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Beyond GARCH: Intraday Insights Into the Exchange Rate and Stock Price Volatility Dynamics in Borsa Istanbul Sectors

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This study investigated the impact of exchange rate volatility on sectoral stock volatility by employing the intraday volatility measure directly calculated from the original data, using daily data from 27 Borsa Istanbul sectors between April 29, 2003, and April 25, 2023. In the literature, GARCH models are commonly used to study the volatility spillovers between exchange rates and stock prices, typically using aggregate data. However, the GARCH family models provide inefficient and biased estimates if they are misspecified. Moreover, using aggregate-level data may lead to biased and misleading conclusions. The research used intraday volatility measures to overcome the shortcomings of GARCH models. The ordinary least squares (OLS), GARCH (1,1) methods, and Garman and Klass (1980) volatility estimator are used. The empirical results showed that the estimates from each method vary significantly, and these disparities in the results might be due to misspecification in GARCH (1,1) models. The intraday volatility model estimation results showed that although stock price volatilities in all sectors are positively and significantly affected by exchange rate volatility, their magnitudes vary significantly. Taken together, this implies the presence of vast heterogeneities in the responses of sectoral stock price volatilities to exchange rate volatility. The results encourage policymakers to pay special attention to these heterogeneities to prevent capital flights and underinvestment. Additionally, the findings assist investors in making more effective decisions by helping them adapt their investment strategies to factor in exchange rate fluctuations and mitigate the impact of unexpected events in the exchange rate market.

Keywords: Exchange rate volatility, GARCH, Stock prices, Türkiye
JEL Code: G10, G12

Stock prices become more volatile in recent years in almost all markets around the globe. Economic turmoil in global markets, largely caused by the COVID-19 pandemic, aftershocks of the 2009 financial crisis and its lasting effects, and the Russia-Ukraine war, has resulted in the disruption of the global supply chain, fluctuations in global output, decelerated growth, increased risk premiums in the debt markets, heightened volatility in financial markets, and eroded confidence indicators worldwide. This trend has progressively shaped macroeconomic and financial variables in the developed and developing markets through global economic dynamics, resulting in amplified fluctuations in their macro-financial credentials (Altintas & Yacouba, 2018).

For several reasons, exchange rate volatility seems to be the most prominent factor among the variables that significantly contribute to the observed upsurge in stock price volatility in recent years. Implementing a free-floating exchange rate in conjunction with financial deregulation has serious implications for capital inflows, financial globalization dynamics, and cross-border investments (Dahir et al., 2018). In globally integrated economies, exchange rate changes play a pivotal role in how climate changes, environmental disasters, and political turmoil manifest as disruptions in supply chains and increased uncertainties, primarily through their influence on international pricing responsiveness.

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Exchange rate dynamics is a widely recognized phenomenon that substantially influences diverse economic indicators, such as trade, investment, and economic growth. Developing economies receive more capital inflows and cross-border investments than developed economies owing to their accelerated growth rates, making them appealing to international investors. In turn, the investment decisions are closely related to the uncertainties observed in exchange rate markets. Furthermore, in emerging market economies like Türkiye, where the currency is frequently exposed to fluctuations arising from internal and external factors, exchange rate volatility can engender many spillover effects across various sectors of the economy. Thus, these effects can bear significant implications for investors, policymakers, and businesses operating within Türkiye, thereby affecting the behavior of the stock market.

The relationship between exchange rates and stock market behavior has been studied for decades, and tremendous literature accumulated over time on the subject. Earlier studies on the relationship between exchange rates and stock markets include Franck and Young (1972), Solnik (1987), Bartov and Bodnar (1994), Ajayi and Mougouė (1996), Jorion (1991), Chow et al. (1997), Joseph and Vezos (2006), Attari and Safdar (2013), Olugbode et al. (2014), Lin (2012), Zhao (2010), Kennedy and Nourzad (2016), Abbas and Badshah (2017), Khan et al. (2018), Agyei et al. (2022), Qureshi et al. (2022), and Hassan et al. (2023). Recent literature has also focused on investigating the intra-day analysis of the aggregate and sectoral stock market returns/volatility (see; Rai & Garg, 2022; Wu et al., 2024). There is a considerable amount of literature on the relationship between exchange rate returns/volatility and stock price returns/volatility in Türkiye. However, previous studies have either focused on individual sectors (Çelik, 2020; Kasman, et al., 2011) or the aggregate stock market (Türsoy, 2017; Sensoy & Sobaci, 2014; Guler, 2020; Mechri et al., 2019; Rjoub, 2012; Mwambuli et al., 2016) and or considered only a few sectors (Çatık et al., 2020; Ozun, 2007; Sivrikaya, 2021). It is worth mentioning that Çatık et al. (2020) study has been the most detailed sectoral analysis of the exchange rate impact on stock price/returns. They conducted a sectoral-level analysis of 12 sectors' stock return responses to exchange rates. However, their analysis only focused on returns and not volatility.

Having reviewed the empirical literature on the relationship between exchange rate volatility and stock market volatility, we identified two noteworthy points that require more in-depth research. Firstly, the findings of previous studies have been generalized over all sectors through aggregate market analysis. Nevertheless, the aggregate estimation of parameters may lead to biased estimates and misleading conclusions (Pesaran et al., 1989; Lee et al., 1990; Lee & Pesaran, 1993; Lee, 1997). This is because the heterogeneity of sector-specific sensitivities to exchange rate fluctuations may vary significantly. The aggregate economy can be disaggregated into units such as firms, households, and sectors, for that matter. Sectors' characteristics, compositions, policies, and regulations vary and that causes the heterogeneities of sectors' responses to policy changes (Kaplan, 2003). Therefore, general conclusions drawn from aggregate data might not apply to individual sectors within the stock market. Additionally, Narayan and Sharma (2011) asserted that markets are heterogeneous because each sector operates under its own set of policies and regulations. Therefore, treating the whole economy, in our case, the whole stock market, as a single entity leads to biased estimates. These relationships may be obscured, leading to invalid estimates and policy conclusions for that matter. On the contrary, sector-specific analysis overcomes these estimation problems and deficiencies as it explores the heterogeneities of the stock market sectors.

