.88)	2.74
		GED	-0.003 (0.002)	0.000*** (0.000)	0.083 (0.085)	0.542*** (0.098)	0.348* (0.201)	0.205 (0.149)	5.868	5.814	5.847	3.131 (0.39)	0.568 (0.86)	2.09
	I-GARCH (1,1)	**Gauss**	0.000 (0.000)	0.000 (0.000)	0.043*** (0.012)	0.956			5.749	5.721	5.738	1.981 (0.71)	3.813 (0.19)	
		Student	0.001** (0.000)	0.000 (0.000)	0.232* (0.139)	0.767			5.853	5.819	5.840	2.584 (0.54)	0.326 (0.93)	
		GED	0.001** (0.000)	0.000 (0.000)	0.058*** (0.015)	0.941			5.851	5.817	5.837	1.952 (0.72)	2.221 (0.42)	

Note: *** denotes significance at the 1% level, and ** at the 5% level and * at the %10 level. The standard deviations of coefficients are in parenthesis and the probability values of the residuals tests are also reported in parenthesis.

Table 8. BIST food, beverage

	Model	Dist.	Parameters						In-Sample Criteria			Residuals Tests		
			c	ω	α	β	δ	λ	AIC	BIC	HQ	Lag(5)	ARCH-LM(5)	Half-Life
Pre-BISTECH Period	GJR-GARCH-in-Mean (1,1)	Gauss	-0.003 (0.003)	0.000*** (0.000)	0.000 (0.018)	0.781*** (0.050)	0.233 (0.197)	0.181*** (0.044)	5.702	5.667	5.688	2.513 (0.50)	2.988 (0.29)	5.07
		Student	-0.003 (0.002)	0.000*** (0.000)	0.000 (0.025)	0.820*** (0.048)	0.306* (0.182)	0.164*** (0.051)	5.783	5.742	5.767	2.987 (0.40)	2.989 (0.29)	6.72
		GED	-0.002*** (0.000)	0.000 (0.000)	0.000 (0.027)	0.804*** (0.110)	0.223*** (0.054)	0.172** (0.071)	5.783	5.743	5.768	2.414 (0.52)	2.804 (0.31)	5.99
	I-GARCH (1,1)	Gauss	0.000 (0.000)	0.000 (0.000)	0.056*** (0.016)	0.943			5.639	5.622	5.632	1.010 (0.85)	2.815 (0.31)	
		Student	0.000 (0.000)	0.000*** (0.000)	0.137*** (0.029)	0.862			5.764	5.741	5.755	1.171 (0.81)	1.442 (0.60)	
		GED	0.000* (0.000)	0.000 (0.000)	0.124*** (0.045)	0.875			5.759	5.736	5.750	1.237 (0.80)	1.304 (0.64)	
Post-BISTECH Period	GJR-GARCH-in-Mean (1,1)	Gauss	-0.000 (0.002)	0.000*** (0.000)	0.212*** (0.057)	0.614*** (0.092)	0.005 (0.229)	-0.025 (0.064)	5.989	5.948	5.973	3.706 (0.29)	1.867 (0.50)	3.37
		Student	-0.003 (0.003)	0.000* (0.000)	0.121** (0.057)	0.730*** (0.120)	0.297 (0.262)	0.007 (0.057)	6.028	5.980	6.009	2.709 (0.46)	1.869 (0.50)	4.45
		GED	-0.002** (0.001)	0.000** (0.000)	0.159*** (0.060)	0.684*** (0.105)	0.207** (0.097)	-0.001 (0.065)	6.030	5.982	6.012	3.785 (0.28)	1.722 (0.53)	4.06
	I-GARCH (1,1)	Gauss	0.000 (0.000)	0.000** (0.000)	0.250*** (0.071)	0.749			5.976	5.956	5.968	4.372 (0.21)	2.076 (0.45)	
		Student	-0.000 (0.000)	0.000 (0.000)	0.113 (0.119)	0.886			6.020	5.993	6.010	4.047 (0.24)	1.443 (0.60)	
		GED	-0.000 (0.000)	0.000 (0.000)	0.166*** (0.077)	0.833			6.023	5.996	6.012	4.325 (0.21)	1.641 (0.55)	

Note: *** denotes significance at the 1% level, and ** at the 5% level and * at the %10 level. The standard deviations of coefficients are in parenthesis and the probability values of the residuals tests are also reported in parenthesis.

