COINTEGRATION AND CAUSALITY RELATIONSHIP BETWEEN BORSA ISTANBUL'S BIST100 AND EXCHANGE RATES

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Cointegration and the Causality Relationship

Between Borsa Istanbul's BIST100 and Exchange Rates

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DECLARATION OF ORIGINALITY

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ABSTRACT

Cointegration and Causality Relationship

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This thesis investigates the relation between the stock prices and the exchange rates(against US dollar) of Turkey, based on the monthly data from January 2003 to February 2019.The study inspects the short-run causal relationship by employing multivariate Granger causality test, and probes the long-run relation of the aforementioned variables using Johansen cointegration test. In addition, by use of multivariate DCC-GARCH method, dynamic conditional correlation among variables are estimated & forecasted for future periods. Empirical results suggest that only one long-term relation exists between these variables, and the direction of causality runs from stock prices to exchange rates. Findings of DCC-GARCH implies that significant dynamic conditional correlation is present among the time series studied. Also, a considerable time varying correlation is established between BIST100 stock prices and real exchange rates, which is in accordance to the result of preceding methods.

ÖZET

Borsa İstanbul ile Döviz Kurları Arasında

Eşbütünleşme ve Nedensellik İlişkisi

Bu tez, Ocak 2003 ile Şubat 2019 arasındaki aylık verilere dayanarak, hisse senedi fiyatları ile Türkiye'nin döviz kurları arasındaki ilişkiyi (ABD dolarına karşı) araştırmaktadır. Çalışma, çok değişkenli Granger nedensellik testi kullanarak kısa dönem dinamik nedensellik ilişkisini incelemekte ve yukarıda belirtilen değişkenlerin Johansen eşbütünleşme testi kullanılarak uzun dönem ilişkilerini araştırmaktadır. Ayrıca, çok değişkenli DCC-GARCH yöntemi kullanılarak, değişkenler arasındaki dinamik koşullu korelasyon gelecekteki dönemler için tahmin edilmiştir. Ampirik sonuçlar, bu değişkenler arasında sadece bir uzun vadeli ilişki olduğunu ve nedenselliğin hisse senedi fiyatlarından döviz kurları yönünde gerçekleştiğini göstermektedir. DCC-GARCH'ın bulguları, zaman aralığında önemli dinamik koşullu korelasyonun mevcut olduğunu göstermektedir. Ayrıca, önceki analizlerin sonucuna uygun bir doğrultuda BIST100 hisse senedi fiyatları ve döviz kuru arasında önemli ölçüde zamana bağlı bir korelasyon bulunduğu gözlemlenmiştir.

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I would like to thank my thesis advisor Assoc. Prof. Gözde Ünal for her constant supports and motivations. She consistently allowed this thesis to be my own work but steered me in the right direction whenever she thought I needed it. I would also like to thank my family and my friends for their continuous support and encouragement.

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CHAPTER 1
INTRODUCTION

How are the exchange rate fluctuations and stock price movements related? Do the changes in exchange rates affect stock prices? Conversely, do the changes in stock prices affect exchange rate? Is there a causal relation between them? If there is a relation, what is the direction of the relation? How can this causality be explained? Nowadays with more commonly observed severe fluctuations in exchange rates, these questions have received extensive attention.

Investors try to analyze and use the relation between exchange rates and stock price movements in predicting their future movements Joseph (2003) explains that the international competitiveness of firms is affected by the exchange rate fluctuations, particularly by influencing input and output prices. In agreement, Kim (2003) supports that with the increasing world trade and capital movement, exchange rate is becoming a more significant factor in determining business profitability and equity prices.

Two main theoretical models show the presence of the relationship between exchange rates and stock price fluctuations, named as; the flow-oriented model, and the stock-oriented model.

1) Flow-oriented models state that changes in the exchange rate lead to changes in stock prices. Dornbusch and Fischer (1980) state that exchange rates are determined by the country’s performances in current account balance and trade balance. Therefore, stock prices and exchange rates are expected to be positively related.

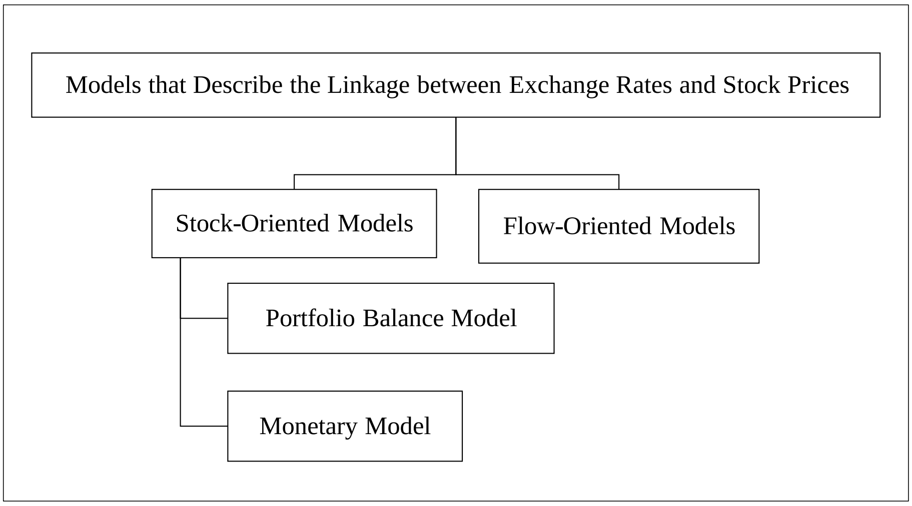

Figure 1. Models that describe the relationship between exchange rates and stock prices

As we know stock prices, which declare present value of future cash flows of firms, should be aligned to the economic viewpoints. Accordingly, this model investigates a positive relationship between exchanges rates and stock prices. When the value of the domestic currency decreases, this leads to a decrease in the costs of exports in foreign markets, resulting in an increase in the amount of competitiveness of the local firms.

2) Stock-oriented models posit that the changes in the stock prices result in changes in exchange rates. These models point up that the capital account is the main factor in determining exchange rates by inflow and outflow of foreign capital.

    a) Portfolio balance models of (Branson, 1983) state that rises in stock prices increase the demand and the interest rate of the domestic currency and a consequent fall in the exchange rate. The direction of the causation is from the stock market to the foreign exchange market, which drives stock prices and exchange rates to move in opposite directions. Frankel (1992) confirms that a negative relationship exists between stock prices and exchange rates in line with the portfolio balance models.

b) Monetary models Gavin (1989) concludes that there is no linkage between mentioned variables except that both variables are influenced by some common factors.

Extensive research has been done in investigating the relationship between exchange rate performance and its effects on stock market for developed countries and emerging markets. In this study, the relation between the fluctuation in Turkish lira versus US dollar and Borsa Istanbul stock prices is investigated. Also, an attempt is made to find the causal relation between them and if the relationship exists, the direction of the causality will be discovered. The sample period for this study is from January 2003 to February 2019. Turkey as an emerging market has reformed its financial system since its financial crisis in 2001. In addition, high level of exchange rate and interest rate volatility has been a continuing characteristic of its economy; these aspects make Turkish stock market a compelling case to this thesis.

Three methods are employed to study the relationship between BIST100 stock prices and exchange rates. The first method named as a Johansen cointegration test is used to examine the long-run relationship between variables. Short-run dynamic examination is done by Granger causality test, which not only indicates the sort of channel through which variables are related, either “stock channel” or “flow channel”, but also estimates the causality between stock prices and exchange rates. The last is known as the dynamic conditional correlation (DCC) method is utilized to estimate dynamic correlation between BIST100 stock prices and real exchange rates with regard to US market.

This thesis is divided into five chapters which are: introduction, literature review, methodology, empirical results and conclusion. The structure of the thesis is described below.

The first chapter presents an introduction to our thesis. Chapter 2 includes the literature review section of the study, which explains two main theoretical models used to indicate the existence of the relationship between exchange rates and stock price fluctuations.

Chapter 3 explains the research methodology. In chapter 4 we performed our analysis on data and discussed results of the study.

In the last chapter, conclusions of this study are provided.

CHAPTER 2

LITERATURE REVIEW

This literature review covers those studies that analyze the relationship between stock market prices and exchange rates both in developed and emerging markets. In literature, both the theoretical studies and the empirical studies reveal conflicting results in explaining the behavior of exchange rates and stock price movements. In empirical studies, the data frequency and the periods chosen, and also other macro variables used were all observed to affect the kind of linkage between these fluctuations in exchange rates and stock market prices.

On the whole, most studies indicated a short-run linkage between exchange rates and stock prices but did not find any long-term relation between dependent and independent variables. Some papers show that many macroeconomic variables such as GDP, inflation rates, interest rates, oil prices, industrial production, money supply, and foreign capital can also influence stock prices.

The literature review will first introduce the studies that use stock-oriented models and then follow with the studies that use flow-oriented models. These classified studies will be mainly explained in chronological order.

2.1 Stock-oriented models

Nieh and Lee (2001) examined the relationship between exchange rate and stock prices for G7 countries. They used Engle-Granger and maximum likelihood cointegration tests and employed vector error correction model (VECM) to analyze daily data from October 1993 to February 1996. According to the results, they found no long-term relationship. In addition, they found that short-run significant relationship appears only for one day after a major fluctuation in certain G7 countries.

By using monthly data and employing co-integration models, Muhammad, Rasheed, and Husain (2002) investigated the long run and short-run relationship between stock prices and exchange rates in India, Bangladesh, Sri Lanka, and Pakistan. They didn’t find an important relationship, at least in the short run. They recommended that both using one markets’ information in anticipating manner of another market and using exchange rate as an expansionary monetary policy to invite foreign investors would not be an effective strategy.

Kim (2003) utilized Johansen’s cointegration method on monthly data to study the linkage between stock prices and aggregate real exchange rate, interest rate, inflation rate, and industrial production for S&P 500 in the United States. He found positive impact from industrial production and negative from real exchange rate, interest rate and inflation on stock prices.

Lean, Halim, and Wong (2005) employed co-integration test based on OLS and Granger causality test on weekly data from January 1, 1991 to December31, 2002 to study the linkage between exchange rates and stock prices in Hong Kong, Indonesia, Japan, Singapore, Malaysia, Korea, Philippines and Thailand. He indicated the existence of Granger causality between two variables only in the Philippines and Malaysia. He failed to show any co-integration relationship between stock prices and exchange rates before or during the 1997 Asian crises, but found some weaker co-integration linkage after the 9-11 terrorist attack.

Phylaktis and Ravazzolo (2005) applied both Johansen cointegration and Granger causality tests to investigate the linkage between exchange rates and stock prices in Hong Kong, Malaysia, Singapore, Thailand and the Philippines. They showed that US stock market works as just a conduit between the foreign exchange market and stock market. They indicated a positive correlation between the real exchange rate and stock market.

Yau and Nieh (2006) investigated the connection between stock prices and exchange rates by utilizing monthly data from January 1991 to July 2005 in Taiwan and Japan. They failed to show any distant future connection between exchange rates and stock prices neither in Japan nor in Taiwan and couldn’t find any sign of short-term linkage between the exchange rate of New Taiwan dollar against Japanese Yen and the stock prices of both countries. They found a two-way causality between Taiwan’s and Japan’s stock prices.

Richards, Simpson, and Evans (2007) applied VAR model, Granger causality and Johansen cointegration tests on daily data from January 2003 to June 2006 to study the linkage between exchange rates and stock prices in Australia. According to the results, causality runs from stock prices to exchange rates, and two variables are cointegrated in the long run.

Rahman and Uddin (2009) studied the relationship between stock prices and exchange rates by using Johansen cointegration test, Granger causality test in Bangladesh, India and Pakistan. They failed to show any long-term correlation between exchange rates and stock prices and concluded that two variables do not have any causal relation.

Kutty (2010) employed both Engle-Granger method of cointegration and Granger causality tests on weekly data since January 1989 to the end of 2006 to examine the short-term and long-term relationship between exchange rates and stock prices in Mexico. He found that the direction of Granger causality in the short-run is from stock prices to exchange rates but failed to show any long-term interrelation between variables.