The second aspect deserving further investigation in the literature is that the family of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, commonly used for modeling volatility, may suffer from model misspecification issues, resulting in inefficient estimates and potentially lead to misleading conclusions about the relationship between exchange rate and stock price volatility. It is a well-known fact that the univariate GARCH models are estimated using the maximum likelihood (ML) estimation method and the validity of ML estimates is very sensitive to the choice of the distribution assumption in the estimation of the empirical model. Engle and González-Rivera (1991) evidenced that the misspecification of the distribution densities could result in a loss of efficiency by 84% of maximum likelihood estimation-based parameter estimates of GARCH models. The available distributions densities used include standard normal (Bollerslev, 1986), Student-t (Bollerslev, 1987), generalized error (Engle & González-Rivera, 1991; Nelson, 1991), gamma (Engle & González-Rivera, 1991), -stable (Mittnik et al., 2002), max-entropic (Rockinger & Jondeau, 2002), and many others. According to Engle and González-Rivera (1991), even if the mean and variance equations are well specified but we do not know the probability density functions, the closest approximation to the true generating mechanism should come from the data. Thus, exchange rate volatility and stock are generally studied using these distribution densities, which may suffer from misspecification issues, resulting in invalid conclusions.

In light of the earlier discussions, the current study attempts to empirically measure the impact of exchange rate volatility on stock price volatility. To restrain from biasedness and inefficiency caused by induced misspecification in the volatility equation from the mean equation of the GARCH family of models, we employ the Garman and Klass (1980) volatility approach, which measures intra-day volatility from the open, close, high, and low log prices of the stock market. Unlike the traditional GARCH family models used in previous studies that rely solely on closing prices for volatility estimation, this approach captures real volatility patterns, including intraday variability and price information. Fiszeder (2018) has highlighted the superior efficiency of variance estimators based on low, high, open, and closing prices, as demonstrated by empirical and simulated evidence from Fiszeder and Perczak (2013), Garman and Klass (1980), Parkinson (1980), Rogers and Satchell (1991), and Yang and Zhang (2000). The study's focus on intraday variability and price information is particularly valuable for investors looking to leverage opportunities in the market. Estimating the parameters of the volatility model overcomes the potential misspecification issues related to GARCH models.

Briefly, this study augments the literature by estimating the relationship between exchange rate volatility and sectoral stock market volatility, considering sectoral heterogeneity. Additionally, the Garman and Klass (1980) technique, known for capturing authentic volatility patterns, is employed to gauge the volatility of both sectoral stock prices and exchange rates. With its focus on intraday variability and price information, this approach is of paramount interest to investors seeking to capitalize on leveraging opportunities. The study, therefore, contributes to the intra-day volatility analysis of financial markets. Moreover, we show that the Garman and Klass (Henceforth GK) volatility estimator-based-simple volatility regression model would not suffer from the usual misspecification issues associated with GARCH models. Consequently, the research findings from this study not only assist investors in making more informed decisions by adapting their investment strategies to account for exchange rate fluctuations but also help them mitigate the impact of unforeseen events in the exchange rate market. In sum, our study contributes valuable insights to aid investors in adapting their investment strategies and managing the impact of unexpected events in the foreign exchange market.

Method

Data

The empirical analysis conducted in this study focuses on the sectoral Turkish stock market from April 29, 2003, to April 25, 2023. The selected period began in 2003 when most sectors' data became available. We utilized daily stock price data for 27 sectors, which encompass all BIST sectors categorized by the Public Disclosure Platform based on the activities of a group of companies. This platform is an electronic system that publicly discloses official Borsa Istanbul and capital market regulations. Table 1 lists the sectors, their index codes, and the number of companies in each sector.

Table 1
Sector details.

Index Name	Index Code	No. of companies
BIST INDUSTRIALS	XUSIN	208
BIST SERVICES	XUHIZ	114
BIST FINANCIALS	XUMAL	129
BIST TECHNOLOGY	XUTEK	33
BIST BANKS	XBANK	12
BIST INFORMATION TECHNOLOGY	XBLSM	31
BIST ELECTRICITY	XELKT	29
BIST LEASING FACTORING	XFINK	7
BIST REAL ESTATE INVESTMENT TRUSTS	XGMYO	43
BIST FOOD BEVERAGE	XGIDA	36
BIST HOLDING AND INVESTMENT	XHOLD	50
BIST TELECOMMUNICATION	XILTM	2
BIST CONSTRUCTION	XINSA	12
BIST WOOD PAPER PRINTING	XKAGT	16

BIST CHEMICAL PETROLEUM PLASTIC	XKMYA	42
BIST MINING	XMADN	6
BIST INVESTMENT TRUSTS	XYORT	9
BIST BASIC METAL	XMANA	24
BIST METAL PRODUCTS MACHINERY	XMESY	38
BIST INSURANCE	XSGRT	6
BIST SPORTS	XSPOR	4
BIST NONMETAL MINERAL PRODUCT	XTAST	21
BIST TEXTILE LEATHER	XTEKS	21
BIST WHOLE AND RETAIL TRADE	XTCRT	23
BIST TOURISM	XTRZM	12
BIST TRANSPORTATION	XULAS	10
BIST CORPORATE	XKURY	51