Table 9. BIST hold and investment

	Model	Dist.	Parameters						In-Sample Criteria			Residuals Tests		
			c	ω	α	β	δ	λ	AIC	BIC	HQ	Lag(5)	ARCH-LM(5)	Half-Life
Pre-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	0.001 (0.001)	0.000*** (0.000)	0.000 (0.012)	0.853*** (0.016)	-0.077 (0.121)	0.154*** (0.033)	5.701	5.666	5.687	3.426 (0.33)	0.444 (0.89)	9.59
		Student	0.000 (0.001)	0.000*** (0.000)	0.000 (0.012)	0.881*** (0.014)	0.017 (0.146)	0.109*** (0.032)	5.757	5.716	5.741	3.761 (0.28)	0.805 (0.79)	10.54
		GED	0.000 (0.001)	0.000*** (0.000)	0.000 (0.007)	0.871*** (0.014)	0.010 (0.079)	0.124*** (0.035)	5.748	5.707	5.732	3.717 (0.29)	0.661 (0.83)	10.06
	I-GARCH (1,1)	**Gauss**	0.000 (0.000)	0.000 (0.000)	0.109 (0.073)	0.890			5.655	5.638	5.648	4.083 (0.24)	0.922 (0.75)	
		Student	0.000 (0.000)	0.000 (0.000)	0.101* (0.059)	0.898			5.736	5.712	5.727	3.985 (0.25)	1.083 (0.70)	
		GED	0.000 (0.000)	0.000 (0.000)	0.098 (0.069)	0.901			5.726	5.703	5.717	4.044 (0.24)	1.065 (0.71)	
Post-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	-0.001 (0.003)	0.000*** (0.000)	0.010 (0.009)	0.949*** (0.007)	0.122 (0.307)	0.031 (0.019)	5.991	5.950	5.975	3.021 (0.40)	5.193 (0.10)	29.13
		Student	-0.004 (0.003)	0.000* (0.000)	0.066 (0.061)	0.516** (0.215)	0.453 (0.316)	0.175 (0.125)	6.040	5.992	6.021	2.363 (0.53)	1.818 (0.51)	1.73
		GED	-0.003*** (0.000)	0.000** (0.000)	0.069 (0.058)	0.562*** (0.182)	0.329*** (0.040)	0.142*** (0.051)	6.039	5.991	6.021	2.613 (0.48)	2.063 (0.45)	1.96
	I-GARCH (1,1)	**Gauss**	0.000 (0.000)	0.000 (0.000)	0.033*** (0.007)	0.966			5.989	5.968	5.981	2.551 (0.49)	4.561 (0.12)	
		Student	0.000 (0.000)	0.000 (0.000)	0.040*** (0.007)	0.959			6.028	6.001	6.018	2.564 (0.49)	3.927 (0.18)	
		GED	0.000 (0.000)	0.000 (0.000)	0.036*** (0.006)	0.963			6.034	6.007	6.023	2.536 (0.49)	4.208 (0.15)	

Note: *** denotes significance at the 1% level, and ** at the 5% level and * at the %10 level. The standard deviations of coefficients are in parenthesis and the probability values of the residuals tests are also reported in parenthesis.

Table 10. BIST technology

	Model	Dist.	Parameters						In-Sample Criteria			Residuals Tests		
			c	ω	α	β	δ	λ	AIC	BIC	HQ	Lag(5)	ARCH-LM(5)	Half-Life
Pre-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	0.000 (0.001)	0.000*** (0.000)	0.188*** (0.053)	0.541*** (0.064)	0.021 (0.121)	0.328*** (0.108)	5.643	5.608	5.629	1.840 (0.65)	3.538 (0.22)	6.18
		Student	0.000 (0.001)	0.000*** (0.000)	0.343*** (0.116)	0.520*** (0.077)	0.020 (0.093)	0.157 (0.138)	5.833	5.793	5.818	1.466 (0.74)	2.783 (0.32)	11.65
		GED	-0.000*** (0.001)	0.000*** (0.000)	0.253*** (0.056)	0.543*** (0.050)	0.060*** (0.007)	0.233*** (0.076)	5.828	5.787	5.812	2.375 (0.53)	3.037 (0.28)	7.64
	I-GARCH (1,1)	**Gauss**	0.001*** (0.000)	0.000*** (0.000)	0.422*** (0.052)	0.577			5.631	5.614	5.625	0.874 (0.88)	1.835 (0.50)	
		Student	0.001*** (0.000)	0.000*** (0.000)	0.471*** (0.076)	0.528			5.839	5.815	5.830	1.125 (0.83)	2.050 (0.46)	
		GED	0.000 (0.000)	0.000 (0.000)	0.053*** (0.009)	0.946			5.769	5.745	5.760	3.055 (0.39)	0.639 (0.84)	
Post-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	-0.006* (0.004)	0.000*** (0.000)	0.062 (0.052)	0.553*** (0.099)	0.536* (0.324)	0.196** (0.085)	5.903	5.855	5.885	0.475 (0.99)	1.665 (0.69)	2.65
		Student	-0.005* (0.003)	0.000*** (0.000)	0.072 (0.068)	0.510*** (0.109)	0.437* (0.249)	0.290** (0.113)	6.001	5.946	5.979	0.625 (0.98)	4.288 (0.15)	2.48
		GED	-0.004*** (0.000)	0.000*** (0.000)	0.067 (0.071)	0.543*** (0.140)	0.404*** (0.072)	0.245*** (0.093)	6.003	5.948	5.982	0.641 (0.98)	4.224 (0.15)	2.65
	I-GARCH (1,1)	**Gauss**	0.000 (0.000)	0.000*** (0.000)	0.322*** (0.055)	0.677			5.874	5.846	5.863	1.046 (0.93)	8.793 (0.01)	
		Student	0.000 (0.000)	0.000** (0.000)	0.549*** (0.135)	0.450			5.982	5.948	5.969	1.282 (0.89)	5.945 (0.06)	
		GED	0.000*** (0.000)	0.000** (0.000)	0.454*** (0.114)	0.545			5.982	5.948	5.969	1.197 (0.91)	8.484 (0.01)	

Note: *** denotes significance at the 1% level, and ** at the 5% level and * at the %10 level. The standard deviations of coefficients are in parenthesis and the probability values of the residuals tests are also reported in parenthesis.

