EFFECTS OF EXCHANGE RATE VOLATILITY AND FIRM-SPECIFIC FEATURES ON THE RATES OF RETURNS OF THE MANUFACTURING FIRMS LISTED IN BORSA İSTANBUL: A CAPM APPROACH

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submitted by **MUSTAFA ASLAN** in partial fulfillment of the requirements for the degree of **Master of Science in Financial Mathematics Department, Middle East Technical University** by,

Prof. Dr. Sevtap Ayşe Kestel
Director, Graduate School of **Applied Mathematics** _______________

Prof. Dr. Ali Devin Sezer
Head of Department, **Financial Mathematics** _______________

Assoc. Prof. Dr. Esma Gaygısız
Supervisor, **Economics, METU** _______________

Examining Committee Members:

Assist. Prof. Dr. Hande Ayaydın Hacıömeroğlu
Business Administration Department, METU _______________

Assoc. Prof. Dr. Esma Gaysısız
Economics Department, METU _______________

Assist. Prof. Dr. Didem Pekkurnaz
Economics Department, Başkent University _______________

Date: _______________

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last Name: MUSTAFA ASLAN

Signature :

ABSTRACT

EFFECTS OF EXCHANGE RATE VOLATILITY AND FIRM-SPECIFIC FEATURES ON THE RATES OF RETURNS OF THE MANUFACTURING FIRMS LISTED IN BORSA İSTANBUL: A CAPM APPROACH

Aslan, Mustafa
M.S., Department of Financial Mathematics
Supervisor: Assoc. Prof. Dr. Esma Gaygısız

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This study examines the effects of the exchange rate volatility and the firm-specific features representing the liquidity, profitability, and leverage performance of firms on excess stock returns for the manufacturing firms listed in Borsa İstanbul (BIST) using dynamic panel data model. The exchange rate volatility is modeled by single-regime generalized autoregressive conditional heteroscedasticity (GARCH) models and Markov-switching GARCH (MSGARCH) models. The MSGARCH models show evidence that the evolution of the volatility process is heterogeneous across the different regimes. The principal component analysis method is employed to 8 financial ratios for the purpose of data reduction to identify the principal components that best represent firm-specific features. 4 components are identified and account for 83% of the total variance in the original dataset of 8 financial ratios.

Empirical results from the dynamic panel data generalized method of moments (GMM) models imply that more volatile exchange rates are associated with much

lower stock returns. The results also suggest that the excess stock returns of manufacturing firms increase with their liquidity, profitability, and leverage.

Keywords: Financial Ratios, Exchange Rate Volatility, Principal Component Analysis, MSGARCH, GMM

ÖZ

BORSA İSTANBULDAKİ İMALAT FİRMALARI İÇİN DÖVİZ KURU OYNAKLIĞININ VE FİRMAYA ÖZGÜ ÖZELLİKLERİN GETİRİ ORANLARINA ETKİSİ: BİR CAPM YAKLAŞIMI

Aslan, Mustafa
Yüksek Lisans, Finansal Matematik Bölümü
Tez Yöneticisi: Doç. Dr. Esma Gaygısız

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Bu çalışmada, döviz kuru oynaklığının ve firmaların likidite, karlılık ve borç performansını temsil eden firmaya özgü özelliklerin Borsa İstanbul'da (BİST) işlem gören imalatçı firmalar için hisse senedi fazlası üzerindeki etkileri dinamik panel veri modeli kullanılarak incelenmiştir. Döviz kuru oynaklığı, tek rejimli GARCH modelleri ve Markov-Switching GARCH (MSGARCH) modelleri ile modellenmiştir. MSGARCH modelleri, oynaklık sürecinin farklı rejimler arasında heterojen olduğuna dair kanıtlar göstermektedir. Temel bileşenler analizi yöntemi, firmaya özgü özellikleri en iyi temsil eden temel bileşenleri belirlemek için veri indirgemesi amacıyla 8 finansal orana uygulanır. 4 bileşen tanımlanmıştır ve 8 finansal oranın orijinal veri setindeki toplam varyansın %83'ünü oluşturmuştur.

Dinamik panel veri GMM modellerinden elde edilen ampirik sonuçlar, çok daha düşük hisse senedi getirileri ile oynak döviz kurunun ilişkili olduğunu göstermektedir. Sonuçlar ayrıca imalat firmalarının fazla hisse senedi getirisinin firmanın likiditesi, karlılığı ve kaldıracı ile arttığını göstermektedir.

Anahtar Kelimeler: Finansal Oranlar, Döviz Kuru Oynaklığı, Temel Bileşen Analizi, MSGARCH, GMM

To My Mother and Free Women

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LIST OF ABBREVIATIONS

ACF	Auto Correlation Function
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
BIST	Borsa İstanbul
DIFF-GMM	Difference Generalized Method of Moments
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
IID	Independent and Identically Distributed
PACF	Partial Auto Correlation Function
SYS-GMM	System Generalized Method of Moments

CHAPTER 1

INTRODUCTION

Firms usually raise their funds to help them pay for their investment projects or finance their short on cash management. Essentially, they can increase funds by taking on debt from the banks and selling bonds or by selling shares in the firm. The sales of shares are firstly sold to investors in the primary market. After the shares are sold, investors can trade them among themselves. Trades of existing shares take place in the secondary market. An investor selling or buying their shares in a firm does not affect the total outstanding number of the firm's shares in the secondary market but does affect stock prices.

Pricing of securities has always been an appealing topic to investors in modern financial economics. In most financial studies, the asset pricing discussions start with Markowitz's Portfolio Theory [1]. The theory inspired Sharpe [2], Lintner [3], and Mossin [4] to propose the single-index Capital Asset Pricing Model (CAPM). According to the model, there is a positive linear relationship between the excess return on a stock and the excess return on the market. Following the CAPM, multi-index models were proposed by Fama and French [5] and Carhart [6].

According to the CAPM and other primary pricing models, there are mainly two sources of risks of stocks or a risky portfolio. The first one is macroeconomic conditions, such as exchange rates, interest rates, inflation, and so on. These macroeconomic factors are also called common source of risk and affect all firms traded on the market. The second is firm-specific factors that have impact on only one firm without affecting other firms traded on the market. The common source of risk cannot be eliminated even with extensive diversification because standard deviation of the market index falls when the number of stocks increases, however, it cannot be zero. The standard deviation that remains after diversification is called systematic (market) risk. Market risk is attributed to risk sources that are caused by macroeconomic factors.

The components of a usual CAPM that shows the linear relationship between the excess stock return and the excess market return can be illustrated as follows:

$$exs_i = \alpha_i + \beta_i emr + \varepsilon_i, \tag{1}$$

where exs_i is the excess stock return of the stock i, and emr is the excess market return. emr is the representation of market risk that cannot be diversified. Multi-factor models allow more variables, such as interest rate, the gross domestic product (GDP) and inflation rate to identify market risk for stock pricing. ε_i denotes the firm specific disturbances that have an impact on the excess returns of stock i. Many studies have focused on identifying the market risk factors and average sensitivity of firms to those factors. Merton [7] first showed that the CAPM can be extended to allow for multiple sources of macroeconomic risk.

Exposure to many sources of risk increased due to the liberalization of financial markets. A stable exchange rate is an important factor for a sound and healthy economy, since the volatile exchange rates affect economic activities and influence monetary policies. Also, exchange rates are crucial for investors who try to increase their returns with diversified portfolios composed of international stocks. Kasman et al. [8] show that exchange rate volatility is one of the major determinants of the stock return volatility of banks listed on Borsa İstanbul (BIST). Moreover, the study of Guler [9] finds a positive relationship between TRY/USD exchange rate volatility and the BIST-100 Index return volatility. The positive impact of exchange rate volatility on the BIST-100 index return volatility might be an indication of capital outflows in Turkey when exchange rates are volatile. Ejaz et al. [10] show the significant negative effect of exchange rate volatility on capital flows by applying the generalized method of moments (GMM) to a panel dataset of 34 developing countries from 1978 to 2015. The study of Jehan et al. [11] analyze the effect of exchange rate volatility on capital flows towards developing countries and show the negative impact of exchange rate volatility on capital flows using dynamic SYS-GMM.

This aim of the thesis is to examine the impact of exchange rate volatility as an additional market risk factor in the CAPM and the effects of firm-specific features associated with the profitability, liquidity, and leverage performance of firms on *exs* in the CAPM. In other words, the thesis tries to construct a multi-factor CAPM in which exchange rate volatility and firm-specific features are additional factors, aside from the excess market return in the model. First, both the single-regime generalized autoregressive conditional heteroscedasticity (GARCH) and Markov-switching GARCH (MSGARCH) methods are applied to the log-returns of exchange rate and compared to correctly estimate the exchange rate volatility. Moreover, MSGARCH model empirically test the heterogeneity of the volatility process across different regimes and define the characteristics of the volatility regimes in the log-returns of exchange rate series. Second, principal component analysis (PCA) is applied to the financial ratios to eliminate the collinearity among the variables and describe the firm-specific features with minimum loss of information in the original dataset of 8 financial ratios. Finally, the dynamic panel data model is used to investigate the effect of the exchange rate volatility estimated by the best volatility model and the firm-specific features determined by PCA using cross-section time-series data over the period of 2010 to 2020, containing 40 quarters, from 84 manufacturing firms listed in the BIST-100 Index.

The dynamic panel data analysis is only employed for manufacturing firms. Banks listed in the BIST-100 are not used in this study because the structure and interpretation of their financial statements are different from those of manufacturing firms, implying that the financial ratios that measure a firm's financial performance differ in terms of the firm’s industry. For instance, while manufacturing firms usually have a high proportion of fixed assets in their total assets, banks have a small portion of fixed assets in their assets and most of the total assets are usually composed of loans. Hence, because of the consistent comparability of financial ratios that are used to determine firm-specific features, only the manufacturing firms listed in the BIST-100 Index are used in the empirical dynamic panel data analysis.

This thesis contributes to the literature in three aspects:

- The study shows that there are regime changes in the GARCH volatility dynamics of the TRY/USD exchange rate log-returns and MSGARCH models outperform traditional single-regime GARCH models based on in-sample-analysis using the Akaike Information Criterion (AIC) and out-of-sample-analysis using backtesting Value at Risk (VaR) estimation. Although previous studies applied the MSGARCH model to the exchange rate, this is the first study to use the exchange rate to examine the asymmetric effects of depreciation and appreciation in MSGARCH models.

- By using dynamic panel GMM, the study finds evidence that the exchange rate volatility estimated by the MSGARCH model is a part of market risk factor that has significant negative impact in explaining stock returns of manufacturing firms listed on the BIST-100 Index.

- The GMM estimators show that the liquidity, profitability, and leverage performance of the manufacturing firms have significant explanatory power in explaining the excess stock returns. Therefore, if the profitability, liquidity and leverage performance of manufacturing firms are considered as firm-specific features, this study finds significant firm-specific factors that affect excess stock returns.

The outline of the thesis is as follows: Chapter 2 comprises a literature review of asset pricing models. The existing literature of the CAPM, multi-factor model, Arbitrage Pricing Theory (APT) model, and Fama French (FF) Three-Factor model are given. Moreover, the literature review on the effect of the exchange rate volatility and firm-specific features on stock returns is provided. Chapter 3 presents the single-regime GARCH and MSGARCH models, and their estimation results in detail. Chapter 4 presents time series analysis of the panel excess stock returns and excess market return, as well as PCA to determine the firm-specific features that are used in the empirical dynamic panel data model. Chapter 5 analyzes the impact of the exchange rate volatility and firm-specific features on the excess stock returns using dynamic panel data model. Chapter 6 summarizes the main results and concludes the thesis.

CHAPTER 2

LITERATURE REVIEW

2.1 A literature Review of Financial Asset Pricing Models

2.1.1 Single-Factor Capital Asset Pricing Model

The CAPM is one of key subject of modern financial economics. In light of the CAPM theory framework introduced in the pioneer works of Sharpe [2], Lintner [3], and Mossin [4], substantial empirical research has been conducted to identify and analyze the determinants of stock returns. The CAPM explains the change in stock prices with the changes in the market index. The equation of CAPM model is as given below:

$$s_{i,t} - r_{f,t} = \alpha_i + \beta_i (r_{M,t} - r_{f,t}) + \varepsilon_{it}, \tag{2}$$

where $s_{i,t}$ is the stock return of firm i at t, $r_{M,t}$ is the market index return at time t, $r_{f,t}$ represents the risk-free interest rate at t, α_i is the constant intercept term of stock return for firm i, β_i is the beta of stock i, and ε_{it} is the white noise disturbance term of the model.

The CAPM implications match the intuition underlying the index models. Hence, it is important to introduce the index model to help understand the theory of the CAPM. Index models are models that are used to link stock returns to returns on both a market index and firm-specific factors. Let us use exs_i to denote the excess stock return, $exs_i = s_{i,t} - r_{f,t}$. emr is the excess return on the market index, which is:

$emr = r_{M,t} - r_{f,t}$. Decomposing this excess return into three components can help express the difference between the macroeconomic and firm-specific features:

$$exs_i = \beta_i emr + \varepsilon_i + \alpha_i \,. \tag{3}$$

The impact of two sources of uncertainty is denoted in the first two terms of the right-hand side of Equation (3). The first one is the excess market return, emr. The changes in this term reflects the impact of the macroeconomic events that usually affect all stocks. The stock's beta, β_i, is the measure of the stock's incremental contribution to the riskiness of the market index. That is, it is the sensitivity of excess return of a particular stock return to changes in the excess market return. A value of β_i that is greater than 1 indicates stocks with larger sensitivity to the market index than the average stocks. These are called as cyclical stocks. On the other hand, a β_i with a value that is less than 1 implies below-average sensitivity and therefore, is called as defensive stocks.

The effect of firm-specific risk is represented by the term, ε_i, in Equation (3). The expected value of ε_i is zero, as the effect of unexpected events must be white noise. Both firm-specific risk and systematic risk contribute to the total variability of the returns.

The term α_i in Equation (3) is not a risk measure. It is called as the stock's alpha, which represents the excess stock return beyond any return due to movements in the market index. The sign of alpha is an important indicator of stock pricing. A positive alpha is appealing to investors and indicates an underpriced stock among stocks with the same sensitivity to the changes in the market index. Stocks with higher alpha values usually provide higher expected returns. On the other hand, stocks with negative alphas are overpriced for any value of beta and they provide lower expected returns.

If we take the expectation of Equation (3), the expected return for stock i is obtained:

$$E(exs_i) = \alpha_i + \beta_i E(emr), \qquad E(\varepsilon_i) = 0 \tag{4}$$

The risk is computed by the variance of return. The risk associated with the return of stock i is decomposed as follows:

$$\boxed{\begin{array}{l} Total\ Risk = Systematic\ Risk + Unsystematic\ Risk \\ (Total\ Variance) = (Explained\ Variance) + (Unexplained\ Variance) \end{array}}$$

where

$$\boxed{\begin{array}{l} Var(exs_i):\ TotalRisk\ (Total\ Variance) \\ \beta_i^2 Var(emr):\ Systematic\ Risk\ (Explained\ Variance) \\ Var(\varepsilon_i):\ Unsystematic\ Risk\ (Unexplained\ Variance) \end{array}}$$

Systematic Risk: This is the part of the total variance that is explained by the variation in the market index due to the uncertainty of the macroeconomic factors.

Unsystematic Risk: This is the part of total variance that is due to the firm-specific factors and diversifiable for the stocks.

To conclude, the index model divides excess stock return into systematic and firm-specific risk. The excess return of each stock is the sum of three components [12]:

- The composition of return due to fluctuations in the market index, which is represented by emr; β_i is the stock's sensitivity to the market.
- The firm-specific risk, ε_i, due to unexpected events that are specific only to this stock.
- The excess return of stock is α_i, if the market-index excess return is zero.

Therefore, the total variance of the excess return of each stock is a total of two components:

- The variation attributed to the general market's uncertainty. This variance is determined by both the variance of the emr, denoted as σ_M^2, and the beta of the stock on the emr.
- The variance of the firm-specific return, ε_i, which is different than market excess return

The CAPM has several assumptions as follows:

1. Markets are equally profitable and perfectly competitive for investors, which means:
    a) No investor has enough power to affect market prices.
    b) All stocks are owned and traded by the public, and investors may trade all of them. Thus, the investment universe includes all risky assets.
    c) All information relevant to stocks freely available to the public.
    d) There is a single risk-free interest rate, r_f, at which all borrowing and lending take place.
    e) Returns are not taxed and no transaction fees that inhibit trading. Thus, all investors make the same profit or loss.

2. All investors have the same perceptions about expected return, variance, and covariance of each stock during the universal planning horizon, implying that:
    a) Investors manage their portfolios for the single-period horizon,
    b) Investors use the same information and consider same portfolio opportunity sets [13]. In other words, they all have homogeneous expectations,
    c) Investors are rational.

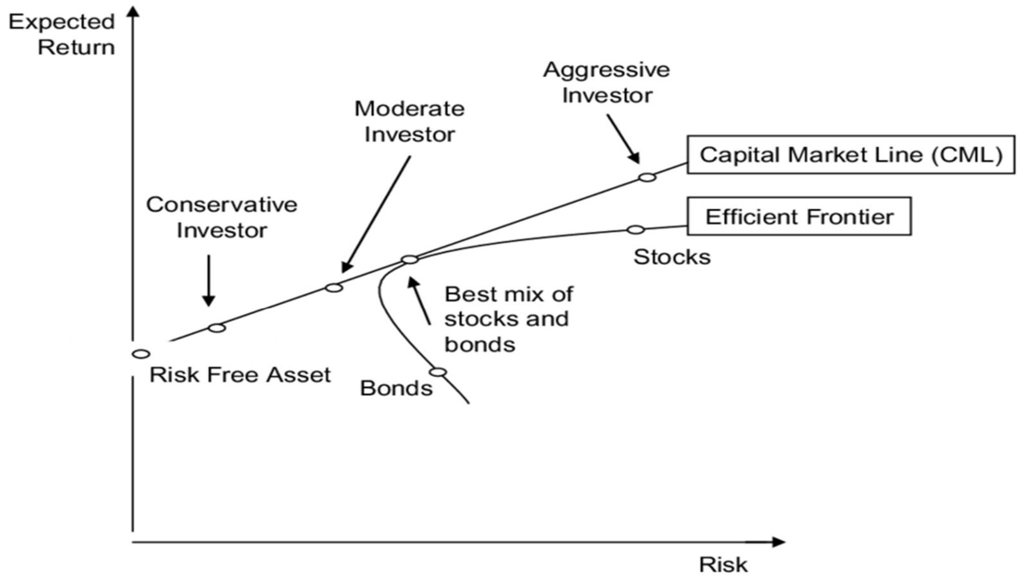
Even though these assumptions ignore uncertainties and complexities in the real economy, they provide valuable insight into the nature of market equilibrium. Given these assumptions, all investors choose the market portfolio, which includes all stocks that are listed on the market index [12]. The proportion of a stock is calculated as the market value of the stock divided by the total market value in the market portfolio.

The market portfolio is on the efficient frontier, which is a collection of portfolios that have the best return for a given degree of risk. Preference of point on the efficient frontier would depend on investors' expectations considering the mean and variance of the stock returns for each investor. However, all investors choose to hold the market portfolio as the best attainable optimal risky portfolio, which is the tangency point of the Capital Market Line (CML) to the efficient frontier, under *homogenous expectations.* It is clearly seen in Figure 2.1 that the tangency point of the CML to the efficient frontier represents the best mix of bonds and stocks (market portfolio) traded in the market. Sharpe [2], Lintner [3], and Mossin [4] state that the market portfolio must be in equilibrium, if all investors chose the market portfolio on the efficient frontier. Then, they select the market portfolio as their optimal risky portfolio and risk-free asset. The weights of these portfolios depend on the risk aversion degree of the investor and the set of portfolios form a straight CML.

The risk premium of the market portfolio is proportionate to risk aversion degree of investors and the variance of the market portfolio:

$$E(r_M) - r_f = \overline{A}\sigma_M^2 , \tag{5}$$

where σ_M^2 represents the variance of the market portfolio return and $\overline{A}$ is the risk aversion degree of the average investor.



Source: Adapted from Campell and Viceira (2002)

Figure 2.1: Capital market line

The beta measures how returns respond to the market portfolio. In other words, beta represents sensitivity of stocks to fluctuations in the overall stock market index. Excess stock returns are proportional to the excess market portfolio and the beta coefficient of the stock.

Although the CAPM has strong assumptions that limit its empirical strength in practice, it is still the most widely used model for predicting stock returns in the finance world. An extensive survey conducted by Graham et al. [14] found that about 75% of financial and portfolio managers use the CAPM to estimate the cost of capital for their investment purposes.

Several studies have been published that follow-up the CAPM theory. These studies have shown that the beta does not measure all risk attributed to stocks. It seems clear from these studies that there are risk factors that have impact on security returns beyond the measurement of beta.

2.1.2 Multi-Factor Capital Asset Pricing Model

The singe-factor CAPM is introduced above as how the variability of stock returns is a decomposition of market risk or systematic risk (emr), as a result of macroeconomic events, and firm-specific effects (ε_i) that can be diversified. Similar to how their betas determine their risk premiums in the usual CAPM model, the risk premiums of stocks can also represent their responsiveness to changes in multiple market risk factors. The models that allow for more than one market risk factor are multi-factor models. The multi-factor CAPM, which Merton [7] first proposed, can better estimate security returns for some markets. A multi-factor CAPM can measure exposure to various macroeconomic and firm-specific risks.