Source: *Authors own creation*

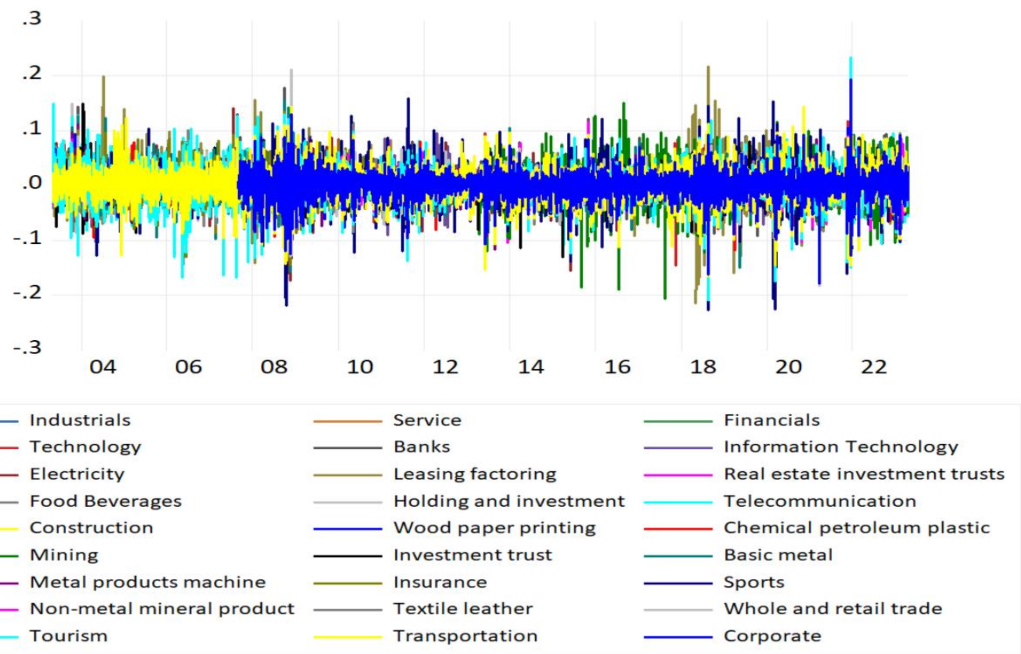
The TL/Dollar nominal exchange rate data is used. The daily stock price data for all sectors and exchange rates were retrieved from the Refinitiv Eikon DataStream (2023). We then computed the daily returns using the following equation.

$$R_{i,t} = lnP_{i,t} - lnP_{i,t-1} \tag{1}$$

where $R_{i,t}$ is the daily continuously compounded returns of the sector i at the time t. $P_{i,t}$ is sector i price at t time. ln denotes the natural log operator. Figure 1 graphically presents the returns series of all 27 sectors. The returns of all sectors exhibit a similar pattern of volatility clustering and persistency.

Figure 1

Plots of the sectoral returns



Source: *Authors own creation*

The GK approach is used to compute all volatility measures. The GK's measure uses all relevant information in stock prices, such as high, low, opening, and closing prices, to estimate volatility, as opposed to GARCH family models, which use only the closing prices that are merely a "snapshot" of the process. High and low prices during the trading interval require continuous monitoring to establish their values. Intuition would then tell us that high/low prices contain more information regarding volatility than close prices (Garman & Klass, 1980). Molnár (2016) contended that GK (1980) volatility is less noisy than Parkinson's (1980) volatility under ideal conditions of Brownian motion with zero drift because it utilizes open and close prices as well in volatility estimations. The GK approach has been used by several researchers (see; Bašta & Molnár, 2018; Enoksen et al., 2020; Fiszeder, 2018; Fiszeder et al., 2019; Haykir & Yagli, 2022; Molnár, 2016). Equation 1 represents the GK (1980) volatility measure.

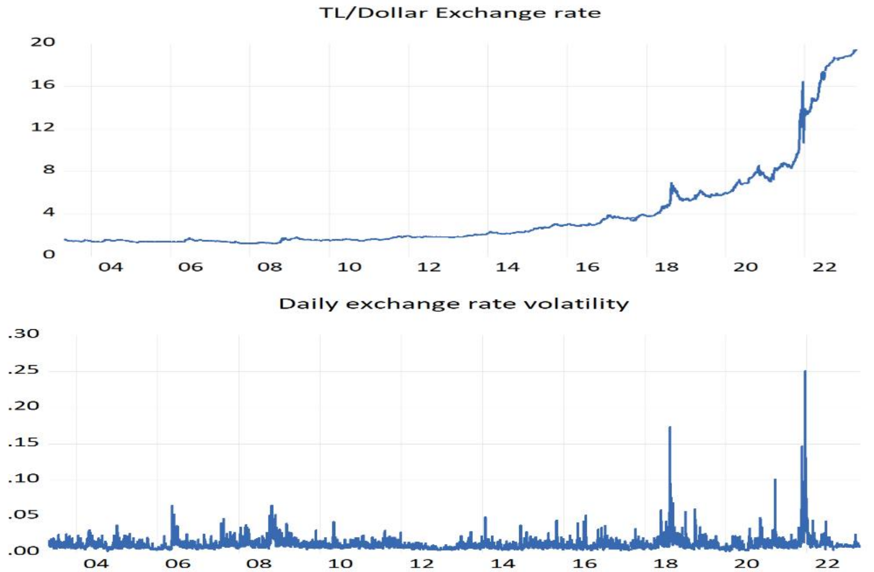
$$EXV_t = \sqrt{\frac{1}{2}(eh_t - el_t)^2 - (2log2 - 1)ec_t^2} \tag{2}$$

where;

$$\mathrm{eh_t} = \log(\mathrm{high_t}) - \log(\mathrm{open_t})$$
$$\mathrm{el_t} = \log(\mathrm{low_t}) - \log(\mathrm{open_t})$$
$$\mathrm{ec_t} = \log(\mathrm{close_t}) - \log(\mathrm{open_t})$$

$\mathrm{EXV_t}$ is the measure of nominal exchange rate volatility in day t, $high_t$ represents the highest rate of the nominal exchange rate traded in day t, low_t is the lowest rate of nominal exchange rate traded in day t, $close_t$ is the closing rate in day t, $open_t$ is the opening exchange rates at the time markets are opened in day t. Figure 2 plots the raw exchange rates and the calculated exchange rate volatility. It shows that the Turkish Lira was most stable between 2010 and the end of 2013, and its volatility was highest between 2018 and 2023.