Chortareas, Cipollini, and Eissa (2011) employed Johansen method of cointegration on monthly data from 1994 to 2006 to examine the effect of oil prices as a connection between the exchange rates and stock markets in Egypt, Kuwait, Oman and Saudi Arabia. According to their result without consideration of oil prices, there isn't any long-run cointegration between two variables. They analyzed linkage among variables for three periods; before the oil prices shock in 1999, after the shock, and full sample period. According to their result; for period before the shock, they failed to show any cointegration among exchange rates, stock prices and oil prices, but for period after the shock they indicated existence of cointegration among variables in Egypt, Oman and Saudi Arabia. Also, while analyzing whole sample period with inclusion of oil prices, they failed to show any cointegration between exchange rates and stock prices. They concluded positive correlation exist between real exchange rates and stock prices in Oman and Egypt, but those two variables are adversely linked in Saudi Arabia. They deducted that stock prices are positively influenced by oil prices in long-run.

Harjito and McGowan Jr (2007) studied the linkage between exchange rates and stock prices with use of Granger causality test and Johansen cointegration test on weekly data from the beginning of 1993 to the end of 2002 in Thailand, Indonesia, Singapore and Philippines. In Singapore and Thailand, they showed that the causality not only runs from exchange rates to the stock prices, but also runs from the stock prices to exchange rates. They concluded that exchange rates and stock prices are cointegrated. According to them in all four economies, cointegration appears to exist between the stock markets.

Liu and Tu (2011) examined the relationship among exchange rate and foreign capital as stock prices in Taiwan. From 2001 to 2007, they used daily data to examine the linkage between variables and to analyze whether or not asymmetric volatility switching, and mean reversal properties exists in these markets. According to their results, overbuying and overselling of foreign capital rates, impacts the fluctuations of the stock price index and the exchange rate. They concluded that the three markets' volatility showed GARCH effects.

Lee, Doong, and Chou (2011) utilized Bivariate STCC- EGARCH model to examine the linkage between stock prices and exchange rates in Indonesia, Korea, Malaysia, the Philippines, Taiwan, and Thailand. They conclude that the price spill-overs from stock market to foreign exchange market is significant in all countries except the Philippines. According to them the volatility of stock market influences the relation between stock market and foreign exchange market.

Parsva, Lean, and economics (2011) employed the model that contains major factors in determining stock prices, such as interest rates, inflation rates and oil prices in Iran, Oman, Kuwait, Jordan, Saudi Arabia and Egypt. By applying Granger causality test and Johansen cointegration method on monthly data from 2004 to 2010, they concluded that long run cointegration exist among all variables. For period before crises in Egypt, Iran and Oman for both long run and short run, they found bi-directional causality between exchange rates and stock prices. Result show that in the short run the direction of causality is from exchange rates to stock prices in Kuwait. They concluded that there was little difference in the behavior of stock returns and exchange rates between the pre and post-crises periods.

Basher, Haug, and Sadorsky (2012) by employing structural VAR globally analyzed the relationship among exchange rates, oil prices and stock prices over the period between January 1988 to December 2008. By analyzing the function of the impulse response, they indicated that the decline in stock prices of emerging markets and US dollar exchange rates was due to positive shock to oil prices in the short run. Changes in oil prices impacts exchange rates in the short run, positive oil price shock results in reducing trade-weighted exchange rates. They concluded that oil prices fall as oil manufacturing increases, however, a positive impact on actual economic activity raises oil prices.

Lin (2012) employed ARDL method of cointegration and Granger causality test on monthly data from January 1986 to December 2010 to analyze short-run and long-run dynamics between stock prices and exchange rates in India, Indonesia, Korea, Philippines, Taiwan, and Thailand. In times of crises, the co-movement between exchange rates and stock prices has intensified in terms of long-run cointegration and short-run causality. He showed that the spill-over impact is mainly from stock price shocks to exchange rates. According to results, analysis of industry's causality has shown that the co-movement is usually impelled by the balance of capital accounts rather than the trade balance. He concludes that during the period of crises and market liberalization, volatility of changes in foreign reserves and interest rates increases.

Wickremasinghe (2012) studied the linkage between exchange rates and stock prices in Sri Lanka. He used Granger causality test, Johansen's cointegration test and variance decomposition analysis on monthly data from January 1986 to December 2004. He failed to show any long-run relationship between variables. He indicated that direction of causality is only from stock prices to US dollar exchange rates and also failed to detect any causality when exchange rates for Japanese yen, Indian rupee and UK pound were regarded. He deducted from the analysis of variance decomposition that the majority of the variance of ASPI is clarified by Indian Rupee.

Büberkökü (2013) employed Granger causality test, Johansen and Engle-Granger cointegration tests to examine short-run and long run dynamics between exchange rates and stock prices in Australia, Canada, England, Germany, Japan, Switzerland, South Korea, Singapore, and Turkey. He found long-run relationship between two variables only in Singapore and failed to find any long-run linkage between stock prices and exchange rates in all other economies. In short run, exchange rates in Canada, Switzerland and Turkey are affected by stock prices, but in Singapore and South Korea exchange rates influence stock prices. He failed to show any causal linkage in Australia, England, Germany and Japan.

Tsagkanos and Siriopoulos (2013) examined long-run and short-run relationship between stock prices and exchange rates in USA and European Union (EU). They applied Johansen test for cointegration, Granger causality test and Structural non- parametric cointegrating regression (SNCR) on monthly data from January 2008 to April 2012. According to their result, in the long-run, stock price fluctuations impact exchange rate movements in the EU, and in the US in the short run.

Khan, Muneer, and Ahmad (2013) applied Engle-Granger causality test and Johansen test for cointegration on several macroeconomic variables to investigate short-run and long run linkage among macro variables, exchange rates and stock prices in Pakistan. Macro variables included CPI, industrial production, market returns, risk-free rate of return, and M2, and monthly data from 1998 to 2008 were employed in analysis. The result indicated that in short-run, both exchange rates and stock prices impact one another, but between these variables no correlation exist in long run. In the long run, risk-free return and market return are not linked to stock prices, but stock prices and industrial production are affiliated. Among inflation, stock prices and supply of money, there is both short-term connection as well as long-term relation.

Moore and Wang (2014) studied the dynamic linkage between real exchange rates and stock prices in relation to the US market for the four developed markets and six Asian emerging markets. By employing the dynamic conditional correlation (DCC) method, they show that the local stock market and the foreign exchange market are fetched together by US stock market, and by this mean it affects these economies. Result indicated the negative relationship between the stock market and foreign exchange markets. They concluded that the current account balance is the driving force of the dynamic linkage between mentioned variables in Asian countries, and the major factor for developed countries in the difference in interest rates.

Ismail and Bin Isa (2009) investigated linkage between nominal stock market index and nominal exchange rate in Poland, Czech Rep, Slovenia, and Hungary. They analyzed the short-run linkages with the VAR approach and long-term relation with cointegration tests, also Granger causality tests were applied for the determination of the exogenous and endogenous variables. Their result indicated the existence of substantial linkage between the stock market index and the foreign exchange rate for Czech Republic, Slovenia and Hungary.

Chkili, Aloui, and Nguyen (2012) with the use of Markov switching VAR models have scrutinized the dynamic relationship between the exchange rates and stock returns for the BRICS countries. Their sample data consists of weekly stock prices and US dollar exchange rates for period between March 1997 and February

2013. They find two different regimes for every market, a low volatility regime and a high volatility regime. They conclude that exchange rates market in BRICS countries show different behavior to major crises occurred during sample period, for example Chinese yuan was the least sensitive to changes in US dollar value and Russian ruble was easily affected by the US dollar fluctuations. According to their result stock markets of BRICS countries remain more in a low volatility regime than in a high volatility regime. They show that due to strong connection between BRICS market and world markets, they react sharply to major external economic and financial shocks, and to be specific exchange rates in emerging countries express more volatility and higher correlation during times of crises. The concluded that because of financial hedging by multinational firms, the dynamics of stock market returns were insensitive to fluctuations in the US dollar exchange rates. They deducted existence of indicative effect of the stock prices on the US dollar exchange rates in BRICS countries, but insignificant impact from exchange rates to stock market returns, hence their results support the stock-oriented model.

Abidin, Walters, Lim, and Banchit (2013) applied Engle-Granger cointegration test on daily data from January 2006 to December 2008 to investigate relationship between exchange rates and stock prices in Australia, Hong Kong, Indonesia, Japan, New Zealand, South Korea, and Thailand. He wasn't able to find any major long-run linkage between stock prices and exchange rates.

Caporale, Hunter, and Ali (2014) probed the relationship between exchange rates and stock returns in the USA, UK, Canada, Japan, the Euro Area, and Switzerland. For their examinations, they applied Granger causality test, Engle-Granger and Johansen trace test for cointegration, Bivariate VAR- GARCH model on weekly data from August 2003 to December 2011. Utilizing Bivariate UEDCC-

GARCH models they showed that in the short run, unidirectional Granger causality exist from stock returns to exchange rate changes in UK and USA, and the direction of causality is opposite in Canada. Also, they found bi-directional Granger causality from stock returns to exchange rates in the Euro area and Switzerland. They indicated that in the USA and in the Euro area, Causality-in-variance from stock returns to exchange rate changes is present, and in Japan it exists in reverse direction, whereas bi-directional feedback is available in Switzerland and Canada. They concluded that the dependence between the two variables has risen during the recent financial crises.

Huy (2016) investigated the dynamic causal relationship between exchange rates and stock prices during pre and post financial crisis in Vietnam over period 2005 to 2015. He applied (S. Johansen & Juselius, 1990) co-integration test to analyze the long-run linkage between exchange rates and stock prices, and by employing (Toda and Yamamoto, 1995) procedure he examined the short-run relationship between mentioned variables. His finding is in conformity with both portfolio approach and flow-oriented approach. His finding for pre-crises period are in accordance to the portfolio approach, and result for post crises period supports the traditional approach.

2.2 Flow-oriented model

Aggarwal (2003) Investigated the effect of exchange rate changes on U.S. stock prices over 1974 and 1978 and found a positive correlation between those variables, denoting that stock prices were elevated by revaluation of the U.S. Dollar.

Abdalla and Murinde (1997) studied the linkage between exchange rates and stock prices in the emerging financial markets of India, Korea, Pakistan and the

Philippines. As a test for cointegration, Granger causality tests were applied on monthly observations of the stock price index and real effective exchange rate over 1985:01 and 1994:07, and result show that exchange rates Granger- cause stock prices in Korea, Pakistan and India, while stock prices Granger-cause exchange rates in the Philippines.

Granger, Huangb, and Yang (2000) used daily data from January 1986 to November 1997 to investigate the relationship between exchange rates and stock prices in Hong Kong, Indonesia, Japan, South Korea, Malaysia, the Philippines, Singapore, Thailand, and Taiwan. By employing Gregory Hansen cointegration test and Granger causality test he concluded that a positive correlation exists between mentioned variables in case of Japan and Thailand and suggested a negative correlation between stock prices and exchange rates for Taiwan. He couldn't find any relationship for Singapore. According to result of the Granger causality test, he shows that exchange rate influences stock prices in eight of the nine countries.

Smyth and Nandha (2003) used daily data from January 1995 to November 2001 to study the relationship between exchange rates and stock prices in India, Pakistan and Sri Lanka. They couldn't find long-run linkage between stock prices and exchange rates and also, they weren't able to show any sign of causality in Bangladesh and Pakistan. They declared that exchange rates influence stock prices in Sri Lanka and India.

Ismail and Bin Isa (2009) used monthly data and Johansen cointegration test and non-linear MS-VAR model to examine linkage between stock prices and exchange rates in Malaysia. They found no long-run relationship between exchange rate changes and the changes in stock indices. They identified regime switching behavior between the exchange rates and stock prices.

Tian and Ma (2010) applied ECM model and ARDL method to cointegration on monthly data from December 1995 to December 2009 to analyze the linkage between major foreign exchange rates and the Shanghai stock price indices. They failed to show any cointegration between mentioned two variables for period before financial liberalization of 2005, but for period after liberalization they indicated existence of cointegration between exchange rates and stock prices. They concluded that there is positive impact from money supply and exchange rates to stock prices.

Alagidede, Panagiotidis, and Zhang (2011) studied the causal linkage between stock markets and foreign exchange markets in Australia, Canada, Japan, Switzerland, and UK by using standard Granger causality method, and Johansen and Saikkonen-Lutkepohl cointegration test between January 1992 and December 2005. They couldn’t find long-run linkage between the variables employing cointegration tests, but for short-run they indicated a casual linkage from exchange rate to stock prices in Canada, Switzerland, and UK. They find weak causal linkage from stock price to exchange rate just for Switzerland.