Let us illustrate a multi-factor CAPM. Suppose the x_j is one of the most critical sources of market risk that is the economywide uncertainties which affect all stocks in the market index. x_j is the factor that is the systematic risk of the market. The stock returns respond to factors and firm-specific disturbances. A multi-factor CAPM describing the excess return on stocks can be written as follows:

$$exs_t = \alpha + \beta_1 emr_t + \sum_{j=1}^{J} \beta_j x_{j,t} + \varepsilon_t , \tag{6}$$

where β_j is the sensitivity of the excess stock return to the x_j factor and $x_{j,t}$ is the factor at time t. The firm-specific disturbances are ε_i in the model. The coefficients, β_1 and β_j, in the model are sometimes called as factor betas and factor loadings.

2.1.3 Arbitrage Pricing Theory

Despite its theoretical perfection, the CAPM has unrealistic assumptions that have been criticized in many academic studies. One of the most widely known models that is against the CAPM is the APT. The APT is developed by Ross [15]. Compared to the CAPM, it estimates expected returns with fewer limited assumptions. In particular, the homogenous expectations assumption is relaxed in the model, and the APT assumes that multiple systematic factors affect stock returns. Ross [15] proposes three key points: 1) There are enough stocks to eliminate diversifiable risk, 2) The stock returns can be predicted using a factor model, and 3) arbitrage opportunities are not possible in an efficient stock market.

The multi-factor version of the APT can be generalized to following form:

$$E(s_i) = F_0 + \beta_{i1}F_1 + \beta_{i2}F_2 + ... + \beta_{iK}F_K + \varepsilon_i, \tag{7}$$

where $\beta_{i1}, \beta_{i2}, ..., \beta_{iK}$ are factor sensitivities that represent how much extra stock return is needed for each extra unit of common factor and $F_0, F_1, F_2, ..., F_K$ are common factors. Since each factor assess the shock in the systematic risk rather than the level of the variable, each has zero expected value. F_0 corresponds risk-free assets; therefore, F_0 is considered as the risk-free rate, r_f. Then, the equation becomes:

$$E(s_i) = r_f + \beta_{i1}F_1 + \beta_{i2}F_2 + ... + \beta_{iK}F_K + \varepsilon_i. \tag{8}$$

To generalize Equation (8), consider a well-diversified portfolio with $r_{p,1}$ rate of returns that has unit sensitivity to F_1, and zero responsiveness to other factors. Thus, the expected returns of this portfolio is $E(r_{p,1}) = r_f + F_1$, and $F_1 = E(r_{p,1}) - r_f$. If the same calculation is repeated for all of the portfolios, then Equation (8) takes the following form:

$$E(s_i) = r_f + \beta_{i1}[E(r_{p,1}) - r_f] + \beta_{i2}[E(r_{p,2}) - r_f] + ... + \beta_{iK}[E(r_{p,K}) - r_f] + \varepsilon_i. \tag{9}$$

Hence, the expected return of stock i is explained by the risk free rate and K common risk premiums multiplied by the sensitivity of security to each K factor.

2.1.4 Fama French Three Factor Model

A three-factor model is proposed by Fama and French [16]. The firm size which is measured by market capitalization, and book-to-market ratio which is calculated as book value per share divided by the stock price, are added to the market portfolio to explain the stock returns. These additional factors are chosen because of the observations that the firm size and market-to-book ratio estimate the average returns on stocks higher than observations consistent with the CAPM. The FF three-factor model and its variables are defined as follows:

$$exs_i = \alpha_i + \beta_{iM} emr_t + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \varepsilon_i, \tag{10}$$

where SMB_t is the size premium (small minus big: the portfolio returns of small stocks $-$ the portfolio returns of large stocks) at time t, and HML_t is the value premium (high minus low: the portfolio returns of stocks with a high book-to-market ratio $-$ the portfolio returns of stocks with a low book-to-market ratio) at time t.

In the model, it is expected that the market index should capture the systematic risk coming from macroeconomic factors. The study of Fama and French suggests that SMB and HMB can be parts of sources of systematic risk that are not captured by beta, and yield return premiums. For example, a firm with a high book-to-market ratio is most probably in financial trouble, and that small stocks can be more sensitive to changes in the macroeconomic factors.

2.2 Literature Review on Effect of Exchange Rate Volatility on Stock Returns

The behavior of the exchange rate volatility has been widely studied using the ARCH-GARCH paradigm pioneered by Engle [17] and developed further by Bollerslev [18], and other scholars. Mlambo et al. [19] conduct a research on the relationship between the stock market and exchange rates in South Africa using monthly data between 2000–2010. Their study reports a poor relationship between the stock market and the exchange rate volatility. Considering the data for Tunisia and Turkey, which are countries of the Middle East and North Africa (MENA), using monthly data from January 2002 to January 2017, Mechri et al. [20] reveal that the exchange rate volatility has a significant effect on stock market movements. Sichoongwe [21] analyzes the effects of the exchange rate volatility on stock returns for Zambia using the GARCH (1,1) model for the period of 2000 to 2015. The study finds that exchange rate volatility negatively affects stock market returns.

2.3 Literature Review on Impact of Firm Specific Features on Stock Returns

The research by Pražák et al. [22] on the Prague Stock Exchange and Warsaw Stock Exchange for the period 2006–2015 shows that the financial leverage ratio has positive impact on stock prices in both countries and the liquidity ratio has a negative effect on stock prices in both countries. The study of Arkan [23] on the Kuwaiti financial market shows that the return on equity (ROE), return on assets (ROA), and the net profit margin have significant positive effects on stock returns for the industrial sector. In line with the findings of Arkan [23], Mirgen et al. [24] show that the net profit margin has a significant positive effect on stock returns by using data from 87 companies listed on the BIST-100 Index over the period of 2012–2017. Using the panel data regression analysis method with the data of 36 firms listed on the BIST-100 Index for 2010–2017, ISIK [25] reports that the stock returns are positively associated with the ROA, earnings per share, market value to book value, and total debt ratio. In the research of Razak et al. [26] on stock returns in the companies traded on the Stock Exchange Indonesia (IDX) between 2014–2018, the results of the common effect model show that the current ratio, total asset turnover, ROA, and debt to equity ratio do not significantly affect stock returns. Ligocká et al. [27] analyze the relationship between the financial ratios and stock prices of food companies listed on European Stock Exchanges from 2005 to 2015. In their analysis, they detect a significant positive relationship between the ROE and stock prices for all European Stock Exchanges. In his study on Indonesian manufacturing companies for the period of 2008–2013, Wijaya [28] observes that the ROA, book value to market value, earnings yield, and dividend yield have significant impacts on stock returns, but the debt-to-equity ratio does not have significant effect on stock returns.

CHAPTER 3

VOLATILITY MODELING OF THE EXCHANGE RATE

Asset return volatility is one of the most commonly used important risk measures in finance. The purpose of this chapter is to model the volatility of the TRY rates of returns on the foreign currency USD. There is a large body of evidence indicating that changes in foreign exchange rates may have significant impacts on domestic economies and financial markets. The progress of globalization necessitates correct quantification and forecasting of exchange rate risks. Therefore, the effects of the volatility of the TRY value against the USD on expected returns of stocks are intended to be analyzed in the forthcoming chapters.

There are many volatility models available in the literature. Among the most widely used of these are the ARCH model (see Engle [18]), GARCH model (see Bollerslev [19]), exponential GARCH (EGARCH) model (see Nelson [23]), and Glosten-Jagannathan-Runkle-GARCH (GJR-GARCH) model (see Glosten et al. [24]). Lamoureux et al. [42] show that volatility estimations by the traditional single-regime GARCH models may not capture the correct variation in the volatility when there are regime shifts in the volatility. Bauwens et al. [29] show that structural breaks in the volatility lead to biased estimates of the GARCH model and incorrect volatility predictions. In order to capture the regime changes in volatility, the parameters of MSGARCH model, whose parameters can change through time based on an unobservable variable, have been proposed. Cai [30] and Hamilton at al. [31] introduce the regime-switching process in the GARCH model to capture potential regime changes. They proposed the switching ARCH (SWARCH) model to capture regime shifts in the volatility process with a first-order Markov Chain process. Gray

[32] also suggests a new method that allows for estimation of the SWGARCH model and removes the infinite path-dependent problem. The study of Haas et al. [33] show that the GARCH process in each state evolves independently from other states. Caporale et al. [34], Timmermann [35], and Klaassen [36] also suggest using the regime-switching GARCH model for risk-management purposes. Furthermore, Ardia et al. [37] show that the MSGARCH model predicts significantly better than the single-regime traditional GARCH model in forecasting the VaR for the log-returns of daily, weekly, and ten-day equity.

In this chapter, single-regime traditional GARCH and MSGARCH models are examined to analyze the exchange rate volatility. Two extensions of the GARCH models are introduced for both the single-regime GARCH and MSGARCH models. The first extension is the standard GARCH model, which assumes that positive and negative shocks will have exactly the same impact on the volatility. The second extension is the GJR-GARCH model, which allows for asymmetric reactions in the volatility process. Those models are estimated and compared to see which are better in modeling the exchange rate volatility. The results are compared using in-sample-analysis and backtesting VaR predictions.

The rest of this chapter is as follows. In the first section, the literature review on the exchange rate volatility in Turkey is provided. In the second section, the GARCH model and its extensions are presented. In the third section, conditional distributions that are assumed for estimations and estimation method of MSGARCH model are given. In the fourth section, the time series properties of the exchange rate return are analyzed. In the fifth section, the volatility estimations are discussed, and traditional single-regime GARCH and MSGARCH models are compared. In the sixth section, the model diagnostics are provided to determine the best predictive model. In the seventh section, the time-series properties of the estimated exchange rate volatility are analyzed.

3.1 Literature Review of the Studies on the Volatility of the Foreign Exchange Rates in Turkey

By using traditional one-regime volatility models, Almisshal [38] shows that the volatility of the daily log-return series of the USD and EUR exchange rates against the TRY, covering the period 2005–2019, reacts differently to the positive and negative shocks by using GJR-GARCH (1,1) model. They show that the traditional asymmetric GJR-GARCH (1,1) model is the most adequate model for estimating the USD/TRY exchange rate and has better volatility forecasts than the symmetric GARCH model; however, they report high persistence conditional variances with the value of 0.97, and propose no reason for the extreme high persistence. Gün [39] examines the weekly log-return series of the USD/TRY exchange rate volatility for 2001–2020 with 972 observations and concludes that the symmetric 2-regime MSGARCH(1,1) model is more successful than traditional GARCH models at describing the volatility behavior of the USD/TRY exchange rate. While the return series is not modeled with a multiple regime MSGARCH model that allows for the asymmetric effects, it is shown that the traditional GARCH model estimates irrationally higher persistence in the USD/TRY exchange rate series. Moreover, no volatility prediction assessment method is provided for a comparison that proves the superiority of regime-switching MSGARCH model. By using the daily log-returns of the currency basket data for 2001–2010, Gur et al. [40] report that the SWARCH (2,1) model is the best volatility model according to lowest AIC and Schwarz information criterion (SIC) value, and has better volatility forecasts among four alternative models, which consist of the ARCH(1), GARCH(2,1), SWARCH(2,1), and SWARCH(2,2). However, they do not use any volatility model that allows for the leverage effect. Between 2002 and 2009, using daily log-returns of the USD/TRY exchange rate, Soytas and Unal [41] observe that there is leverage and asymmetry effects for the daily data, and the traditional GJR-GARCH (1,1) is the best model in predicting the volatility according to the root-mean-square error criteria.

Similarly, the findings of Kayral [42] support the existence of leverage effects and among the alternative models, such as the symmetric ARCH-M(1), ARCH(1), GARCH-M(1,1), GARCH(1,1), and asymmetric EGARCH-M(1,1), EGARCH(1,1), TARCH(1,1) and TARCH-M(1,1) models, the TARCH(1,1) is proven to be superior in modeling the conditional heteroscedasticity for the period of 2002–2015 based on the AIC and BIC value. Nevertheless, he also reports results with extremely high persistence that is close to 1 and no reason is given for the high persistence.

3.2 Selected GARCH Models

3.2.1 Traditional GARCH Models

Engle [17] suggests that the volatility process of the series depends on the past squared error terms at time t. when conditional volatility is not constant, Engle proposes that it is better to estimate the mean and the variance of a time-series at the same time.

Consider variable Y_t, where $t = \{0,1,...\}$ is time index. Let Ω_{t-1} be the information set available at time $t-1$. Let also the mean equation describing the dynamics of Y_t be:

$$Y_t = E_{t-1}(Y_t \mid \Omega_{t-1}) + u_t , \quad (11)$$

where the deviation from the conditional mean $E_{t-1}(Y_t \mid \Omega_{t-1})$ at time t is u_t. Assume that ε_t is a random variable with $E(\varepsilon_t) = 0$, $Var(\varepsilon_t) = 1$, and distribution D is as follows:

$$\varepsilon_t \sim D(0,1,\zeta) , \quad (12)$$

where ζ denotes other distributional parameters. Let

$$u_t = \varepsilon_t \sqrt{h_t} \ , \tag{13}$$

where h_t is the variance following the $ARCH(q)$ process:

$$Var_{t-1}(Y_t \mid \Omega_{t-1}) = h_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j u^2{}_{t-j} \ . \tag{14}$$

The following conditions must be satisfied to ensure that the conditional variance of u_t is positive:

$$\alpha_0 > 0 \text{ and } \alpha_j \geq 0 \text{ for all } j = 1, \ldots, q \ .$$

Furthermore, $\sum_{j=1}^{q} \alpha_j < 1$ is the stability condition for the weak stationarity of the ARCH process.

According to Engle [43], one of the downsides of the ARCH model is that it is like a moving average rather than an autoregression. From this point, Bollerslev [18] proposed the inclusion of the lagged conditional variance terms. He publishes an article, which is entitled as Generalised Autoregressive Conditional Heteroskedasticity as a new extension of GARCH models.

The $GARCH(p,q)$ model has the following form:

$$Var_{t-1}(Y_t \mid \Omega_{t-1}) = h_t = \alpha_0 + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{j=1}^{q} \alpha_j u^2{}_{t-j} \ . \tag{15}$$

The model states that parameter, h_t, depends both on past values of the shocks, which are lagged squared residuals, and on the lagged conditional variance terms, which are captured by lagged h_t terms. For the $GARCH(p,q)$ model, Nelson and Cao [44] show that sufficient conditions for the conditional variance of u_t to be positive are as follows:

$$\alpha_0 > 0 \text{ and } \alpha_j \geq 0 \ \forall j = 1,...q \ , \quad \beta_i \geq 0 \text{ for all } i = 1,...p \ .$$

Here, $\sum_{j=1}^{q} \alpha_j + \sum_{i}^{p} \beta_i < 1$ is the sufficient condition for the weak stationarity $GARCH(p,q)$ model. The sum $\sum_{j=1}^{q} \alpha_j + \sum_{i}^{p} \beta_i < 1$ is commonly used as the measure of the volatility persistence for the general $GARCH(p,q)$ model.

One important extension of the GARCH model that aims to capture asymmetries in volatility of the series in terms of negative and positive shocks is the GJR-GARCH model, which is developed by Zakoian [45] and Glosten et al. [46]. To take into account the asymmetries, when the shocks are negative, a dummy variable is introduced to the variance equation to check if there is a significant difference. The volatility equation of the $GJR-GARCH(p,q)$ model is:

$$\begin{gathered} Var_{t-1}(Y_t \mid \Omega_{t-1}) = h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{i=1}^{q} \gamma_i u_{t-i}^2 I_{t-i} + \sum_{j=1}^{p} \beta_j h_{t-j} \\ I_{t-i} = \begin{cases} 1 & \text{if } u_{t-i} < 0 \\ 0 & \text{if } u_{t-i} \geq 0 \end{cases} \end{gathered} \tag{16}$$

Here, $I_{t-i} = 1$ is for a negative u_{t-i}, and 0 otherwise. When γ_i has a positive value, negative shocks with the same magnitude tend to increase volatility more than positive shocks with the same magnitude.

The sufficient condition for the positivity of the variance requires that:

$$\alpha_0 > 0, \ \ \alpha_i \geq 0 \ \textit{for all } i = 1,...,q, \ \beta_i \geq 0 \ \textit{for all } j = 1,...,p, \ \alpha_i + \gamma_i \geq 0 \ \textit{for all } i = 1,...,q$$

The stability condition is:

$$\sum_{i=1}^{q}\left[\alpha_i + \frac{1}{2}\gamma_i\right] + \sum_{i=1}^{p}\beta_i < 1 .$$

3.2.2 Markov-Switching GARCH Models

The parameters of MSGARCH model changes over time based on a discrete Markov process.

The variable of interest is denoted by y_t at time t. It is assumed that y_t has a zero mean and is not autocorrelated, which means $E[y_t]=0$ and $E[y_t y_{t-l}]=0$ must hold for $l \neq 0$ and all $t > 0$.

Regime-switching is allowed in the conditional variance process. The information set that is observed up to time $t-1$ is denoted by Ω_t, that is, $\Omega_t = \{y_{t-i}, i > 0\}$. Following Ardia et al. [37], the Markov-switching GARCH specification can then be defined as:

$$y_t \mid (s_t = k, \Omega_{t-1}) \sim D(0, h_{k,t}, \xi_k) , \tag{17}$$

where $D(0, h_{k,t}, \xi_k)$ represents a continuous distribution with a zero mean, time-varying variance $h_{k,t}$, and extra shape parameters obtained in the vector ξ_t [1]. The Markov-switching GARCH model is characterized by the stochastic variable s_t, which is defined on the discrete space $\{1, ..., K\}$. The standardized innovations of the MSGARCH model are defined as: $\eta_{k,t} = y_t / \sqrt{h_{k,t}} \overset{iid}{\sim} D(0, h_{k,t}, \xi_k)$.

---

[1] The parametric formulation of the $D(0, h_{k,t}, \xi_k)$ can change across different regimes. The notation $D(0, h_{k,t}, \xi_k)$ would be more appropriate in this circumstance [37].

It is assumed that s_t follows an unobserved first-order ergodic homogeneous Markov chain according to a $K \times K$ transition probability matrix P :

$$P = \begin{pmatrix} p_{11} & \cdots & p_{1K} \\ \vdots & \ddots & \vdots \\ p_{K1} & \cdots & p_{KK} \end{pmatrix}, \tag{18}$$

where $p_{i,j} = P[s_t = j \mid s_{t-1} = i]$ represents the probability of a transition from state $s_{t-1} = i$ to state $s_t = j$. Also, the following limitations should hold: and $\sum_{j=1}^{K} p_{i,j} = 1,\ \forall_i \in \{1,...,K\}$ and $0 < p_{i,j} < 1\ \forall_{i,j} \in \{1,...,K\}$. $E[y_t^2 \mid s_t = k, \Omega_{t-1}] = h_{k,t}$ is the variance of y_t, which is conditional on the $s_t = k$, given the parametrization of $D(\cdot)$. In the MS-GARCH model of Haas et al. [33], $h_{k,t}$ for $k = 1, \ldots, K$ are assumed to following K different GARCH processes that evolve in parallel.

As defined by Haas et al. [33], it is assumed that the conditional variance of y_t follows a GARCH model. Therefore, conditionally on regime $s_t = k$, $h_{k,t}$ is a function of y_{t-1}, $h_{k,t-1}$, and the additional vector of parameters θ_k for each regime:

$$h_{k,t} = h(y_{t-1}, h_{k,t-1}, \theta_k), \tag{19}$$

where $h(\cdot)$ represents a Ω_{t-1}-measurable function that describes the filter for the conditional variance and ensures positiveness. The beginning value of the variance iterations, $h_{k,1}$ $(k = 1,...,K)$, is set equal to the unconditional variance of regime k .

The specifications of important MSGARCH-type models are briefly presented as below:

MSARCH model

Engle's [17] ARCH model is given by:

$$h_{k,t} = \alpha_{0,k} + \alpha_{1,k} y_{t-1}^2 \tag{20}$$

for $k = 1,...,K$. we have $\theta_k = (\alpha_{0,k}, \alpha_{1,k})'$ in this case. It is required that $\alpha_{0,k} > 0$ and $\alpha_{1,k} \geq 0$ to ensure positivity. Stability condition in each regime is achieved by requiring that $\alpha_{1,k} < 1$.

MSGARCH model

Bollerslev's [18] GARCH model is given by:

$$h_{k,t} = \alpha_{0,k} + \alpha_{1,k} y_{t-1}^2 + \beta_k h_{k,t-1} \tag{21}$$

for $k = 1,...,K.$ we have $\theta_k = (\alpha_{0,k}, \alpha_{1,k}, \beta_k)'$ in this case. It is required that $\alpha_{0,k} > 0,$ $\alpha_{1,k} > 0,$ and $\beta_k \geq 0$ to ensure positivity. Weak stationarity for each regime is achieved by requiring that $\alpha_{1,k} + \beta_k < 1$.

GJR-MSGARCH model

The asymmetric effects of shocks in the conditional volatility process can be captured by the GJR model of Glosten, Jagannathan, and Runkle [46]. The model is given by:

$$h_{k,t} = \alpha_{0,k} + (\alpha_{1,k} + \gamma_k \mathrm{I}\{y_{t-1} < 0\}) y_{t-1}^2 + \beta_k h_{k,t-1} \tag{22}$$

$$\mathrm{I} = \begin{cases} 1 & \text{if } y_{t-1} < 0 \\ 0 & \text{if } y_{t-1} \geq 0 \end{cases}$$

for $k=1,...,K$, $\mathrm{I}\{\cdot\}$ is the dummy variable that takes value 1 if the condition holds, and 0 otherwise. The parameter $\gamma_k \geq 0$ checks the asymmetric degree in the conditional variance response to the past shock in regime k. In this case, the parameters are $\theta_k = (\alpha_{0,k}, \alpha_{1,k}, \gamma_k, \beta_k)'$. It is required that $\alpha_{0,k} > 0$, $\alpha_{1,k} > 0$, $\gamma_k \geq 0$, and $\beta_k \geq 0$ to ensure positivity. Weak stationarity condition in each regime is achieved by requiring that $\alpha_{1,k} + \gamma_k E[\eta_{k,t}^2 \mathrm{I}\{\eta_{k,t} < 0\}] + \beta_k < 1$.

