# RELATIONSHIP BETWEEN VOLATILITY OF STOCK MARKET ILLIQUIDITY AND EXCHANGE RATE VOLATILITY: THE CASE OF BORSA ISTANBUL[*]

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**ABSTRACT**

Low liquidity (illiquidity) of a market is considered to have important asset pricing implications such that the higher the transaction costs the lower will be the asset prices and higher the rates of return. This is due to an illiquid asset offering higher rate of return to compensate the investors for having liquidity cost. According to John Maynard Keynes, an asset is defined to be liquid when "it is more certainly realizable at short notice without loss". The major aim of this paper is to analyze the relationship between exchange rate volatility and volatility of stock market illiquidity for Borsa Istanbul. In this way the effects of external shocks and the exchange rate volatility as the risk indicator for an open economy will be investigated. Volatility of stock market illiquidity and exchange rate volatility are estimated by applying different approaches available in the relevant literature. Afterwards the relationship between these two variables is analyzed by using Moon and Yu approach. Based on empirical findings some policy recommendations are made for market players.

**Keywords:** Liquidity, Volatility, Risk Indicator, Moon and Yu Approach

**JEL Classification:** G12, C10, E44

## SIĞ BİR HİSSE SENEDİ PİYASASI OYNAKLIĞI İLE DÖVİZ KURU OYNAKLIĞININ İLİŞKİSİ: BORSA ISTANBUL ÖRNEĞİ

**ÖZ**

Varlık fiyatlamasında piyasa likiditesinin önemli sonuçlara sahip olduğu değerlendirildiğinde, işlem maliyetleri ne kadar yüksek olursa, varlık fiyatları o kadar düşük; buna göre getiri oranları da o kadar yüksek olmaktadır. Bunun nedeni, düşük likiditeye sahip bir varlığa yatırım yapan yatırımcıların

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katlandığı likidite maliyetlerini telafi etmek amacıyla daha yüksek getirinin olmasından kaynaklanmaktadır. John Maynard Keynes'e göre, bir varlık, "kısa sürede kayıpsız ve emin bir şekilde el değiştirebiliyorsa" likiditeye sahip olarak tanımlanmaktadır. Bu çalışmanın temel amacı, Borsa İstanbul için döviz kuru oynaklığı ile Borsa likiditesinin oynaklığı arasındaki ilişkiyi analiz etmektir. Böylece açık ekonomi için risk göstergesi olarak dış şokların ve döviz kuru oynaklığının etkileri araştırılacaktır. Borsa İstanbul'un likiditesinin oynaklığı ve döviz kuru oynaklığı, ilgili literatürdeki farklı yaklaşımları uygulayarak tahmin edilmektedir. Daha sonra bu iki değişken arasındaki ilişki Moon ve Yu Yaklaşımı kullanılarak analiz edilmiştir. Ampirik bulgulara dayanarak piyasa oyuncuları için politika önerileri yapılmıştır.



**Anahtar Kelimeler:** Likidite, Oynaklık, Risk Göstergesi, Moon ve Yu Yaklaşımı

**JEL Sınıflandırması:** G12, C10, E44

## 1. INTRODUCTION

In this paper, it has been proposed that expected excess stock return reflects compensation for expected market low liquidity, i.e. illiquidity. In other words, expected excess stock return is an increasing function of expected market illiquidity. In addition, exchange rate volatility is related to the risk premium of an economy. Hence, the more volatile exchange rates means the higher risk premium. Given the importance of market liquidity for both investors and companies, it is essential to discover what determines stock market illiquidity. On the other hand, there are few studies on determining the relationship between volatility of stock market illiquidity and exchange rate volatility in the literature. Preceding studies mostly analyze the stock characteristics and market characteristics, i.e. stock price, return, volatility, trading volume and market structure respectively. Although the importance of market liquidity in asset pricing has been identified comprehensively in the literature, there is a few study about what causes stock market illiquidity to vary over time. This paper examines whether volatility of stock market illiquidity and /or exchange rate volatility can be used as a proxy for risk indicator for stock markets and exchange markets respectively and /or vice versa. This paper aims to contribute relevant literature by analyzing this relationship based on a new technique, namely Moon and Yu Approach. BIST-100 index of Borsa Istanbul and USD Exchange rates are used to determine how volatility of stock market illiquidity is affected by exchange rate volatility by applying the liquidity measure developed by Amihud (2002).