In another study of Turkish market, Kasman, Vardar, and Tunç (2011) have analyzed the impact of interest rate and exchange rate volatility on Turkish banks' stock returns over July 1999 to April 2009. By using standard OLS and GARCH model, they indicated that interest rate and exchange rate changes have a major negative influence on the conditional bank stock returns. They showed the significant role of market return in defining the dynamics of conditional return of bank stocks. According to their finding the fluctuations in exchange rates amplifies the bank stock return volatilities.

Katechos (2011) applied maximum likelihood regression with GARCH on weekly data from January 1999 to August 2010 in Australia, Euro Zone, Japan, New

Zealand, Switzerland, UK and USA. He showed that the global stock market returns, and exchange rates are related, and the nature of the currencies specifies the sign of this linkage. So that positive correlation exists between value of higher yielding currencies and global stock market returns, whereas there is negative relation between values of lower yielding currencies and global stock market returns.

Lean, Halim, and Wong (2005) used Granger causality test, Gregory-Hansen test for cointegration, and Panel Lagrange Multiplier (LM) cointegration test on weekly data from January 1990 to June 2005 to investigate short-run and long-run dynamics between exchange rates and stock prices in Hong Kong, Indonesia, Japan, Korea, Malaysia, Philippines, Singapore, and Thailand. According to their result, slight sign of a long-run equilibrium relationship exists between stock prices and exchange rates. The two variables' predictive power is limited to the short term, although not applicable to all economies.

By employing VAR ANST GARCH-M model on daily data from January 2001 to December 2007, Liu and Tu (2011) studied the relationship between stock prices and exchange rates in Taiwan. According to them overbuying and overselling rates of foreign capital impacts the fluctuations of the stock price index and exchange rate. They observed asymmetric mean-reverting behavior in all of the conditional means. They concluded that the three markets' volatility has GARCH effects.

By applying Johansen test on quarterly data between 1988 and 2009 in Namibia, Eita (2012) tried to investigate the determinants of stock prices. Result indicated that exchange rates, economic activity, interest rates, inflation and money supply impact the stock prices. He showed that with rising money supply and economic activity, stock prices rise and as inflation and interest rates rise stock prices fall. Exchange rates, GDP, money supply and inflation remove the equilibrium of the stock market.

Inegbedion (2012) employed Cochran-Orcutt autoregressive model to study the relationship between stock prices and exchange rates in Nigeria. Results indicate that the negative relationship is present between exchange rates and stock prices. According to the results there is no significant relationship between stock prices and interest rates and inflation, respectively. He concluded that there is significant joint impact of all the variables on stock prices.

Kollias, Mylonidis, and Paleologou (2012) studied the linkage between exchange rates and stock returns in Europe. They employed Rolling Granger causality test and Rolling cointegration test on daily data from January 2002 to December 2008. They failed to find any long-run relationship between the variables. They concluded that during normal times, stock returns are influences by exchange rate, and during crises exchange rates are affected by stock returns.

Tsai (2012) applied Quantile regression approach on monthly data from January 1992 to December 2009 to analyze the linkage between exchange rates and stock prices in Singapore, Thailand, Malaysia, Philippines, South Korea, and Taiwan. Stock prices and exchange rates are adversely affected if the exchange rates are radically low or high. He indicated that the relationship changes depending on the market circumstances.

Aslam and Ramzan (2013) used NLS and ARMA techniques to study relationship between CPI, discount rate, per capita income, stock prices and real effective exchange rate index in Pakistan. They showed that Karachi stock price index is negatively affected by discount rates and inflation. They concluded that per capita income and real effective exchange rate index have a positive impact on the

Karachi stock price index. They also found that discount rate affects the index of stocks the most.

With applying Granger causality test and Johansen test for cointegration on monthly data from December 1979 to December 2010, Groenewold and Paterson (2013) analyzed the relation between exchange rates, commodity prices and stock prices in Australia. According to the results, all three variables are cointegrated in the long run with the incorporation of commodity prices, but no cointegration exist between exchange rates and stock prices, when commodity prices were not considered. They indicated that when considering only stock prices and exchange rates, there is no causality in either direction between them. Also, they argued that in the short run, exchange rates have an impact on commodity prices, so that stock prices are influenced by commodity prices.

Unlu (2013) examined the long-run and short-run dynamics between stock prices, exchange rates and oil prices in Malaysia, Indonesia, Singapore, Thailand and the Philippines. He used Granger causality test, Panel cointegration (Engel-Granger) and monthly data from January 2006 to December 2012. According to the results, among exchange rates, stock prices and oil prices, there is a long-run relationship. He indicated that in the long-run linkage, direction of causality is from exchange rates and oil prices to stock prices, but there is no causality in opposite direction. He found that in the short run, the causality between oil prices and stock prices is bi-directional.

Sensoy and Sobaci (2014) studied the dynamic relationship between exchange rate, interest rate and the stock market of Turkey from January 2003 to September 2013. By applying DCC modelling of (Aielli, 2013) they indicated that between dollar appreciation against Turkish lira and Turkish stock market returns a positive linkage exists. Their finding is inconsistent with the results reported by (Roll,1992) and (Chow, Lee, and Solt, 1997). They unveiled that global political and economic conditions affect Turkey’s stock and exchange markets, are basis for the upwards volatility shifts. According to their results the severe changes in the dynamic correlations don’t have a long run contagion affect between these markets and these changes fade away in the short run.

Tuncer and Turaboglu (2014) examined the linkage between some macro variables and stock prices in Turkey. They utilized multivariate vector error correction model (VECM) and Johansen test for cointegration to analyze quarterly data from 1990 to 2008. According to the results of Johansen’s cointegration test, long-run relationship between stock prices and the other variables was revealed. They found that in short run, real effective exchange rate and stock prices impact GDP, but no causal relationship appears to exist between treasury bills and GDP. They indicated that from real effective exchange rates to stock prices, causality exists. They concluded that due to lack of effect of all the variables on exchange rates, so the exchange rate is an exogenous in comparison.

Yang, Tu, and Zeng (2014) applied Granger causality test in quantiles on daily data to study the relationship between stock prices and exchange rates in India, Indonesia, Japan, Korea, Malaysia, Philippines, Singapore, Taiwan, and Thailand. All countries except Thailand have feedback relations between exchange rates and stock prices during the Asian financial crises, and in Thailand exchange rates are affected by stock returns. They indicated that the causal effects over various quantiles and periods are heterogeneous. They concluded that he majority of foreign exchange and stock markets are adversely correlated.

Mendy and Widodo (2018) have tried to diagnose the Indonesia rupiah per US dollar turning points using a univariate two-state Markov switching autoregressive model, which captures regime shifts behavior in both the mean and the variance of the mentioned variable. They concluded that significant events have impact on the performance of the Indonesian rupiah per US dollar exchange rate.

CHAPTER 3

METHODOLOGY

In this thesis for investigating the relationship between the stock prices and the exchange rates, several tests and methodologies were used. The first methodology which first was proposed by (Engle and Granger, 1987) is cointegration. Cointegration is a statistical characteristic of a set of variables in the time series and is defined as following; when two time series are integrated at the same level and their linear combination is stationary, then the two series are cointegrated. Here are some of important properties of cointegrated series:

a) Common trends exist among series
b) Series can be shown as one having moving average, MA.
c) There is a model for equilibrium correction

The second technique is multivariate Granger causality test which examines short-run dynamic. This method not only specifies the sort of channel through which variables are linked, but also estimates the causality between stock prices and exchange rates. The last method is the method of dynamic conditional correlation (DCC) to estimate the linkage between exchange rates and stock prices. Engle (2002) introduced the DCC as a novel class of multivariate models for the first time. Engle represented the DCC as having the flexibleness of the univariate GARCH models and also the parsimonious parametric models for the correlation. However, the DCC models are not linear, but are estimated using univariate or two step methods and usually operate properly in different conditions.

3.1 Time series

A time series is a chain of time ordered data points. Time is the independent variable in a time series and the goal is usually to make a future forecast.

However, in dealing with time series, some other important factors also exist. Factors such as being stationary, being seasonal, and being auto correlated. But for our studies the most significant consideration is stationarity of time series.

3.2 Stationarity

If in a stochastic process mean and variance stay constant over time, then this process is called stationary. Trend in the mean is the most common cause reason of violation of stationarity that may be due to either the existence of a unit root or a deterministic trend. Stochastic shocks have persisted impacts in the case of unit root and stochastic shocks only have transitory impacts in the case of trend stationarity. Trend in mean could be due to either the presence of unit root or deterministic trend. In former case, stochastic shocks have permanent effects, and the process is not mean-reverting. In the latter case, shocks have transitory effects, and the process is mean-reverting.

Figure 2 is summary of non-stationary models in time-series.

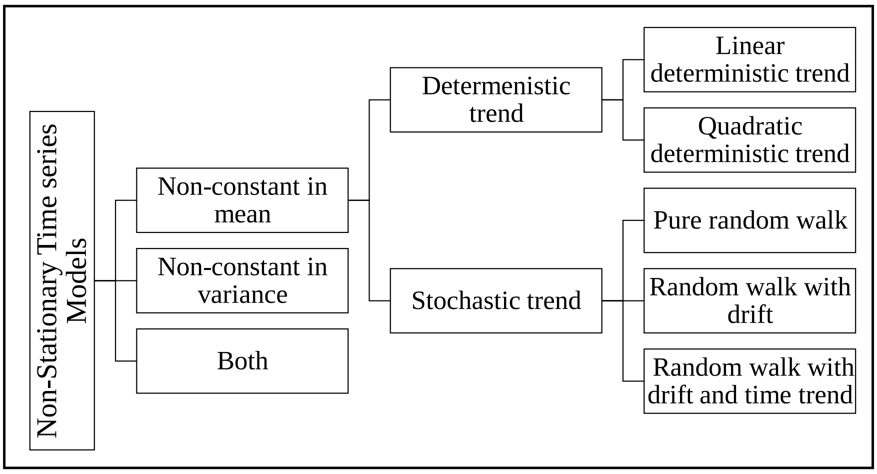

Figure 2. Types of non-stationarity models in time series

Most of the real-world data is non-stationary in nature, and non-stationarity can bring problems, we need to make non-stationary series stationary to be able to use that for forecasting. Most economic and financial series have a single root unit and process with one or more-unit roots can be made stationary through differencing.

3.3 Order of integration

The integration order of a time series, known as I(*d*), is a statistical description that indicates the minimum number of differences needed to obtain stationary series. A non-stationary series y_t with integration order of *d*, in order to become a stationary series, must be differentiated *d* times. It must be considered that all stationary processes are I (0), but not all I (0) processes are stationary.

3.4 Determining the order of integration

For determining the order of integration, an associated Dickey-Fuller test is performed. The null hypothesis of Dickey-Fuller test is that time series is non-stationary. Suppose that we have a series X_t with unknown order of integration, if by applying ADF test we could reject the null hypothesis of non-stationarity, then series is I (0). But if it wasn’t possible to reject the null, we take the first difference of our time series X_t, then we draw a plot of that particular series and if our series now looks stationary then difference ΔX_t is stationary, so we can say X_t was I(1). On the other hand, if our plotted series don’t look stationary, then ΔX_t is not stationary, then X_t is I (2) or above.

3.5 Testing for non-stationarity

Dickey and Fuller carried out the first and pioneering tests for a unit root in a time series (Dickey and Fuller, 1979). The main goal of the test is to test the null hypothesis of the existence of a unit root against the alternative hypothesis of the series is stationary.