Table 11. BIST insurance

	Model	Dist.	Parameters						In-Sample Criteria			Residuals Tests		
			c	ω	α	β	δ	λ	AIC	BIC	HQ	Lag(5)	ARCH-LM(5)	Half-Life
Pre-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	-0.001 (0.001)	0.000*** (0.000)	0.101*** (0.022)	0.828*** (0.016)	0.181 (0.150)	0.004 (0.030)	6.224	6.189	6.210	2.339 (0.54)	7.239 (0.03)	9.87
		Student	-0.000 (0.001)	0.000*** (0.000)	0.091*** (0.025)	0.850*** (0.022)	0.123 (0.145)	0.010 (0.043)	6.334	6.293	6.318	2.391 (0.52)	9.036 (0.01)	12.77
		GED	-0.000** (0.000)	0.000*** (0.000)	0.095*** (0.024)	0.834*** (0.021)	0.145*** (0.046)	0.009 (0.041)	6.326	6.285	6.310	2.302 (0.54)	7.445 (0.02)	10.27
	I-GARCH (1,1)	**Gauss**	0.000 (0.000)	0.000 (0.000)	0.119 (0.122)	0.880			6.209	6.191	6.202	1.694 (0.69)	5.613 (0.07)	
		Student	0.000*** (0.000)	0.000 (0.000)	0.134*** (0.031)	0.865			6.336	6.313	6.327	1.851 (0.65)	6.244 (0.05)	
		GED	0.000 (0.000)	0.000 (0.000)	0.126 (0.078)	0.873			6.323	6.299	6.314	1.590 (0.71)	4.875 (0.11)	
Post-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	-0.003* (0.001)	0.000*** (0.000)	0.124*** (0.021)	0.718*** (0.026)	0.510** (0.255)	-0.036 (0.044)	6.920	6.873	6.902	1.301 (0.89)	2.257 (0.41)	3.49
		Student	-0.002 (0.003)	0.000** (0.000)	0.254** (0.101)	0.520** (0.143)	0.381 (0.510)	-0.111 (0.1090)	6.978	6.923	6.956	1.320 (0.88)	4.065 (0.16)	2.48
		GED	-0.001** (0.000)	0.000*** (0.000)	0.188*** (0.048)	0.605*** (0.047)	0.335*** (0.105)	-0.079 (0.079)	6.963	6.909	6.942	1.663 (0.80)	3.425 (0.23)	2.65
	I-GARCH (1,1)	**Gauss**	0.000*** (0.000)	0.000 (0.000)	0.002** (0.001)	0.997			6.894	6.866	6.883	2.646 (0.52)	8.108 (0.01)	
		Student	0.000*** (0.000)	0.000 (0.000)	0.005*** (0.001)	0.994			6.952	6.918	6.939	3.801 (0.25)	7.323 (0.02)	
		GED	0.000** (0.000)	0.000 (0.000)	0.003*** (0.001)	0.996			6.994	6.910	6.931	3.970 (0.23)	7.947 (0.02)	

Note: *** denotes significance at the 1% level, and ** at the 5% level and * at the %10 level. The standard deviations of coefficients are in parenthesis and the probability values of the residuals tests are also reported in parenthesis.