The paper proceeds as follows. Section 2 introduces relevant literature on the illiquidity and volatility measures used in this study for stock returns and USD exchange rates respectively. Empirical works of liquidity and volatility models on Borsa Istanbul are briefly discussed. Section 3 presents the data and methodology for analyzing the relationship between volatility of stock market illiquidity and exchange rate volatility. The empirical findings are summarized and discussed briefly in Section 4. Based on empirical findings, concluding remarks are made for practitioners and market players which could be used for establishment of risk management strategies.



## 2. LITERATURE REVIEW

It is a fact that the illiquidity concept is usually defined as an undesirable function for a well organized financial market. Li et al. (2006) state that trading volume, time, and transaction costs are the key elements of good measure of liquidity. According to Khan and Baker (1993), illiquidity measure is related to the liquidity ratio known as the Amivest measure, the ratio of the sum of the daily volume to the sum of the absolute return. Amihud et al. (1997) and Berkman and Eleswarapu (1998) make use of the liquidity ratio to investigate the effect of volatility of stock market liquidity on the values of stocks that are subject to changes in their trading methods. In this paper, the same measurement approach is applied for BIST 100 index to calculate illiquidity indicator for volatility of BIST 100 index.

There are several empirical studies on the positive return–illiquidity relationship in the relevant literature. As said by Amihud and Mendelson (1980) illiquidity is related to adverse selection costs and inventory costs of investors since it reflects the impact of order flow on price. These authors propose the hypothesis on the relationship between stock return and stock liquidity is explained that return increases in illiquidity. Besides, Brennan and Subrahmanyam (1996) analyze the price response to order size with the fixed cost of trading by using intra-day continuous data on transactions and quotes in order to determine stock illiquidity in relation to the price impact. Based on their empirical findings they (1996) conclude that illiquidity positively affect stock returns.

Harris and Raviv (1993) introduce another interpretation used for illiquidity measure based on the disagreement between traders about new information. According to these authors, disagreement among investors induces increase in trading volume. As a consequence, illiquidity measure is considered as a measure of "consensus belief" about new information among investors. Empirical work of Butler et al. (2005) show that illiquid stocks have higher flotation costs for equity issuance. Lipson and Mortal (2009) argue that the cost of equity is higher for firms with illiquid equity than for firms with more liquid equity.

According to Kyle (1985), there is a positive relationship between the order flow or transaction volume and price change, generally called the price impact. This relationship is defined based on the belief that market makers cannot distinguish between order flow whether it is generated by informed traders or by noise traders, and hence they set prices with an increasing function of the imbalance in the order flow which may indicate informed trading. Kyle’s (1985) model is usually estimated by the methodology proposed by Glosten and Harris (1988) and Hasbrouck (1991). Principally, it is the slope coefficient in a regression of transaction-by-transaction price changes on the signed order size, where orders are categorized into ‘‘buy’’ or ‘‘sell’’ by the proximity of the transaction price to the preceding bid and ask quotes. In addition, necessary adjustments are made for prior information on price changes and order size and, also fixed order placement costs.