For starting the Dickey-Fuller test, an AR process is introduced as follows:

$$X_t = \alpha + \rho X_{t-1} + \varepsilon_t$$

Whereas α is a constant term. In above equation if $\alpha = 0$ then we have a pure random walk without drift, but if $\alpha = 1$ then we have a model with a stochastic time trend or random walk with drift. Also ρ is slope parameter, and ε_t is error term. In Dickey Fuller test there is no need to explicitly specify the type of random process in advance. The null and alternative hypothesis of Dickey Fuller test for above equation is as following:

H_0: $\rho = 1 \Rightarrow$ Time series is not stationary

H_1: $\rho < 1 \Rightarrow$ Time series is stationary

If we just test ρ here whether ρ is different from 1, but the problem is under the null hypothesis both X_t and X_{t-1} are nonstationary and when we have time series which are nonstationary the Normal Central Limit Theorem said apply, so it is not like we can just test ρ using a sort of t-test, it is preferred to take X_{t-1} from both sides, so we have

$$X_t - X_{t-1} = \alpha + (\rho - 1)X_{t-1} + \varepsilon_t$$

$$\Delta X_t = \alpha + \delta X_{t-1} + \varepsilon_t$$

Under the null hypothesis here that $\rho = 1$ this particular δ term would vanish, where as if we have $\rho < 1$ we are going to have stationary process. An actual way to test whether we have a stationary time series, or we have a unit root is just to calculate an ordinary T-statistic on δ term, specifically on the estimated value of $\hat{\delta}$ which is called delta hat, then if we compare that T-statistic with a T-distribution then that would let to determine whether or not we had a stationary time series or a non-stationary time series, but problem is under the null hypothesis being true, X_{t-1} is itself non stationary so the ordinary central limit theorem don't apply for when we are thinking about the estimators for δ or the least square estimators of $\hat{\delta}$, it's not the case that under a large sample size that δ has a given T-distribution or normal distribution. Dickey-Fuller tabulated the asymptotic distribution of the least squares estimators for $\hat{\delta}$ under the null hypothesis of it being a unit root. We can just compare our ordinary T-statistic with the values of Dickey Fuller distribution. While comparing if $t < DF_{critical}$ then we reject the null hypothesis, but if $t > DF_{critical}$ we do not reject the null hypothesis.

3.6 Augmented Dickey-Fuller test

If we have more complicated and higher order autoregressive model, the augmented Dickey-Fuller test is used to investigate stationarity of our time series. The null hypothesis for the augmented Dickey-Fuller test is that a unit root exists, and the alternative hypothesis is slightly different depending on the type of equation is used. The basic alternative is stationary time series. The augmented Dickey-Fuller statistic used in the test is a negative number and the more negative it is, the more strongly the hypothesis that at some level of confidence there is a unit root is rejected (Greene, 2003). The idea of augmented Dickey-Fuller test by using an AR (3) model is described as following:

$$y_t = \theta_1 y_{t-1} + \theta_2 y_{t-2} + \theta_3 y_{t-3} + \varepsilon_t$$

where

$$\begin{cases} \theta_1 : \text{First lag coefficien} \\ \theta_2 : \text{Second lag coefficien} \\ \theta_3 : \text{Third lag coefficien} \\ \varepsilon_t : \text{Error term} \end{cases}$$

Characteristic Polynomial: $\theta(L) \ = \ 1 - \theta_1 L - \theta_2 L^2 - \theta_3 L^3$

Unit root means characteristic polynomial evaluated in one is equal to zero:

$\theta(1) \ = \ 0 \ \Rightarrow \qquad 1 - \theta_1 - \theta_2 - \theta_3 \ = \ 0$

This is restriction that involves all three parameters and in general we do not want to test this restriction on all three parameters at once we would rather want to form reformulate the model here so that we can perform the test for a unit root based on a single coefficient so that's what we do now we start with the model here. So, the first thing we do is we simply rewrite the model in the following way:

$y_t - \ y_{t-1} \ = \ (\theta_1 - 1)y_{t-1} + \theta_2 y_{t-2} + \ \theta_3 y_{t-3} \ + \ \varepsilon_t$ add: $\pm\theta_3 y_{t-2}$

$= \ (\theta_1 - 1)y_{t-1} + (\theta_2 + \theta_3)y_{t-2} \ - \theta_3(y_{t-2} - y_{t-3}) + \varepsilon_t$ add: $\pm(\theta_2 + \theta_3)y_{t-1}$

$= \ (\theta_1 + \theta_2 + \theta_3 - 1)y_{t-1} - (\theta_2 + \theta_3)(y_{t-1} - y_{t-2}) - \theta_3(y_{t-2} - y_{t-3}) + \varepsilon_t$

$\Delta y_t \ = \ \pi y_{t-1} + c_1 \Delta y_{t-1} + c_2 \Delta y_{t-2} + \varepsilon_t$

This is the same model as before but written in a different representation, so we have new set of parameters, but we know exactly how the parameters of the original AR (3) model are linked to the representation we have here.

We had a unit root in the original model if:

Unit root $\quad 1 - \theta_1 - \theta_2 - \theta_3 \ = \ 0$

So $-\pi \ \ = \ 0 \ \ \Longrightarrow \ \pi \ = \ 0$ this is exactly what we want to test.

This equation and this model we have here could easily be extended to include more lags that three then we would start with an AR(p) model, we would rewrite it exactly the same way we have.

$$\Delta y_t = \pi y_{t-1} + \sum_{j=1}^{p-1} c_j \Delta y_{t-j} + \varepsilon_t$$

So, the test is a test of the null hypothesis of a unit root which is as following:

$$\begin{cases} H_0 : \pi = \mathbf{0} \\ H_1 : \pi < \mathbf{0} \end{cases}$$

If $t_{\pi=0} <$ Critical Value then H_0 is rejected.

3.7 Cointegration

According to Phylaktis and Ravazzolo (2005), it is possible to define the relationship between two countries 'stock prices and real exchange rates as:

$$P_t^{BIST} = \alpha_0 + \alpha_1 S_t^T + \alpha_2 P_t^{SP500} + \gamma_t$$

Where

P_t^{BIST} : Borsa Istanbul stock prices

P_t^{SP500} : S&P500 stock prices

S_t^T : Exchange rate

γ_t : Disturbance term

Entire data used in the equation above are represented in real terms and converted by natural logarithms. The real exchange rate is used instead of the nominal exchange rates as proposed by Chow et al. (1997) because it better represents an economy's competitive position when compared to world markets. The US stock market, which reflect the world capital markets, is included in the analysis as a possible link between the foreign exchange and the local stock markets. As stated earlier, while determining exchange rate, "flow-oriented models" and "stock-oriented models", two models will be regarded. The impact of these two distinct models, which is represented by coefficient α_1, can be either positive or negative.

Testing the hypothesis that there is a statistically significant relation among Turkey's domestic stock prices and the real exchange rate and US stock prices could now achieved by testing the presence of a cointegrated combination of the three series.

There are two main methods to test for existence of cointegration, the Engle-Granger method is suitable for the two-variable case. For the multivariate case, where the maximum possible number of cointegrating relationship is (*n-1*), the Johansen procedure must be followed.

We use the likelihood ratio test as demonstrated by (Johansen and control, 1988) and (Johansen and Juselius, 1990) to execute the co-integration test. The following relationship can be defined to continue with:

$$Y_t \equiv (P_t^{BIST}, S_t^T, P_t^{SP500})$$

Where

$$\begin{cases} P_t^{BIST} & : \text{Borsa Istanbul stock prices in real terms} \\ S_t^T & : \text{Real exchange rate for Turkish lira against US dollar} \\ P_t^{SP500} & : \text{S\&P500 stock prices in real terms} \end{cases}$$

If Y_t is cointegrated, a vector error correction model can be produced.

The VECM model is given as:

$$\Delta Y_t = \mu + \sum_{i=1}^{k-1} G_i \, \Delta \mathrm{Y}_{t-i} + G_k Y_{t-1} + \varepsilon_t$$

Where

$$\begin{cases} \mu & \Rightarrow \quad 3 \times 1 \ \text{vector of drift} \\ G & \Rightarrow \quad 3 \times 3 \ \text{matrices of parameters} \\ \varepsilon_t & \Rightarrow \quad 3 \times 1 \ \text{white noise vector} \end{cases}$$

The null-hypothesis of Johansen trace statistics shows that at most r cointegrating vectors $0 \leq r \leq n$ exist, and $(n-r)$ common stochastic trend is:

$$trace = -T \sum_{i=r+1}^{n} ln(1-\hat{\lambda}_i)$$

where

$\hat{\lambda}_i \Rightarrow n-r$ smallest squared canonical correction of Y_{t-1} with respect to ΔY_t corrected for lagged differences

$T \Rightarrow$ used sample size for estimation

3.8 Multivariate Granger causality tests

Besides investigating the long-run co-movements of foreign exchange and stock markets, short-run and long-run dynamics examinations is done by conducting Granger causality test for cointegrating systems. The test findings will explain the wider scale effect of each variable on the relationship. More precisely, as described previously, the test findings will yield a deeper insight of what sort of channel is at work, “stock channel” or “flow channel”.

Suggested by Phylaktis and Ravazzolo (2005), a multivariate Granger causality test could be implemented in order to assess the causality between exchange rates and stock prices. The specifications of the test are built on (Dolado and Lütkepohl, 1996) works. A number of advantages exists in the recommended methodology. To start with, the methodology leads to Wald tests with standard asymptotic χ^2- distributions. This prevents possible pre-test biases involved with the standard procedure, which is to estimate an error correction model in case of cointegrated variables. The technique used is performed on the least square estimators of the VAR process parameters given in the variable levels. This methodology causes for cointegration of variables; therefore, unit roots testing is not required, however, will nevertheless be carried out for clarity. The approach is built on the premise that non-standard asymptotic characteristics of the Wald test on the parameters of cointegrated VAR systems are induced by the singularity of the asymptotic distribution of the least square estimators. The method removes the singularity, if fitted VAR process has an order that exceeds its real order. They demonstrated that this method results in a non-singular allocation of the associated parameters.

The next steps must be followed in order to implement the method. First, the VAR lag structure is generated by testing a VAR (k) with standard Wald test against VAR (k+1), where $k \geq 1$. The next stage is to fit a VAR (k+1) and apply standard Wald testing on the first k VAR coefficient matrix, after confirmation that the true data generation process is a VAR (k). So, the estimation for undifferenced VAR of the VECM of equation is as following:

$$Y_t = \mu + A_1 Y_{t-1} + \ldots + A_p Y_{t-k} + \varepsilon_t$$

Where

$A_i \Rightarrow$ 3 × 3 coefficient matrix

If we expand above equation for our analysis, we have:

$$\begin{bmatrix} P_{BIST} \\ S_T \\ P_{SP500} \end{bmatrix} = \begin{bmatrix} A_{10} \\ S_{20} \\ A_{30} \end{bmatrix} + \begin{bmatrix} A_{11}(L) & A_{12}(L) & A_{13}(L) \\ A_{21}(L) & A_{22}(L) & A_{23}(L) \\ A_{31}(L) & A_{32}(L) & A_{33}(L) \end{bmatrix} \begin{bmatrix} P_{BIST,t-1} \\ S_{T,t-1} \\ P_{US,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{P_{BIST}} \\ \varepsilon_{S_t} \\ \varepsilon_{P_{US}} \end{bmatrix}$$

Where

$A_{i0} \Rightarrow$ parameters of interception terms

$A_{ij} \Rightarrow$ polynomial in the lag operator L

3.9 Dynamic conditional correlation

3.9.1 The DCC method's foundation

Following the Malliaropulos (1998), the design of the DCC methodology used for this study can be defined. He provides a theoretical model of the link between the real exchange rate and the stock return differentials between two economies. He outlines the relative stock price represented in the home currency between foreign and domestic economies, with all variables in logarithms. Relative stock price for the case of our studies is as following:

$$\rho_t = S_{BIST} - S^*_{SP500} - e_t \tag{1}$$

Where variables are defined as:

$$\begin{cases} S_{BIST} & \Rightarrow & \text{Borsa Istanbul stock prices} \\ S^*_{SP500} & \Rightarrow & \text{S\&P500 stock prices} \\ e_t & \Rightarrow & \text{Number of domestic currencies per unit of foreign currency} \end{cases}$$

And the real exchange rate is defined as:

$$q_t = e_t + p^*_t - p_t \tag{2}$$

Where the variables are defined as:

$$\begin{cases} p_t \Rightarrow \text{Domestic price} \\ p_t^* \Rightarrow \text{Foreign price} \end{cases}$$

As proposed by Baxter and Crucini (1994) and Huizinga (1987), the real exchange rate is considered to consist of permanent (q_t^p) and temporary (q_t^T) factors. So, the real exchange rate is defined as:

$$q_t = q_t^p + q_t^T \tag{3}$$

Where q_t^p and q_t^T are defined as:

$$\begin{cases} q_t^p = \mu + q_{(t-1)}^p + \varepsilon_t^p & (4) \\ q_t^T = \theta q_{(t-1)}^T + \varepsilon_t^T & (5) \end{cases}$$