Table 12. BIST leasing, factoring

	Model	Dist.	Parameters						In-Sample Criteria			Residuals Tests		
			c	ω	α	β	δ	λ	AIC	BIC	HQ	Lag(5)	ARCH-LM(5)	Half-Life
Pre-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	-0.000 (0.002)	0.000*** (0.000)	0.045 (0.034)	0.515*** (0.137)	0.081 (0.217)	0.311*** (0.108)	5.813	5.778	5.800	2.320 (0.54)	0.716 (0.95)	2.08
		Student	-0.003 (0.003)	0.000* (0.000)	0.055 (0.050)	0.599*** (0.183)	0.234 (0.239)	0.195 (0.139)	5.968	5.927	5.952	2.087 (0.59)	0.033 (0.99)	2.43
		GED	-0.000 (0.000)	0.000* (0.000)	0.058 (0.046)	0.722*** (0.141)	0.000 (0.000)	0.152 (0.121)	6.007	5.966	5.992	2.830 (0.43)	0.145 (0.97)	4.48
	I-GARCH (1,1)	**Gauss**	0.000* (0.000)	0.000*** (0.000)	0.222*** (0.045)	0.777			5.768	5.751	5.762	2.088 (0.59)	0.542 (0.87)	
		Student	0.000 (0.000)	0.000 (0.000)	0.155*** (0.059)	0.844			5.966	5.943	5.957	2.655 (0.47)	0.070 (0.99)	
		GED	0.000 (0.000)	0.000*** (0.000)	0.140*** (0.031)	0.859			6.004	5.981	5.995	2.312 (0.54)	0.145 (0.97)	
Post-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	0.008*** (0.002)	0.000** (0.000)	0.404** (0.174)	0.572*** (0.158)	-0.413*** (0.143)	-0.258* (0.154)	5.267	5.226	5.251	7.420 (0.04)	1.331 (0.63)	4.19
		Student	0.003* (0.001)	0.000*** (0.000)	0.567** (0.222)	0.422** (0.111)	-0.138 (0.114)	-0.174 (0.195)	5.474	5.427	5.456	4.533 (0.19)	9.693 (0.00)	6.82
		GED	0.002*** (0.000)	0.000*** (0.000)	0.396*** (0.049)	0.528*** (0.042)	-0.145*** (0.016)	-0.180*** (0.068)	5.468	5.420	5.450	4.021 (0.25)	3.668 (0.20)	3.82
	I-GARCH (1,1)	**Gauss**	0.001*** (0.000)	0.000*** (0.000)	0.307*** (0.058)	0.692			5.238	5.218	5.230	2.348 (0.53)	1.836 (0.50)	
		Student	0.001*** (0.000)	0.000*** (0.000)	0.633*** (0.107)	0.366			5.480	5.452	5.469	4.412 (0.20)	24.70 (0.00)	
		GED	0.000*** (0.000)	0.000** (0.000)	0.484*** (0.147)	0.510			5.468	5.440	5.457	2.662 (0.47)	4.532 (0.13)	

Note: *** denotes significance at the 1% level, and ** at the 5% level and * at the %10 level. The standard deviations of coefficients are in parenthesis and the probability values of the residuals tests are also reported in parenthesis.

Table 13. BIST metal products, mach

	Model	Dist.	Parameters						In-Sample Criteria			Residuals Tests		
			c	ω	α	β	δ	λ	AIC	BIC	HQ	Lag(5)	ARCH-LM(5)	Half-Life
Pre-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	0.000 (0.001)	0.000*** (0.000)	0.000 (0.030)	0.782*** (0.035)	0.043 (0.135)	0.296*** (0.056)	5.628	5.593	5.615	2.527 (0.50)	1.664 (0.55)	9.63
		Student	-0.000 (0.001)	0.000*** (0.000)	0.000 (0.044)	0.834*** (0.050)	0.120 (0.137)	0.164*** (0.042)	5.728	5.687	5.712	2.973 (0.41)	1.953 (0.48)	7.91
		GED	-0.001 (0.000)	0.000*** (0.000)	0.000 (0.039)	0.802*** (0.048)	0.173 (0.166)	0.219*** (0.058)	5.711	5.670	5.695	3.587 (0.31)	1.760 (0.52)	7.54
	I-GARCH (1,1)	**Gauss**	0.001*** (0.000)	0.000*** (0.000)	0.210*** (0.026)	0.789			5.575	5.558	5.569	1.947 (0.63)	1.239 (0.66)	
		Student	0.001*** (0.000)	0.000** (0.000)	0.134*** (0.029)	0.865			5.705	5.682	5.696	2.293 (0.55)	1.393 (0.62)	
		GED	0.000 (0.000)	0.000** (0.000)	0.157*** (0.035)	0.842			5.680	5.657	5.671	2.173 (0.57)	1.075 (0.71)	
Post-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	-0.006*** (0.002)	0.000*** (0.000)	0.016** (0.007)	0.865*** (0.012)	0.567*** (0.208)	0.082*** (0.031)	6.006	5.965	5.990	1.502 (0.73)	1.937 (0.48)	8.65
		Student	-0.008* (0.004)	0.000** (0.000)	0.000 (0.040)	0.785** (0.068)	0.723* (0.408)	0.138** (0.055)	6.066	6.019	6.048	1.486 (0.74)	2.322 (0.40)	4.43
		GED	-0.007*** (0.001)	0.000*** (0.000)	0.000 (0.000)	0.818*** (0.018)	0.620*** (0.129)	0.118*** (0.038)	6.056	6.008	6.038	1.539 (0.73)	2.507 (0.36)	5.29
	I-GARCH (1,1)	**Gauss**	0.000 (0.000)	0.000 (0.000)	0.030*** (0.006)	0.969			6.000	5.980	5.992	2.348 (0.53)	3.138 (0.27)	
		Student	0.000 (0.000)	0.000 (0.000)	0.044*** (0.008)	0.955			6.052	6.025	6.041	2.197 (0.57)	2.257 (0.41)	
		GED	0.000 (0.000)	0.000 (0.000)	0.036*** (0.006)	0.963			6.050	6.023	6.039	2.281 (0.55)	2.685 (0.33)	

Note: *** denotes significance at the 1% level, and ** at the 5% level and * at the %10 level. The standard deviations of coefficients are in parenthesis and the probability values of the residuals tests are also reported in parenthesis.