Figure 2
Daily nominal exchange rate prices and volatility



Source: *Authors own creation*

Econometric model

The study analyzes the correlation between sectoral stock market volatility and exchange rate volatility while comparing two volatility measures. The researchers used a multiple-asset pricing model, where the sectoral indices represent all the market's risky assets, and the average market returns proxy the market portfolio. The study also employs a multiple-risk asset regression model, as in Equation 3.

$$\mathrm{R_{i,t}} = \beta_0 + \beta_{\mathrm{i,m}}\mathrm{R_{M,t}} + \beta_{\mathrm{i,ex}}\mathrm{EXV_t} + \varepsilon_{\mathrm{i,t}} \tag{3}$$

where $R_{i,t}$ is the daily returns of the i^{th} sector in period t, EXV_t is the GK volatility of the nominal exchange rate in period t, $R_{M,t}$ is the daily market average returns, calculated at each t as;

$$R_{M,t} = \frac{\sum_{n=1}^{N} R_{i,t}}{N} \tag{4}$$

where N denotes the total number of sectors. The average market returns are used to represent the total market returns. The coefficient of the total market return, $\beta_{\mathrm{i,m}}$, is the market beta, which gauges the sensitivity of the return of the i^{th} sector to the return of the common factor or the market portfolio returns.

We used equation 4 to assess the impact of exchange rate volatility on sectoral-level market volatility, as measured by the GK volatility estimator.

$$\mathrm{SV_{i,t}} = \beta_0 + \beta_{i,s}\mathrm{SV_{i,t-1}} + \beta_{i,ex}\mathrm{EXV_t} + \varepsilon_{i,t} \tag{5}$$

where $SV_{i,t}$ is the sector-specific volatility. The lag sector-specific sector volatility ($\mathrm{SV_{i,t-1}}$) captures the impact of possible missing variables in the regression model, which reduces the chance of model misspecification. Equations 3 and 5 are estimated using the Huber-White robust standard error correction method for autocorrelation and heteroskedasticity.

The second stage of the model specification continues with the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. Engle (1982) pioneered the GARCH family of models, which was later extended by Bollerslev (1986) and Taylor (1987).

GARCH models require the estimation of the conditional mean and the conditional volatility model. For comparison purposes, we use the reduced form of the asset pricing model as the conditional mean equation.

$$\mathrm{R_{i,t}} = \alpha_{i,0} + \alpha_{i,1}\mathrm{R_{M,t}} + \alpha_{i,2}\mathrm{EXV_t} + \varepsilon_{i,t} \tag{6}$$

Where $\alpha_{i,0}$ is the constant term, $R_{i,t}$ is the compounded daily returns of the i^{th} sector. $\alpha_{i,1}$ is the sector's responsiveness to the total market return. $\alpha_{i,2}$ measures sectoral returns' responsiveness to exchange rate volatility. $\varepsilon_{i,t}$ is the disturbance term, known to have non-normal distribution with mean 0 and heteroskedastic, i.e., $\varepsilon_{i,t} \sim N(0, \sigma_{i,t}^2)$.

Then, the conditional variance model is used in the GARCH modeling, which involves incorporating several factors to determine the conditional variance. These factors include a long-term volatility term ω_i, which is a weighted average, sensitivity to the squared residuals of the previous period, the ARCH term $\varepsilon_{i,t-1}^2$, and the previous period's fitted conditional volatility from the model, the GARCH term $\sigma_{i,t-1}^2$, for the i^{th} sector. The GARCH(1,1) is used because of its simplicity and being the most robust of the family of volatility models (Engle, 2001). Moreover, the GARCH (1,1) is arguably the most fundamental volatility model, and this model illustrates the general idea well. Equation 7 expresses the GARCH (1,1) model.

$$\sigma_{i,t}^2 = \omega_i + \sum_{i=1,q} \delta_i \varepsilon_{i,t-1}^2 + \sum_{j=1,p} \rho_i \sigma_{i,t-1}^2 \tag{7}$$

where $\varepsilon_{i,t} = \sigma_{i,t}^2 \vartheta_{i,t}$ and $\vartheta_{i,t} \sim N(0,1)$. δ_i is the coefficient of the ARCH term and ρ_i is the coefficient of the past fitted conditional volatility, the GARCH term. We assumed the Generalized Error Distribution (GED) of the error because GARCH with GED distribution models has been observed to outperform all models (Kumar & Patil, 2016).

The volatility of an asset may depend on other factors besides its historical fluctuations (Napari & Parlaktuna, 2022). Following the approach of Engle and Patton (2007), Kur et al. (2021), Glosten et al. (1993), Sakarya and Ekinci (2020), and Napari and Parlaktuna (2022), the GK measure of exchange rate volatility is added to the conditional variance equation. Therefore, the GARCH-X equation can be written as;

$$\sigma_{i,t}^2 = \omega_i + \sum_{i=1,q} \delta_i \varepsilon_{i,t-1}^2 + \sum_{j=1,p} \rho_i \sigma_{i,t-1}^2 + \theta_i EXV_t \tag{8}$$

where θ_i measures the sensitivity of the sector i^{th} volatility to the exchange rate volatility, and $\mathrm{EXV_t}$ is the volatility of the TL/Dollar exchange rate in period t.

Results and Discussion

The study assesses the impact of volatility, measured by GK (1980), on stock market sectoral volatility and compares it to an analogous model for the GARCH (1,1) mean equation. The ordinary least squares (OLS) are used to estimate multiple linear regression, using the Huber-White approach to obtain robust standard errors. We report the results for the two analogous models side-by-side for each sector in Table 2.