There are various empirical studies on the volatility interaction of Borsa Istanbul and exchange rate volatility. Tokat (2013) argues that the shock and volatility transmission from US dollar market to domestic gold market and the volatility pattern of ISE 100 index seem to be isolated from the global gold and dollar markets. In this work, all parameters are observed to be affected by their past shocks by showing a heteroskedastic feature. Cicek (2014) analyzes inter-market price and volatility spillover effects among Istanbul Stock Exchange 100- Index, Turkish government debt securities, and foreign exchange based on Multivariate EGARCH Model and there is no long run relationship among three markets. Turkyilmaz and Balibey (2014) examine the asymmetric long memory property in volatility of the Turkish Stock Market. They provide important findings for investors and market participants since the empirical results display long term persistence and the presence of asymmetric effects of shocks in volatility of Turkish Stock Market. Akar (2015) determines the relationship between stock returns and volatility of liquidity in Turkish Stock Market. According to Akar (2015), the empirical results show that while stock size and Amihud illiquidity criteria sort the stocks in the same way, stock return standard deviation criterion produces different ranking. Akar (2015) concludes that especially the use of models that allow asymmetry and take structural breaks into account can provide significant results. In that respect, this paper contributes to the literature by using asymmetric models to analyze the relationship between the volatility of Turkish stock market illiquidity and exchange rate volatility, which is explained in the following sections.

## 3. DATA AND METHODOLOGY

### 3.1. Data

The illiquidity measure used in this empirical study is calculated from daily stock data of Borsa Istanbul (BIST) on returns and trading volume. In this work, daily return series of each listed company which are quoted at BIST 100 index of Borsa Istanbul is used for the period of Jan 2nd, 2003 to August 18th, 2015. The absolute value of total returns of BIST 100 index are listed to obtain cross section data for this empirical analysis. Afterwards the absolute value of returns are divided by the total volume of BIST 100 index to get "illiquidity indicator" on a daily basis[1].

In addition to BIST 100 index return data, daily USD exchange rates are used to calculate USD return series for the same period. USD exchange rates data is obtained from Central Bank Republic of Turkey (CBRT).

### 3.2. Methodology

Engle (1982) developed the autoregressive conditional heteroskedastic (ARCH) models Bollerslev (1995) developed the generalized ARCH (GARCH) which could approximate second-order nonlinear processes by allowing the first and second moments of the returns to depend on its past values. This paper employs such models to capture the characteristics of return generating processes with the mean and variance equations are as follows:

$$z_t = \mu_t + u_t,\ u_t \sim N(0,\ \sigma_t^2) \quad (1)$$

$$h_t = \omega + \alpha_1 u_{t-1}^2 + \beta h_{1t-1} \quad (2)$$

Where $z_t$ denotes the stationary series, $\mu_t$ is a constant, $u_t$ are normally distributed error terms. The conditional variances are given by Equation 2.

[1] Illiquidity indicator is calculated based on the formula used by Amihud et al. (1997).

In the study of French, Schwert, and Stambaugh (1987), the stock return is defined to be related to its stock return volatility. Hence in the volatility equation, the conditional variance is a function of its previous period's variance and pervious period's squared errors. The sum of the coefficients of the lagged errors (GARCH term) and lagged conditional variances (ARCH term) should be less than one to verify the stability of the volatility process.

Hafner and Herwartz (HH) (2006) and Moon and Yu (MY) (2010) approaches are applied for the above mentioned series to determine whether there is any causality in variance and/or volatility spillover between them.

Cheung and Ng (CN) (1996) and Hong (2001) have pioneering works on the causality in variance tests. These works are based on cross-correlation functions (CCF) of standardized residuals obtained from univariate general autoregressive conditional heteroscedasticity (GARCH) estimations. According to Hafner and Herwartz (2006) the CCF based on Portmanteau test is expected to be suffering from significant over sizing in small and medium samples when there is a leptokurtic volatility process. Another drawback of CN's approach is that the results from CCF based volatility spillover testing approach is sensitive to the orders of leads and lags which leads to an issue regarding the robustness of findings. In other words, an inappropriate lead and lag order choice in the CCF test distorts its performance and thereby leads to the risk of selecting a wrong order of the CCF statistic. The HH approach based on Lagrange multiplier (LM) principle overcomes the drawbacks of Cheung and Ng's approach and it has practical for empirical illustrations.