3.3 Conditional Distribution and Estimation Method

The determination of the conditional distribution for the standardized innovations, $\eta_{t,k}$, in each regime completes the model specification. Standard normal distribution could not be sufficient to define the fat tail property of the financial returns. To take into account the fat tail feature of the data, student-t and generalized error distribution (GED) are proposed by Bollerslev (1987) and Nelson [47], respectively.

In the case of normal distribution, the probability density function (PDF) of the standardized innovations is given by:

$$f_N(\eta_{t,k}) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\eta_{t,k}^2}, \qquad \eta_{t,k} \in \mathbb{R}. \tag{23}$$

When standardized innovations are assumed to follow student-t distribution, the PDF of the standardized student-t distribution is as follows:

$$f_S(\eta_{t,k}, \nu) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{(\nu-2)\pi}\,\Gamma\left(\frac{\nu}{2}\right)} \left(1 + \frac{\eta_{t,k}^2}{\nu-2}\right)^{-\frac{\nu+1}{2}}, \qquad \eta_{t,k} \in \mathbb{R}, \tag{24}$$

where $\Gamma(\cdot)$ represents the Gamma function. ν is the degree of freedom and should be greater than 2. If $\nu = \infty$, the student-t distribution is equivalent to the normal distribution. This implies that a lower ν implies fatter tails.
When the GED is the distribution assumption, the PDF of the standardized GED is defined as:

$$f_{GED}(\eta_{t,k}, \nu) = \frac{\nu e^{-\frac{1}{2}|\eta_{t,k}/\lambda|^{\nu}}}{\lambda 2^{(1+1/\nu)}\Gamma(1/\nu)}, \quad \lambda = \left(\frac{\Gamma(1/\nu)}{4^{1/\nu}\Gamma(3/\nu)}\right)^{1/2}, \quad \eta_{t,k} \in \mathbb{R}, \qquad (25)$$

where ν represents the shape parameter. When $\nu = 2$, the GED becomes a standard normal distribution. While the normal distribution has fatter tails than the GED when $\nu > 2$, it has fatter tails than the normal distribution when $\nu < 2$.

If the innovations are assumed to follow skewed distributions, Fernández and Steel [48] propose a method to add skewness into any standardized distribution with an extra parameter, $\xi > 0$. When $\xi = 1$, the distribution becomes symmetric.

The computational simplicity of the Gaussian likelihood technique could exceed the loss in estimation efficiency with big datasets, while the cost of not precisely characterizing the distributional of the innovation leads to a loss of estimation efficiency [49]. With this in mind, in this study, the GARCH models are estimated under different specifications for the distribution of innovations. The student t, skewed normal, skewed student t, and skewed GED are used for the GARCH estimations, and they are denoted as *S*, *skN*, *skS*, and *skG*, respectively.

Herein, 24 GARCH models are applied to the full range of the data using Maximum Likelihood procedures. First, the likelihood for the MSGARCH model specifications is generated by a vector of the model parameters, $\Psi = (\theta_1, \xi_1, ..., \theta_k, \xi_k, P)$, according to Equation (17). Given past observations, Ω_{t-1}, and parameters of model, Ψ, $f(y_t \mid \Psi, \Omega_{t-1})$ is the density of y_t.

Then, the conditional density of y_t in the state $s_t = k$ given Ψ and Ω_{t-1} is achieved as follows:

$$f(y_t \mid \Psi, \Omega_{t-1}) = \sum_{i=1}^{K}\sum_{j=1}^{K} p_{i,j} z_{i,t-1} f_D(y_t \mid s_t = j, \Psi, \Omega_{t-1}), \tag{26}$$

Where the filtered probability of state i at time $t-1$, $z_{i,t-1} = P[s_{t-1} = i \mid \Psi, \Omega_{t-1}]$, is achieved via Hamilton's filter [50, 51]. $p_{i,j}$ represents the transition probability of moving from state i to state j. Finally, the likelihood function is derived from Equation (26) is as follows:

$$\ell(\Psi \mid \Omega_T) = \prod_{t=1}^{T} f(y_t \mid \Psi, \Omega_{t-1}). \tag{27}$$

Maximizing the logarithm of Equation (27) provides the maximum likelihood estimator $\hat{\Psi}$.

3.4 Time Series Properties of the TRY/USD Exchange Rate Return

For the period between January 1, 2010 and March 31, 2020, the daily value of the TRY against the USD log-returns is calculated as a continuously compounded series using the daily TRY/USD exchange rate according to the following formula:

$$FX_t = \ln(usd_t / usd_{t-1}) * 100, \tag{28}$$

where $FX_t =$ log returns of the TRY/USD exchange rate: value of the TRY against the USD for day t, and $usd_t =$ closing 1 TRY value in terms of the USD at day t.

FX is used as an abbreviation for the TRY/USD exchange rate log-returns in the rest of this study. Examining the time plot of the FX series in Figure 3.1, it is clearly seen that the volatility of the series increases in July 2016, in the third quarter of 2018, and at the end of first quarter of 2019. As Table 3.1 shows, the unconditional distribution of the FX is leptokurtic and negatively skewed. As seen in Figure 3.2, whether the FX are normally distributed is examined. The Jarque-Bera normality test confirms that the FX are not normally distributed, at a confidence level of 99%.

The stationarity property of the FX series is examined. Table 3.1 shows the Augmented Dickey-Fuller (ADF) test [52] results for the FX series. According to the AIC, the ADF unit root model without a constant and the trend augmented with 13 lags is the best equation for the returns. The autocorrelation function (ACF) of the residuals from the unit root model is provided (see Figure A.2) in Appendix A. The ACF plot shows that there is no remaining autocorrelation in the residuals of the unit root model of the FX series. Therefore, there is no unit root in the series, and it is stationary.

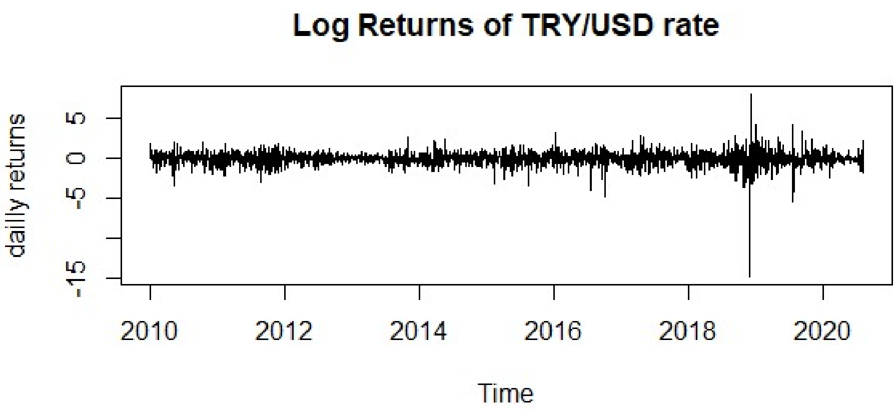


Figure 3.1: TRY/USD Exchange Rate Log Returns

Table 3.1: Descriptive Statistics of the Exchange Rate Returns and AR(4) Residuals

	Original Series	Residual Series
Mean	–0.06	–0.001
Minimum	–14.76	–14.02
Maximum	8.00	6.98
Median	–0.02	0.03
Standard Deviation	0.89	0.87
Skewness	–1.84 (0.000)	–1.82 (0.000)
Kurtosis	35.08 (0.000)	29.58 (0.000)
ADF Statistic	–12.45 (0.01)	–12.12 (0.01)
Jarque-Bera	138.73 (0.000)	99.00 (0.000)
Values in parentheses are p-values		

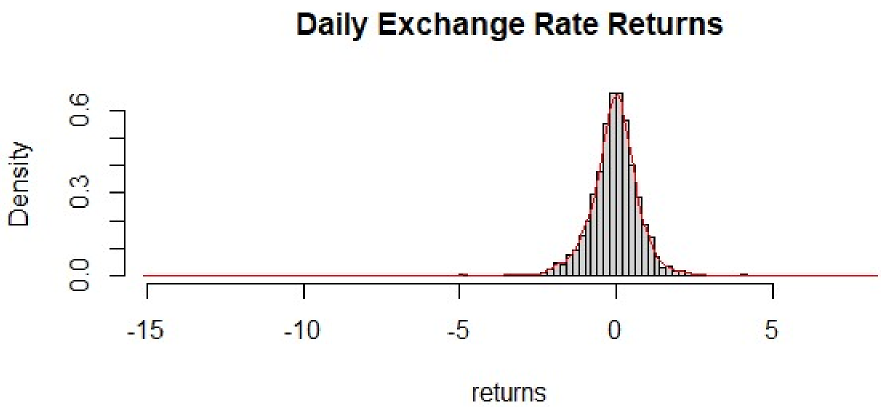


Figure 3.2: Histogram of the Daily Exchange Rate Returns

The ACF and PCF plots of the FX (see Figure A.1) in Appendix A show that there is a serial correlation in the FX series until lag 3. Since the FX series are serially correlated, one of the volatility modeling assumptions, $E[y_t y_{t-l}] = 0$, is violated. Therefore, the Auto Regressive Integrated Moving Average (ARIMA) model is employed as a mean equation for the FX. Different ARIMA models are calculated and compared. The AR(4) model is selected as the best mean equation for the FX series using the AIC. The estimation results of the AR(4) mean model with standard errors in parentheses are shown in Table 3.2. The results show that the first, second, third, and fourth lagged values of the FX are statistically significant in explaining the current FX .

As the final step of determining the mean model, it is necessary to check for any remaining serial correlations in the model. The ACF results of the AR(4) model given (see Figure A.3) in Appendix A suggest that there are no strong autocorrelations in the residuals from the mean model, except for minor spikes at lags 13 and 19. Hence, the AR(4) time series model is adequate for the FX .

Table 3.1 reveals that the residuals obtained from the constructed AR(4) mean equation for the series are still leptokurtic and asymmetric. This result is a good indication of the presence of the time varying heteroscedastic variance structure in modelling the FX .

Table 3.2: Results of the AR(4) Mean Model for Volatility Modeling

	Dependent variable: FX_t
FX_{t-1}	0.0758^{***}
	(0.0193)
FX_{t-2}	-0.0785^{***}
	(0.0193)
FX_{t-3}	-0.0949^{***}
	(0.0193)
FX_{t-4}	0.0424^{**}
	(0.0193)
Intercept	-0.0555^{***}
	(0.0160)
Number of Observations	2,672
Log Likelihood	–3433.59
AIC	6879.18
Note:	*p**p***p< 0.01

The presence of heteroscedasticity in the residuals of the AR(4) model is investigated by examining the ACF and partial ACF (PACF) of the squared and absolute residuals in Figure A.4 and A.5 in Appendix A. It can be observed that the squared and absolute residuals have a strong serial correlation until lag 40. Consequently, the ACF and PACF of the squared and absolute residuals show that the daily FX series has significant ARCH effects.

For further confirmation, the Ljung-Box statistics [53] are estimated with the squared residuals, and the Lagrange multiplier test of Engle [17] is used. Table 3.3 shows that the Ljung-Box statistics of the squared residuals show extremely high Q-statistics at lags 20 and 20, with p-values close to zero, and the Lagrange multiplier test (ARCH test) with the null hypothesis that there is no ARCH effect in the residuals give a high F-ratio for lags 20 and 40, with p-values also close to zero. These tests confirm that there are strong ARCH effects in the FX . As a result of this, ARCH-GARCH models must be used in order to model the variance of the series.

Table 3.3: Ljung-Box and ARCH LM Test Results

Method	Statistic	Lags	p-value
Box-Ljung test	666.35	20	0.000
	755.82	40	0.000
ARCH LM-test	407.54	20	0.000
	442.25	40	0.000

3.5 Volatility Model Estimations

In this section, the estimation results of the two types of traditional GARCH models mentioned in Section 3.2.1 and the two types of MSGARCH models mentioned in Section 3.2.2 will be presented.

3.5.1 In Sample Analysis

To compare the goodness of the models in sample analysis, the AIC [54] values are used. The number of estimated parameters for the MSGARCH models is at least two times higher than that for single-regime GARCH models. Therefore, while making a comparison between the single-regime GARCH and MSGARCH models, the Schwarz's Bayesian Information Criteria (SBIC) [55] test is not applicable, since the SBIC penalizes additional parameters that are larger than those of the AIC. The model with the smaller value of information criteria is preferable. The AIC and SBIC are computed as follows:

$$AIC = \frac{-2\ell}{T} + \frac{2k}{T} \text{ and } SBIC = \frac{-2\ell}{T} + \frac{2\ln(T)}{T}, \tag{29}$$

where ℓ represents the value of the likelihood function, T is the number of observations and k is the number of parameters. Herein, 24 models are fitted to the daily data. Table 3.4 reports the AIC values of all of the estimated models. For all of the volatility and distribution specifications, it is noticed that the 3- and 2-regime MSGARCH models usually provide lower AIC values than their traditional single-regime GARCH counterparts.

In addition, skewed and fat-tailed distributions have smaller AIC values for all of the regime specifications. Therefore, the parameter estimates of the best in-sample single-regime GARCH and multiple-regime MSGARCH models, which are estimated with *skS* distribution and *skG*, are reported in Table 3.5.

Table 3.4: AIC Values of all of the Estimated GARCH Models

Distribution	***S***	***skN***	***skS***	***skG***
Singe-regime				
Standard GARCH	5797. 9199	5929.9406	5770.9734	5805.3606
GJR-GARCH	5785.4617	5912.8312	5760.3290	5795.5392
Two-regimes				
Standard MSGARCH	5775.7534	5789.0661	5751.6707	5767.7331
GJR-MSGARCH	5750.2410	5773.4418	5740.7558	5744.6322
Three-regimes				
Standard MSGARCH	5773.4316	5763.8131	5746.3605	5756.1738
GJR-MSGARCH	5768.6359	5745.6782	5740.6613	5740.2875

The SBIC values are also checked. In contrast to the AIC, the SBIC suggests that the single-regime GARCH models provide the most accurate description of the data. As it is stated before, this is because of the large number of estimated parameters in MSGARCH models.

The signs and the magnitude of the predicted coefficients for all of the models show the positivity of the conditional variance and the weak stationarity of the models. Almost all of the parameter estimates are significantly different from zero at a significant level of 5%. The positive coefficient of γ in all of the single-regime GJR-GARCH and GJR-MSGARCH models suggests that negative shocks increase the volatility more than the positive ones, and this asymmetric effect confirms that past negative observations have a bigger impact on the conditional volatility than past positive shocks of the same magnitude. This result is expected because depreciation of the TRY means a negative shock (bad news) for the Turkish economy, so a larger depreciation in the TRY has a larger effect on the volatility than a larger appreciation in the TRY with the same magnitude.

The significant parameters of the MSGARCH models imply that the FXV process heterogeneously evolves across the different regimes. In order to see the existence of different volatility regimes, unconditional variances in each volatility regime are calculated. The results shown in Table 3.6 reveal that the unconditional variance of the third volatility regime is at least three times higher than that of the first volatility regime, and the unconditional variance of the second regime is about two times higher than that of the first regime for all of the estimated 3-regime MSGARCH models. In 2-regime MSGARCH models, the unconditional variance of the second volatility regime is usually much higher than that of the first volatility regime. These findings confirm that the process of the FXV is characterized by multiple regimes. Moreover, the big difference between the variance of each regime shows the need for volatility models that allow regime switching. It is interesting to notice that the degree of volatility persistence within the low volatility regime is higher than that of the high volatility regime, which is analyzed using the 3-regime GJR-MSGARCH (*skG*) results, since it come out to be the best fit with the minimum AIC value. Moreover, the same inference can be attributed to other estimated multiple-regime MSGARCH models.

As shown in Table 5.1, the results of the 3-regime GJR-MSGARCH model estimated with *skG* show that in addition to different reactions to past FX: $\gamma_1 = 0.0008$, $\gamma_2 = 0.0680$, and $\gamma_3 = 0.5986$, the volatility persistence in the three regimes is distinct. While the first regime reports $\alpha_{1,1} + \frac{1}{2}\gamma_1 + \beta_1 = 0.8661$ with an unconditional volatility value of 0.32, the second regime reports $\alpha_{1,2} + \frac{1}{2}\gamma_2 + \beta_2 = 0.9770$ with an unconditional volatility value of 0.68, and the third regime reports $\alpha_{1,3} + \frac{1}{2}\gamma_3 + \beta_3 = 0.6739$ with an unconditional volatility value of 1.78. In short, the second regime is characterized by the highest persistence of volatility process with low unconditional volatility and weak volatility reaction to past TRY depreciation. On the other hand, the third regime is characterized by the lowest persistence of the volatility process with the highest unconditional volatility and the highest volatility reaction to past TRY depreciation. Compared to the third regime, the first regime has higher persistence with the lowest unconditional volatility and the lowest volatility reaction to past TRY depreciation. Clearly, the second regime would be regarded by market participants as “turbulent market conditions”, with extremely high persistence and low reaction to past USD appreciations, while the third regime would be regarded as “relatively tranquil market conditions”, with lower persistence and strong reaction to past USD appreciations.

Furthermore, all of the single-regime GARCH models have extremely high persistence, which is greater than 0.97. For example, the singe-regime GJR-GARCH with skewed GED has $\alpha_{1,1} + \frac{1}{2}\gamma_1 + \beta_1 = 0.9843$. This result is consistent with findings of Lamoureux et al. [56] that the high persistence in volatility of single-regime GARCH models is caused by regime changes in the volatility process.

Table 3.5: Summary Results of Markov Regime Switching GARCH Models

	GJR MSGARCH (*skG*) (r-3)	GJR MSGARCH (*skS*) (r-3)	MSGARCH (*skG*) (r-3)	MSGARCH (*skS*) (r-3)	GJR MSGARCH (*skG*) (r-2)	GJR MSGARCH (*skS*) (r-2)	MSGARCH (*skG*) (r-2)	MSGARCH (*skS*) (r-2)	GJR GARCH (*skG*) (r-1)	GJR GARCH (*skS*) (r-1)	GARCH (*skG*) (r-1)	GARCH (*skS*) (r-1)
1 Regime												
$\alpha_{0,1}$	0.0147 (0.0031)*	0.0113 (0.0005)*	0.0033 (0.0012)*	0.0041 (0.0050)	0.0040 (0.0028)*	0.0048 (0.0006)*	0.0028 (0.0011)*	0.0049 (0.0020)*	0.0100 (0.0032)*	0.0095 (0.0030)*	0.0106 (0.0034)*	0.0105 (0.0034)*
$\alpha_{1,1}$	0.0209 (0.0087)*	0.0012 (0.0001)*	0.0033 (0.0022)*	0.0042 (0.0100)	0.0159 (0.0146)*	0.0275 (0.0051)*	0.0606 (0.0198)*	0.0638 (0.0255)*	0.0487 (0.0228)*	0.0446 (0.0216)*	0.0965 (0.0458)*	0.0944 (0.0441)*
β_1	0.8448 (0.0252)*	0.9637 (0.0010)*	0.9645 (0.0109)*	0.9563 (0.0465)*	0.9319 (0.0057)*	0.9345 (0.0020)*	0.9300 (0.0033)*	0.9226 (0.0053)*	0.9060 (0.0057)*	0.9098 (0.0053)*	0.8902 (0.0061)*	0.8923 (0.0060)*
γ_1	0.0008 (0.0003)*	0.0203 (0.0011)*			0.0772 (0.0465)*	0.0439 (0.0066)*			0.0591 (0.0206)*	0.0602 (0.0198)*		
ν_1	1.9828 (0.2238)*	7.6472 (0.2571)*	2.0392 (0.2609)*	83.4424 (137.2706)	1.8463 (0.5717)*	8.0997 (0.7610)*	1.5600 (0.0815)*	7.7614 (1.2371)*	1.3939 (0.0479)*	6.7563 (0.7554)*	1.3796 (0.0474)*	6.4912 (0.7074)*
ξ_1	0.9334 (0.0808)*	0.8459 (0.0252)*	0.9339 (0.0883)*	0.9215 (0.0852)*	0.8823 (0.0419)*	0.8965 (0.0275)*	0.9663 (0.0421)*	0.8982 (0.0280)*	0.8601 (0.0194)*	0.8698 (0.0234)*	0.8589 (0.0223)*	0.8670 (0.0231)*
2 Regime												
$\alpha_{0,2}$	0.0083 (0.0020)*	0.0064 (0.0003)*	0.0149 (0.0038)*	0.0149 (0.0052)*	0.3215 (1.3284)	0.5747 (0.0174)*	0.2351 (0.1604)*	0.7249 (0.0056)*				
$\alpha_{1,2}$	0.0001 (0.0000)*	0.0001 (0.0000)*	0.0313 (0.0150)*	0.0446 (0.0209)*	0.0040 (0.1218)	0.0151 (0.0082)*	0.3787 (0.3837)*	0.4572 (0.0030)*				
β_2	0.9429 (0.0039)*	0.8986 (0.0008)*	0.9368 (0.0072)*	0.9225 (0.0101)*	0.4213 (1.6207)	0.3509 (0.0028)*	0.4078 (0.1782)*	0.1692 (0.0018)*				
γ_2	0.0680 (0.0125)*	0.1725 (0.0082)*			0.3893 (3.2147)	0.6818 (0.0139)*						
ν_2	2.2808 (0.2205)*	98.9212 (0.0533)*	1.5674 (0.0933)*	7.6754 (1.3839)*	1.0672 (1.1246)	10.403 (1.1858)*	1.1396 (0.2711)*	8.5099 (0.2967)*				
ξ_2	0.8639 (0.0530)*	0.9331 (0.0331)*	0.9943 (0.0514)*	0.9187 (0.0352)*	0.8238 (0.2664)*	0.028 (0.0031)*	0.6082 (0.0569)*	0.0328 (0.0270)*				