As argued before, misspecification can decrease the validity of volatility estimates from GARCH family models as the mean and the variance equations are estimated simultaneously using the maximum likelihood method. The results reported in Table 2 depict differences in the magnitude and direction of the parameter estimates from the two analogous reduced asset pricing models. The market beta estimates in both estimations marginally differ from each other, which could result from the misspecification of the models. Additionally, the exchange rate volatility elasticity estimates from the two analogous models vary in direction, magnitude, and significance level. The disparities in the estimates may be due to misspecifications and wrong assumptions of the distribution density function of the GARCH (1,1) mean equation. Engle and González-Rivera (1991) found that the wrong specification of the distribution densities and the parameter estimates of GARCH models could lose up to 84% of their efficiency. Therefore, the GARCH modeling of volatility estimates would be biased and invalid.

Table 2
Estimation results of return equations

	Multiple linear regression returns equation			GARCH (1,1) mean returns equation		
Sectors	*Cons.* (β_0)	$R_{M,t}$ ($\beta_{i,m}$)	*EXV* ($\beta_{i,er}$)	*Cons.* ($\alpha_{i,0}$)	$R_{M,t}$ ($\alpha_{i,1}$)	*EXV* ($\alpha_{i,2}$)
Industry	-0.0001	0.9608***	0.0152	-2.70E-05	0.953757***	0.006916
	(0.0002)	(0.0045)	(0.0142)	(0.000121)	(0.004397)	(0.010699)
Service	0.0002	0.9225***	-0.0127	0.000179	0.922509***	-0.012699
	(0.0002)	(0.0073)	(0.0168)	(0.000428)	(0.011883)	(0.023208)
	-0.0005	1.1814***	0.0293	-0.001049***	1.207029***	0.072204***
Financials	(0.0003)	(0.0091)	(0.0267)	(0.000209)	(0.007692)	(0.019629)
Technology	0.0003	1.0009***	-0.0182	-0.000337	0.966373***	-0.036539
	(0.0003)	(0.0107)	(0.0237)	(0.000327)	(0.009057)	(0.022678)
Banking	-0.0005	1.2482***	0.0245	-0.001419***	1.284181***	0.100831***
	(0.0005)	(0.0136)	(0.0443)	(0.000318)	(0.009958)	(0.030532)
Information Technology	0.0005	0.9706***	-0.0487**	-0.000281	0.941094***	-0.068828***
	(0.0003)	(0.0111)	(0.0199)	(0.000242)	(0.006968)	(0.019119)
Electricity	0.0004	0.9815***	-0.0569**	-0.000451**	0.960012***	-0.054875**
	(0.0003)	(0.015)	(0.0248)	(0.000225)	(0.015750)	(0.025391)
	0.0006	1.0009***	-0.0549	0.000324***	0.902721***	-0.120584***
Leasing factoring	(0.0006)	(0.0177)	(0.0487)	(2.53E-05)	(0.003383)	(0.000265)
Real estate investment	0.0001	0.9962***	-0.0359	7.48E-05	0.982284***	-0.061326***
trusts	(0.0003)	(0.0102)	(0.0255)	(0.000245)	(0.010062)	(0.021668)
Food Beverages	0.0003	0.8521***	-0.028	9.14E-05	0.849249***	-0.029987
	(0.0003)	(0.0124)	(0.0272)	(0.000294)	(0.013745)	(0.023723)
Holding and investment	-0.0005**	1.0934***	0.032	-0.000588***	1.096007***	0.033051*
	(0.0002)	(0.0075)	(0.0203)	(0.000197)	(0.007858)	(0.017064)
Telecommunication	-0.0005	0.9594***	0.0257	-0.000554	0.913672***	-0.002693
	(0.0005)	(0.0164)	(0.0429)	(0.000438)	(0.016213)	(0.039532)
Construction	0.0001	0.8483***	0.0099	-0.000279	0.815574***	-0.005873
	(0.0006)	(0.0203)	(0.0444)	(0.000430)	(0.015174)	(0.035913)
Wood paper printing	0.0006*	0.9843***	-0.0627**	0.000350	0.957269***	-0.081864***
	(0.0003)	(0.0105)	(0.0273)	(0.000324)	(0.010801)	(0.027457)
Chemical Petroleum	-0.0003	0.9604***	0.0357	-0.000134	0.951360***	0.003088
Plastic	(0.0004)	(0.0103)	(0.0313)	(0.000270)	(0.008274)	(0.022639)
Mining	0.0005	1.0991***	-0.0414	-0.001820*	1.086648***	0.038124
	(0.0007)	(0.0284)	(0.0412)	(0.001007)	(0.030129)	(0.077642)
	0.0006	0.8646***	-0.0631	0.000857	0.779316***	-0.134427**
Investment trust	(0.0006)	(0.0142)	(0.0511)	(0.000594)	(0.024800)	(0.056410)
Basic metal	-0.0006	1.0497***	0.0650**	-0.001042***	1.014713***	0.067629**
	(0.0004)	(0.0123)	(0.0291)	(0.000359)	(0.010767)	(0.031736)
Metal products machine	0.0001	0.9997***	-0.0023	3.45E-06	0.987579***	-0.015818
	(0.0002)	(0.0085)	(0.0193)	(0.000267)	(0.007884)	(0.022131)
Insurance	0.0005**	0.9786***	-0.0410**	0.000478*	0.916740***	-0.069676***
	(0.0002)	(0.0078)	(0.0167)	(0.000277)	(0.012973)	(0.025757)
Sports	0.0004	0.8224***	-0.0588	-0.000313***	0.685135***	-0.091445***
	(0.0008)	(0.0238)	(0.0636)	(1.63E-06)	(0.004255)	(0.000937)
Non-metal mineral product	0.0004	0.9001***	-0.0405*	0.000527**	0.868344***	-0.083552***
	(0.0003)	(0.0092)	(0.0246)	(0.000232)	(0.007462)	(0.020610)
Textile leather	0.0006**	0.9173***	-0.0528**	0.000588***	0.876999***	-0.085258***
	(0.0003)	(0.011)	(0.0234)	(0.000215)	(0.009967)	(0.014951)
Whole and retail trade	0.0007**	0.8449***	-0.0475*	-2.45E-05	0.824015***	-0.028320
	(0.0003)	(0.0134)	(0.0284)	(0.000245)	(0.009509)	(0.019285)
Tourism	0.0002	1.0167***	-0.0359	-0.000103	0.934684***	-0.078663
	(0.0007)	(0.0178)	(0.0572)	(0.000606)	(0.014907)	(0.060510)
Transportation	0.0002	1.0642***	0.0098	-0.000547	1.061327***	-0.006937
	(0.0004)	(0.0146)	(0.0332)	(0.000430)	(0.015443)	(0.039123)
Corporate	-0.0004**	1.0399***	0.0221	-0.000498***	1.062513***	0.036756***
	(0.0002)	(0.0073)	(0.0152)	(0.000150)	(0.005667)	(0.013604)