Hafner and Herwartz (2006) summarize the LM test in three stages in order to test the null hypothesis of non-causality in variance:

1. After calculating the standardized residuals for the two stationary series i and j, $\hat{\varepsilon}_{it}$ and $\hat{\varepsilon}_{jt}$, estimate a GARCH (1,1) model for these residuals and obtain the standardized residuals of this equation, $\hat{\xi}_{it}$, the derivatives, $\hat{x}_{it}$, and volatility process of the GARCH model.
2. Secondly, $\hat{\xi}_{it}^{2} - 1$ is regressed on the derivatives and volatility process indicators obtained from GARCH model in Stage 1.

3. Finally, LM test statistics is calculated, namely $\lambda_{LM}$ , is equal to the number of observations times the degree of explanation of the regression ($R^2$) in Stage 2. Regarding the critical value for LM test, $\chi_{(n)}$ distribution will be used where *n* is the number of indicators in volatility process.

HH (2006) approach is used for determining the presence and direction of causality in variance. However HH does not provide any information about the magnitude for the causality. For this reason, Moon and Yu (2010) propose a new approach to analyze the size of impact for volatility spillover which is explained below:



1. Firstly, the dependent $x_{it}$ and independent variables $y_{jt}$ are defined based on the information that the market which commence the shock is dependent variable and the market which is influenced by this shock is independent variable.
2. Secondly, lagged values of dependent $x_{it-1}$ and independent $y_{jt-1}$ variables are included to the estimation of volatility mean equation.
3. Finally, the squared residual of independent variable $U_{jt}^2$ is included to the estimation of volatility variance equation. If the coefficient of the squared residual of independent variable is statistically significant, then this means that there is a considerable volatility spillover process for the related series.

Considering the fact that there may be a change in variance, Inclan and Tiao's (IT) (1994) ICSS algorithm is used to detect sudden change points in variance leading to structural breaks. When the series has multiple variance change points, then it is difficult for ICSS algorithm to detect the correct variance change points in different intervals. For this reason, Sanso et al. (2004) [2]argue that there are some limitations in the ICSS algorithm which invalidates its use in financial time series analysis. In order to overcome these limitations, Sanso et al. propose the AIT algorithm as a modification of IT's approach which is a non-parametric adjustment based on the Bartlett kernel. In that case, AIT algorithm is used with an iterative procedure, i.e. once the break point is detected, then the sample series is further segmented to look for another break

[2] Sanso et al's Gauss Code is applied in this analysis which is available at the web link: http://www.eco.ub.es/~carrion/catala/icss.zip

point. After identifying all the break points in the series, then GARCH models are estimated with and without change points in variance.

## 4. EMPIRICAL FINDINGS

The major aim of this work is to analyze the relationship between series of both volatility of USD exchange rates and volatility of illiquidity indicator for BIST 100 index to determine the causality and the volatility spillover. The empirical findings are summarized as follows:



### 4.1. Descriptive Statistics

First of all, descriptive statistics of volatility series for Illiquidity Indicator of BIST 100 index (BL) and volatility of USD exchange rates (EX) are obtained and shown at Table 1. The major characteristic of time series is that they usually have leptokurtic (fat tailed) process. Third and fourth moments of the series provide information about this process, i.e. their skewness both have a negative sign which indicate left skewed distribution. The Jarque Berra (JB) test results of both EX and BL indicates that these series are not normal and hence, the null hypothesis is rejected for both of them.

Considering EX, median value is greater than skewness value which means that recurring return series are mostly cumulated at the right hand side of the mean of EX. The clustering is positioned higher than the mean of EX, i.e. financially this indicates a high risk level for the exchange rate market. Generally speaking, this is a sign of negative expectations for the investors in this market. Kurtosis value of EX is estimated as (22.8) and this means that there is high volatility in the exchange rate market and also this indicates a time varying variance for EX. For this reason EX data is analyzed to determine whether there is a heteroscedasticity in the process. The optimal lag indicator is estimated to be (9) based on AIC criteria. F (50, 2312) value of EX is calculated as (11.631) based on ARCH test results. F value is greater than the critical value and hence the null hypothesis is rejected. In other words, there is time varying variance for EX series.