Table 3.5: (continued)

	GJR MSGARCH (*skG*) (r-3)	**GJR MSGARCH (*skS*) (r-3)**	**MSGARCH (*skG*) (r-3)**	**MSGARCH (*skS*) (r-3)**	**GJR MSGARCH (*skG*) (r-2)**	**GJR MSGARCH (*skS*) (r-2)**	**MSGARCH (*skG*) (r-2)**	**MSGARCH (*skS*) (r-2)**	**GJR GARCH (*skG*) (r-1)**	**GJR GARCH (*skS*) (r-1)**	**GARCH (*skG*) (r-1)**	**GARCH (*skS*) (r-1)**
3 Regime												
$\alpha_{0,3}$	0.4036 (0.0507)*	1.6805 (0.0279)*	0.1627 (0.1885)	0.4889 (0.0106)*								
$\alpha_{1,3}$	0.0001 (0.0001)*	0.0000 (0.0000)*	0.4568 (0.3884)	0.4021 (0.0152)*								
β_3	0.3745 (0.1087)*	0.2168 (0.0013)*	0.5176 (0.0164)*	0.3531 (0.0108)*								
γ_3	0.5986 (0.2702)*	0.7801 (0.0779)*										
ν_3	0.9136 (0.1741)*	99.8941 (0.0053)*	1.1866 (0.3831)*	98.6864 (1.3572)*								
ξ_3	0.8296 (0.0406)*	0.0292 (0.0010)*	0.5187 (0.0384)*	0.0269 (0.0830)*								
Transition Probabilities												
P_{11}	0.9856	0.9849	0.9883	0.9871	0.9807	0.9598	0.9329	0.9753				
P_{22}	0.7379	0.9936	0.9022	0.9273	0.9546	0.6389	0.7582	0.7563				
P_{33}	0.3726	0.7979	0.6443	0.5555								
AIC	5740.287	5740.661	5756.173	5746.360	5744.632	5740.755	5767.733	5751.670	5795.539	5760.329	5805.360	5770.973

Note: Standard-errors are in parenthesis. *, **, * indicate significance at 1%, 5%, and 10%, respectively. Abbreviations of conditional distributions assumed for the estimations are in parenthesis. 1-regime, 2-regime, and 3-regime are denoted by r-1, r-2 and r-3 in parenthesis, respectively.**

Table 3.6: Unconditional Variances in Each Volatility Regime

	Regime-1	Regime-2	Regime-3
Three-regimes			
GJR-MSGARCH (*S*)	0.33	0.62	4.29
GJR-MSGARCH (*skN*)	0.32	0.63	4.32
GJR-MSGARCH (*skS*)	0.69	0.68	2.34
GJR-MSGARCH (*skG*)	0.33	0.62	1.18
MSGARCH (*S*)	0.32	0.64	1.31
MSGARCH (*skN*)	0.32	0.61	6.26
MSGARCH (*skS*)	0.32	0.67	1.40
MSGARCH (*skG*)	0.32	0.68	1.78
Two-regimes			
GJR-MSGARCH (*S*)	0.74	0.77	
GJR-MSGARCH (*skN*)	0.50	3.26	
GJR-MSGARCH (*skS*)	0.57	1.66	
GJR-MSGARCH (*skG*)	0.60	0.96	
MSGARCH (*S*)	0.46	1.00	
MSGARCH (*skN*)	0.45	5.23	
MSGARCH (*skS*)	0.60	1.37	
MSGARCH (*skG*)	0.55	1.02	

The parameter estimates of the transition probabilities $p_{ij} = \Pr\left[s_t = j \mid s_{t-1} = i\right]$ show that the probability of changing states is quite low when the volatility process stays in the first and the second regime, but the third regime changes its state more frequently in the 3-regime GJR-MSGARCH (*skG*) model. In the other models, the probabilities for staying within the state are higher than 55% for all of the regimes. While the probabilities for staying within the state are P_{11}, P_{22}, and P_{33}, moving from one state to the other are denoted by P_{12}, P_{21}, P_{31}, P_{13}, P_{32}, and P_{23} for the 3-regime MSGARCH models.

The degrees of freedom of the *skG* distribution, v, does not indicate any big difference between the regimes. The degrees of freedom are lower than 2 in most of the regimes of the MSGARCH models and in all of the single-regime GARCH models. The same inference can be attributed to models estimated with the student-t distributions (*S*) for all of the models. This means that all of the regimes have fatter tails than the normal distribution, except the second regime of 3-regime GJR-MSGARCH (*skG*) and the first regime of 3-regime of symmetric MSGARCH (*skG*), which are the second lowest and the lowest volatility regimes in the model, respectively. This means that the high volatility regime has fatter tails than the low ones. In addition, the significant asymmetry parameter, ξ, of the skewed distributions clearly confirms that the distribution of the FX series is not symmetric in all of the models estimated with skewed distributions.

Moreover, the unconditional probability of being in the low and high volatility regimes is computed for all of the estimated multiple-regime MSGARCH models. As shown in Table 3.7, the probability of being in the second regime is much greater than the probability of being in the first and third regime in all of the 3-regime MSGARCH models, except for GJR-MSGARCH (*skS*). For all of the 2-regime MSGARCH models, the probability of being in the first regime is much higher than being in the second regime.

Table 3.7: Stable Probabilities of the States in Multiple-Regime MSGARCH Models

	State 1	**State 2**	**State 3**
Three regimes			
GJR-MSGARCH (*S*)	0.13	0.82	0.05
GJR-MSGARCH (*skN*)	0.13	0.81	0.06
GJR-MSGARCH (*skS*)	0.58	0.38	0.03
GJR-MSGARCH (*skG*)	0.13	0.62	0.25
MSGARCH (*S*)	0.12	0.66	0.22
MSGARCH (*skN*)	0.13	0.80	0.07
MSGARCH (*skS*)	0.12	0.76	0.12
MSGARCH (*skG*)	0.12	0.69	0.19
Two regimes			
GJR-MSGARCH (*S*)	0.54	0.46	
GJR-MSGARCH (*skN*)	0.93	0.07	
GJR-MSGARCH (*skS*)	0.90	0.10	
GJR-MSGARCH (*skG*)	0.70	0.30	
MSGARCH (*S*)	0.60	0.40	
MSGARCH (*skN*)	0.92	0.08	
MSGARCH (*skS*)	0.91	0.09	
MSGARCH (*skG*)	0.78	0.22	

In order to display how the volatility regimes evolve over the estimation period, Figure 3.3 shows the smoothed probabilities of being in different regimes for the FX obtained using the 3-regime GJR-MSGARCH (*skG*) model. Smoothed probabilities enable us to make inference about which volatility regime the process is in at date t based on observation obtained at date $t-1$. Smoothed probabilities of the volatility regimes are estimated using $P(s_t = i \mid \hat{\Psi}, \Omega_T)$ for all $t = 1,\ldots,T$. The graphs of the smoothed probabilities clearly show the existence of three different volatility regimes in the FX series. The 3-regime GJR-MSGARCH (*skG*) model identifies that most of the sample period is characterized by the second and third regimes, which are high volatility regimes, while the lowest volatility regime (first regime) describes the periods from the beginning of 2010 to the end of 2012, the end of 2016 to the beginning of 2017, the first half of 2019, and the beginning of 2020. More importantly, Figure 3.3 reveals that FX exhibits structural breaks around the end of 2012, middle of 2016, end of 2019, and beginning of 2020.

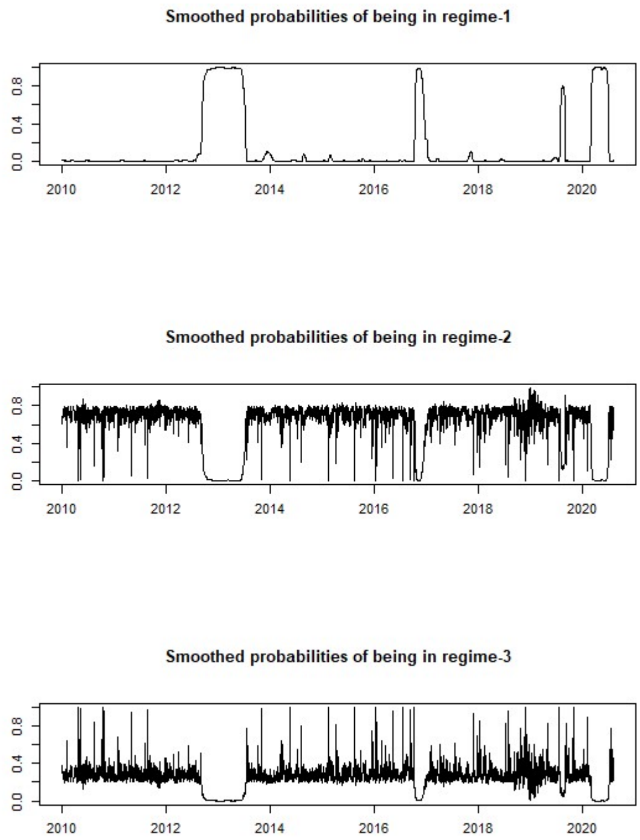


Figure 3.3: Smoothed probabilities of being in volatility regimes

3.5.2 Out of Sample Analysis with Backtesting Value-At-Risk Forecasting

In order to check which models correctly predict the one-day ahead VaR, 24 models are compared using out of sample analysis with backtesting. A fitted model for VaR prediction must offer a correct percentage of VaR violations and their correct independent distribution through time.

3.5.2.1 Value at Risk Estimation

The VaR is a risk metric that assesses the probability of observing a loss bigger or equal to a specified threshold value, $\alpha \in (0,1)$, over a given time period. Let $y_t \in FX$ series. The VaR can be computed as follows:

$$VaR = V_t \times \sigma \times \sqrt{T}\ , \tag{30}$$

where V_t is the value of the underlying assets, σ is the standard deviation of the asset, T is the time period, and α is the significance level. On the other hand, the standard definition of the VaR is:

$$\Pr\left[y_t < VaR_{t|t-1}(\alpha) \,|\, \Omega_{t-1} \right] = \alpha\,, \tag{31}$$

where Ω_{t-1} indicates the set of information available at time $t-1$. The VaR forecast in $t+1$ at risk level of α is defined as:

$$VaR_{t+1}^{\alpha} = \inf\left\{ y_{t+1} \,|\, F(y_{t+1} \,|\, \Omega_t) = \alpha \right\}. \tag{32}$$

Here, $F(y_{t+1} \,|\, \Omega_t)$ is the one-step ahead cumulative distribution function (CDF) evaluated in y. The expected shortfall (ES) measures the expected loss below the VaR level.

The ES is obtained as:

$$ES_{t+1}^{\alpha} = E\left[y_{t+1} \mid y_{t+1} \leq VaR_{t+1}^{\alpha}, \Omega_t \right] \tag{33}$$

3.5.2.2 Backtesting

The VaR is questioned due to its various drawbacks. VaR models are efficient when their predictive power is strong. Hence, testing the performance of VaR models has become a common practice. It is called as backtesting. Backtesting is a statistical method that calculates the difference between actual and estimated losses during the backtesting process. In other words, the frequency of exceptions during a certain time span is statistically checked to see whether it agrees with the given confidence level.

Backtesting procedures are based on VaR exceptions. Let $I_t(\alpha)$ be the indicator function associated with *ex-post* observation of α level of VaR violation at time t.

$$I_t(\alpha) = \begin{cases} 1 & \text{if } y_t < VaR_{t|t-1}(\alpha) \\ 0 & \text{else} \end{cases} \tag{34}$$

Christoffersen [57] shows that the violation process, $I_t(\alpha)$, must satisfy the following two assumptions for VaR forecasts to be valid:

- The unconditional coverage (UC) hypothesis: the unconditional probability of a violation equals to the coverage rate, α:

$$\Pr\left[I_t(\alpha) = 1 \right] = E\left[I_t(\alpha) \right] = \alpha \,. \tag{35}$$

- The independence (IND) hypothesis: Violations of VaR that are observed at two different dates have to be independently distributed. $I_t(\alpha)$ and $I_s(\alpha)$ are independently distributed for $t \neq s$.

Two well-known backtesting methods, the conditional coverage (CC) test by Christoffersen [57] and the dynamic quantile (DQ) test by Engle and Manganelli [58], are introduced to measure the performance of GARCH models.

a) Conditional Coverage Test of Christoffersen (1998)

Christoffersen [57] assumes that the violation process, $I_t(\alpha)$, can be represented as a Markov chain with matrix of transition probabilities is given by:

$$\Pi = \begin{pmatrix} \pi_{00} & \pi_{01} \\ \pi_{10} & \pi_{11} \end{pmatrix}, \tag{36}$$

where $\pi_{ij} = \Pr\left[I_t(\alpha) = j \mid I_{t-1}(\alpha) = i\right]$ is the probability of being in state j at time t, conditioned on being in state i at time $t-1$. Then, the null hypothesis of the conditional efficiency (the CC) is defined as the following:

$$H_0 = \Pi = \Pi_\alpha = \begin{pmatrix} 1-\alpha & \alpha \\ 1-\alpha & \alpha \end{pmatrix}. \tag{37}$$

The unconditional coverage hypothesis is accepted if the null hypothesis is accepted. The probability of a violation at time t equals to the α regardless of the state at time $t-1$. Moreover, the probability of a violation at time t is independent of the state at time $t-1$. A likelihood ratio statistic, which is denoted as LR_{CC}, allows us to the null hypothesis of the conditional efficiency. Under H_0, Christoffersen shows that:

$$LR_{CC} = -2\left\{\ln L\left[\Pi_\alpha, I_1(\alpha),\ldots,I_T(\alpha)\right] - \ln L\left[\hat{\Pi}, I_1(\alpha),\ldots,I_T(\alpha)\right]\right\} \xrightarrow[T\to\infty]{L} \chi^2(2), \tag{38}$$

where $\hat{\Pi}$ is the maximum likelihood estimator of the transition matrix with the alternative hypothesis and $L\left[\Pi, I_1(\alpha),\ldots,I_T(\alpha)\right]$ is the is the log-likelihood of violations $I_t(\alpha)$ associated with a transition matrix Π, such as:

$$L\left[\Pi, I_1(\alpha),...,I_T(\alpha)\right] = (1-\pi_{01})^{n_{00}}\pi_{01}^{n_{01}}(1-\pi_{11})^{n_{10}}\pi_{11}^{n_{11}}, \tag{39}$$

where n_{ij} is the number of times $I_t(\alpha)=j$ and $I_{t-1}(\alpha)=i$ occurs.

b) Dynamic Quantile Test of Engle and Manganelli (2004)

Engle and Manganelli [58] suggest a backtesting approach based on a linear regression model. To test the conditional efficiency hypothesis, this model links present violations to previous violations. Let $Hit(\alpha)=I_t(\alpha)-\alpha$ be the demeaned process that is associated with $I_t(\alpha)$:

$$Hit_t(\alpha)=\begin{cases}1-\alpha & \text{if } y_t < VaR_{t|t-1}(\alpha)\\ -\alpha & \text{else}\end{cases}. \tag{40}$$

The linear regression model is as follows:

$$Hit_t(\alpha)=\delta+\sum_{k=1}^{K}\beta_k Hit_{t-k}(\alpha)+\sum_{k=1}^{K}\gamma_k z_{t-k}+\varepsilon_t, \tag{41}$$

where the z_{t-k} variables (past returns y_{t-k}, squared past returns y_{t-1}^2, etc.) belong to the information set Ω_{t-1}. The conditional efficiency null hypothesis test is equivalent to assessing the joint nullity of coefficients δ, β_k, and γ_k:

$$H_0:\delta=\beta_k=\gamma_k=0, \qquad \forall k=1,...,K, \tag{42}$$

Since under null:

$$E\left[Hit_t(\alpha)\right]=E\left[I_t(\alpha)-\alpha\right]=0 \iff \Pr\left[I_t(\alpha)=1\right]=\alpha. \tag{43}$$

The Wald statistic is used to test whether these coefficients are zero. If we indicate $\Psi = (\delta, \beta_1, ..., \beta_K, \gamma_1, ..., \gamma_K)'$ as the vector of the $2K + 1$ parameters in this model and Z the matrix of the predictors of model (41), the Wald statistic, denoted as DQ_{CC}, then verifies:

$$DQ_{CC} = \frac{\hat{\Psi}' Z' Z \hat{\Psi}}{\alpha(1-\alpha)} \xrightarrow[T \to \infty]{L} \chi^2(2K+1), \tag{44}$$

where $\hat{\Psi}$ is the ordinary least squares (OLS) estimate of Ψ.

3.5.2.3 Backtesting Results

Accuracy of the VaR is backtested, and then the CC test statistic [57] and DQ test statistic [58] are computed. 1450 log-returns are used for the rolling window estimation of the data ranging from 05-01-2010 to 27-07-2015, and a backtest over 1221 out-of-sample observations is run for a period ranging from 27-07-2015 to 31-03-2020.

Table 3.8 reports the p-values of the CC and DQ tests for the one-day ahead VaR forecast at 5% and 1%. In most cases, the multiple-regime MSGARCH models forecast the VaR correctly at both 5% and 1%. Hence, the null hypothesis of the accurate VaR forecasting for the multiple-regime MSGARCH models, at both 5% and 1%, is not rejected in most cases. In particular, although the null hypothesis of the accurate VaR at 1% is rejected for most of the models based on the p-values of DQ and CC tests, the multiple-regime MSGARCH models perform better predictions with higher p-values than the single-regime traditional GARCH models. Furthermore, Figure 3.4 and 3.5 depict the behavior of the VaR values for the FX at 5% and 1%, respectively.

Table 3.8: Accuracy of the VaR Predictions

	CC Test				DQ Test			
Conditional Distributions	*S*	*skN*	*skS*	*skG*	*S*	*skN*	*skS*	*skG*
				VaR 5% risk level				
1 Regime								
SGARCH	0.2902	0.5099	0.6257	0.3459	0.0018	0.0940	0.1336	0.0835
GJR-GARCH	0.4026	0.6258	0.7006	0.5463	0.1197	0.6632	0.8218	0.6638
2 Regime								
SGARCH	0.1975	0.3578	0.3174	0.4584	0.0161	0.0143	0.0041	0.1252
GJR-GARCH	0.1975	0.5842	0.3552	0.7403	0.0013	0.1313	0.0070	0.6901
3 Regime								
SGARCH	0.1123	0.1814	0.3404	0.1714	0.0026	0.0027	0.0008	0.0006
GJR-GARCH	0.2602	0.3113	0.1714	0.3362	0.0047	0.0913	0.0333	0.0668
				VaR 1% risk level				
1 Regime								
SGARCH	0.0015	0.0046	0.6257	0.1600	0.00001	0.0004	0.0001	0.0001
GJR-GARCH	0.0026	0.0015	0.7006	0.0200	0.0005	0.00001	0.0363	0.0002
2 Regime								
SGARCH	0.0089	0.0290	0.3174	0.2105	0.0161	0.0003	0.0236	0.0364
GJR-GARCH	0.0165	0.0026	0.3552	0.0150	0.0007	0.0003	0.0337	0.0003
3 Regime								
SGARCH	0.0089	0.0290	0.3404	0.0290	0.00003	0.0001	0.0001	0.0205
GJR-GARCH	0.0089	0.1140	0.1714	0.1600	0.0071	0.0114	0.0004	0.0151