Note. Huber/White is used to make the estimates robust to heteroskedasticity and autocorrelation of the errors.

Source: *Authors own creation*

The research proceeds with the analysis of the volatility equations. We directly measured volatility using the GK measure to avoid misspecification issues that can result in invalid estimates. Table 3 presents the results for a simple OLS regression model of volatility and the GARCH (1,1) variance equation for comparison. The models are estimated using the Huber-White standard error correction procedure to obtain robust standard errors. The GK volatility estimator estimates volatility from low, high, closing, and opening prices and has less noise compared to the GARCH model (Molnár, 2016). Additionally, according to empirical and simulated evidence by Fiszeder and Perczak (2013), GK (1980), Parkinson (1980), Rogers and Satchell (1991), Yang and Zhang (2000), variance estimators based on low, high, open, and closing prices are 5 to 7 times more efficient than estimators constructed exclusively on closing prices. Our results in Table 3 indicate that the volatility model with the GK volatility estimator produced a more significant model compared to the GARCH (1,1) variance model. Each component of the model is statistically significant at a 1% level. The misspecification issues that may arise from the mean equation can render the estimates of variance equation parameters biased and invalid. As evident from Table 3, the estimates of the exchange volatility coefficient in the GARCH (1,1) variance equation are insignificant for a reasonable number of sectors, which could have been obscured by misspecification issues. Therefore, GK's volatility estimator-based model provides better and more accurate estimates than the GARCH (1,1) model.