Table 14. BIST real estate

	Model	Dist.	Parameters						In-Sample Criteria			Residuals Tests		
			c	ω	α	β	δ	λ	AIC	BIC	HQ	Lag(5)	ARCH-LM(5)	Half-Life
Pre-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	0.003 (0.003)	0.000*** (0.000)	0.002 (0.017)	0.813*** (0.042)	-0.198 (0.225)	0.111*** (0.031)	5.560	5.525	5.547	3.691 (0.29)	0.137 (0.97)	5.84
		Student	0.002 (0.002)	0.000*** (0.000)	0.074* (0.042)	0.834*** (0.050)	-0.093 (0.149)	0.077 (0.054)	5.713	5.672	5.697	2.660 (0.47)	0.109 (0.98)	9.11
		GED	0.000*** (0.000)	0.000*** (0.000)	0.052* (0.031)	0.807*** (0.042)	-0.044*** (0.015)	0.094** (0.044)	5.704	5.664	5.689	2.801 (0.44)	0.106 (0.98)	7.14
	I-GARCH (1,1)	**Gauss**	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.999			5.502	5.484	5.495	6.838 (0.05)	8.439 (0.01)	
		Student	0.000** (0.000)	0.000*** (0.000)	0.181*** (0.033)	0.818			5.713	5.690	5.705	2.599 (0.48)	0.110 (0.98)	
		GED	0.000 (0.000)	0.000*** (0.000)	0.186*** (0.033)	0.813			5.699	5.675	5.690	2.526 (0.50)	0.167 (0.97)	
Post-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	-0.000 (0.002)	0.000*** (0.000)	0.284*** (0.088)	0.680*** (0.083)	-0.001 (0.210)	-0.180** (0.078)	5.976	5.936	5.961	3.835 (0.27)	1.310 (0.64)	5.15
		Student	-0.002 (0.002)	0.000*** (0.000)	0.177* (0.098)	0.487*** (0.120)	0.251 (0.202)	0.112 (0.128)	6.123	6.075	6.104	3.221 (0.36)	0.561 (0.86)	2.12
		GED	-0.001*** (0.000)	0.000*** (0.000)	0.208 (0.074)	0.531*** (0.127)	0.171*** (0.031)	0.030 (0.155)	6.114	6.066	6.095	3.438 (0.33)	0.639 (0.84)	2.47
	I-GARCH (1,1)	**Gauss**	-0.000 (0.000)	0.000*** (0.000)	0.343*** (0.089)	0.656			5.957	5.936	5.949	2.883 (0.42)	0.581 (0.85)	
		Student	0.000 (0.000)	0.000** (0.000)	0.468*** (0.121)	0.531			6.116	6.089	6.106	3.192 (0.37)	0.058 (0.85)	
		GED	0.000 (0.000)	0.000** (0.000)	0.426*** (0.124)	0.573			6.108	6.081	6.097	2.893 (0.42)	0.698 (0.82)	

Note: *** denotes significance at the 1% level, and ** at the 5% level and * at the %10 level. The standard deviations of coefficients are in parenthesis and the probability values of the residuals tests are also reported in parenthesis.

Table 15. BIST sports

	Model	Dist.	Parameters						In-Sample Criteria			Residuals Tests		
			c	ω	α	β	δ	λ	AIC	BIC	HQ	Lag(5)	ARCH-LM(5)	Half-Life
Pre-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	-0.002 (0.002)	0.000*** (0.000)	0.321*** (0.104)	0.650*** (0.087)	0.145 (0.160)	-0.220** (0.102)	5.127	5.092	5.114	2.454 (0.51)	1.433 (0.61)	4.64
		Student	0.000 (0.000)	0.000*** (0.000)	0.604*** (0.206)	0.501*** (0.095)	-0.069 (0.085)	-0.212 (0.184)	5.371	5.331	5.356	3.953 (0.25)	2.234 (0.42)	692.73
		GED	0.000*** (0.000)	0.000*** (0.000)	0.464** (0.121)	0.526*** (0.049)	-0.023*** (0.002)	-0.185 (0.147)	5.391	5.351	5.376	3.881 (0.26)	2.262 (0.41)	6.41
	I-GARCH (1,1)	**Gauss**	-0.000 (0.000)	0.000*** (0.000)	0.308*** (0.044)	0.691			5.103	5.085	5.096	4.675 (0.18)	2.085 (0.45)	
		Student	-0.000 (0.000)	0.000*** (0.000)	0.493*** (0.094)	0.506			5.376	5.352	5.367	4.311 (0.21)	2.137 (0.44)	
		GED	0.000 (0.000)	0.000** (0.000)	0.456*** (0.109)	0.543			5.395	5.372	5.386	4.549 (0.19)	2.567 (0.35)	
Post-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	0.001 (0.001)	0.000 (0.000)	0.081*** (0.018)	0.936*** (0.010)	-0.089 (0.095)	-0.058*** (0.018)	5.221	5.181	5.206	3.415 (0.33)	2.420 (0.38)	60.53
		Student	-0.001 (0.002)	0.000* (0.000)	0.213** (0.101)	0.664*** (0.138)	0.074 (0.137)	0.039 (0.103)	5.343	5.295	5.324	2.270 (0.55)	0.311 (0.93)	6.41
		GED	-0.000 (0.000)	0.000*** (0.000)	0.091*** (0.021)	0.903*** (0.019)	0.007* (0.004)	-0.040 (0.030)	5.348	5.300	5.330	2.962 (0.41)	1.869 (0.50)	27.53
	I-GARCH (1,1)	**Gauss**	-0.000 (0.000)	0.000 (0.000)	0.050** (0.024)	0.949			5.215	5.194	5.207	2.644 (0.47)	3.329 (0.24)	
		Student	0.000 (0.000)	0.000 (0.000)	0.274** (0.127)	0.725			5.349	5.322	5.338	2.307 (0.54)	0.094 (0.98)	
		GED	0.000 (0.000)	0.000 (0.000)	0.081 (0.065)	0.918			5.352	5.325	5.342	2.805 (0.44)	1.266 (0.65)	