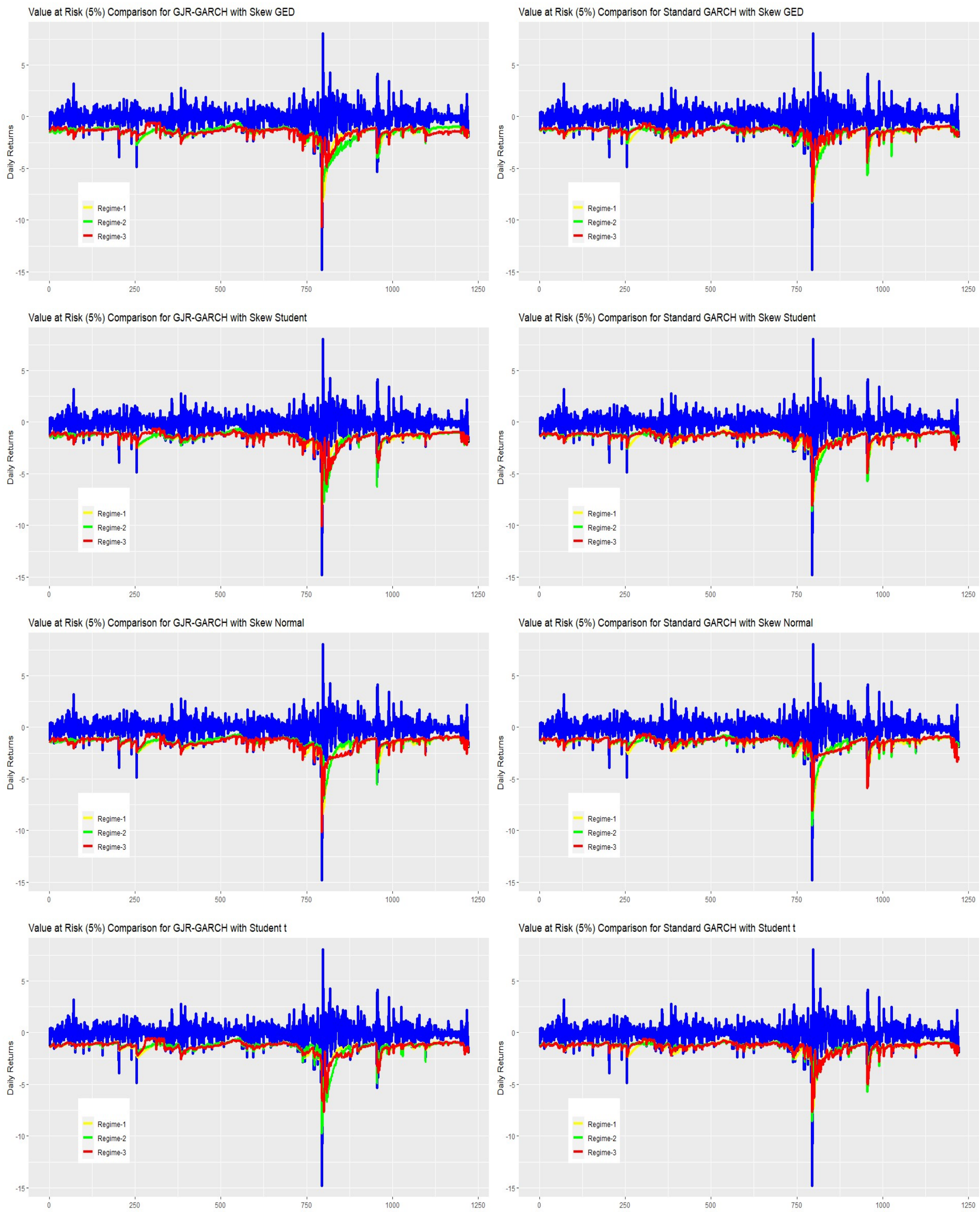


Figure 3.4: Value-at-risk (5%) calculations with the GJR-MSGARCH models

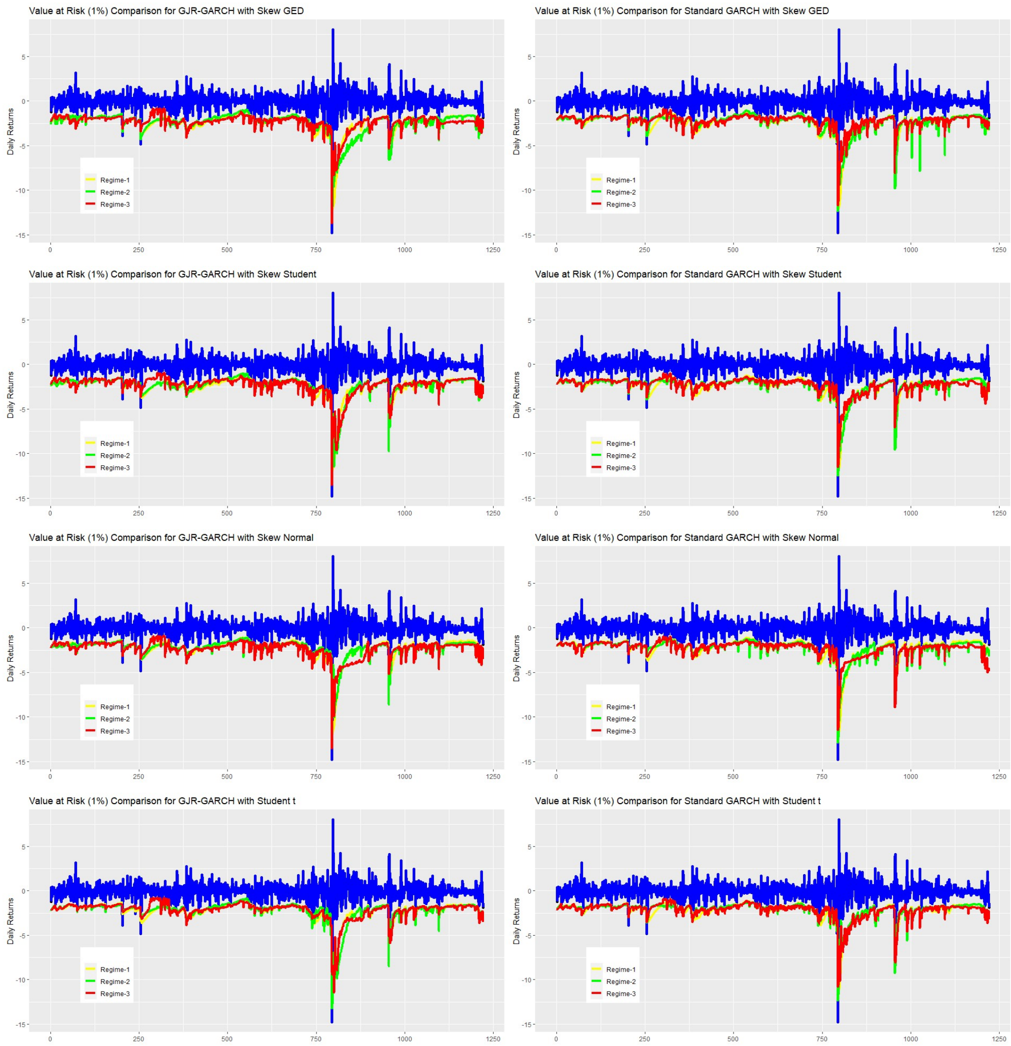


Figure 3.5: Value-at-risk (1%) calculations with the GJR-GARCH models

3.6 Model Diagnostics

It is critical to check if a fitted model is appropriately specified and if the data supports model assumptions, before accepting and interpreting its results. If some important model assumptions appear to be violated, the model should be reestablished and tested until the fitted model adequately models the daily data. The standardized residuals are an essential tool in examining the appropriateness of the model. If the MSGARCH volatility model is specified properly, the standardized residuals are defined as:

$$\eta_{k,t} = y_t / \sqrt{h_{k,t}} \overset{iid}{\sim} D(0, h_{k,t}, \xi_k), \tag{45}$$

When the model is appropriately specified, they are approximately independently and identically distributed.

All of the multiple-regime models fit the data well. However, the 3-regime GJR-MSGARCH (*skG*) is preferred as the best model based on the lowest AIC value in sample analysis, and it provides better VaR predictions with higher p-values of CC and DQ tests when compared to the other models. Hence, only the diagnostic tests for the 3-regime GJR-GARCH (*skG*) model are presented in this section.

The skewed GED assumption of the innovations is examined via plotting the quantile-quantile (QQ) normal scores plot. Deviations from a dark-line pattern in the QQ plot (see Figure A.6), which can be found in Appendix A, show evidence for non-normality and gives insight on the distributional form of the standardized residuals. The skewness and the kurtosis of the standardized residuals were –0.5757 and 2.6728, respectively. The p-value of the Jarque-Bera test equals 0.000, so the non-normality assumption in the model cannot be rejected.

The standardized residuals should obey the assumed marginal distribution in the estimation [59]. As shown in Table 3.1, the residuals from the AR(4) model unsurprisingly have a skewness of –1.82 and kurtosis of 29.57, and the Jarque-Bera test shows a p-value of 0.00. Therefore, it is reasonable that a skewed GED should be employed for the innovations to model skewness and non-normality of the residuals.

A correctly specified GARCH model should have squared standardized residuals with no serial correlation and no conditional heteroscedasticity. Except for a marginal correlation at lag 4, the squared standardized residuals look reasonable. The ACF and PACF plots (see Figure A.7) of the squared standardized residuals, $\eta_{k,t}^2$, can be found in Appendix A. Moreover, the fitted model is satisfactory in explaining the conditional mean and variance of the FX series, according to the Ljung-Box statistics and ARCH test. The Ljung-Box statistics for $\eta_{k,t}^2$ provides Q-statistics with p-values of 0.37 and 0.16 for lags 20 and 40, respectively, and the ARCH test for $\eta_{k,t}$, with a null hypothesis of no ARCH effect, gives $\chi_{(20)}^2 = 21.04$ with a p-value of 0.39 and $\chi_{(40)}^2 = 48.05$ with p-value of 0.18.

Based on diagnostic statistics, the fitted 3-regime GJR-MSGARCH (*skG*) model is adequate in modeling volatility of the daily FX series. The estimated volatilities retrieved from the 3-regime GJR-MSGARCH (*skG*) model are used as a common market risk factor in Chapter 5 to determine if there is significant relationship between the exchange rate volatility and excess stock returns.

3.7 Time Series Properties of the Exchange Rate Volatility Variable

As is clearly stated before, the exchange rate volatility variable is used as a determinant of excess stock returns. Since this estimated volatility variable is an important input for the stock pricing analysis in the later chapters, this section is devoted to examining the time series properties of the volatility variable, which is obtained from the best model determined in the former section.

The exchange rate volatility variable is represented by FXV in the rest of the study. The FXV is computed as the square root of the variance estimates of the 3-regime GJR-MSGARCH model with skew GED innovations.

Figure 3.6 gives the FXV series of the model. The volatility is too high during the middle of 2016, the fourth quarter of 2018, and the first quarter of 2019. The time plots of all of the estimated FXV series from the 24 models are provided in Figure B.1 and B.2 in Appendix B.

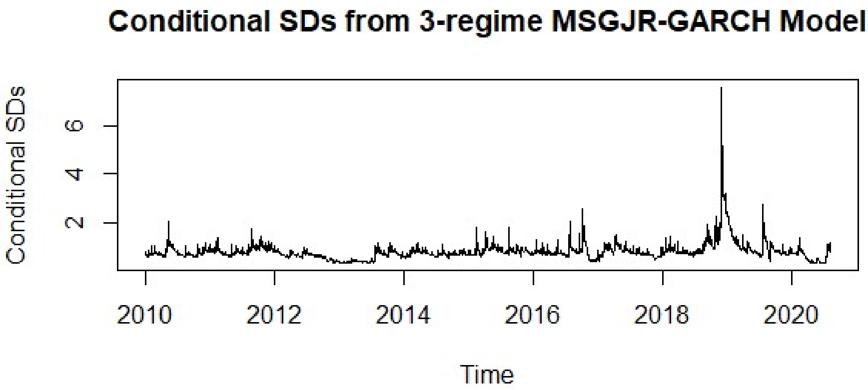


Figure 3.6: Conditional Standard Deviation Series for the 3-Regime GJR-MSGARCH

Table 3.9 depicts the positive skewness and leptokurtosis in the daily FXV variable, indicating that it is not normally distributed.

Table 3.9: Summary Statistics of the Exchange Rate Return Volatility

	Daily FXV
Mean	0.78
Standard Deviation	0.37
Minimum	0.33
Maximum	7.59
Skewness	5.96 (0.000)
Kurtosis	70.36 (0.000)
Jarque-Bera	567.699 (0.000)

Note: Values in parentheses are p-values.

Since the quarterly period basis is used in the dynamic panel data model in Chapter 5 because of the quarterly disclosure of financials of firms, the estimated daily FXV series are transformed into a quarterly frequency by taking the average of the daily FXV in order to be in line with the time basis of the econometric model in Chapter 5.

Table 3.10 shows that the quarterly FXV is still positively skewed and leptokurtosis, and the non-normality of the quarterly FXV is confirmed by the Jarque-Bera test. The time plot of the quarterly FXV is shown in Figure 3.7.

Table 3.10: Summary Statistics of the Quarterly Exchange Rate Return Volatility

	Quarterly FXV
Mean	0.78
Standard Deviation	0.28
Minimum	0.39
Maximum	2.23
Skewness	3.30 (0.000)
Kurtosis	15.33 (0.000)
Jarque-Bera	531.66 (0.000)
Values in parentheses are p-values.	

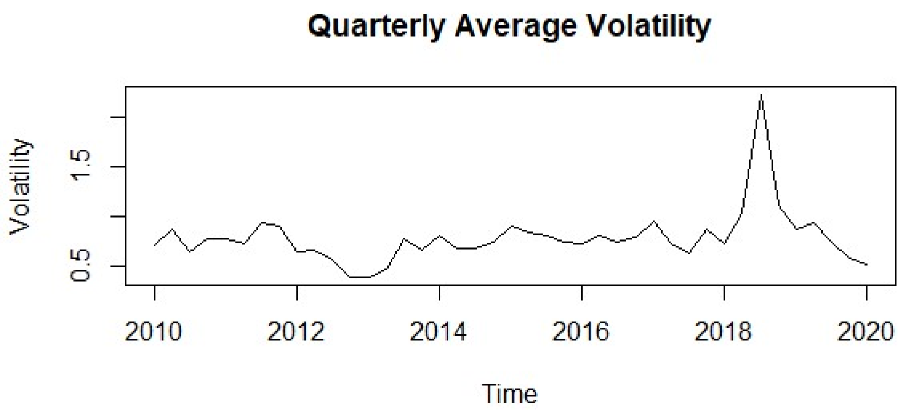


Figure 3.7: Time Plot of The Quarterly Average Volatility

The presence of a unit root in the quarterly FXV series is examined using the ADF test. The lag length is determined using the AIC. An ADF equation with 1 lag and intercept is determined. The null hypothesis of the unit root in the quarterly FXV is not rejected with p-value of 0.055 at a confidence level of 95%.

CHAPTER 4

DATA AND TIME SERIES PROPERTIES

Three-stage methodology is used in this thesis to study the effects of the exchange rate volatility and the firm-specific features on the excess stock returns. First, the exchange rate volatility is estimated using single-regime traditional GARCH models and multiple-regime MSGARCH models. Second, in this chapter, the financial ratios are described and the PCA method is employed for the financial ratios, for the purpose of data reduction to identify the principal components that best represent the firm-specific features: profitability, liquidity, and leverage performance of the firms. Finally, the effects of the exchange rate volatility and firm-specific features on the excess stock returns are analyzed using the dynamic panel data model. Before employing the empirical dynamic panel data, the definition of the variables that are the inputs of the models developed using the usual CAPM and the time series properties of the excess stock returns and the excess market return are presented in this chapter.

4.1 Stock Price Data and Time Series Properties of the Excess Stock Returns

The BIST-100 Index is a capitalization-weighted index which is composed of firms from various sectors. The BIST-100 Index is used for the analysis because of its huge transaction volume and depth. The monthly closing prices for each stock are obtained from www.finnet.com.tr. The data for the monthly closing stock prices of the firms chosen in this study spans the period between January 2010 and March 2020, comprising 120 months. In order to be in line with the disclosure of the companies' financial statements, the monthly data is transformed into the quarterly data by calculating the average prices over the three months in each quarter. The analysis considers a sample of 84 manufacturing firms listed on the BIST-100 Index for 40 quarters in the period of January 2010 to March 2020. Calculations of the log-returns of the quarterly stock prices and excess stock returns are shown in Table 4.1. The method that is used for testing the stationarity in the panel excess stock returns is introduced, and the results of the panel unit root test is analyzed in the next section.

Table 4. 1: Definition of the Excess Stock Return, Excess Market Return, and Treasury Bill Interest Rate

Variables	***Symbol and Definition***
Treasury Bill Interest Rates at Time t	$r_{f,t}$
Market Rates of Returns at Time t	$r_{M,t} = ln\left((BIST-100\ Index)_t/(BIST-100\ Index)_{t-1}\right)$
Rates of Returns of Stock i at time t	$s_{i,t} = \ln\left[\dfrac{StockPrice_{i,t}}{StockPrice_{i,t-1}}\right]$
Excess Market Return	$emr_t = r_{M,t} - r_{f,t}$
Excess Rates of Return	$exs_{i,t} = s_{i,t} - r_{f,t}$

4.1.1 Panel Unit Root Test for the Excess Stock Returns of Manufacturing Firms

The panel unit root tests suggested by Levin, Lin, and Chu [60] and Im, Pesaran, and Shin [61], denoted as LLC test and IPS test, respectively, assume that individuals are cross-sectional independent. Both methods are used to test the non-stationarity null hypothesis, but while the LLC test allows for balanced panels with N cross-sectional units and T time series observations, the IPS test allows for unbalanced panels with N cross sectional units and T_i time series observations for each $i=1,...,N$. In their studies, Banerjee, Marcellino, and Osbat [62, 63] measure the performance of panel unit root tests when the panel individuals are cross-correlated and they find that the LLC and IPS tests would over-reject the null the non-stationarity hypothesis when there are common sources among series of individuals. To solve the problem of the over-rejection of null hypothesis when the panel members are cross-correlated, Pesaran [64] proposed a cross-sectional augmented IPS (CIPS) which allows for cross-sectional correlation using a common factor as a representation of the data.

Before proceeding to testing panel stationarity and deciding which tests to use, the cross-sectional dependence (CD) is taken into account by using the Pesaran's [65] CD test.

Let N be the cross-sectional units and T_{ij} be the time-series observations, the Pesaran's [65] CD test is as follow:

$$CD = \sqrt{\frac{2}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\sqrt{T_{ij}}\rho_{ij}\right), \tag{46}$$

and the distribution of the test is standard normal. Only complete paired observations are taken into account, if the panel is unbalanced. $T_{ij} = \min(T_i, T_j)$ and T_i is the number of observations for unit i. $T_{ij} = T$ for each i and j, if the panel is balanced. ρ_{ij} is the product-moment correlation coefficient of a panel time series, defined as:

$$\rho_{ij} = \frac{\sum_{t=1}^{T} y_{it} y_{jt}}{\left(\sum_{t=1}^{T} y_{it}\right)^{1/2}\left(\sum_{t=1}^{T} y_{jt}\right)^{1/2}}. \tag{47}$$

Here, y_{it} represents the observations for unit $i \in \{1,...,N\}$, and y_{jt} shows the observations for unit $j \in \{1,...,N\}$ with $i \neq j$. The Pesaran's [65] CD test has the following hypotheses:

H_0: No CD among panel individuals,

H_1: CD among panel individuals.

The Pesaran's [65] CD test is used for panels of the excess rates of return $(exs_i,\ i \in \{1,...,N\})$. The results of CD test show that the absence of CD is rejected among panels, with a CD value of 109.97 and p-value of 0.000 at a significant level of 5%. Hence, the Pesaran's CIPS test [64] is used to test the panel unit root in exs due to the presence of CD.

To test the panel stationarity, Pesaran [64] suggests a cross-sectionally ADF (CADF) test, where the cross-sectional averages of the first differences and lagged levels of the individual time-series are added to Dickey and Fuller [52] regressions. He also suggests a CIPS test, which is simply an average of the CADF tests of individuals.

Common factors are added to CADF regression to explain cross-sectional correlations among variables, and they are used to solve the problem of dimensionality. Theoretical considerations in financial economics are frequently related to common factor structures. For example, many microeconomic models assume factors that exist in data of variables data, such as the CAPM and APT models used in finance. [66]. For a panel of Y_{it} data with N cross-sectional units and T time series observations, A simple dynamic linear model is proposed by Pesaran [64],

$$Y_{i,t} = (1 - \delta_i)\mu_i + \delta_i Y_{i,t-1} + u_{i,t} \qquad i = 1,...,N, \quad t = 1,...,T \ , \tag{48}$$

the errors with one-factor structure:

$$u_{i,t} = \lambda_i f_t + \varepsilon_{i,t} \tag{49}$$

The disturbances are assumed to be serially uncorrelated and the idiosyncratic errors, $\varepsilon_{i,t},\ i = 1, ...,N,\ t = 1, ..., T$ are assumed to be independently distributed across both cross-sections and over time, have a zero mean, variance σ_i^2. With the mean zero and constant variance σ_f^2, the common factor, f_t, is serially uncorrelated. Without the loss of generality, σ_f^2 is a set equal to one. $\varepsilon_{i,t}$, and λ_i and f_t are assumed to be mutually independent for all of the i and t.

(48) and (49) can be written as:

$$\Delta Y_{i,t} = \alpha_i - (1-\delta_i)Y_{i,t-1} + \lambda_i f_t + \varepsilon_{i,t}, \tag{50}$$

where $\Delta Y_{i,t} = Y_{i,t} - Y_{i,t-1}$ and $\alpha_i = (1-\delta_i)\mu_i$ The unit root hypothesis suggested by Pesaran (2007) $\delta_i = 1$ for all of the i is tested against the possibiliy of a heterogenous alternative $\delta_i < 1$ for $i = 1,...,N$. Pesaran [64] employs a test based on the t-ratio of OLS estimation of $\hat{b}_i$ in the following CADF regression for the unit root null hypothesis:

$$\Delta Y_{i,t} = \alpha_i + b_i Y_{i,t-1} + c_i \bar{Y}_{i,t} + d_i \Delta\bar{Y}_{i,t-1} + \varepsilon_{i,t}, \tag{51}$$

where $\bar{Y}_{i,t} = \frac{1}{N}\sum_{i=1}^{N} Y_{i,t}$, $\Delta\bar{Y}_{i,t} = \frac{1}{N}\sum_{i=1}^{N}\Delta Y_{i,t}$, and $\varepsilon_{i,t}$ is the regression error.

The cross-sectional averages of $\bar{Y}_{i,t}$ and $\Delta\bar{Y}_{i,t}$, are added to (50) as a representation of the unobserved common factor f_t.

Following Im et al. [61], Pesaran [64] suggests a cross-sectional augmented version of the IPS-test:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i, \tag{52}$$

and the distribution of this test is non-standard. For various combinations of N and T, critical values are provided. The t-ratio of b_i in the CADF regression (51) provides $CADF_i$, which is the CADF statistic for the ith cross-sectional unit. The $CADF_i$ statistics will not be cross-sectionally independent because of the presence of the common factor. Additional lags of $\Delta Y_{i,t}$ and $\Delta \overline{Y}_{i,t}$ must be added to the ADF regression (51), if there is autocorrelation in the common factors or idiosyncratic errors.

The cross-sectionally augmented IPS-test has the following hypotheses:

H_0 : The panel series are not stationary,

H_1 : The panel series are stationary.

The stationarity of panel exs series is tested at 1, 2 and 3 lag orders with the cross-sectionally augmented IPS-test. exs is stationary with a p-value of 0.01 at all of the lag levels at a confidence interval of 95%.