Table 3
Estimation results of volatility equations

	GK volatility equations			GARCH (1,1) variance equations			
Sector	*Cons.* (β_0)	$SV_{i,t-1}$ ($\beta_{i,s}$)	*EXV* ($\beta_{i,er}$)	*Cons.* (ω_i)	*ARCH (1)* (δ_i)	*GARCH (1)* (ρ_i)	*EXV* (θ_i)
Industrials	0.0047***	0.4157***	0.3002***	9.12E-07	0.087403***	0.774001***	0.000201**
	(0.0004)	(0.0239)	(0.031)	(6.22E-07)	(0.023896)	(0.093505)	(0.000101)
Service	0.0059***	0.4222***	0.2558***	5.37E-05***	0.150000***	0.600000***	0.000000
	(0.0004)	(0.0239)	(0.0344)	(1.96E-05)	(0.043627)	(0.133863)	(4.3E-104)
	0.0085***	0.3561***	0.3201***	3.44E-06***	0.127751***	0.601829***	0.000998***
Financials	(0.0005)	(0.0184)	(0.0384)	(1.08E-06)	(0.013395)	(0.053226)	(0.000227)
Technology	0.0069***	0.4482***	0.2994***	7.38E-06**	0.128443***	0.790206***	0.000428**
	(0.0005)	(0.0257)	(0.0371)	(3.05E-06)	(0.026450)	(0.052958)	(0.000214)
Banking	0.0100***	0.3585***	0.3712***	1.90E-06	0.160977***	0.687352***	0.001622***
	(0.0006)	(0.0204)	(0.046)	(1.70E-06)	(0.019609)	(0.047764)	(0.000422)
Information Technology	0.0081***	0.4342***	0.2525***	4.23E-06***	0.109037***	0.829145***	0.000515***
	(0.0005)	(0.0247)	(0.036)	(1.63E-06)	(0.011821)	(0.016666)	(0.000133)
Electricity	0.0078***	0.4734***	0.2713***	5.82E-06*	0.113458***	0.837473***	0.000376
	(0.0006)	(0.0212)	(0.0413)	(3.27E-06)	(0.040482)	(0.068039)	(0.000325)
	0.0076***	0.5767***	0.2549***	8.34E-06*	0.252492***	0.681191***	0.001757***
Leasing factoring	(0.0008)	(0.03)	(0.0472)	(4.44E-06)	(0.037458)	(0.043132)	(0.000536)
Real estate investment	0.0074***	0.4468***	0.2151***	9.49E-06***	0.139111***	0.681708***	0.000865***
trusts	(0.0004)	(0.0214)	(0.0307)	(3.08E-06)	(0.022376)	(0.064485)	(0.000277)
Food Beverages	0.0081***	0.4225***	0.2215***	4.73E-06	0.101414**	0.835504***	0.000504
	(0.0005)	(0.0211)	(0.0346)	(3.54E-06)	(0.039928)	(0.093316)	(0.000518)
Holding and investment	0.0076***	0.4021***	0.2840***	2.77E-06	0.089180***	0.784347***	0.000415
	(0.0004)	(0.0188)	(0.0339)	(1.97E-06)	(0.026135)	(0.116303)	(0.000321)
Telecommunication	0.0088***	0.4502***	0.3009***	8.02E-07	0.061678**	0.918698***	0.000406
	(0.0006)	(0.0205)	(0.0517)	(1.34E-06)	(0.027756)	(0.043025)	(0.000317)
Construction	0.0084***	0.4553***	0.1867***	5.30E-06	0.111368***	0.797815***	0.001352***
	(0.0006)	(0.0314)	(0.0378)	(4.42E-06)	(0.023421)	(0.053606)	(0.000522)
Wood paper printing	0.0080***	0.4519***	0.2187***	6.41E-06	0.116354***	0.811708***	0.000306*
	(0.0005)	(0.0212)	(0.0379)	(3.93E-06)	(0.034583)	(0.073089)	(0.000183)
Chemical Petroleum	0.0075***	0.3915***	0.3006***	6.72E-06**	0.092628***	0.736083***	0.001155***
Plastic	(0.0005)	(0.0215)	(0.0333)	(2.75E-06)	(0.018684)	(0.066074)	(0.000401)
Mining	0.0132***	0.4367***	0.2579***	0.000133***	0.204304***	0.516181***	0.002904*
	(0.001)	(0.0263)	(0.0725)	(4.22E-05)	(0.042915)	(0.115484)	(0.001714)
	0.0061***	0.5342***	0.1773***	7.88E-06	0.210011***	0.633962***	0.001610***
Investment trust	(0.0005)	(0.0262)	(0.0293)	(4.81E-06)	(0.038883)	(0.073053)	(0.000444)
Basic metal	0.0105***	0.2546***	0.4845***	4.04E-06*	0.093305***	0.828061***	0.000988***
	(0.0005)	(0.0187)	(0.0407)	(2.07E-06)	(0.015761)	(0.035678)	(0.000330)
Metal products machine	0.0069***	0.3970***	0.2976***	3.02E-06	0.089311***	0.834430***	0.000290
	(0.0004)	(0.0216)	(0.0291)	(1.93E-06)	(0.027886)	(0.073597)	(0.000193)
Insurance	0.0069***	0.5002***	0.2019***	3.51E-06*	0.105331***	0.803746***	0.000674**
	(0.0003)	(0.0127)	(0.0186)	(1.94E-06)	(0.025205)	(0.064860)	(0.000338)
Sports	0.0085***	0.5238***	0.1613***	1.20E-05*	0.231863***	0.680305***	0.003078***
	(0.0007)	(0.0353)	(0.0429)	(6.83E-06)	(0.032035)	(0.042796)	(0.000789)
Non-metal mineral	0.0051***	0.4680***	0.2069***	2.20E-06**	0.129704***	0.804084***	0.000250***
product	(0.0004)	(0.0258)	(0.0277)	(9.95E-07)	(0.027375)	(0.046680)	(9.63E-05)
Textile leather	0.0069***	0.4320***	0.2603***	1.32E-05**	0.143368***	0.638837***	0.001067*
	(0.0005)	(0.0247)	(0.0336)	(6.05E-06)	(0.032337)	(0.136894)	(0.000632)
Whole and retail trade	0.0076***	0.4175***	0.2444***	8.61E-06**	0.124601***	0.734197***	0.001063***
	(0.0007)	(0.0308)	(0.0397)	(3.43E-06)	(0.024495)	(0.064407)	(0.000362)
Tourism	0.0109***	0.4421***	0.2781***	1.04E-05**	0.135889***	0.799805***	0.000896**
	(0.0007)	(0.0221)	(0.0442)	(4.78E-06)	(0.025869)	(0.044711)	(0.000365)
Transportation	0.0095***	0.4073***	0.3654***	4.49E-06	0.081149***	0.878905***	0.000582
	(0.0005)	(0.0201)	(0.0378)	(3.00E-06)	(0.027143)	(0.049147)	(0.000380)
Corporate	0.0053***	0.4350***	0.2939***	7.85E-08	0.038796***	0.955373***	8.47E-06
	(0.0004)	(0.0244)	(0.0317)	(7.70E-08)	(0.010733)	(0.013347)	(1.00E-05)

Note. Huber/White makes the estimates robust to heteroskedasticity and autocorrelation of the errors.

Source: Authors own creation

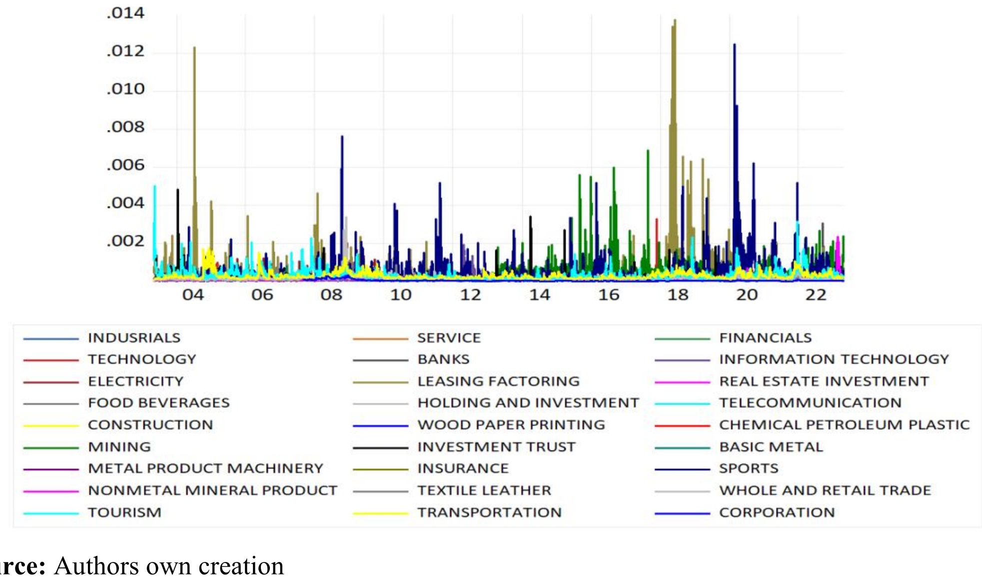
We then interpret the estimated OLS model with the GK volatility estimator. The results show the estimate of lag volatility for each sector impacts the current volatility positively and is statistically significant at the 1% level. Generally, exchange rate volatility significantly and positively transmits to all sectors of the BIST market. We observe that the exchange rate's volatility is transmitted most to the basic metal sector. The banking sector is the second most receptive to exchange rate volatility, preceded by the transportation sector. Çatık et al. (2020) reported similar findings in which the banking sector was the most exposed sector to exchange rate risk. On the contrary, the sports sector is the least responsive to exchange rate volatility, accompanied by the investment trust and construction sectors. This is because the activities of the sports sector do not depend on exports and imports, unlike the basic metal sector, which heavily relies on imports for its raw materials. The banking sector is also highly responsive to exchange rate volatility, as fluctuations can affect assets denominated in foreign currencies and lead to uncertainty about future debt costs. Similarly, transportation companies, especially those involved in shipping and logistics, are highly sensitive to exchange rate volatility due to their heavy dependence on oil prices for operations. Fluctuations in exchange rates can impact fuel costs, affecting profit margins and stock price volatility.