Note: *** denotes significance at the 1% level, and ** at the 5% level and * at the %10 level. The standard deviations of coefficients are in parenthesis and the probability values of the residuals tests are also reported in parenthesis.

Table 16. BIST W and retail trade

	Model	Dist.	Parameters						In-Sample Criteria			Residuals Tests		
			c	ω	α	β	δ	λ	AIC	BIC	HQ	Lag(5)	ARCH-LM(5)	Half-Life
Pre-BISTECH Period	GJR-GARCH-in-Mean (1,1)	Gauss	-0.002 (0.001)	0.000*** (0.000)	0.000 (0.003)	0.822*** (0.015)	0.193 (0.127)	0.204*** (0.041)	5.668	5.633	5.665	1.604 (0.71)	2.103 (0.44)	8.90
		Student	-0.002* (0.001)	0.000*** (0.000)	0.000 (0.013)	0.869*** (0.016)	0.228** (0.112)	0.135*** (0.041)	5.724	5.683	5.708	1.613 (0.71)	3.697 (0.20)	10.69
		GED	-0.001* (0.000)	0.000*** (0.000)	0.000 (0.007)	0.861*** (0.017)	0.138** (0.056)	0.149*** (0.042)	5.731	5.690	5.715	1.706 (0.68)	2.847 (0.31)	10.48
	I-GARCH (1,1)	Gauss	0.000* (0.000)	0.000*** (0.000)	0.163*** (0.027)	0.836			5.617	5.599	5.610	1.623 (0.70)	3.457 (0.23)	
		Student	0.000** (0.000)	0.000*** (0.000)	0.124*** (0.025)	0.875			5.708	5.685	5.700	1.741 (0.68)	5.163 (0.10)	
		GED	0.000** (0.000)	0.000* (0.000)	0.132*** (0.032)	0.867			5.711	5.688	5.703	1.696 (0.69)	4.296 (0.15)	
Post-BISTECH Period	GJR-GARCH-in-Mean (1,1)	Gauss	0.007*** (0.000)	0.000*** (0.000)	0.001*** (0.000)	0.997*** (0.00)	-0.639*** (0.024)	0.005*** (0.000)	5.960	5.919	5.944	3.477 (0.32)	2.207 (0.42)	191.09
		Student	-0.007*** (0.002)	0.000 (0.000)	0.000*** (0.000)	0.999*** (0.000)	0.595*** (0.187)	-0.002*** (0.000)	6.034	5.986	6.015	3.445 (0.33)	2.253 (0.41)	652.92
		GED	0.006*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.999*** (0.000)	0.519*** (0.063)	-0.001*** (0.000)	6.037	5.989	6.018	3.495 (0.32)	2.381 (0.39)	632.65
	I-GARCH (1,1)	Gauss	0.000 (0.000)	0.000 (0.000)	0.008*** (0.002)	0.991			5.955	5.934	5.947	3.936 (0.26)	2.593 (0.35)	
		Student	-0.000 (0.000)	0.000 (0.000)	0.026*** (0.004)	0.973			6.033	6.005	6.022	4.185 (0.23)	2.236 (0.42)	
		GED	-0.000 (0.000)	0.000 (0.000)	0.010*** (0.001)	0.989			6.038	6.010	6.027	3.930 (0.26)	2.545 (0.36)	

Note: *** denotes significance at the 1% level, and ** at the 5% level and * at the %10 level. The standard deviations of coefficients are in parenthesis and the probability values of the residuals tests are also reported in parenthesis.