Considering BL which has similar to the findings of EX, median value is greater than skewness value which means that recurring return series are mostly cumulated at the right hand side of the mean of BL. BL has a high level of kurtosis value (89.45) which provides information about a high sensitivity level for economic and political events in Turkey. Based on the skewness and kurtosis values of BL, time varying variance is determined by applying ARCH test. According to the ARCH test results, BL has heteroscedastic form. The optimal lag indicator is estimated to be (12) based on AIC criteria. F (50, 2310) value of BL is calculated as (1.43) based on ARCH test results. F value is greater than the critical value and hence the null hypothesis is rejected. In other words, there is time varying variance for BL series.

**Table 1: Descriptive Statistics for Volatility of USD Exchange Rates and Volatility of Illiquidity Indicator of BIST 100 Index**

| **Parameters** | **EX** | **BL** |
|---|---|---|
| Mean | 0.000318 | -0.000478 |
| Median | -0.000195 | 0.002670 |
| Maximum | 0.070408 | 5.696464 |
| Minimum | -0.119352 | -5.733206 |
| Std. Dev. | 0.008732 | 0.297123 |
| Skewness | -0.183512 | -0.064044 |
| Kurtosis | 22.82948 | 89.45648 |
| | | |
| Jarque-Bera | 39547.35 | 986665.5 |
| Probability | 0.000000 | 0.000000 |
| | | |
| | | |
| Observations | 3178 | 3178 |

### 4.2. Volatility Analysis

Volatility analysis is carried out in three stages as follows: Firstly, series are investigated to determine whether they have time varying variance in their process. Secondly, series are analyzed to provide information about existence of weakly stationary process or not. Thirdly, volatility modeling and estimation methods are applied to get empirical findings. In this paper, Hafner and Herwarzt and also Moon and Yu approaches are implemented for analyzing the volatility causality and spillover effects.

After having the descriptive statistics of above mentioned series, it is necessary to investigate whether these series are stationary or not to start volatility analysis. For this reason, the stability of these return series are analyzed by using unit root test. The Augmented Dickey Fuller (ADF) unit root test results are shown at Table 2. The estimated values of both EX and BL are less than the critical values, hence both of these series has weakly stationary process.

Because of the test statistics, including significant skewness, excess kurtosis it is reasonable to use GARCH family models based on Bollerslev (1995). In this way, both the time variation in the volatilities of BIST 100 and USD exchange rate returns are captured as well as the inter market dependence of the returns and the return volatilities between them.

**Table 2: ADF Test Results for Volatility of USD Exchange Rates and Volatility of Illiquidity Indicator of BIST 100 Index**

| BL | | EX | |
|---|---|---|---|
| **Costant*** | **Non Costant**** | **Costant*** | **Non Costant**** |
| -30.05 | -30.056 | -48.12 | -48.06 |
| %1 -3.43* %5 -2.86* with costant unit test significant level<br>%1 -2.56** %5 -1.94** non constant unit root tets | | | |

Since both of these series has weakly stationary process, it is possible to make volatility analysis as follows.

### 4.2. Hafner and Herwartz Approach

Hafner and Herwartz (HH) Approach is estimated for BL and EX and the results are shown at Table 3. HH Approach gives information about the significant causality for both EX and BL series. This means there is a dual relationship between these two series.

**Table 3- Causality Analysis with Hafner and Herwartz Approach**

| | |
|---|---|
| BL → EX | 9.63<br>(0.0081)* |
| EX → BL | 21.34<br>(0.000023)* |

(*) indicate significant results

On the other hand, HH Approach does not provide information about the magnitude of causality between these series. In order to overcome this issue, Moon and Yu (MY) Approach is used to estimate volatility spillover between EX and BL as follows.

### 4.3. Moon and Yu Approach

The volatility spillover effect is analyzed for two sided estimations. One of them is volatility spillover from EX to BL and second one is from BL to EX volatility spillover. The estimation results are shown at Table 4 and Table 5 respectively.

Considering variance equation of EX to BL, coefficients satisfy the necessary conditions such that all the coefficients (w, α , β ) are positive and (α + β<1) , i.e. it is equal to 0,8646. There is a significant volatility spillover effect from EX to BL based on MY Approach results. The coefficient of residual term for EX is significant and high value. However, it should be considered since the value of volatility of EX is too small.