4.2 BIST-100 Index and Time Series Properties of the Excess Market Return

The quarterly market index is calculated by averaging the closing monthly market index in each quarter. For the period between January 2010 and March 2020, the quarterly market return is calculated as a continuously compounded series using the BIST-100 price index, and the excess market rate of return, emr, is calculated according to the formula in Table 4.1. Although the BIST-100 Index value is not stationary due to its trending behavior (see Figure 4.1), the emr series typically fluctuates around a constant zero mean, as shown in Figure 4.2.

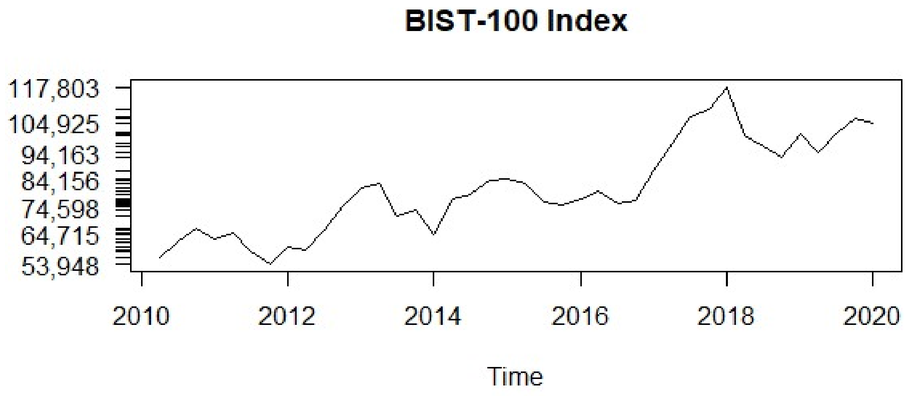


Figure 4.1: Time plot of the BIST-100 Index

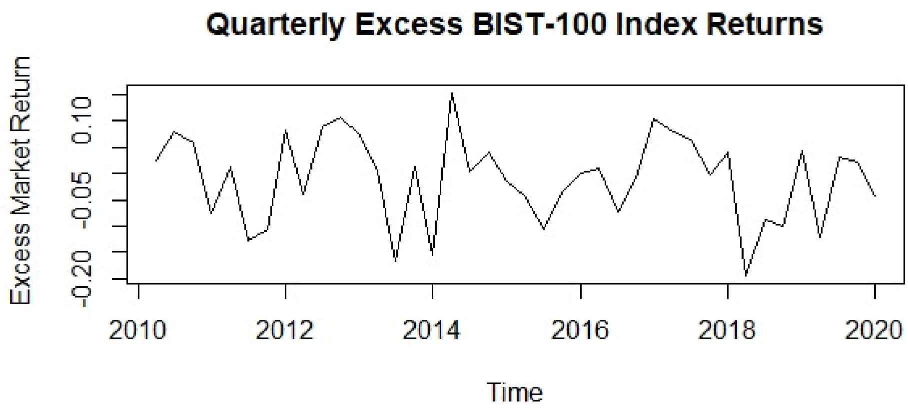


Figure 4.2: Time Plot of the Quarterly Excess Market Return

The stationarity of the *emr* for the BIST-100 Index is tested during the sample period. The ADF test [52] is used for this purpose. The equation for the ADF test is as follows:

$$\Delta Y_t = \alpha_0 + \gamma Y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \mu_t . \tag{53}$$

and the ADF statistic is non-standard. Additional lagged terms of the ΔY_{t-i} are added to the test to eliminate autocorrelation. The lag length, p, on additional terms is determined by the AIC or the SBIC. The ADF test has the following hypotheses:

H_0 : The data are not stationary,

H_1 : The data are stationary.

Using the AIC, 2 lags of the emr are identified for the ADF equation. The emr is stationary with a p-value of 0.020 at a confidence level of 95%.

4.3 One-Year Treasury Bill Interest Rate

The one-year treasury bill interest rate, r_f, is considered as a risk-free interest rate for construction of the CAPM to calculate the exs and emr. The one-year treasury bill interest rate is divided by four, since the frequency of the stock returns and market returns is quarterly for the dynamic panel data model in Chapter 5.

4.4 Principal Component Analysis (PCA) Approach in Determining the Firm Specific Features

The purpose of this section is to identify the principal components of the financial ratios that best represent the profitability, liquidity, and leverage performance of firms in the BIST-100. PCA is a technique for categorizing data patterns and displaying them in a way that emphasizes their similarities and differences. The fundamental benefit of PCA is that it allows for the compression of data without any loss of information by reducing the dimension [67].

4.4.1 Data

A total of 8 financial ratios are employed as a representation of the important financial performance indicators that are frequently used as a measure of profitability, liquidity, and leverage. The quarterly balance sheets and income statements of 84 manufacturing firms are obtained from www.finnet.com.tr for the sample period, and the financial ratios of the interest are calculated for each firm using the formulas that are shown in Table 4.2

Table 4.2: Definitions of the Financial Ratios

Financial Ratios	***Symbol and Definition (Quarterly)***
Profitability Ratios	
Return on Assets (ROA)	roa = (Net Income) / (Total Assets)
Return on Equity (ROE)	roe = (Net Income) / (Shareholder's Equity)
Operating Profit Margin	opm = (Operating Profit) / (Revenue)
Liquidity Ratios	
Current Ratio	crr = (Current Assets) / (Short Term Liabilities)
Quick Ratio	qr = (Current Assets-Inventory-Prepaid Expenses) / (Short Term Liabilities)
Cash Ratio	cr = (Cash and Cash Equivalents) / (Short Term Liabilities)
Leverage Ratios	
Leverage Ratio	lr = (Total Liabilities) / (Total Assets)
Debt to Equity Ratio	der = (Total Liabilities) / (Shareholder's Equity)

To identify the principal components, 8 financial ratios that reflect the liquidity, profitability, and leverage ratios are used. In order to avoid the multicollinearity among the financial ratios and reduce the number of dimensions in the original financial ratio dataset, this analysis aims to eliminate the financial ratios that have no significant impact, obtaining several components that can be used in determining some scores that describe the main features of the financial performance.

The correlation matrix of the 8 financial ratios is presented in Table 4.3. The correlation matrix is applied to 2,868 observations for each financial ratio using unbalanced panel of 84 firms with their 27-40 quarters ($84 \times [27-40] = 2{,}868$). Before applying the PCA, this step is required to detect the strong and weak correlations. The correlation matrix shows that there are positive linear correlations among the profitability and liquidity ratios, which means that these variables vary in the same directions. For example, the correlation between *roa* and *roe*, and the *qr* and *cr* coefficient of 0.42 and 0.99, respectively. These correlated financial ratios are almost equally important indicators for measuring the financial performance of the firms. Therefore, the motivation in using PCA is to identify highly correlated financial ratios that best feature the financial profiles of the firms. This is done so that the econometric analysis in Chapter 5 will suffer less from the lack of accuracy and reliability.

Table 4.3: Correlation Matrix for the Financial Ratios

	roa	*opm*	*roe*	*crr*	*cr*	*qr*	*lr*	*der*
roa	1	0.03	0.42	0.11	0.22	0.26	–0.41	–0.03
opm	0.03	1	0.01	0.01	0.01	–0.00	–0.00	0.00
roe	0.42	0.01	1	0.02	0.06	0.07	–0.16	–0.12
crr	0.11	0.01	0.02	1	0.87	0.88	–0.29	–0.02
cr	0.22	0.01	0.06	0.87	1	0.99	–0.43	–0.02
qr	0.26	–0.00	0.07	0.88	0.99	1	–0.47	–0.03
lr	–0.41	–0.00	–0.16	–0.29	–0.43	–0.47	1	0.07
der	–0.03	0.00	–0.12	–0.02	–0.02	–0.03	0.07	1

4.4.2 Principal Component Analysis

PCA is a dimension reduction method that identifies a smaller set of variables instead of the original larger set of variables [67]. The PCA method finds a lower dimensional representation of a data set that covers as much of the information as possible [68].

Suppose that we have κ observations for each feature of p features, $X_1,...,X_p,...,X_{\mathcal{p}} \in X$, and in matrix form we have: $X_{\kappa\times\mathcal{p}} = \left[[X_1]_{\kappa\times1}.....[X_{\mathcal{p}}]_{\kappa\times1}\right]$. The PCA produces dimensions, each of which is a linear combination of the p features [67]. The first principal component of a set of features $X_1, X_2,..., X_p$ is the normalized linear combination of these features with the vector of loadings, $\Theta_1 = [\theta_{1,1} \quad . \quad . \quad . \quad \theta_{1,\mathcal{p}}]$,

$$Z_1 = \theta_{1,1}X_1 + ... + \theta_{1,p}X_p + ... + \theta_{1,\mathcal{p}}X_{\mathcal{p}}, \tag{54}$$

that maximizes $Var(Z_i)$ subject to the constraint $\sum_{j=1}^{p}\theta_{j1}^2 = 1$:

$$\underset{\Theta_1}{\text{maximize}} \;\; \Theta_1 \boldsymbol{V} \Theta_1' \;\; \text{subject to} \;\; \Theta_1\Theta_1' = 1 \tag{55}$$

where V is the variance-covariance matrix of features $\{X_1,...,X_{\mathcal{p}}\}$ with eigenvalues $\lambda_1 \geq ..... \geq \lambda_{\mathcal{p}} \geq 0$ and their associated eigenvectors $\{\vartheta_1,.....,\vartheta_{\mathcal{p}}\}$. The maximization producer requires that $\Theta_1 = \vartheta_1$, where $\vartheta_1 = [\vartheta_{1,1} \quad . \quad . \quad . \quad \vartheta_{1,\mathcal{p}}]$ is the eigenvector corresponding to the first eigenvalue, and $Var[Z_1] = \lambda_1$. Then, the first principal component is:

$$Z_1 = \vartheta_{1,1}X_1 + ... + \vartheta_{1,\mathcal{p}}X_{\mathcal{p}} \tag{56}$$

In order to find the components other than the first one, the above maximization procedure is repeated by adding more constraints. For example, finding the second component requires one more constraint that the first component and the second component are not correlated: $Cov[Z_1, Z_2] = 0$. If the third component is investigated, then the additional constraints are: $Cov[Z_1, Z_2] = 0$, $Cov[Z_1, Z_3] = 0$ and $Cov[Z_2, Z_3] = 0$ [67].

The ℓth principal component is [67]:

$$Z_\ell = \vartheta_{\ell,1}X_1 + ... + \vartheta_{\ell,\mathcal{p}}X_{\mathcal{p}} \tag{57}$$

where $\Theta_\ell = \vartheta_\ell$ and ϑ_ℓ is the eigenvector that corresponds to the ℓth largest eigenvalue λ_ℓ. Note that $Var[Z_\ell] = \lambda_\ell$. The elements of vector ϑ_ℓ are factor loadings on features $\{X_1,...,X_{\mathcal{p}}\}$ for the ℓth principal component Z_ℓ.

It is important to note that the sum of the variances of features $\{X_1,...,X_{\mathcal{p}}\}$ is [69]:

$$Var[X_1] + ... + Var[X_{\mathcal{p}}] = Var[Z_1] + ... + Var[Z_{\mathcal{p}}] = \lambda_1 + ... + \lambda_{\mathcal{p}} \tag{58}$$

Moreover, the proportion of the contribution of the first ℓ principal components is:

$$\frac{Var[X_1]+\ldots+Var[X_\ell]}{Var[X_1]+\ldots+Var[X_{\mathcal{P}}]}=\frac{\lambda_1+\ldots+\lambda_\ell}{\lambda_1+\ldots+\lambda_{\mathcal{P}}} \tag{59}$$

In some applications, the original features are standardized [69]: $\dfrac{X_p - E[X_p]}{\sqrt{Var[X_p]}}$.

4.4.3 Estimation Results of the Principal Component Analysis

PCA is employed to financial ratios using matrix form of $X_{2,868\times 8}=\left[[X_1]_{2,868\times 1}.....[X_8]_{2,868\times 1}\right]$ where $X_p \in (roa,\ opm,\ roe,\ crr,\ cr,\ qr,\ lr,\ der)$. The principal components with eigenvalues that are greater than 1 are retained. The eigenvalues of each component and the percentage of variance that is explained by each principal component are given in Table 4.4. The first component with the highest variation has an eigenvalue of 3.18, representing roughly 40% of the variance. With the other three factors, the total of the four components covers approximately 83% of the total variance of the financial ratios. That is, the first four components carry 83% of the information in the dataset. As the other four components do not explain enough variance, they are not retained. Note that the last four eigenvalues are much lower than 1. Therefore, the contribution of the first four components is considered adequate to explain the total variation in the data set.

The scree plot in Figure 4.3 depicts the percentage of variance that is explained by each of the principal components in the financial ratio data.

Table 4.4: Eigenvalues and Percentage of Variance Explained

Principal Components	Eigenvalue	Variance (%)	Cumulative Variance (%)
PC1	3.18	39.80	39.80
PC2	1.46	18.31	58.11
PC3	1.00	12.56	70.67
PC4	0.98	12.25	82.92
PC5	0.74	9.25	92.18
PC6	0.48	5.94	98.12
PC7	0.14	1.74	99.86
PC8	0.01	0.14	100.00

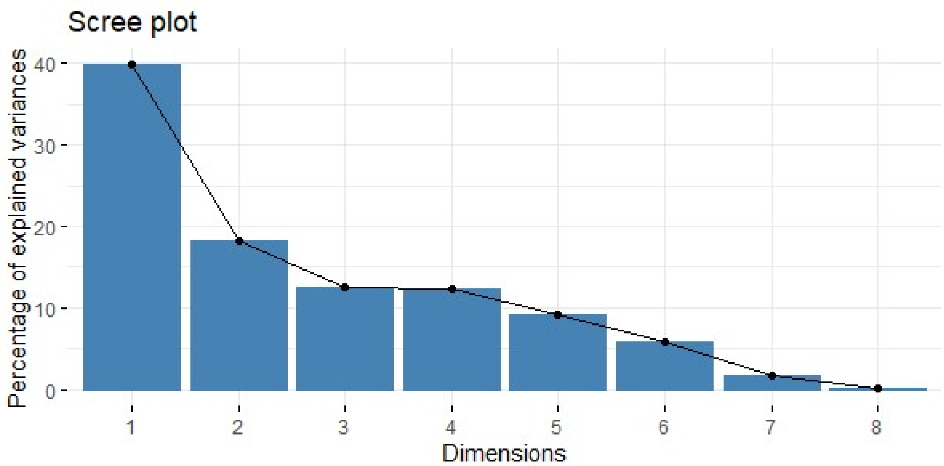


Figure 4.3: Percentage of Variance Explained by Each of the Principal Components

At a glance, the graphic representation of the variables allows the reader to visualize the financial ratios that contributed positively and negatively to components 1 and 2, as shown in Figure 4.4.

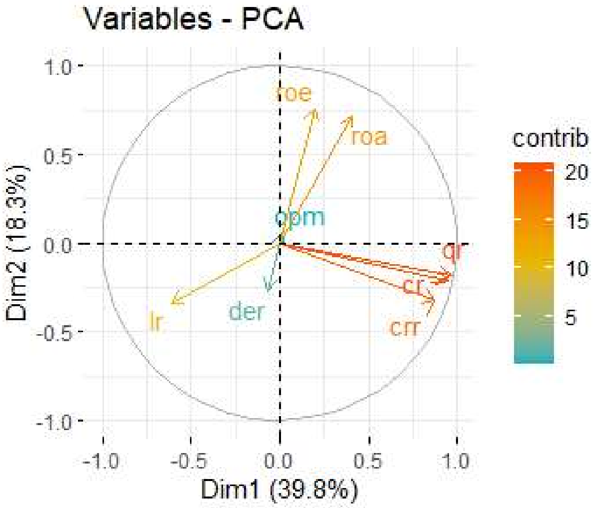


Figure 4.4: Contribution of the Financial Ratios for Components 1 and 2

The principal component scores are used as firm-specific features. The loading vectors of all of the components are given in Table 4.5. The classifications of the principal components are based on these loading scores. Based on the classification of the components, the proxy variable of the first principal component scores (PC-1) is named the *liquidity factor*, since the first loading vector is approximately weighted equally on the liquidity ratios, which are *crr*, *qr*, and *cr*, with much less weight on *roa* and *roe*, which represent profitability. The proxy variables of the other three principal component scores are named *profitability factor-1* for the *roa* and *roe*, *profitability factor-2* for the *opm*, and *leverage factor* for the *der.* Hence, the firm-specific features are determined as the *liquidity factor*, *profitability factor-1*, *profitability factor-2*, and *leverage factor*, to be used in the dynamic panel data model.

Table 4.5: Loading Vectors of the Principal Components

	PC-1	PC-2	PC-3	PC-4	PC-5	PC-6	PC-7	PC-8
roa	0.228	0.594	–0.107	0.231	–0.123	0.713	–0.075	–0.028
opm	0.008	0.044	–0.897	–0.439	–0.019	–0.034	0.003	0.014
roe	0.108	0.627	0.022	0.028	0.623	–0.453	0.015	0.006
crr	0.489	–0.267	0.013	–0.066	0.239	0.045	–0.787	–0.083
cr	0.534	–0.176	–0.001	–0.028	0.100	0.029	0.495	–0.654
qr	0.543	–0.152	0.014	–0.014	0.070	0.036	0.335	0.750
lr	–0.340	–0.279	–0.000	–0.104	0.716	0.514	0.134	0.036
der	–0.038	–0.220	–0.429	0.859	0.113	–0.127	–0.001	0.003

4.4.4 Panel Time Series Properties of the Firm-Specific Features

Before testing the panel unit root in the firm-specific features, the Paseran's [65] CD test is applied to the panel firm-specific features to test the CD. As shown in Table 4.6, the null hypothesis for no CD for all of the firm-specific features is strongly rejected, with a p-value of 0.000.

Table 4.6: Pesaran's CD Test Results for the Principal Components

Firm-specific features	CSD Statistic	p-value	Alternative Hypothesis
Liquidity factor	53.83	0.000	Cross-sectional dependence
Profitability factor-1	88.98	0.000	
Profitability factor-2	84.51	0.000	
Leverage factor	86.6	0.000	

After the presence of CD is confirmed for all of the firm-specific features, the Pesaran's CIPS test [64] is used to examine the stationarity in the firm-specific features. The AIC is used to select the lag length, beginning from a maximum lag length of $p_{\max} = 6$, and the lag order is found to be 2 for all of the firm-specific features. The null hypothesis of CIPS test is that all of the panels are non-stationary.

The results in Table 4.7 fail to reject this hypothesis for the *liquidity factor* and reject the null hypothesis for *profitability factor-1, profitability factor-2*, and *leverage factor*. Therefore, while the *liquidity factor* panel time series has a unit root, *profitability factor-1, profitability factor-2*, and *leverage factor* are stationary. The *leverage factor* panel time series is differenced to avoid spurious regression in the empirical dynamic panel data models in Chapter 5.

Table 4.7: Pesaran's Cross-Sectionally Augmented IPS-Test Results for the Principal Components

Firm-specific features	CIPS Test	p-value	Alternative Hypothesis	Lag Order
Liquidity factor	–0.66	0.10	Stationarity	2
Profitability factor-1	–1.65	0.01		
Profitability factor-2	–1.80	0.01		
Leverage factor	–1.81	0.01		

4.4.5 Summary of the PCA Findings

The loading vectors of the principal components show that liquidity is critical in the manufacturing industry, since *crr*, *cr* and *qr* have the greatest wights of the first principal component, representing the liquidity ratios. The second principal component displays the profitability ratios to measure the firm's financial performance with the *roa* and *roe*. The third component also represents profitability ratios with the *opm*. The last significant component shows that the *der* is an important leverage ratio in measuring financial performance in terms of leverage performance. The set of 4 components based on principal component analysis is utilized in the chapter 5 for dynamic panel data model to determine the main firm-specific features.

CHAPTER 5

EMPRICAL ANALYSIS OF THE STOCK RETURNS OF MANUFACTURING FIRMS

In the previous chapters, the exchange rate volatility is estimated using the 3-regime GJR-MSGARCH model (*skG*). Moreover, the firm-specific features, which are the *liquidity factor*, *profitability factor-1*, *profitability factor-2*, and *leverage factor*, are determined via PCA.

The main motivation of this chapter is, aside from the excess market return as a determinant of excess stock returns as in the CAPM, to analyze the impacts of the exchange rate volatility and firm-specific features on the excess stock returns of manufacturing firms using the dynamic panel data model. By applying the GMM technique to a panel of manufacturing firms listed in the BIST-100 Index, the effects of the excess market return, exchange rate volatility, and firm-specific features on excess stock returns are analyzed.

5.1 The Model

In econometrics, panel data combines time series and cross sections, and they have various advantages over traditional cross-sectional or time series data sets [70]:

- Model parameters are estimated more accurately. Panel data usually provide a vast number of observations to researchers, increase degrees of freedom and decrease multicollinearity among explanatory variables, and therefore enhance the efficiency of econometric estimations.

- Individual heterogeneity is controlled by panel data. According to panel data, firms, countries, state and individuals are heterogeneous. This heterogeneity is not captured by time-series and cross-section studies.

- Multicollinearity is a problem in time-series studies. With a panel across individuals, this is less likely because the cross-section dimension provides a lot of variability, resulting in more useful data on independent variables.

- Panel data are better for analyzing the adjustment dynamics. Cross-sectional distributions that seem to be quite steady hide a lot of changes.

Panel data also allow an investigation of the dynamic econometric relationship in which the variables adjust over time, which is an important property that is exploited in this thesis, since the current level of $exs_{i,t}$ depends not only on the emr_t, FXV, and firm-specific features as regressors, but also on the previous value of the dependent variable, $exs_{i,t-1}$. In other words, one lagged level of exs is included in the list of regressors and appears on the right-hand side of the model specification.