Table 17. BIST wood, paper, printing

	Model	Dist.	Parameters						In-Sample Criteria			Residuals Tests		
			c	ω	α	β	δ	λ	AIC	BIC	HQ	Lag(5)	ARCH-LM(5)	Half-Life
Pre-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	-0.001 (0.001)	0.000*** (0.000)	0.232*** (0.069)	0.582*** (0.062)	0.066 (0.139)	0.115 (0.086)	5.904	5.869	5.890	0.937 (0.87)	1.465 (0.60)	5.10
		Student	-0.001 (0.000)	0.000*** (0.000)	0.209*** (0.019)	0.744*** (0.026)	0.123 (0.075)	0.039 (0.073)	6.076	6.035	6.060	1.181 (0.81)	1.280 (0.65)	25.60
		GED	0.005 (0.002)	0.000*** (0.000)	0.204*** (0.073)	0.692*** (0.056)	0.000 (0.000)	0.077 (0.090)	6.059	6.019	6.044	0.923 (0.87)	1.512 (0.58)	10.56
	I-GARCH (1,1)	**Gauss**	-0.000 (0.000)	0.000*** (0.000)	0.433*** (0.063)	0.566			5.898	5.881	5.892	0.956 (0.86)	2.109 (0.44)	
		Student	0.000 (0.000)	0.000*** (0.000)	0.257*** (0.043)	0.742			6.081	6.057	6.072	0.976 (0.86)	1.449 (0.60)	
		GED	0.000 (0.000)	0.000*** (0.000)	0.301*** (0.064)	0.698			6.064	6.040	6.055	1.007 (0.85)	1.884 (0.49)	
Post-BISTECH Period	**GJR-GARCH-in-Mean (1,1)**	**Gauss**	-0.002 (0.003)	0.000*** (0.000)	0.053 (0.042)	0.689*** (0.081)	0.202 (0.264)	0.138** (0.064)	5.767	5.727	5.752	2.180 (0.57)	0.834 (0.78)	3.33
		Student	-0.000 (0.002)	0.000** (0.000)	0.045 (0.043)	0.755*** (0.081)	0.100 (0.214)	0.149** (0.068)	5.842	5.794	5.824	2.052 (0.60)	0.368 (0.92)	5.20
		GED	-0.001* (0.000)	0.000** (0.000)	0.049 (0.045)	0.704*** (0.106)	0.133** (0.065)	0.165** (0.076)	5.840	5.792	5.822	2.148 (0.54)	0.511 (0.88)	3.88
	I-GARCH (1,1)	**Gauss**	0.000 (0.000)	0.000*** (0.000)	0.293*** (0.053)	0.706			5.736	5.716	5.728	2.064 (0.60)	0.296 (0.94)	
		Student	0.000 (0.000)	0.000* (0.000)	0.156*** (0.047)	0.843			5.832	5.805	5.821	1.979 (0.62)	0.310 (0.93)	
		GED	0.000 (0.000)	0.000*** (0.000)	0.223*** (0.047)	0.776			5.826	5.799	5.816	2.038 (0.60)	0.255 (0.95)	

inconclusive evidence that the effects of sudden shocks on volatility have become more evident for most of the sub-indexes in the post-BISTECH period.

The β parameter shows the effect of the volatility of a previous period on current volatility. The beta parameter is statistically significant for all estimated models regardless of model type, period and distribution. These findings suggest that the current volatility is largely explained by the volatility of the previous period. After the BISTECH transition, the effect of the volatility of the previous period on current volatility decreased for the sub-sectors BIST Electricity; BIST Food, Beverage; BIST Insurance; BIST Leasing, Factoring and BIST Real Estate, while it increased for the other sub-sectors.

Our examination of the presence of asymmetries reveals that they exist before and after the BISTECH transition in both of the main indexes, BIST 100 and BIST 30. The positive sign of the λ parameter indicates that negative shocks increase volatility more than positive shocks. This effect is visible in both indexes. The effect of negative shocks on volatility increases for both the BIST 100 and BIST 30 after the BISTECH transition. As for the sub-indexes, we find that the BIST Banks; BIST Basic Materials; BIST Corporate Governance; BIST Electricity; BIST Technology; BIST Metal Products, Mach.; BIST W. and Retail Trade; BIST Chem., Petrol, Plastic; BIST Hold. and Investment; BIST Food, Beverage; BIST Leasing, Factoring and BIST Real Estate indexes have significant asymmetrical effects in the pre-BISTECH period. The λ parameter has a positive sign for these indexes, which suggests that negative shocks have a greater impact on volatility than positive shocks. However, the asymmetries disappear for the BIST Chem., Petrol, Plastic; BIST Hold. and Investment and BIST Food, Beverage indexes after the BISTECH transition. Furthermore, the asymmetry parameter returns to negative for the BIST Leasing, Factoring and BIST Real Estate indexes. The asymmetries emerge with a positive sign for the BIST Wood, Paper, Printing index in the post-BISTECH period. Lastly, there are no asymmetries in the BIST Insurance index in both periods, while negative and significant asymmetry parameters are observed in the BIST Sports index.

The δ parameter, which shows the relationship between risk and return, is statistically insignificant for most indexes in both periods. The relationship between risk and return is significant only for the BIST 100 and BIST 30 indexes in the pre-BISTECH period, but the sign of the parameter for these indexes is negative as opposed to what is expected. The parameter turns out to be insignificant for the BIST 30 index in the post-BISTECH period. The negative sign of the parameter suggests that returns are decreasing, while risk increases for main indexes in both periods. In addition, the risk and return relationship is only positive and significant for the BIST Technology; BIST Insurance and BIST Metal Products, Mach. Indexes, while it is negative and significant for BIST Chem., Petrol, Plastic; BIST Leasing; Factoring and BIST W. and Retail Trade in the post-BISTECH period.