Where:

$$\begin{cases} q_t^p \Rightarrow \text{The permanent component is a random walk} \\ \mu \Rightarrow \text{Drift} \\ \varepsilon_t^p \Rightarrow \text{Serially uncorrelated innovations} \end{cases}$$

$$\begin{cases} q_t^T \Rightarrow \text{Follows a first order autoregressive process with } 0<\theta<1 \\ \varepsilon_t^T \Rightarrow \text{Serially uncorrelated innovations} \end{cases}$$

Likewise, according to Fama and French (1988) and Poterba and Summers (1987), it is presumed that the relative stock price incorporates both permanent and temporary components, p_t^P and p_t^T respectively.

$$\rho_t = \rho_t^P + \rho_t^T \qquad (6)$$

Where each component is defined as:

$$\rho_t^P = \gamma + \rho_{t-1}^P + \eta_t^P \qquad (7)$$

$$\rho_t^T = \phi\rho_{t-1}^T + \eta_t^T , 0 < \phi < 1 \qquad (8)$$

Both η_t^P and η_t^P which are serially uncorrelated innovations, have been assumed that they are respectively uncorrelated with ρ_t^P andρ_t^T. Furthermore, the expected changes in the real exchange rate and stock prices differential could also be outlined as:

$$E_{t-1}\Delta\rho_t = E_{t-1}\Delta(S_{BIST} - S^*{}_{SP500} - e_t) \qquad (9)$$

$$E_{t-1}\Delta q_t = E_{t-1}\Delta(e_t + p^*{}_t - p_t) \qquad (10)$$

Where E_{t-1} is expectation at time $t-1$ given all available information. Eq. 9 and Eq.10 could also be similar to the uncovered interest rate parity added to stock returns with a risk premium where both foreign exchange risk and relative stock return risk may be included in the risk premium $E_{t-1}\Delta\rho_t$. One of the major risk factors in global equity investment is foreign exchange risk. The expected deviation from relative purchasing power parity (PPP) is indicated in the Eq. 10. The model's real stock return differential can be presented as:

$$\Delta z_t = \Delta(s_t - p_t) - \Delta(s_t^* - p_t^*) \tag{11}$$

The following equation can now be described from Eq. 9 and Eq.10 after the components have been rearranged:

$$E_{t-1}\Delta\rho_t = E_{t-1}\Delta z_t - E_{t-1}\Delta q_t \tag{12}$$

From Eq. 12 it can be extracted that the expected stock return differential is equal to the expected real stock differential but deducted by the expected change in the real exchange rate. A temporary component of the series can replace the unobservable expected change. Therefore, the following expressions are respectively obtained from Eq. 4, Eq. 5, Eq. 7 and Eq. 8.

$$E_{t-1}\Delta q_t = \mu + (\theta - 1)q_t^T \tag{13}$$

$$E_{t-1}\Delta\rho_t = \gamma + (\phi - 1)\rho_t^T \tag{14}$$

The expected real depreciation is linked to the temporary component of the real exchange rate while expected risk premium is tied to the temporary components of the stock price differential. By replacing Eq. 13 and Eq. 14 with Eq. 12, we obtain the dynamic relationship as:

$$\rho_t^T = -\frac{(\mu+\gamma)}{(\phi-1)} - \{\frac{(\theta-1)}{(\phi-1)}\}q_t^T + \{\frac{1}{(\phi-1)}\}E_t\Delta z_t \qquad (15)$$

Since both parameters of the autoregressive terms, θ and ϕ, are between the interval of 0 and 1, therefore the temporary component of the relative stock price is more probable to be negatively linked with the temporary deviations of the real exchange rate from PPP. A negative correlation would imply that an appreciation of exchange rates would occur when stock price rises, and a depreciation of exchange rates can happen when stock prices decreases. Empirical findings, as stated earlier, significantly vary on the relationship's causal direction whether it is positive or negative. In the monetary sector, the dynamic movement can be described, and the negative prediction is compliant with the portfolio model to exchange rate determination (Phylaktis & Ravazzolo, 2005).

3.9.2 The DCC model

According to Engle (2002) the bivariate GARCH model with DCC specification can be used in analyzing the connection between real exchange rates (q_t) and stock price differentials (ρ_t). The conditional mean equation can be described from this relationship as:

$$y_t = \mu + \varepsilon_t \quad \& \quad \varepsilon_t|\xi_t - 1 \sim N(0, H_t) \qquad (16)$$

Where

$y_t \Rightarrow [y_{1t}, y_{2t}]'$ a 2×1 vector which contains the series of stock price differentials and real exchange rates

$\mu \Rightarrow 2 \times 1$ vector of constant

$\varepsilon_t \Rightarrow [y_{1t}, y_{2t}]'$ vector of innovations conditional at time t$-1(\xi_t - 1)$

In addition, it is assumed that the error term is conditionally multivariate normal with zero mean and variance-covariance matrix defined as:

$$H_t = D_t C_t D_t \qquad (17)$$

$D_t \Rightarrow 2 \times 1$ diagonal matrix of the time varying standard deviations from univariate GARCH models with $\sqrt{h_{i,t}}$ on the i^{th} diagonal

$C_t \Rightarrow 2 \times 2$ time varying symmetric conditional correlation matrix

As mentioned, the components in D_t follow the following univariate GARCH process:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \qquad (18)$$

Where

$\omega_i \Rightarrow$ Constant term

$\alpha_i \Rightarrow$ The conditional volatility (ARCH effect)

$\beta_i \Rightarrow$ Volatility persistence

Expansion of the DCC model correlation can be defined as:

$$Q_t = (1 - q_a - q_b)\bar{Q} + q_a \varepsilon_{t-1}\varepsilon_{t-1}' + q_b Q_{t-1} \qquad (19)$$

Where:

$Q_t \Rightarrow \{q_{ij}\}_t$ a 2×2 conditional variance-covariance matrix of residuals with its time- invariant variance-covariance matrix $Q = E(\varepsilon_T \varepsilon_t')$

$q_i \Rightarrow$ Non-negative scalar parameters satisfying $q_a + q_b < 1$

Subsequently, Q_t is scaled to obtain an accurate matrix of correlation C_t as it doesn't have unit diagonal elements in above Eq. 18.

$$C_t = diag(Q_t)^{1/2} Q_t diag(Q_t)^{-1/2} \qquad (20)$$

The form of a typical element in C_t is $\rho_{ij} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}$, $i, j = 1,2$ and $i \neq j$ which is the main element in the DCC methodology, because it represents the conditional correlation between stock price differentials and real exchange rates.

CHAPTER 4

EMPIRICAL RESULTS

4.1 The Data

Data used for this research was obtained from Thomson Reuters Eikon DataStream. The sample period chosen for this study is from February 2003 to February 2019. Timeseries used for this thesis are the following; monthly price index of BIST National 100, monthly price index of S&P500, monthly Turkish lira to US dollar exchange rate, monthly Turkish consumer price index, and monthly US consumer price index.

4.2 Cointegration results for Johansen test

Before running Johansen cointegration test we should identify the order of our time series and time series should be in log form and nonstationary. The best way to identify and confirm non-stationarity of time series is to plot their graph. According to Figure 3 our time-series are non-stationary over period of analysis. Also, for the purpose our studies ADF test has been done on time series.

Theory of Johansen test is applied by using “urca” and “vars” packages in the R statistical environment. At the first stage, the unit root tests are tested on all three log time series, and result confirms non-stationarity of log time series which are coherent with visual inspection of series graphs of Figure 3. By applying diff function on log data, and testing with ADF test, it is understood that return series are stationary, which leads to the conclusion that our time series at first stage are I (1). These results are correspondent with the graphs of Figure 4 which indicates that returns series are stationary.

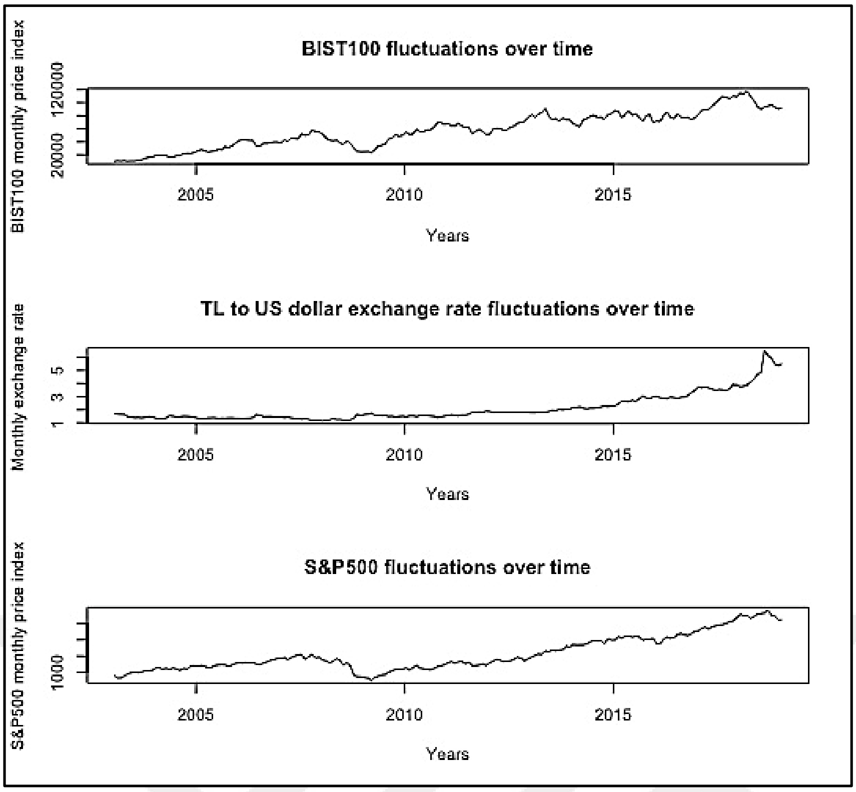

Figure 3. Graph of BIST100 and S&P500 and exchange rates

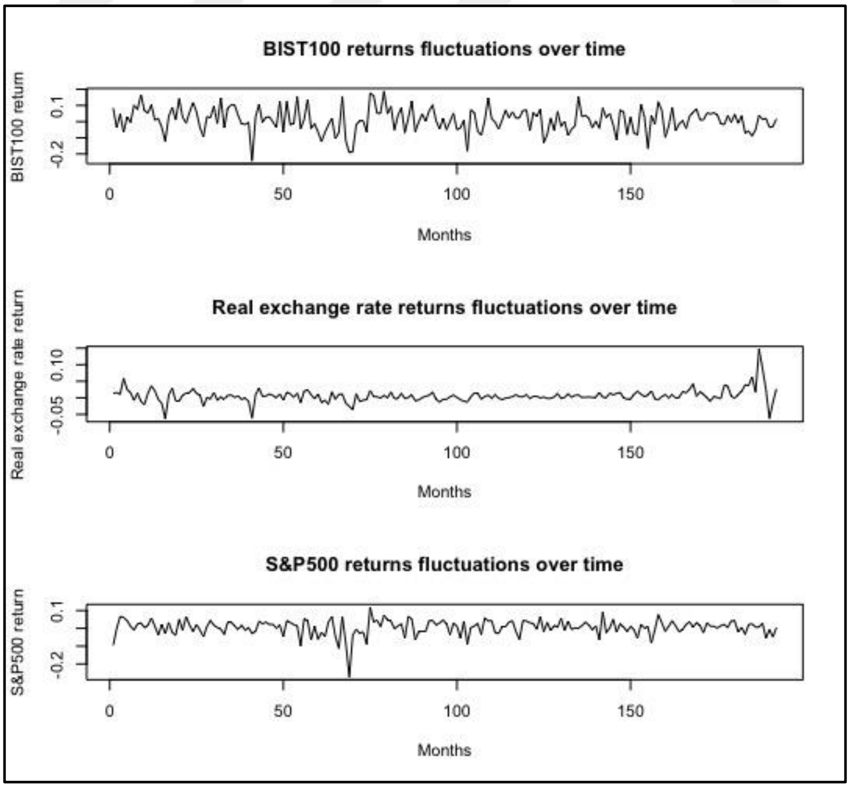

Figure 4. Graph of BIST100 and S&P500 and exchange rates (return format)

After pretesting and confirming that all variables have same order of Integration, which is I (1), now we can proceed to Johansen co-integration test. In Johansen test using undifferenced data is preferred, and by this test, the existence of cointegration relation among variables is analyzed, moreover we can identify the number of co-integrated vectors in our series.