In this study, the unbalanced panel data contains 84 firms (N = number of individuals) and 27–40 periods (T = number of observations). The following dynamic panel data model is estimated

$$exs_{i,t} = \beta_0 exs_{i,t-1} + \beta_1 emr_t + \sum_{k=1}^{4} \delta_k FXV_{t-k} + \sum_{j=1}^{n} \gamma_j ff_{i,t,j} + \alpha_i + \alpha_t + u_{i,t}, \quad (59)$$

with firm $i \in \{1,...,84\}$, time $t \in \{2010Q2,.....,2020Q1\}$ and firm specific feature $p \in \{1,2,3,4\}$ where
$\{ff_1, ff_2, ff_3, ff_4\} = \{liquidity\ factor, profitability\ factor\ 1, profitability\ factor\ 2, leverage\ factor\}$.
$exs_{i,t}$ is the excess stock return, $exs_{i,t-1}$ denotes the lagged excess stock return, emr_t is the excess market return, FXV_{t-k} represents the quarterly volatility of the

TRY/USD exchange rate, the firm-specific features are denoted by $ff_{i,t,j}$, and finally, the variables α_i and α_t denote the time invariant firm-specific effects and time-specific effects, respectively. $u_{i,t}$, is the idiosyncratic error component.

Due to the inclusion of the lagged dependent variable, estimating a dynamic relationship with a pooled OLS or fixed effect (FE) model will lead to bias and inconsistency since the lagged dependent variable is correlated with the error term, it is assumed that it is not itself serially correlated [71]. The strict exogeneity assumption of the estimators is violated by the dynamic model because of the presence of stock specific effects, α_i, in Equation (59) result in a correlation between the lagged dependent variable and the individual FE. As a result of this, the OLS method provides upward biased and inconsistent estimates of the coefficient of the lagged dependent variable. Since $exs_{i,t}$ is dependent on the time invariant individual effects, α_i, then $exs_{i,t-1}$ will also be dependent on α_i.

Moreover, the FE OLS estimator produces upward biased and inconsistent estimates. The purpose of the FE OLS is to eliminate the unobservable time invariant stock FE, α_i, in order to eliminate the inconsistency caused by the dependence of $exs_{i,t-1}$ on α_i, which is resolved by a within transformation. Nevertheless, the FE OLS does not eliminate all of the inconsistency caused by the OLS. In order to show the inconsistency of the FE OLS, Equation (59) is simplified to:

$$exs_{i,t} = \beta_0 exs_{i,t-1} + \alpha_i + u_{i,t}, \tag{60}$$

where $\alpha_i \sim iid(0,\sigma_\alpha^2)$ and $u_{it} \sim iid(0,\sigma_u^2)$ are assumed to be independent of each other. $E(u_{it}u_{js}) = \sigma_u^2$ if $i=j$ and $t=s$, and $E(u_{it}u_{js}) = 0$ otherwise.

For a within transformation, Equation (60) is differenced by its average over time:

$$(exs_{i,t} - \overline{exs}_i) = \beta_0(exs_{i,t-1} - \overline{exs}_i) + (\alpha_i - \alpha_i) + (u_{i,t} - \overline{u}_i). \tag{61}$$

The time invariant FEs, α_i, are eliminated by subtracting their mean. Then, the FE OLS is applied to estimate β_0 by standard OLS estimation. Since $\bar{u}_i$ contains $u_{i,t-1}$, which is correlated with $esr_{i,t-1}$ and $u_{i,t}$ is correlated with $\overline{esr_i}$, which contains $esr_{i,t}$, The regressor, $(exs_{i,t-1} - \overline{exs_i})$, is correlated with $(u_{i,t} - \bar{u}_i)$. Therefore, the FE OLS estimator also cannot solve the problem of endogeneity in the dynamic relationship and this leads to a downward bias for the β_0 [72]. This means that $exs_{i,t-1}$ is endogenous and we will face dynamic panel bias [73], when the model with the FE OLS is estimated.

In order to solve the endogeneity problem that arises with the introduction of the lagged dependent variable, Arellano and Bond [74] propose DIFF-GMM estimation, which is applied to estimate the lagged dependent variable.

A simple autoregressive model with no regressors is illustrated as follows:

$$y_{it} = \gamma y_{i,t-1} + \theta X_{it} + v_{it} \qquad i = 1,\ldots,N;\ \ t = 1,\ldots,T \tag{62}$$

where y_{it} represents the $exs_{i,t}$, X_{it} is other exogenous variables, emr_t, FXV_t and $ff_{i,t,j}$, and v_{it} corresponds to $\alpha_i + u_{i,t}$ in the Equation (59).

Arellano and Bond [74] proposes that if the orthogonality conditions between the $y_{i,t-1}$ and the errors v_{it} are exploited, additional instruments are achieved in a dynamic panel data model.

To obtain an efficient and consistent estimate of γ as $N \to \infty$ with fixed T, Equation (62) is differenced to remove the individual effects

$$y_{it} - y_{i,t-1} = \gamma(y_{i,t-1} - y_{i,t-2}) + \theta(X_{it} - X_{i,t-1}) + (v_{it} - v_{i,t-1}) \tag{63}$$

and $(v_{it} - v_{i,t-1})$ is MA (1) with unit root. For $t = 4$, we observe this relationship, we have

$$y_{i4} - y_{i3} = \gamma(y_{i3} - y_{i2}) + \theta(X_{i4} - X_{i3}) + (v_{i4} - v_{i3}) \tag{64}$$

In this case, y_{i1} and y_{i2} are valid instruments for $(y_{i3} - y_{i2})$ because y_{i1} and y_{i2} are uncorrelated with $(v_{i4} - v_{i3})$. This process continues by adding more valid instrument for each forward period, and at the end, for the period T, matrix of valid instruments, W_i, containing $y_{i1}, y_{i2}, ..., y_{i,T-2}$, is obtained:

$$W_i = \begin{pmatrix} [y_{i1}] & & & & 0 \\ & [y_{i1}, y_{i2}] & & & \\ & & \cdot & & \\ & & & \cdot & \\ & & & & \cdot \\ 0 & & & & [y_{i1}, y_{i2}, ..., y_{i,T-2}] \end{pmatrix} \qquad i = 1, ..., N. \tag{65}$$

$W = [W_1', ..., W_N']'$ is the matrix of instruments and the moment equations are $E[W_i' \Delta v_i] = 0$. When additional strictly exogenous regressors X_{it} exist as in Equation (62) with $E(X_{it}, v_{it}) = 0$ for all $t = 1, 2, ...T$, all the X_{it} are valid instruments for the first-differenced Equation (62). Thus, $[X_{i1}', X_{i2}', ...X_{iT}']$ should be included in each diagonal element of W_i in (65). The differenced Equation (64) is multiplied by W' to obtain

$$W'\Delta y = W'(\Delta y_{-1})\gamma + W'(\Delta X) + W'\Delta v \tag{66}$$

The differenced error term Δv_i has a zero mean and variance $E(\Delta v_i \Delta v_i') = \sigma_v^2 (I_N \otimes G)$, where $\Delta v_i' = (v_3 - v_2, ..., v_T - v_{T-1})$ and

$$G = \begin{pmatrix} 2 & -1 & 0 & . & . & . & 0 & 0 & 0 \\ -1 & 2 & -1 & . & . & . & 0 & 0 & 0 \\ . & . & . & . & & & . & . & . \\ . & . & . & & . & & . & . & . \\ . & . & . & & & . & . & . & . \\ 0 & 0 & 0 & . & . & . & -1 & 2 & -1 \\ 0 & 0 & 0 & . & . & . & 0 & -1 & 2 \end{pmatrix} \tag{67}$$

is $(T-2)\times(T-1)$, since Δv_i is MA(1) with a unit root.

The Arellano and Bond [74] estimator performs generalized least squares on Equation (66) using the G matrix to get a one-step consistent estimators:

$$\begin{aligned} \begin{pmatrix} \hat{\gamma}_1 \\ \hat{\theta}_1 \end{pmatrix} &= [(\Delta y_{-1}, \Delta X)' W (W'(I_N \otimes G)W)^{-1} W'(\Delta y_{-1}, \Delta X)]^{-1} \\ &\times [(\Delta y_{-1}, \Delta X)' W (W'(I_N \otimes G)W)^{-1} W'(\Delta y)] \end{aligned} \tag{68}$$

In order to operationalize these estimators, the differenced residuals which are obtained from the consistent estimators of $\hat{\gamma}_1$ and $\hat{\theta}_1$ are replaced by Δv. The resulting estimators are the two-step Arellano and Bond [74] GMM estimators:

$$\begin{pmatrix} \hat{\gamma}_2 \\ \hat{\theta}_2 \end{pmatrix} = [(\Delta y_{-1}, \Delta X)' W \hat{V}_N^{-1} W'(\Delta y_{-1}, \Delta X)]^{-1} \times [(\Delta y_{-1}, \Delta X)' W \hat{V}_N^{-1} W'(\Delta y)] \tag{69}$$

where $V_N = \sum_{i=1}^{N} W_i'(\Delta v_i)(\Delta v_i)' W_i$,

Another crucial point to note is that the consistency and efficiency of the GMM estimator depend on the fact that the errors are autocorrelated. If there is no second-order autocorrelation in the first-differenced equation's idiosyncratic errors, then the estimators ($\hat{\gamma}_1$ and $\hat{\gamma}_2$) are consistent. The first-order serial correlation is expected due to differencing and should not be a problem. Hence, Arellano and Bond [74] suggest testing the hypothesis that the second-order autocovariances for all of the periods in the sample are zero, based on the residuals from the first difference equations. Moreover, Arellano and Bond [74] suggest the Sargan test of over-identifying restrictions and the null hypothesis of the Sargan test implies that all instruments are valid.

Blundell and Bond [75] show that the lagged-level of instruments of the Arellano and Bond estimator get weakened when γ is close to unity or when $\sigma_\alpha^2 / \sigma_u^2$ becomes large, since the lagged levels are poor instruments in the differenced equations. Therefore, a system estimator is proposed by Blundell and Bond [75] to correct this problem. They show that an additional stationarity restriction on the starting conditions allows the use of an extended difference (DIFF)-GMM, called a system (SYS)-GMM estimator, which uses the lagged differences of y_{it} as instruments for equations in the levels, in addition to the lagged levels of y_{it} as instruments for equations in the first differences.

5.2 Estimation Results

Table 5.1 gives the findings of the one-step and two-step DIFF-GMM and the one-step and two-step SYS-GMM estimates. The findings of the pooled OLS and FE model are also given in columns (1) and (2) of Table 5.1.

The pooled OLS and FE models are also estimated to compare with the DIFF-GMM and SYS-GMM in order to check the sensitivity of the results. As explained before, the pooled OLS estimator is biased upward and the FE estimator is biased downward for the lagged explanatory variable $exs_{i,t-1}$. Thus, we might expect that a consistent autoregressive coefficient $exs_{i,t-1}$ will lie between the pooled OLS and FE estimations, or not be significantly higher than the former or significantly lower than the latter [72]. The estimated coefficient of the GMM models on the lagged dependent variable is much higher than the FE estimate and barely lower or higher than the pooled OLS.

The two-step DIFF-GMM estimator provides estimate of 0.1226 for $exs_{i,t-1}$, with an standard error of 0.0242. Despite the fact that the estimate is much lower than the one-step DIFF-GMM estimate of 0.1337 presented in the third column of Table 5.1, there is apparently a small increase of some 4.7% in the standard error of this estimate. This loss in the estimation can be expected in the absence of heteroskedastic errors in the one-step DIFF-GMM estimation since the two-step estimator is robust to the presence of heteroscedasticity or autocorrelation [76]. Moreover, while the estimate of the two-step SYS GMM (0.1313) is lower than that of the one-step SYS-GMM (0.1414), the standard error of the two-step SYS GMM estimate is 8.8% higher than that of one-step SYS-GMM estimate, indicating the absence of homoscedastic errors in the one-step SYS-GMM estimation.

By construction, the first differences of serially uncorrelated original errors should possess serial correlation, since $\Delta v_{it} = (v_{it} - v_{i,t-1})$ is correlated with $\Delta v_{i,t-1} = (v_{i,t-1} - v_{i,t-2})$ because of the presence of $v_{i,t-1}$ in both terms, but the differenced residuals should not exhibit significant second-order, AR(2), serial correlation. The Arellano test for AR(1) reveals first-order autocorrelation, as expected, at 5% significance. Particularly, the absence of the second order autocorrelation in the errors is not rejected by the Arellano test for AR(2) for the four GMM models at 5% and 10% significance, which keep the model safe with respect to autocorrelation in the errors.

Table 5.1: GMM Estimation Results

	Dependent variable: $exs_{i,t}$					
	Pooled	Fixed OLS	DIFF-GMM (1)	DIFF-GMM (2)	SYS-GMM (1)	SYS-GMM (2)
$exs_{i,t-1}$	0.1329^{***}	0.1163^{***}	0.1337^{***}	0.1226^{***}	0.1414^{***}	0.1313^{***}
	(0.0166)	(0.0169)	(0.0231)	(0.0242)	(0.0227)	(0.0247)
emr_t	0.8920^{***}	0.8896^{***}	0.9053^{***}	0.9001^{***}	0.8742^{***}	0.8669^{***}
	(0.0311)	(0.0312)	(0.0410)	(0.0440)	(0.0389)	(0.0386)
FXV_{t-1}	-0.0336^{***}	-0.0361^{***}	-0.0295^{***}	-0.0330^{***}	-0.0345^{***}	-0.0358^{***}
	(0.0091)	(0.0092)	(0.0098)	(0.0104)	(0.0097)	(0.0101)
FXV_{t-2}	-0.0265^{***}	-0.0283^{***}	-0.0276^{***}	-0.0278^{***}	-0.0256^{***}	-0.0255^{***}
	(0.0095)	(0.0095)	(0.0094)	(0.0104)	(0.0094)	(0.0095)
FXV_{t-3}	-0.0327^{***}	-0.0335^{***}	-0.0318^{***}	-0.0348^{***}	-0.0318^{***}	-0.0332^{***}
	(0.0096)	(0.0096)	(0.0114)	(0.0135)	(0.0114)	(0.0111)
FXV_{t-4}	-0.0448^{***}	-0.0457^{***}	-0.0475^{***}	-0.0443^{***}	-0.0433^{***}	-0.0445^{***}
	(0.0089)	(0.0089)	(0.0096)	(0.0109)	(0.0095)	(0.0093)
Liquidity factor	0.0042^{**}	0.0045^{**}	0.0022^{**}	0.0019	0.0042^{***}	0.0043^{***}
	(0.0020)	(0.0020)	(0.0010)	(0.0014)	(0.0010)	(0.0011)
Profitability factor-1	0.0130^{***}	0.0160^{***}	0.0053^{*}	0.0038	0.0126^{***}	0.0130^{***}
	(0.0021)	(0.0026)	(0.0030)	(0.0034)	(0.0029)	(0.0032)
Profitability factor-2	-0.0044^{*}	-0.0049^{**}	-0.0021^{*}	-0.0017	-0.0043^{***}	-0.0043^{***}
	(0.0024)	(0.0025)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Leverage factor	0.0068^{***}	0.0075^{***}	0.0003	-0.0004	0.0067^{***}	0.0068^{***}
	(0.0024)	(0.0025)	(0.0019)	(0.0015)	(0.0020)	(0.0020)
Constant	0.0179^{***}					
	(0.0025)					
Sargan Test			0.09	0.19	0.18	0.31
Difference Sargan Test					0.09	0.11
Arellano-Bond test for AR(1)			0.00	0.00	0.00	0.002
Arellano-Bond test for AR(2)			0.27	0.24	0.28	0.45
Wald test for coefficients			0.00	0.00	0.00	0.00
Observations	2,868	2,868	2,868	2,868	2,868	2,868
R^2	0.2800	0.2795				
Adjusted R^2	0.2775	0.2553				
F Statistic	111.0968^{***} (df = 10; 2857)	107.6100^{***} (df = 10; 2774)				

Note: *p**p***p< 0.01

Robust standard errors are in parenthesis. The models are estimated with difference and system GMM. (1) and (2) represent the one-step and two step estimators for both models, respectively. For the diagnostic tests: the Sargan test of the validity of overidentification restriction, Arellano-Bond test for serial correlation and Wald test for testing power of independent variables, and p-values are reported. The null hypothesis of the Sargan test is Ho: overidentifying restrictions are valid. The null hypothesis of the Arellano-Bond test for serial correlation is Ho: no autocorrelation. The null hypothesis of the Wald test is Ho: Slope coefficients of the model are zero jointly.

Furthermore, in addition to all available instruments for $(exs_{it} - exs_{i,t-1})$, the first 25 values of emr_t and the first values of other exogenous variables are employed as instruments since, by assumption, exogenous variables are strictly exogenous for the GMM estimation. The null hypothesis that all instruments are valid at 5% is rejected by the Sargan test of overidentification for the DIFF-GMM and SYS-GMM estimation results. The Hansen-Sargan test is very sensitive to the problem of large number of instrumens. Roodman [77] reports that the p-value of the Sargan test is usually very high, resulting in non-rejecting of the validity of the moment, implying that too many instruments (instrument proliferation) can overfit endogenous variables. Hence, the collapsing method, proposed by Roodman [77], is employed to the GMM models in order to avoid the overfitting problem that is caused by instrument proliferation. According to the difference Sargan test statistics[2], the null hypothesis of the validity of the additional instruments used in the SYS-GMM estimation is not rejected at significance levels of 1% and 5%. This suggests that the SYS-GMM parameter estimates appear to be better than the DIFF-GMM estimates for estimation (see Table 5.1). Hence, the interpretations of results are based on the SYS-GMM estimates. Additionally, the estimated models with the DIFF-GMM and SYS-GMM pass the diagnostic test of the validity of the regressors, the Wald test. All of the explanatory variables are jointly significant at a significance level of 1%.

At first glance one can see that $exs_{i,t-1}$ is the first lag of the dependent variable and seems to be negatively associated with the $exs_{i,t}$ in the current period. This also approves the dynamic specification of the model.

Moreover, the coefficient of the imply that the exs is significantly sensitive to the emr. As the coefficient of the emr is less than 1, it can be concluded that the manufacturing firms are not the main drivers of the market index relative to the other firms in different sectors.

[2] Difference Sargan test: Ho: the additional moment conditions are valid. Nonrejection of additional instruments indicates the use of the SYS-GMM [72]

The first, second, third, and the fourth lagged values of the FXV is significantly negative, indicating that the more volatile exchange rates in previous four quarters are associated with a lower exs for the manufacturing firms. This finding shows that there is a strong FXV pass-through to the exs of the firms in manufacturing. This can be explained by the fact that most of the imported raw materials denominated in USD in the manufacturing industry are sensitive to the FXV. The profitability of the firms are negatively affected by the more volatile exchange rate because of uncertain input prices, which result in a lower value of equity. The studies of Mechri, Hamad, and Peretti [20], and Sichoongwe [21] are in line with this finding that the FXV negatively decreases excess stock returns. On the other hand, Mlambo and Maredza [19] argued that there is very weak relationship between the FXV and the stock market.

The estimated coefficients of the four firm-specific features are statistically significant. The higher liquidity ratios, corresponding to the *liquidity factor*, are associated with a higher exs. A liquid firm is able to pay its short-term debt more effectively and has more flexibility to use its liquid assets for profitable investment projects in future; therefore, an investor might buy shares of the firm's stock, expecting that the future profits of the firm are a sign of dividend payment or increase in stock price. This finding contradicts that of Pražák & Stavárek [22], who find a negative relationship between liquidity and stock prices, and that of Razak et al. [26], who find that liquidity does not significantly affect stock returns, and these contradictions can be attributed to the characteristic of the economic condition of the countries.

The signs of the estimated coefficients of the *profitability factor-1* and *profitability factor-2* are positive and negative, respectively, but the sum of both coefficients turns out to be positive. This reflects that the profitability of the firms is positively related with the exs. This finding contradicts those of Razak et al. [26] and Wijaya [28], but is in line with those of Arkan [23], Mirgen et al. [24], IŞIK [25], and Ligocká and Stavárek [27]. These different findings could be the result of different sample sizes, employing different estimation methods, and using different financial ratios. The coefficient of *leverage factor* is positive and highly significant, reflecting that the leverage ratios are significant in explaining the expected stock returns. This finding supports the empirical findings of Pražák & Stavárek [22] and IŞIK [25]; however, it contradicts those of Razak et al. [26] and Wijaya [28].

The results clearly confirm that the liquidity, profitability, and leverage performance of the firms are firm-specific determinants of the exs of the manufacturing firms. Moreover, they can be considered as firm-specific factors that have an impact on stock returns.

CHAPTER 6

CONCLUSIONS

This thesis focuses on analyzing the effects of the exchange rate volatility and firm-specific features on excess stock returns for manufacturing firms listed on the BIST-100 Index.

Since the exchange rate volatility, FXV, is considered as a common macroeconomic factor for modeling stock returns in the CAPM, it deserves a separate chapter in this study. In order to test the FXV as another explanatory variable for modeling excess stock returns (exs), the volatility modeling chapter is devoted to determining the best fitting volatility model for log-returns of the TRY/USD rate, FX, series. The analysis confirmed that the daily FX series has positive skewness and leptokurtosis, and exhibits regime changes in their volatility dynamics and leverage effects. The results of the in-sample and out-of-sample analysis show that the regime-switching MSGARCH models perform better than the single-regime traditional GARCH models. Although single-regime traditional GARCH models are mostly used in academic research, they can lead to incorrect risk predictions in the presence of switching regimes in the conditional volatility process [78]. Under the assumption of skewed GED distributed innovations, the 3-regime GJR-MSGARCH(1,1), allowing for asymmetric effects, is found to be the most appropriate among the 24 models according to both the AIC and backtesting VaR predictions. The most striking implications of this model are that the FX series exhibits regime changes in their volatility process, and the depreciation of the TRY tends to cause more of an increase in the volatility when compared to the appreciation.