Finally, we present the half-life of volatility values, which show the duration of volatility's return to its average after a shock. The increase in this value suggests that the effects of shocks on volatility have become more permanent. The duration of volatility's return to its average after a shock lasts about 11 days for BIST 100 and BIST 30 in the pre-BISTECH period. This rises to 75 days for BIST 100 and 85 days for BIST 30 in the post-BISTECH period. Therefore, it can be understood that the effect of shocks on the volatility of BIST 100 and BIST 30 becomes more persistent in the post-BISTECH period. In the other sub-indexes, mixed results are obtained again the duration of volatility's return to its average after the BISTECH transition increases dramatically for most of the indexes of BIST Banks; BIST Chem., Petroleum and Plastic; BIST Corporate Governance; BIST Hold. and Investment; BIST Sports and BIST W. and Retail Trade, while it declines in the majority of other indexes.

CONCLUSION

Technological developments are one of the most fundamental factors affecting market conditions today. These innovations integrating into the financial system can change its functioning. High-frequency trading and algorithmic trading, which are relatively new developments in financial markets, have significant effects on several market indicators such as liquidity, competition, price efficiency, market quality and volatility. However, the direction and magnitude of these effects is not yet fully known. The studies freshly emerging in this field usually examine markets in developed countries. Therefore, this study examines the effects of these two new technological processes on volatility by taking into account asymmetry, and risk and return for Borsa Istanbul. Unlike in other studies, a more general and long-term approach is preferred. To this end, the behaviors of the main and sub-sector indexes of Borsa Istanbul are examined and compared for the periods before and after the transition to the BISTECH system, which made HFT and AT activities possible. In this framework, data covering November 14, 2012 to June 7, 2018 is analyzed by using the GJR-GARCH-in-Mean and I-GARCH models.

Although the findings of the study do not give a definite conclusion in terms of understanding the effects of HFT and AT on volatility, it has demonstrated that, in general, there has been an increase in the volatility of some important indexes in the post-BISTECH period. Thus, evaluating the findings of the indexes that HTF and AT activities are more intense may be more informative. The companies included in the BIST 30 and BIST Banks indexes carry considerable weight within the composition of Borsa Istanbul. Furthermore, more than 50% of the shares of the companies in these two indexes are held by foreign and institutional investors. From this point, it can be assumed that the behaviors of these two indexes are more determinative in terms of understanding the effects of HFT and AT on the volatility of Borsa Istanbul. The findings show us that volatility increases significantly in these indexes for the post-BISTECH period. In particular, the duration of volatility returns to average after shock increases about 7 times for BIST 100 and about 8 times for BIST 30 after BISTECH transition. We also show that the impact of the volatility of the previous period on current volatility increases in the post-BISTECH period. Our results on volatility are in parallel with the results of studies examining developed country examples, including those of Zhang (2010), Kirilenko et al. (2011), Scholtus et al. (2014), Boehmer et al. (2015), Kalejian and Mukerji (2016), and Hasbrouck (2018). However, our findings do not provide sufficient evidence to argue that HFT and AT activities definitely increase volatility. Therefore, the results should be interpreted with caution, and this indirect implication that HFT and AT activities increase volatility needs to be supported by further investigation.

Consequently, and although innovations in financial technologies are important for market development, these developments can have significant disruptive effects on financial markets. Once a market function changes, it takes time for all market participants to adapt to this change. The markets may be very uncertain and fragile during these transition periods. HFT and AC activities can create potential negative externalities for other market participants, and thus it is likely that traditional investors could in particular be harmed. Therefore, regulatory authorities must closely monitor the technological developments in financial markets and design appropriate safeguarding mechanisms against the potential disruptive effects. Even though it is stated in the literature that HFT and AT activities contribute positively to market efficiency in the short term, the long-term consequences of these technologies are still uncertain.

This research can be improved in several ways. First, analyses can be repeated by selecting the companies with higher levels of HFT and AT activities. In addition, future research could focus on intraday volatility using high-frequency data. On the other hand, future studies, from a comparative perspective, could examine the effects of HFT and AT activities on market participants who are using and not using AT and HFT activities. These interrogations will help us to understand the effects of HFT and AT on developing country markets in a deeper way.

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KEY TERMS AND DEFINITIONS

Adverse Selection: Adverse selection is a problem created by asymmetric information. When sellers and buyers do not have same information level before the transaction in the market, the adverse selection problem arises.

Algorithmic Trading: Algorithmic trading is a system producing automated trading orders based on certain rules which use mathematical formulas run by computers.

BISTECH: BISTECH is a technological infrastructure that allows algorithmic trading and high-frequency trading operations in Borsa Istanbul.

Borsa Istanbul: Borsa Istanbul is an institution that provides storage and exchange services for Turkish and foreign-funded banks operating in Turkey's capital market.

Half-Life Volatility: Half-life volatility is a measurement that calculates the duration of volatility's return to its average after a shock.

High-Frequency Trading: High-frequency trading is an automated trading platform that transacts a large number of orders in fractions of a second.

Volatility: The fluctuation of the price of a security or the market in a short period of time. The price of a high-volatility security is characterized by rapid and extreme changes.