Table 1. ADF Test for Log BIST100

Test Statistic	-2.7938	4.505	4.9488
Significance level	1%	5%	10%
τ_3	-3.99	-3.43	-3.13
ϕ_2	6.22	4.75	4.07
ϕ_3	8.43	6.49	5.47

Table 2. ADF Test for Log S&P500

Test Statistic	-1.7994	2.2511	1.6197
Significance level	1%	5%	10%
τ_3	-3.99	-3.43	-3.13
ϕ_2	6.22	4.75	4.07
ϕ_3	8.43	6.49	5.47

Table 3. ADF Test for Log Real Exchange Rate

Test Statistic	0.9271	4.0163	2.5714
Significance level	1%	5%	10%
τ_3	-3.99	-3.43	-3.13
ϕ_2	6.22	4.75	4.07
ϕ_3	8.43	6.49	5.47

Under the assumption of no cointegration among variables the rank of matrix $\pi = 0$. There is two possible test statistic to choose from depending on the alternative hypothesis. If the null hypothesis of no cointegration among variables against the alternative of one or more cointegrating vectors is desired, then $\lambda_{\text{trace}}(0)$ must be calculated.

Several types of Johansen test are performed on series such as cointegration among three variables were examined at first step, and then cointegration between 2 variables one by one was tested.

According to Table 4 29.24 falls behind the 5% critical value of the λ_{trace} statistic, which is 34.91, therefore the null hypothesis of no cointegrating vector at 5% significance level couldn't be rejected.

Also, from Table 4, since 15.93 couldn't exceed the 5% critical of value of 22, it can easily be understood that rejecting the null hypothesis of no cointegrating vector against the specific alternative of one cointegrating vector, is not possible. Consistent with the result of Johansen test in Table 4, it can be concluded that no cointegration exist among three variables.

Table 4. Johansen Test Results for n = 3

Null Hypothesis	Alternative Hypothesis	value	10%	5%	1%
λ_{trace} tests		λ_{trace} value			
$r \leq 2$	$r > 2$	2.98	7.52	9.24	12.97
$r \leq 1$	$r > 1$	13.31	17.85	19.96	24.60
$r = 0$	$r > 0$	29.24	32.00	34.91	41.07
λ_{max} tests		λ_{max} value			
$r \leq 2$	$r = 3$	2.98	7.52	9.24	12.97
$r \leq 1$	$r = 2$	10.34	13.75	15.67	20.20
$r = 0$	$r = 1$	15.93	19.77	22.00	26.81

Table 5 which shows the Johansen test result between BIST100 and exchange rates. In accordance with result of test for the null hypothesis of r = 0 against the alternative of r = 1, which r is the number of cointegrating vectors, test statistic 23.68 is larger than the critical value of 15.67 at 5% significance level, hence the null hypothesis of no cointegrating vector is rejected, and the alternative hypothesis of one cointegrating vector is accepted. Consistent with test results, the test of the null hypothesis r = 1 against the alternative of r = 2, can't be rejected at 1% significance level, but barely rejected at 95% confidence level.

Table 5. Johansen Test Results for BIST100 and Real Exchange Rate

Null Hypothesis	Alternative Hypothesis	λ_{max} value	10%	5%	1%
$r \leq 1$	$r = 2$	9.33	7.52	9.24	12.97
$r = 0$	$r = 1$	23.68	13.75	15.67	20.20

These are the cointegration relations			
	L_BIST.l1	L_RealEXCH.l1	constant
L_BIST.l1	1.000000	1.0000000	1.0000000
L_RealEXCH.l1	-7.014408	-0.1705628	-3.35727
constant	-11.811466	-11.0491388	-10.53318

According to Johansen test, the maximum number of cointegrating vector equals to number of variables-1, so in our case we have one cointegrating vector between BIST100 and real exchange rates, which means there is a long run relationship between them. Due to existence of long run association between BIST100 and exchange rate, it is possible to estimate the vector error correction model. According to Table 5 we extract cointegrating vector as:

$$S = 1 \times (BIST100) - 7.014408 \times (real\ exchange\ rate) - 11.811466$$

In accordance with Table 6, which indicates the result of Johansen test between S&P500 and exchange rate, the following result can be perceived. Since 13.30 is smaller than the critical value at 5% significance level, which is 15.67, we fail to reject the null hypothesis of r = 0, and as a result it can be concluded that there is no cointegration between S&P500 and Exchange rate.

Table 6. Johansen Test Results for S&P500 and Real Exchange Rate

Null Hypothesis	Alternative Hypothesis	λ_{max} value	10%	5%	1%
$r \leq 1$	$r = 2$	4.19	7.52	9.24	12.97
$r = 0$	$r = 1$	13.30	13.75	15.67	20.20

Table 7 indicates the result of Johansen test between BIST100 and S&P500. The null hypothesis of r = 0 against the alternative of r = 1 was tested, and since test statistic 10.10 couldn't surpass critical value of 15.67 at 5% significance level, it wasn't possible to reject the null hypothesis. We conclude that no cointegration vector exists between BIST100 and S&P500.

Table 7. Johansen Test Results for BIST100 and S&P500

Null Hypothesis	Alternative Hypothesis	λ_{max} value	10%	5%	1%
$r \leq 1$	$r = 2$	2.63	7.52	9.24	12.97
$r = 0$	$r = 1$	10.10	13.75	15.67	20.20

Tables 4, 5, 6 and 7 indicate test results for analyzing existence of cointegration among three variables. In all cases the null hypothesis of no-cointegration among variable couldn't be rejected, except for the cointegration between BIST100 and real exchange rate. As a result, there is only one cointegration vector between BIST100 and real exchange rate.

4.3 Granger causality test results

Before running Granger causality, we should be sure about stationarity of our data, since our log prices were I (1), first difference function were applied on them and they became stationary. For checking stationarity of data ADF test were used, and results confirm that there is no unit root for data used in Granger test.

Result of multivariate Granger causality test among three variables is indicated in Table 8. We couldn't reject the null hypothesis of no causality among three variables except for first case. The null hypothesis of BIST100 returns do not Granger causes real exchange returns and S&P500 returns was rejected due to small p-value, and alternative hypothesis of BIST100 returns Granger causes real exchange returns and S&P500 returns is accepted. For in depth analysis, Granger causality between all three variables with different null hypotheses were tested. In all situations, due to high p-value it wasn't possible to reject the null hypotheses, except for the null hypothesis of BIST100 returns do not Granger-cause real exchange returns. Aforementioned hypothesis was rejected due to small *p*-value of 0.03641 and alternative hypothesis of Granger causality from BIST100 returns to real exchange rate returns was accepted. Therefore, we can conclude that past values of BIST100 could be useful in predicting the future values of real exchange rate. Results of multivariate Granger causality tests are consistent with the results of Johansen test. In the Johansen test only one cointegration relation between BIST100 and real exchange rate is found, and direction of causality is from BIST100 to real exchange rates.

Table 8. Granger Causality Test with VAR among RetBIST and RetREX and RetSP

Granger causality H_0	RetBIST do not Granger-cause RetREX RetSP		
F-Test = 5.8205	*df1* = 2	*df2* = 561	*p*-value = 0.003148
H_0	No instantaneous causality between: RetBIST and RetREX RetSP		
Chi-squared = 46.489	*df* = 2		*p*-value = 8.035e-11

Granger causality H_0	RetREX do not Granger-cause RetBIST RetSP		
F-Test = 0.4267	*df1* = 2	*df2* = 561	*p*-value = 0.6529
H_0	No instantaneous causality between: RetREX and RetBIST RetSP		
Chi-squared = 16.778	*df* = 2		*p*-value = 0.0002274

Granger causality H_0	RetSP do not Granger-cause RetBIST RetREX		
F-Test = 2.8261	*df1* = 2	*df2* = 561	*p*-value = 0.06009
H_0	No instantaneous causality between: RetSP and RetBIST RetREX		
Chi-squared = 44.386	*df* = 2		*p*-value = 2.3e-10

Table 9. Testing Granger Causality with VAR between RetBIST and RetREX

Granger causality H_0	RetBIST do not Granger-cause RetREX		
F-Test = 4.4091	*df1* = 1	*df2* = 376	*p*-value = 0.03641
H_0	No instantaneous causality between: RetBIST and RetREX		
Chi-squared = 15.362	*df* = 1		*p*-value = 8.873e-05

Granger causality H_0	RetREX do not Granger-cause RetBIST		
F-Test = 0.00049798	*df1* = 1	*df2* = 376	*p*-value = 0.9822
H_0	No instantaneous causality between: RetREX and RetBIST		
Chi-squared = 15.362	*df* = 1		*p*-value = 8.873e-05

Table 10. Testing Granger Causality with VAR between RetBIST and RetSP

Granger causality H_0	RetBIST do not Granger-cause RetSP		
F-Test = 0.89732	*df1* =1	*df2* = 376	*p*-value = 0.3441
H_0	No instantaneous causality between: RetBIST and RetSP		
Chi-squared = 43.325	*df* = 1		*p*-value = 4.637e-11

Granger causality H_0	RetSP do not Granger-cause RetBIST		
F-Test = 0.36084	*df1* =1	*df2* = 376	*p*-value = 0.5484
H_0	No instantaneous causality between: RetSP and RetBIST		
Chi-squared = 43.325	*df* = 1		*p*-value = 4.637e-11

Table 11. Testing Granger Causality with VAR between RetREX and RetSP

Granger causality H_0	RetREX do not Granger-cause RetSP		
F-Test = 0.78122	*df1* = 1	*df2* = 376	*p*-value = = 0.3773
H_0	No instantaneous causality between: RetREX and RetSP		
Chi-squared = 9.3213	*df* = 1		*p*-value = 0.002265

Granger causality H_0	RetSP do not Granger-cause RetREX		
F-Test = 1.0041	*df1* = 1	*df2* = 376	*p*-value = 0.317
H_0	No instantaneous causality between: RetSP and RetREX		
Chi-squared = 9.3213	*df* = 1		*p*-value = 0.002265

4.4 DCC results

As we know volatility clustering periods in most of economic time series is observed, in which high volatile and low volatile clustering exist during these time periods. In many economic time series probabilities of time varying volatility is higher than constant volatility. We are not able to capture time varying volatility with ARIMA models, since ARIMA model's conditional variance is invariant, but by using GARCH models we can properly model these time varying volatilities. GARCH models permit a series' conditional variance to rely on previous error performance. In many risk management techniques conditional variance is a measure of risk, and concurrently estimating the conditional volatility of the variables often are sensible in a data set with a number of variables. The idea that contemporary shock to variables could be correlated with one another benefits multivariate GARCH models. For example, we might presume that volatilities among BIST100 returns, real exchange returns and S&P500 returns are interrelated. It is possible that shocks to the Borsa Istanbul stock prices might increase the uncertainty of the Turkish lira exchange rate against US dollar and increase the volatility of exchange market. In this part with assuming the possibility that the shocks are correlated; volatility of variables has been modeled and estimated by multivariate GARCH model.

With using "rmgarch" and "rugarch" packages both written by (Alexios Ghalanos, 2019) and by DCC-GARCH method, dynamic conditional correlation among our variables have been analyzed.

Prior to start DCC-GARCH analysis we need to fit our series to ARIMA models. Normal distribution of residuals and having neither serial correlation in the squared residuals nor ARCH effect are essential characteristics of a fine fitted model.

Tests for assessing no autocorrelation is done by Ljung-Box test, which is a quantitative mean for investigating the null hypothesis of independency in residuals. Also, test for conditional heteroscedasticity is done by ARCH LM test in R software's "tseries" package.

As it is indicated in Table 12 all *p*-values are greater than 0.05, as a result we have independent residuals, which means innovations are independent and our fitted model is fine.