**Table 4: Volatility Spillover from EX to BL**

| | Parameters | Normal | Student-t | GED |
|---|---|---|---|---|
| Mean Equotion | C | 0.00102<br>0.225 | 0.000212<br>0.050 | 0.0013<br>0.313 |
| | EX(-1) | -0.142<br>-0.185 | -0.5046<br>-0.8421 | -0.555<br>-0.886 |
| | BL(-1) | -0.307<br>-14.413* | -0.299<br>-14.26* | -0.296<br>-14793* |
| Variance Equotion | W | 0.005<br>6.381** | 0.015<br>4.544* | 0.00932<br>4.369* |
| | A | 0.0784<br>6.94* | 0.133<br>4.413* | 0.1111<br>4.296* |
| | B | 0.7862<br>34.79* | 0.568<br>7.475* | 0.68<br>11.962* |
| | $(U_{EX}(-1))^2$ | 60.208<br>8.72* | 35.120<br>2.523* | 52.486<br>4.053* |
| | STD T-DIST. DOF | | 7.255<br>11.554* | |
| | GED | | | 1.358<br>35.57* |
| Diaagnostics Test | F(5,2401) | 0.83 | 0.088 | 0.2465 |
| | F(10,2391) | 0.55 | 0.0611 | 0.1827 |
| | F(30,2329) | 0.69 | 0.419 | 0.5668 |
| | Q (5) | 4.31 | 0.448 | 1.2717 |
| | Q(10) | 5.83 | 0.618 | 1.8694 |
| | Q(30) | 20.544 | 12.742 | 16.87 |

(*) indicate significant results

For instance, the last value of EX volatility is equal to 0.0000671. If this value is multiplied by the value of $(U_{EX}(-1))^2$ on the Table 4 (0.0000671*60.208=0.004039), then the volatility of EX will have a spillover to BL. This indicates that there is a significant spillover effect from EX to BL. The estimations are made by using three different distributions, i.e. normal, student *t* and GED distributions. The major aim of this estimation is to provide information about the characteristics of data for volatility analysis. Coefficient[3] of Student *t* distribution is estimated as 7.25 (greater than 2) and hence there is an excess kurtosis for the series.

**Table 5: Volatility Spillover from BL to EX**

| | Parameters /Coefficients | Normal | Student-t | GED |
|---|---|---|---|---|
| Mean Equation | C | 0.000232<br>0.158423 | 0.000232<br>0.158348 | 0.000232<br>0.158348 |
| | EX(-1) | 0.017630<br>0.304016 | 0.017630<br>0.303922 | 0.017630<br>0.303922 |
| | BL(-1) | 9649.765<br>0.052466 | 9649.765<br>0.052465 | 9649.765<br>0.052465 |
| Variance Equation | W | 7.62E-05<br>6.245387* | 7.62E-05<br>3.842664* | 7.62E-05<br>3.842664* |
| | A | 0.150000<br>2.581551* | 0.150000<br>2.447012* | 0.150000<br>2.447012* |
| | B | 0.600000<br>8.487012* | 0.600000<br>6.130664* | 0.600000<br>6.130664* |
| | $(U_{BL}(-1))$^2 | 0.000000<br>0.000000 | 0.000000<br>0.000000 | 0.000000<br>0.000000 |
| | STD T-DIST. DOF | | 20.00<br>2.015* | |
| | GED | | | 2.000000<br>16.56* |

(*) indicate significant results

There is a high volatility for BIST 100 index liquidity for that period. This Student *t* estimation results does not provide any information about the asymmetric characteristics for the series. Hence there is a need for additional volatility analysis by using GED distribution to understand the nature of asymmetric process. If the asymmetric/symmetric position did not taken into consideration, the volatility coefficients, especially the persistence of indicators for volatility will be calculated higher than they were expected. Coefficient[4] of GED is estimated as 1.358 and since this value is less than 2, there is a leptokurtic process for the series. This means that tail effects are high impact for the series. The diagnostic tests for MY Approach include ARCH test and Q-squared tests and the related diagnostic test results indicate that there is no