In selecting and describing the firm-specific features, PCA is employed to the dataset of the financial ratios in order to reduce the number of dimensions and remove collinearity. The firm-specific features are named based on the loading vectors. The first firm-specific feature is named *liquidity factor* for *crr*, *qr*, and *cr*. The second firm-specific feature is named *profitability factor-1* for the *roa* and *roe*. The third firm-specific feature is named *profitability factor-2* for the *opm*. The fourth firm-specific feature is named *leverage factor* for the *der*.

After modeling the FXV and selection of the firm-specific features, GMM is employed to the dynamic panel data model to see the effect of the FXV and the firm-specific features on the excess stock returns. The estimated GMM results suggest that the higher FXV in the previous 4 quarters tends to decrease the stock returns, which implies that the pass-through of the FXV to the stock returns has increased, which can be considered as an indicator of the uncertainty associated with lower stock returns. This finding can be explained by the study of Erduman et al. [79], in which imported raw materials and intermediate goods constitute about 75% of Turkey's total imports, and the import content of production stays stable from 2002 to 2018 for the Turkish economy, indicating the widespread use of imported inputs in domestic production. The manufacturing firms that cannot use hedging strategies to protect themselves against the high FXV are probably exposed to high input costs due to the high proportion of imported inputs, which result in lower profitability and poor financial performance in returns, and indeed lower excess stock returns. The fact that the exchange rate volatility has a decreasing effect on the excess stock returns indicates higher capital outflows when the exchange rate is volatile. This conclusion supports the findings of Ejaz et al. [10] and Jehan et al. [11], showing that exchange rate volatility has a negative effect on the capital inflows. Furthermore, the firm-specific features represented by *liquidity*, *profitability*, and *leverage factors* are statistically significant in explaining the excess stock returns.

In addition to the emr as a market risk factor in the multi-factor CAPM, this study shows that introducing the FXV as a new market risk factor into the model brings insight into different aspects of the return generation mechanism for stocks of manufacturing firms in Borsa İstanbul. Moreover, the firm-specific features are firm-specific factors that are determinants of excess stock returns in the multi-factor CAPM.

As a result, this study contributes to the literature by analyzing the effects of the FXV, as well as the importance of *liquidity*, *profitability*, and *leverage factors* of manufacturing firms, on stock pricing by representing extensive evidence from the BIST-100 Index.

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APPENDICES

APPENDIX A TIME SERIES PLOTS

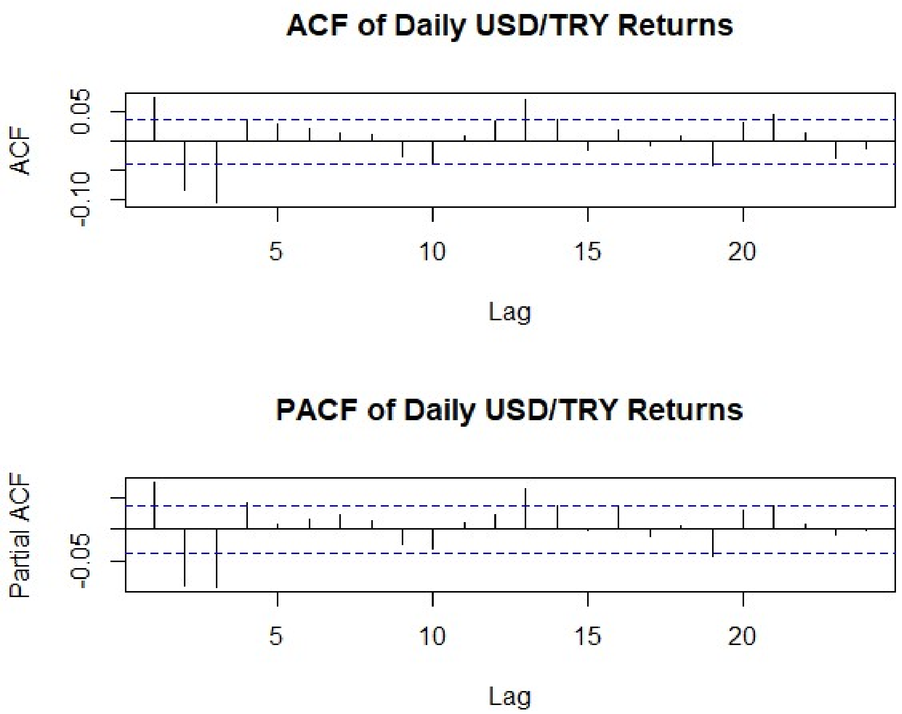

Figure A.1: ACF and PACF of returns of the TRY/USD exchange rate

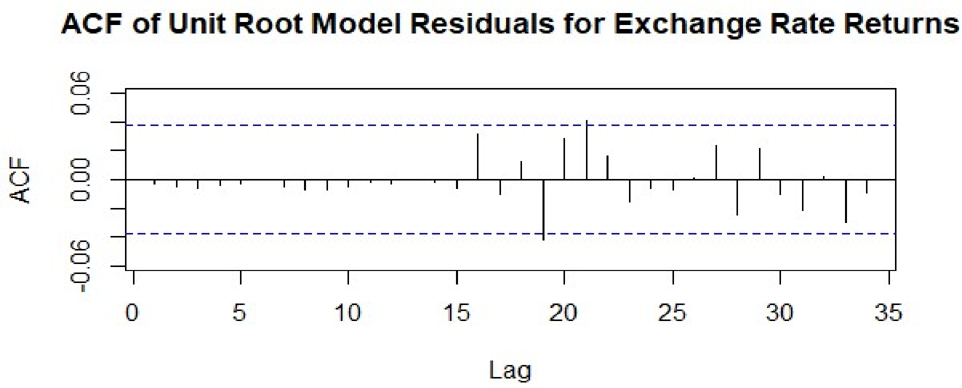

Figure A.2: ACF of the unit root model for the TRY/USD exchange rate returns

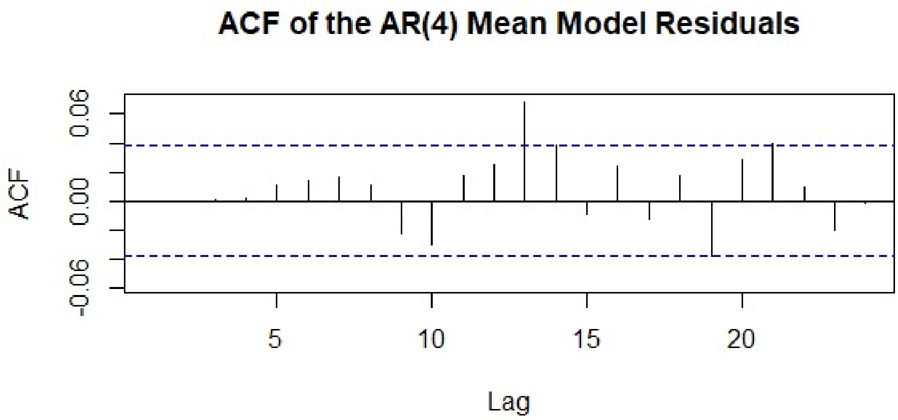

Figure A.3: ACF of the AR(4) mean model residuals

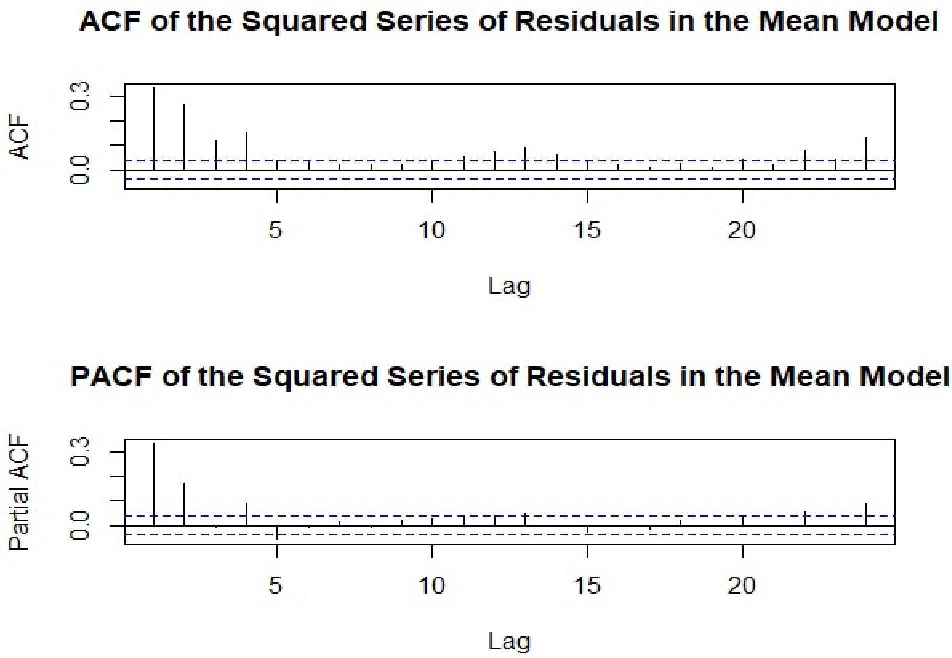

Figure A.4: ACF and PACF of the squared series of residuals in the mean model

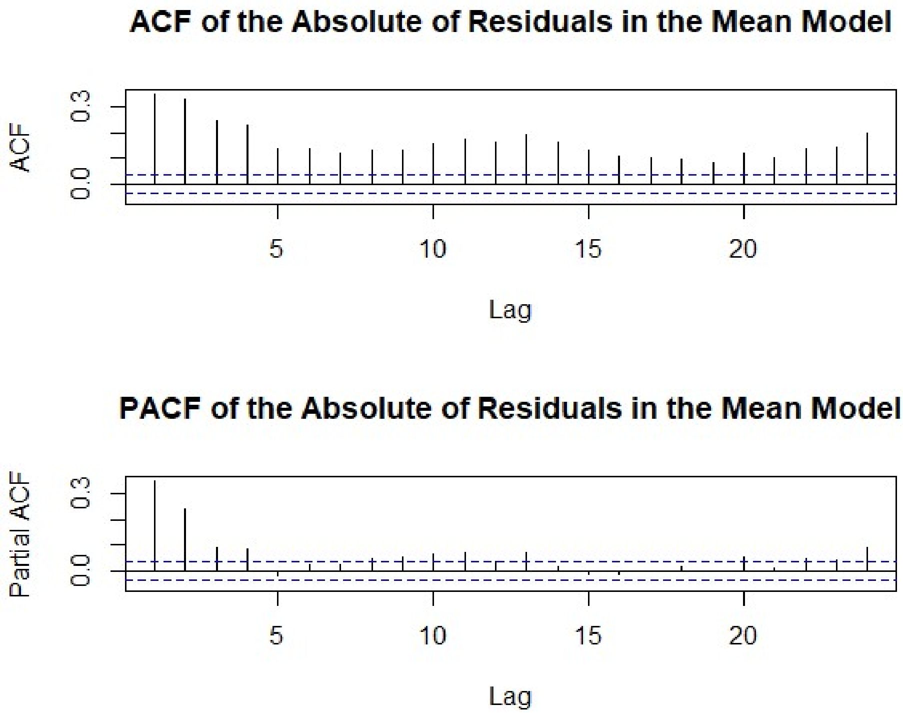

Figure A.5: ACF and PACF of the absolute of residuals in the mean model

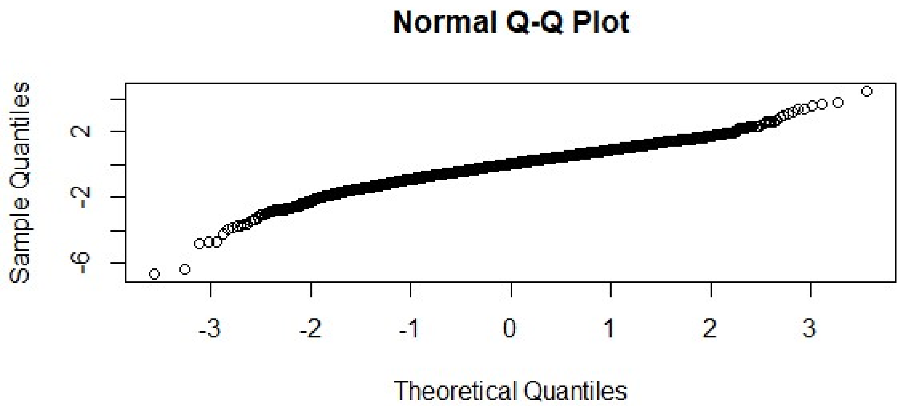

Figure A.6: QQ plot of standardized residuals

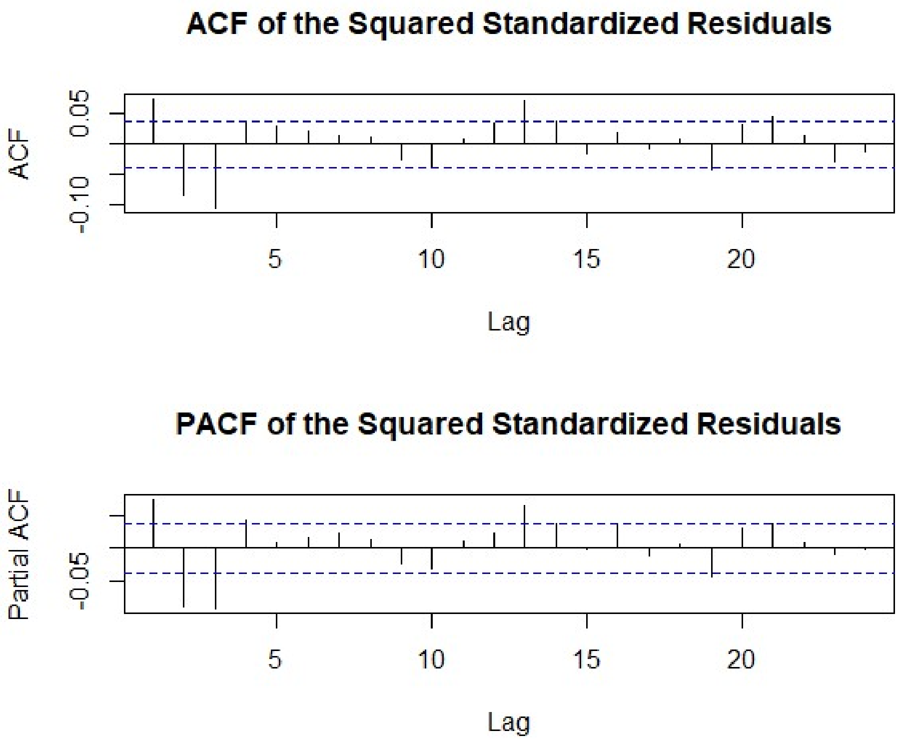

Figure A.7: ACF and PACF of the squared standardized residuals

APPENDIX B VOLATILITY PLOTS

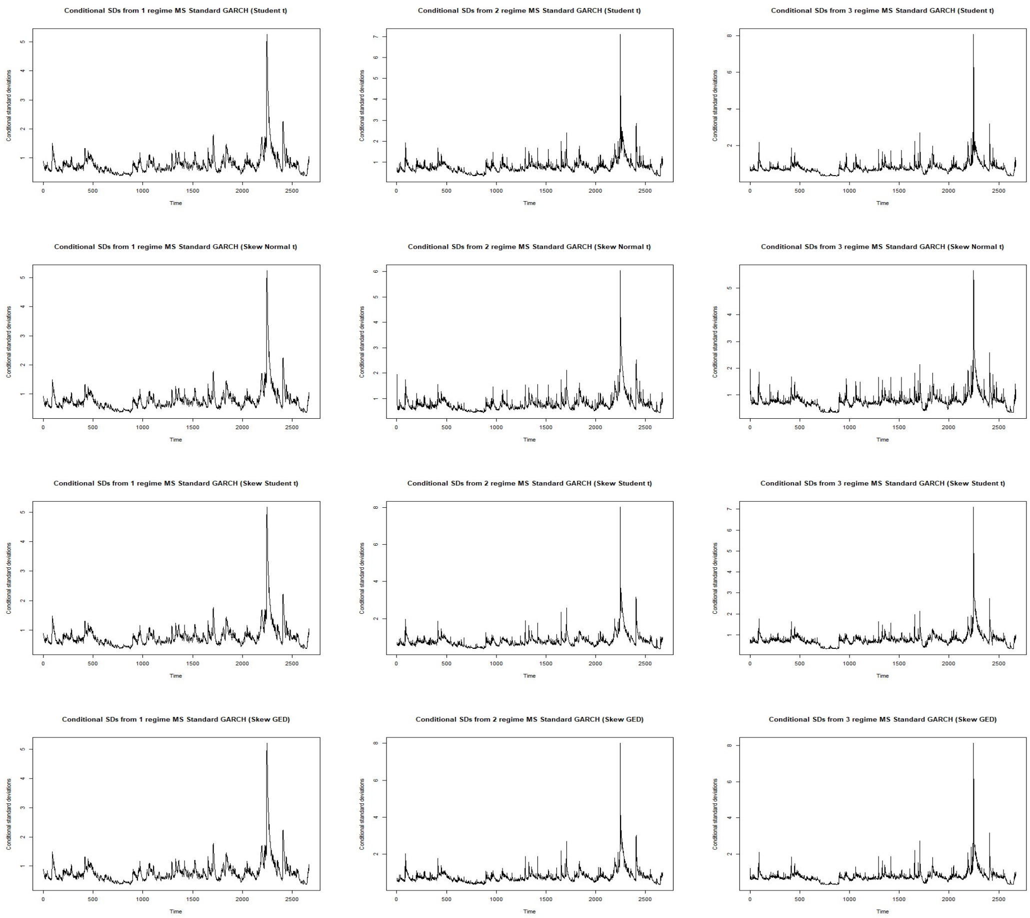

Figure B.1: Conditional standard deviation series for all of the estimated standard GARCH models

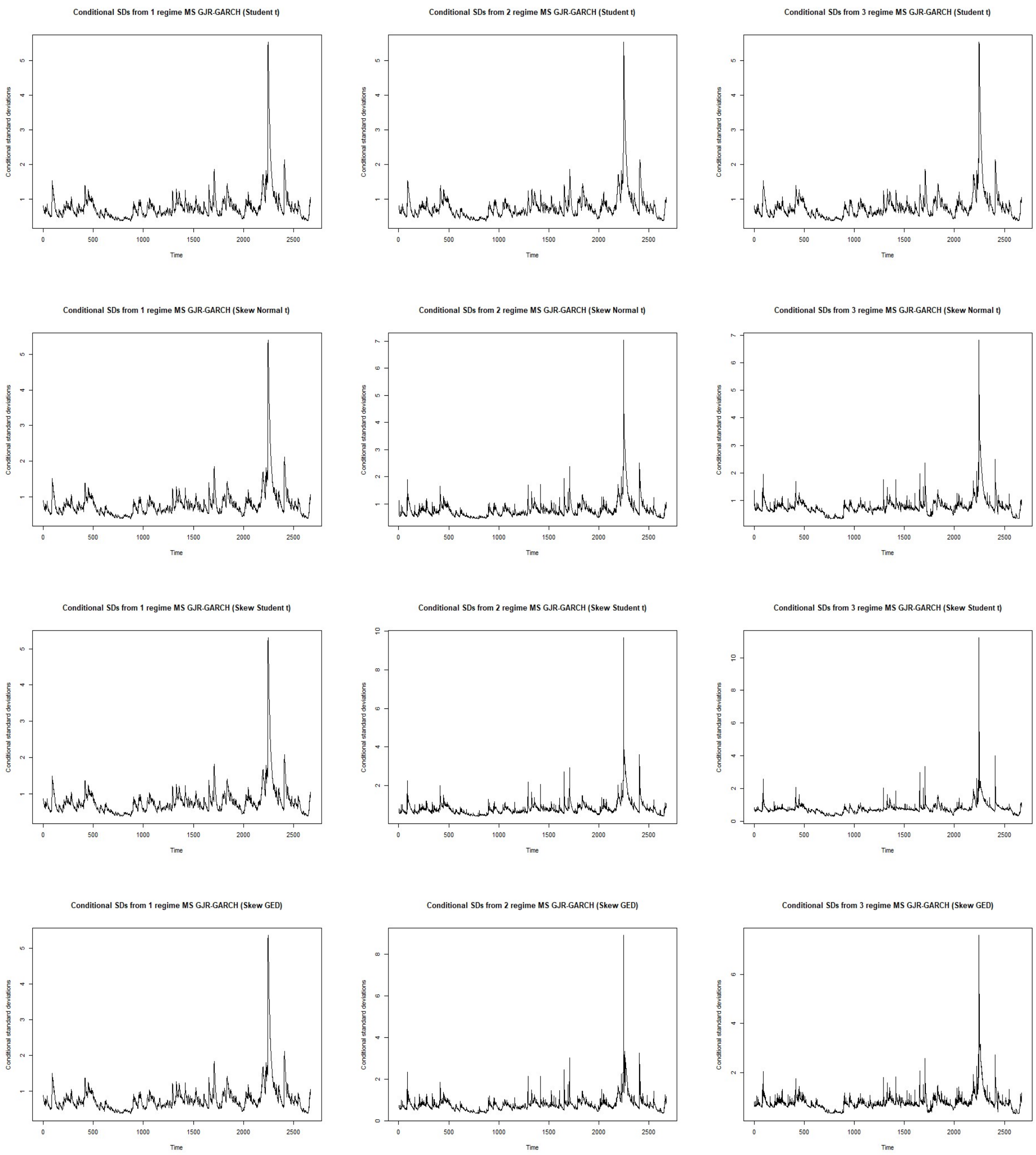

Figure B.2: Conditional standard deviation series for all of the estimated GJR-GARCH models