The basic metal, banking, and transportation sectors are sensitive to changes in exchange rates. This means that these sectors are more at risk of being affected by fluctuations in exchange rates and may see reduced investment during times of high exchange rate volatility. On the other hand, the sports investment trust and construction sectors are the least affected by exchange rate volatility. This could be due to differences between sectors, such as their characteristics, compositions, policies, and regulations, leading to variations in how they respond to changes in exchange rates. Therefore, policymakers and investors should pay close attention to these sectoral differences during periods of high exchange rate volatility.

Figures 3 show the conditional variance for all 27 sectors from the GARCH (1,1) estimations in a stacked graph. The figure reveals a similar pattern of conditional variance across all sectors. Conditional variance peaked in 2021 for all sectors and was also high in the early months of 2020, coinciding with the start of the COVID-19 pandemic. There are noticeable spikes in the conditional variance between 2015 and 2020, corresponding to the attempted coup in 2016 and the 2018 forex exchange rate market crackdown. Additionally, the conditional variances of all sectors were relatively low throughout 2012, indicating a stable period for the Turkish economy. The graphical observations suggest that the most volatile sectors during the global and domestic economic turmoil in 2020 and beyond appear to be "leasing factoring" and sports.

Figure 3

Conditional variance from GARCH (1,1)



Source: Authors own creation

Conclusions and Recommendations

The study investigates the impact of exchange rate volatility on sectoral returns and volatility by comparing volatility measured by the GK estimator and GARCH-modelled volatility. The ordinary least square-based multiple regressions and the GARCH (1,1) model were employed to estimate two volatility equations. Daily data for 27 BIST sectors from April 29, 2003, to April 25, 2023, were used. Considering 27 sectors, sector heterogeneity has been explored as all sectors may not respond the same to exchange rate volatility, which complements previous studies for the Turkish stock market. Additionally, the study complements the literature by employing the GK (1980) method to measure the volatility of both sectoral stock prices and exchange rate, which is superior in capturing the real volatility patterns, i.e., intraday variability and information in prices, that are of high interest to investors who take leverage opportunities. This approach also overcomes the misspecification issues common to GARCH models.

We estimated two analogous return equations, one for the GARCH (1,1) mean equation, and the other for a simple OLS-independent reduced asset pricing model. We observed that although the two models are analogous to each other, the parameter estimates vary remarkably from each other in terms of magnitude, direction, and significance level. In GARCH models, because the mean and the variance equations are estimated simultaneously using the maximum likelihood method, misspecification in the mean equation can lead to invalid/biased and inefficient parameter estimates in the conditional volatility (variance) equation. This misspecification may emanate from omitted variables from the mean equation or wrong assumption of the distribution density function, which, according to Engle and González-Rivera (1991), can reduce the efficiency of GARCH models up to 84%. The study further compared the GK-based volatility model to the GARCH (1,1) variance equation results. We observed that the GK-based volatility model produced more significant and reliable estimates than the GARCH (1,1) model. According to the GARCH (1,1) results, the parameter estimates for the exchange rate volatility were insignificant for a reasonable number of the sectors in the analysis, which could be emanating from misspecification issues. The GK estimator-based model is more efficient and robust compared to GARCH (1,1) because variance estimators based on low, high, open, and closing prices are 5 to 7 times more efficient than estimators constructed exclusively on closing prices (Molnár, 2016).

According to the GK-based model, all sectoral stock market volatilities respond positively to exchange rate volatility, but the impact varies across sectors. The basic metal sector is the most responsive to exchange rate volatility, followed by the banking and transportation sectors. This is because the basic metal sector is import-dependent and highly sensitive to exchange rate fluctuations. On the other hand, the banking sector is more susceptible to risks associated with exchange rate fluctuations due to the nature of financial institutions. Exchange rate volatility can lead to uncertainty about future debt costs, increase the risk of bank assets and liabilities, and ultimately lead to a decrease in the stock valuation of banks. As a result, these sectors may experience underinvestment during periods of high exchange rate volatility. Conversely, the sports sector is the least affected by exchange rate volatility, followed by the investment trust and construction sectors. This is logical as the activities of these sectors are not dependent on exports/imports. The variations in sectors' responses to exchange rate volatility may be attributed to differences in characteristics, compositions, policies, and regulations across sectors, leading to heterogeneous responses to fluctuations in exchange rates.

The study recommends policymakers and investors pay special attention to the basic metal, banking, and transportation sectors during periods of high exchange rate volatility to avoid capital flight and underinvestment. The results of this research lead to more effective decision-making processes by assisting investors in adjusting their investment strategies to account for exchange rate variations. The findings also help investors reduce the impact of unexpected events in the foreign exchange market by providing insight into which stock market sectors are affected by exchange rate fluctuations. Diversification, therefore, improves the stability and resilience of investment portfolios in response to changes in the exchange rate market.

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