Table 12. Ljung-Box Test Results

Data	χ^2	*df*	*p*-value
BIST100 return residuals	12.694	12	0.3917
BIST100 return squared residuals	10.268	12	0.5925
Real exchange rate residuals	11.009	12	0.5282
Real exchange rate squared residuals	19.824	12	0.07049
S&P500 return residuals	13.119	12	0.3604
S&P500 return squared residuals	13.027	12	0.3671

According to result of Table 13 we fail to reject the null of no ARCH effect in squared residuals of BIST100 and S&P500 return, and real exchange rate, which means that our fitted model doesn't show ARCH effect.

Table 13. ARCH LM Test Results

Data	χ^2	*df*	*p*-value	Null hypothesis
BIST100 return squared residuals	3.9891	12	0.9836	no ARCH effect
Real exchange rate squared residuals	3.9058	12	0.9851	no ARCH effect
S&P500 return squared residuals	0.27949	12	1	no ARCH effect

Based on the results from both Tables 12 and Table 13, it is possible to run multivariate DCC-GARCH to model the volatility in our series. The estimates of

DCC (1, 1)-GARCH (1, 1) model are presented in the Table 14. Among estimated GARCH model parameters, β_{BIST} and $\beta_{S\&P100}$, which are respectively coefficients for lagged variances of BIST100 returns and S&P500 returns, have higher statistical significance than others. Due to high significance of β_{BIST} and $\beta_{S\&P100}$ parameters, higher persistence in shocks to the conditional volatility exists in these markets, and the larger magnitude of β_{BIST} signifies that BIST100 returns persist more in volatility than that of S&P500 and real exchange rate. Since sum of α and β is almost equal to unity in BIST100 market which denotes a high persistence of the conditional variance, consequently volatility in the GARCH models of this markets display a high persistence. The Figure 5 confirms our results, by indicating that BIST100 return residuals show higher volatility and higher persistence in volatility over time period than the other time series.

The impacts of standardized lagged shocks and the lagged dynamic conditional correlation on current dynamic conditional correlation are respectively captured by *dcca1* and *dccb1*. As it is indicated in Table 14 these time-varying correlation parameters have high statistical significance, which signifies presence of considerable time-varying dynamic correlation. If sum of the DCC parameters were equal to zero, then we would have constant conditional correlation, but according to our results sum of dcca1 and dccb1 is very close to unity, means that conditional correlations are highly persistent. In addition, because sum of the DCC parameters are less than one, we conclude that the dynamic correlation rotates around a fixed level. Also, joint significance of *dcca1* and *dccb1*, confirms that DCC-GARCH model is appropriately specified for the given time series.

Table 14. DCC-GARCH Parameters

	Estimate	Std. Error	*t* value	Pr (> |t|)
BIST100				
μ_{BIST}	0.011626	0.006037	1.925730	0.054138
ω_{BIST}	0.000132	0.000503	0.262747	0.792746
α_{BIST}	0.036222	0.044018	0.822887	0.410572
β_{BIST}	0.937562	0.122552	7.650322	0.000000
Shape $_{BIST}$	13.355553	11.300553	1.181849	0.237265
Real exchange rate				
μ_{RER}	0.003452	0.004034	0.855711	0.392158
ω_{RER}	0.000009	0.000175	0.049064	0.960868
α_{RER}	0.240553	0.293099	0.820723	0.411804
β_{RER}	0.758447	1.870052	0.405575	0.685055
Shape $_{RER}$	4.133284	10.622763	0.389097	0.697204
S&P100				
$\mu_{S\&P100}$	0.009707	0.002773	3.500915	0.000464
$\omega_{S\&P100}$	0.000154	0.000140	1.098232	0.272103
$\alpha_{S\&P100}$	0.127324	0.092002	1.383934	0.166379
$\beta_{S\&P100}$	0.777332	0.142748	5.445474	0.000000
Shape $_{S\&P100}$	5.912417	2.483591	2.380592	0.017285
dcca1	0.044056	0.006231	7.070979	0.000000
dccb1	0.940413	0.010958	85.815965	0.000000

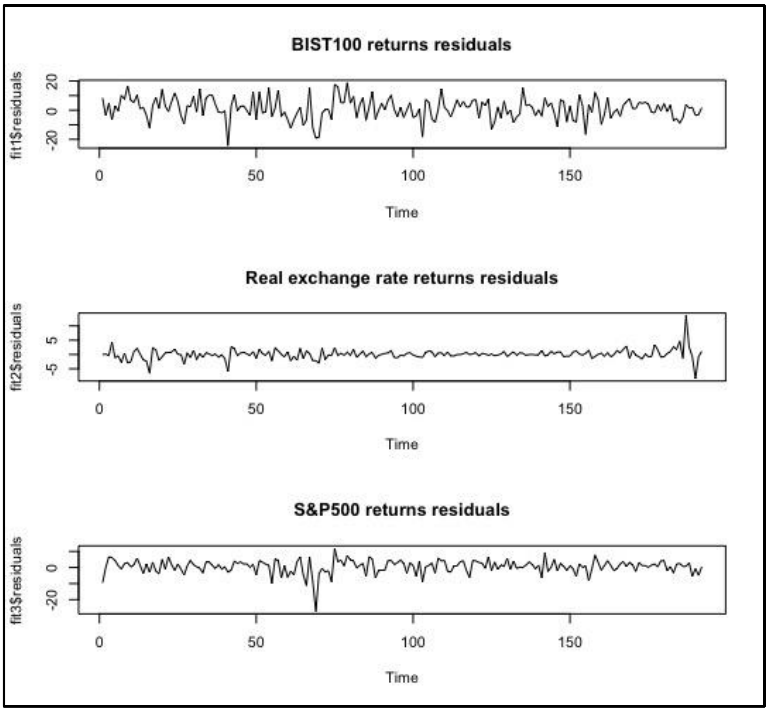

Figure 5. Residuals of fitted ARIMA model

While estimating a multivariate volatility model, we are concerned in the estimated covariance or correlation matrices. Figure 6 indicate time-varying correlation among our time series. As it can be seen from Figure 6, high similarity exist between the correlation of BIST100& RER and the correlation of RER&SP500 , where in both cases the correlation varies between -0.2 and 0.4 , and also significant variation exist between dynamic conditional correlation of BIST100 and S&P500 returns over time with the varying correlation between 0.3 and 0.6. Moreover, dynamic conditional correlation between BIST100 & RER returns shows less volatility than others, especially for a long period of time (between 50th and 100th observation) almost shows no change, which implies that BIST returns and real exchange rate returns are more correlated with each other as well confirms our results from both multivariate Granger causality test and Johansen cointegration test , that suggested only one cointegrated vector is between BIST100 and real exchange rate, and direction of causality is from BIST100 returns to real exchange rate returns.

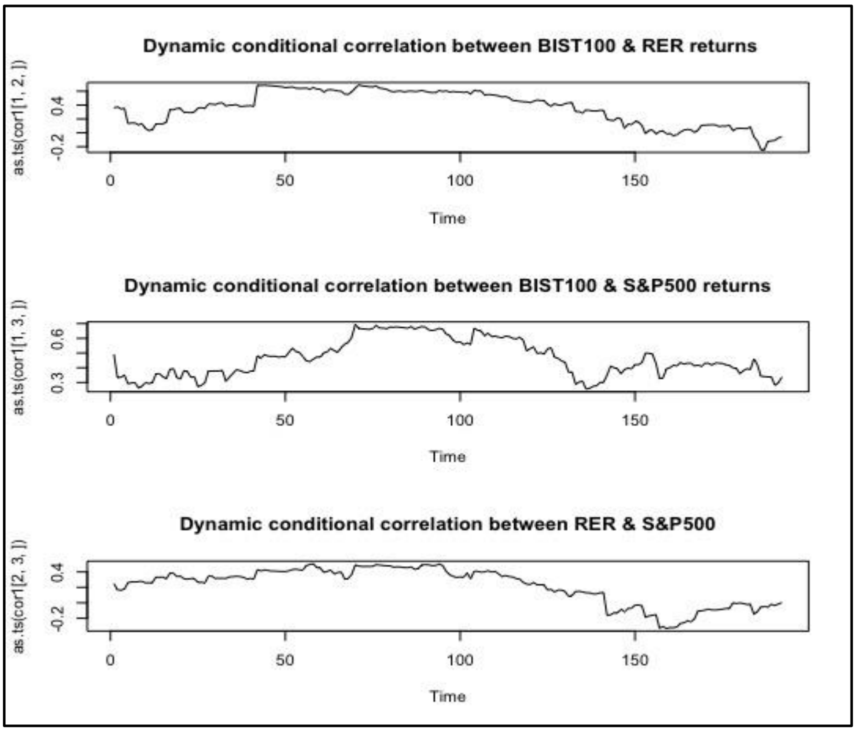

Figure 6. Correlation among our series

In the next step our estimated model is used to generate covariance or correlation matrix forecasts. Figure 7 indicates the result for DCC-GARCH forecast plots for our series.

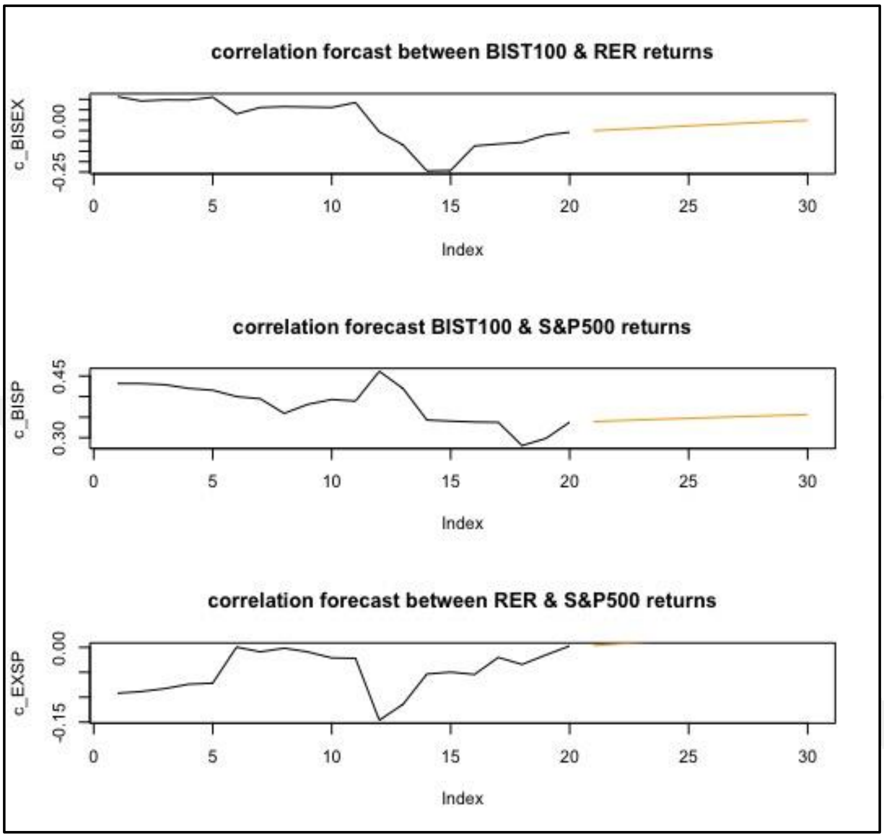

Figure 7. DCC-GARCH model forecasted correlation for next 10 months

Forecasted dynamic correlation for future 10 months, are based on previous 20 months observations. According to Figure 7 dynamic correlation between BIST100 & RER returns was positive at the beginning of observation, then decreased and became negative. In the short-run for the future over the coming next 10 months we expect slightly negative weak correlation.

According to figure above in the all correlation between variables there is a sharp fall in correlation then started to increase again. Correlation between BIST100 and RER shows less volatility and is forecasted that will increase for next 10 months.

CHAPTER 5

CONCLUSION

This thesis investigates the relation between the fluctuation in Turkish lira versus US dollar and Borsa Istanbul stock prices. Both short-run and long-run relationship between Borsa Istanbul prices and exchange rates (against US dollar) were examined.

Attempts was made to identify the presence of cointegration between these variables. Examination were done to find the causality relation between BIST100 stock prices and exchange rates, and to discover the direction of this causality. Furthermore, dynamic conditional correlation between stock prices and exchange rates was estimated and time-varying correlation between them was predicted for future months.