[3] Coefficient is equal to 2 means there is a symmetric distribution for the series and close to the normal distribution. In this case, the kurtosis will be about 3. If the coefficient is larger than 2, this indicates an excess kurtosis for the series. If the coefficient is less than 2, this means low kurtosis for the series.
[4] Coefficient of GED is equal to 2 means that there is symmetric nature. If the coefficient is greater than 2, then there is a thin tail and if the coefficient is less than 2, then there is a fat tail for the series.

time varying variance for the estimated equation (F test) and there is no autocorrelation for the estimated equation (Q-squared test) since the null hypothesis are both accepted.

All the coefficients of variance equation are positive and satisfy the necessary conditions for volatility analysis. The volatility spillover from BL to EX by using MY Approach and the empirical results are shown at Table 5. Based on the empirical results, there is no volatility spillover from BL to EX since the coefficient of residual for BL is not significant. The coefficient of Student *t* distribution is equal to 20.0 which indicates that there is a high volatility in BL series. On the other hand, there is a symmetric characteristic in the BL process since coefficient of GED distribution is equal to 2.0. The coefficient for residuals of BL is not significant. The diagnostic test results are not significant at all, and for that reason the test results are not shown at the Table 5.

## 5. CONCLUDING REMARKS

Based on the above mentioned volatility analysis, the sensitivity for economic and political events or announcements are high for both of the series. Although a significant dual or bivariate causality relationship for volatility of both BL and EX is found based on HH Approach, this finding is not supported by MY Approach. The events having impact on exchange rate volatility is also effective for the BL. However the reverse case is not valid for the series, i.e. there is no impact from BL to EX in Turkey. This means that the investors and decision makers have different behavioral aspects about BL and EX. Investors and decision makers in stock market consider exchange rate volatility, however the reverse is not necessarily true, i.e. investors and decision makers in exchange rate market are not influenced by stock market illiquidity. Stock market illiquidity indicator could not be used as a proxy for risk indicator for the exchange rate market in Turkey. On the other hand, USD exchange rate volatility could be used as a proxy for risk indicator for the volatility of stock market illiquidity. When analyzing the illiquidity indicators for stock markets, it is recommended to analyze both trading volume and return series together to come up with reliable empirical results. According to the empirical findings, there is an acceptance that the increase in volatility of the foreign exchange market will lead to a decrease in liquidity (illiquidity) in stock markets as a risk premium. This is parallel to findings in the literature.

It is a fact that shares traded in the Turkish market are predominantly bank stocks. The investors on the bank stocks determine the liquidity of the Turkish market. Considering investor profiles at the Borsa Istanbul, there is a concentration of foreign investors in Turkey. The preferences of foreign investors are affected by volatility in foreign exchange rates. When there is an increase in the volatility of exchange rates, foreign investors are reducing their trading volume on Borsa Istanbul, i.e. mostly on bank stocks. The banking sector is more responsive to volatility of foreign exchange since the banks are sensitive to the exchange rates and constantly determine their position accordingly.

In terms of the Turkish Economy, the prospect of empirical findings indicates that exchange rate volatility may have an effect on stock market illiquidity as well as effects on returns. In general, a decrease in the liquidity of a market (illiquidity) leads the economy to lose its economic vitality. In this respect, if it is taken into consideration that the stock market is a liquidity-providing instrument for the assets representing the capital; it can be argued that the illiquidity is a situation or probability that would prevent correct pricing from occurring in the stock markets. From this point of view, the liquidity of stock markets is more important than the price movements. This is one of the important reasons why the volatility of the exchange rates will reduce the liquidity in the stock market. Hence, it can be said that the relationship between exchange rate volatility and the volatility of stock market illiquidity has a structure supporting the findings. In addition to the illiquidity indicator used in this study, studies using the existing indicators in the literature will lead to the emergence of new theoretical contributions.

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