Results from cointegration method suggest that only one cointegrated vector exists between Borsa Istanbul stock prices and exchange rates. Multivariate Granger test results found only one causal relation from BIST100 prices to exchange rates but failed to find any causal relation in reverse direction. Based on multivariate Granger causality test results BIST100 prices Granger causes Turkish lira exchange rates against US dollar, therefore past values of BIST100 stock prices can be helpful in forecasting future values of the exchange rates in Turkey. Dynamic conditional correlation findings imply the existence of dynamic conditional correlation among variables and suggests that volatility is more persistent in Turkish stock market than the volatility in foreign exchange market. Due to high significance of DCC parameters, the results have proven the usefulness of DCC-GARCH method for establishing a time-varying conditional correlation. Estimated conditional correlation between stock prices and exchange rates shows that the sign of the correlation was positive for the earlier observations, whereas it became negative after a while, but for the future observations positive correlation is forecasted. According to the results of applied methodologies, our results are in agreement with portfolio balance model.

REFERENCES

Abdalla, I. S., & Murinde, V. (1997). Exchange rate and stock price interactions in emerging financial markets: Evidence on India, Korea, Pakistan and the Philippines. *Applied financial economics*, *7*(1), 25-35.

Abidin, S., Walters, C., Lim, K. L., & Banchit, A. (2013). Cointegration between stock prices and exchange rates in Asia-Pacific countries. *Investment Management and Financial Innovations*, *5*(2), 142-146.

Aggarwal, R. (2003). Exchange rates and stock prices: A study of the US capital markets under floating exchange rates.

Aielli, G. P. (2013). Dynamic conditional correlation: on properties and estimation. *Journal of Business & Economic Statistics*, *31*(3), 282-299.

Aslam, M. T., & Ramzan, M. (2013). Impact of consumer price index, real effective exchange rate index, per capita income and discount rate on Pakistan's stock market index. *International Journal of Research in Commerce, Economics and Management*, *3*(5), 10-14.

Basher, S. A., Haug, A. A., & Sadorsky, P. (2012). Oil prices, exchange rates and emerging stock markets. *Energy Economics*, *34*(1), 227-240.

Baxter, M., & Crucini, M. J. (1994). *Business cycles and the asset structure of foreign trade* (No. w4975). National Bureau of Economic Research.

Branson, W. H. (1983). A model of exchange-rate determination with policy reaction: evidence from monthly data.

Büberkökü, Ö. (2013). The Relationship Between Stock Prices And Exchange Rates: Evidence From Developed And Developıng Countries. *The ISE Review*, *13*(52), 1-16.

Caporale, G. M., Hunter, J., & Ali, F. M. (2014). On the linkages between stock prices and exchange rates: Evidence from the banking crisis of 2007–2010. *International Review of Financial Analysis*, *33*, 87-103.

Chkili, W., Aloui, C., & Nguyen, D. K. (2012). Asymmetric effects and long memory in dynamic volatility relationships between stock returns and exchange rates. *Journal of International Financial Markets, Institutions and Money*, *22*(4), 738-757.

Chortareas, G., Cipollini, A., & Eissa, M. A. (2011). Exchange rates and stock prices in the MENA countries: what role for oil?. *Review of Development Economics*, *15*(4), 758-774.

Chow, E. H., Lee, W. Y., & Solt, M. E. (1997). The exchange-rate risk exposure of asset returns. *Journal of Business*, 105-123.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*(366a), 427-431.

Dolado, J. J., & Lütkepohl, H. (1996). Making Wald tests work for cointegrated VAR systems. *Econometric Reviews*, *15*(4), 369-386.

Dornbusch, R., & Fischer, S. (1980). Exchange rates and the current account. *The American Economic Review*, *70*(5), 960-971.

Eita, J. H. (2012). Modelling macroeconomic determinants of stock market prices: Evidence from Namibia. *Journal of Applied Business Research (JABR)*, *28*(5), 871-884.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, *20*(3), 339-350.

Engle, R. F., & Granger, C. W. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica: journal of the Econometric Society*, 251-276.

Fama, E. F., & French, K. R. (1988). Dividend yields and expected stock returns. *Journal of financial economics*, *22*(1), 3-25.

Frankel, J. A. (1992). Monetary and portfolio-balance models of exchange rate determination. In *International economic policies and their theoretical foundations* (pp. 793-832). Academic Press.

Gavin, M. (1989). The stock market and exchange rate dynamics. *Journal of international money and finance*, *8*(2), 181-200.

Ghalanos, A. (2012). rmgarch: Multivariate GARCH models. R package version 0.98.

Ghalanos, A. (2018). rugarch: Univariate GARCH models., 2012a. *R package version*, 1-0.

Granger, C. W., Huangb, B. N., & Yang, C. W. (2000). A bivariate causality between stock prices and exchange rates: evidence from recent Asianflu☆. *The Quarterly Review of Economics and Finance*, *40*(3), 337-354.

Greene, W. H. (2003). *Econometric analysis*. Pearson Education India.

Groenewold, N., & Paterson, J. E. (2013). Stock Prices and Exchange Rates in A ustralia: Are Commodity Prices the Missing Link?. *Australian Economic Papers*, *52*(3-4), 159-170.

Harjito, D. A., & McGowan Jr, C. B. (2007). Stock price and exchange rate causality: The case of four asean countries. *Southwestern Economic Review*, *34*, 103-114.

Huizinga, J. (1987, January). An empirical investigation of the long-run behavior of real exchange rates. In *Carnegie-Rochester conference series on public policy* (Vol. 27, pp. 149-214). North-Holland.

Huy, T. Q. (2016). The linkage between exchange rates and stock prices: Evidence from Vietnam. *Asian Economic and Financial Review*, *6*(7), 363.

Inegbedion, H. E. (2012). Macroeconomic determinants of stock price changes: Empirical evidence from Nigeria. *Indian Journal of Finance*, *6*(2), 19-23.

Ismail, M. T., & Bin Isa, Z. (2009). Modeling the interactions of stock price and exchange rate in Malaysia. *The Singapore Economic Review*, *54*(04), 605-619.

Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration—with applications to the demand for money. *Oxford Bulletin of Economics and statistics*, *52*(2), 169-210.

Joseph, N. L. (2003). Predicting returns in US financial sector indices. *International journal of forecasting*, *19*(3), 351-367.

Kasman, S., Vardar, G., & Tunç, G. (2011). The impact of interest rate and exchange rate volatility on banks' stock returns and volatility: Evidence from Turkey. *Economic Modelling*, *28*(3), 1328-1334.

Katechos, G. (2011). On the relationship between exchange rates and equity returns: A new approach. *Journal of International Financial Markets, Institutions and Money*, *21*(4), 550-559.

Khan, F., Muneer, S., & Ahmad, A. M. (2013). Relationship between stock prices and economic variables: Sectoral analysis. *Актуальні проблеми економіки*, (5), 544-553.

Kim, K. H. (2003). Dollar exchange rate and stock price: evidence from multivariate cointegration and error correction model. *Review of Financial economics*, *12*(3), 301-313.

Kollias, C., Mylonidis, N., & Paleologou, S. M. (2012). The nexus between exchange rates and stock markets: evidence from the euro-dollar rate and composite European stock indices using rolling analysis. *Journal of economics and finance*, *36*(1), 136-147.

Kutty, G. (2010). THE RELATIONSHIP BETWEEN EXCHANGE RATES AND STOCK PRICES: THE CASE OF MEXICO. *North American Journal of Finance & Banking Research*, *4*(4).

Lean, H. H., Halim, M., & Wong, W. K. (2005). *Bivariate causality between exchange rates and stock prices on major Asian countries*. Monash University.

Lee, C. H., Doong, S. C., & Chou, P. I. (2011). Dynamic correlation between stock prices and exchange rates. *Applied financial economics*, *21*(11), 789-800.

Lin, C. H. (2012). The comovement between exchange rates and stock prices in the Asian emerging markets. *International Review of Economics & Finance*, *22*(1), 161-172.

Liu, H. H., & Tu, T. T. (2011). Mean- reverting and Asymmetric Volatility Switching Properties of Stock Price Index, Exchange Rate and Foreign Capital in Taiwan. *Asian Economic Journal*, *25*(4), 375-395.

Malliaropulos, D. (1998). International stock return differentials and real exchange rate changes. *Journal of International Money and finance*, *17*(3), 493-511.

Mendy, D., & Widodo, T. (2018). Two Stage Markov Switching Model: Identifying the Indonesian Rupiah Per US Dollar Turning Points Post 1997 Financial Crisis.

Moore, T., & Wang, P. (2014). Dynamic linkage between real exchange rates and stock prices: Evidence from developed and emerging Asian markets. *International Review of Economics & Finance*, *29*, 1-11.

Muhammad, N., Rasheed, A., & Husain, F. (2002). Stock prices and exchange rates: Are they related? evidence from south asian countries [with comments]. *The Pakistan Development Review*, 535-550.

Nieh, C. C., & Lee, C. F. (2001). Dynamic relationship between stock prices and exchange rates for G-7 countries. *The Quarterly Review of Economics and Finance*, *41*(4), 477-490.

Parsva, P., & Lean, H. H. (2011). The analysis of relationship between stock prices and exchange rates: Evidence from six Middle Eastern financial markets. *International research journal of finance and economics*, *66*, 157-171.

Pfaff, B. (2008). *Analysis of integrated and cointegrated time series with R*. Springer Science & Business Media.

Pfaff, B. (2008). VAR, SVAR and SVEC models: Implementation within R package vars. *Journal of Statistical Software*, *27*(4), 1-32.

Pfaff, B. (2008). *Analysis of integrated and cointegrated time series with R*. Springer Science & Business Media.

Phylaktis, K., & Ravazzolo, F. (2005). Stock prices and exchange rate dynamics. *Journal of international Money and Finance*, *24*(7), 1031-1053.

Poterba, J. M., & Summers, L. H. (1987). Finite lifetimes and the effects of budget deficits on national saving. *Journal of Monetary Economics*, *20*(2), 369-391.

Rahman, M. L., & Uddin, J. (2009). Dynamic relationship between stock prices and exchange rates: Evidence from three South Asian countries. *International Business Research*, *2*(2), 167-174.

Richards, N., Simpson, J., & Evans, J. (2007). The interaction between exchange rates and stock princes: An Australian context.

Roll, R. (1992). Industrial structure and the comparative behavior of international stock market indices. *The Journal of Finance*, *47*(1), 3-41.

Sensoy, A., & Sobaci, C. (2014). Effects of volatility shocks on the dynamic linkages between exchange rate, interest rate and the stock market: The case of Turkey. *Economic Modelling*, *43*, 448-457.

Smyth, R., & Nandha, M. (2003). Bivariate causality between exchange rates and stock prices in South Asia. *Applied Economics Letters*, *10*(11), 699-704.

Tian, G. G., & Ma, S. (2010). The relationship between stock returns and the foreign exchange rate: the ARDL approach. *Journal of the Asia Pacific economy*, *15*(4), 490-508.

Toda, H. Y., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of econometrics*, *66*(1-2), 225-250.

Tsagkanos, A., & Siriopoulos, C. (2013). A long-run relationship between stock price index and exchange rate: A structural nonparametric cointegrating regression approach. *Journal of International Financial Markets, Institutions and Money*, *25*, 106-118.

Tsai, I. C. (2012). The relationship between stock price index and exchange rate in Asian markets: A quantile regression approach. *Journal of International Financial Markets, Institutions and Money*, *22*(3), 609-621.

Tuncer, I., & Turaboglu, T. T. (2014). Relatioship between stock prices and economic activity in Turkish economy. *Актуальні проблеми економіки*, (2), 111-121.

Unlu, U. (2013). Oil price, exchange rate and stock market in ASEAN-5 countries. *The Empirical Economics Letter: A Monthly International Journal of Economics*, *12*(5), 551-557.

Wickremasinghe, G. B. (2012). Stock prices and exchange rates in Sri Lanka: Some empirical evidence. *Innovations*, *9*, 4.

Yang, Z., Tu, A. H., & Zeng, Y. (2014). Dynamic linkages between Asian stock prices and exchange rates: new evidence from causality in quantiles. *Applied Economics*, *46*(11), 1184-1201.

Yau, H. Y., & Nieh, C. C. (2006). Interrelationships among stock prices of Taiwan and Japan and NTD/Yen exchange rate. *Journal of Asian Economics*, *17*(3), 535-552.