The Effect Of External Crises On Exchange Liquidity Level And Investigation Of Directional Predictability in Türkiye

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Abstract

The purpose of this research article is to examine the effect of the Asian Financial Crisis, the Dot-Com Bubble and the European Debt Crisis on different liquidity levels related to the BIST100 index, the existence of directional predictability and to find an answer to the question of what is the sign and duration of the effect if the relevant effect exists. For this purpose, *Cross-Quantilogram* is used as the econometric method. According to the findings, in periods when BIST100 index liquidity is high and moderate, it is concluded that the crises have a liquidity-increasing effect and the crisis periods taken into account over the *Financial Stress Indicator* variable play a role in the directional prediction of the *Liquidity* variable. In periods when liquidity is at low levels, it is seen that the crises have a positive effect again on the liquidity level, but this time, the crisis periods are not effective in predicting the direction of the liquidity variable.

Keywords: Financial Stress, Bid-Ask Spread, Efficient Discrete Generalized Estimator, Liquidity, Cross-Quantilogram

JEL Classification: C13, C53, C58

Türkiye'de Dış Kaynaklı Krizlerin Borsa Likidite Düzeyi Üzerindeki Etkisi ve Yönlü Öngörülebilirliğin İncelenmesi

Özet

Çalışmanın amacı; Asya Finansal Krizinin, Dot-Com Balonunun ve Avrupa Borç Krizinin BİST100 indeksine ilişkin farklı likidite düzeyleri üzerindeki etkisinin ve yönlü öngörülebilirliğinin varlığını analiz etmek, ilgili etkinin mevcut olması durumunda işaretinin ve süresinin ne olduğu sorusuna yanıt bulmaktır. Araştırmanın amacı doğrultusunda, Han vd. (2016) tarafından ortaya koyulan *Çapraz Kantilogram* yöntemi kullanılmaktadır. Elde edilen bulgular incelendiğinde; BİST100 indeksi likiditesinin yüksek ve orta düzeyde seyrettiği dönemlerde, söz konusu krizlerin likidite arttırıcı etkisinin olduğu ve *Finansal Stres Göstergesi* değişkeni üzerinden dikkate alınan kriz dönemlerinin *Likidite* değişkeninin yönünün öngörülmesinde rol oynadığı sonucuna varılmaktadır. Likiditenin düşük düzeylerde seyrettiği dönemlerde ise krizlerin likidite düzeyi üzerinde yine pozitif bir etkisinin olduğu ancak bu defa, kriz dönemlerinin likidite değişkeninin yönünün öngörülmesinde etkili olmadığı görülmektedir.

Anahtar Kelimeler: Finansal Stres, Alım-Satım Farkı, Etkin Kesikli Genelleştirilmiş Tahminci, Likidite, Çapraz Kantilogram

JEL Sınıflandırması: C13, C53, C58

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1. Introduction

Financial markets are highly affected by social, political and economic events, uncertainties, domestic and international news (announcements) and investor sentiment. In the literature, many studies have been carried out on the measurement of uncertainties (risks) related to these markets, using different methods, but when financial instruments and markets are mentioned, liquidity levels are important as well as risks because the liquidity level of a financial market plays an important role both in terms of market efficiency and especially its potential to cause a systemic crisis.

National stock markets are indicative about the state of the countries' financial markets. It is very important to determine the effects of negative events that may have an impact on the stock market liquidity levels and the sign of these effects, if any, considering the possibility of a collapse in the national economy through the financial system. As a result of a possible systemic crisis, the supply and demand side of the economy can suffer great damage. In this respect, besides the possible impact on stock market liquidity levels, determining the sign and persistance of the effect is also important in terms of the probability of damage that may occur.

The ability to predict the movement direction regarding liquidity levels, which occurs as an increase or decrease, is of great importance in terms of detecting possible negative situations concerning liquidity levels in advance and taking necessary measures before any risk arises. Therefore, another reason for carrying out this study is the need to determine whether external financial and economic crises have an effect on the movement direction of the different liquidity levels related to the BIST100 index. Thus, it can be determined whether foreign crises that may occur in the future will serve as a leading indicator in terms of taking necessary measures before they turn into a possible systemic crisis in the country.

For the reasons mentioned in the previous paragraphs, the aim of this study is to analyze the effect and directional predictability of Asian Financial Crisis, Dot-Com Bubble and European Debt Crisis on BIST100 index liquidity levels by making use of the Financial Stress Indicator (FSI) variable and to answer the question of what is the sign and duration of the effect if the relevant effect exists.

There are different liquidity measures that take into account the criteria of market width, market depth and market resilience in measuring the degree of liquidity. In this study, the liquidity measure called the bid-ask spread, which is based on all of the explicit and implicit transaction costs, is used in the estimation of the liquidity level. As in many studies, it can be said that transaction costs have a direct effect on net earnings, which is a focal point for investors, as an important reason for using the liquidity proxy variable based on transaction costs.

In the literature, different estimators have been put forward in the estimation of bid-ask spreads, which are used to create the liquidity proxy variable based on transaction costs. Roll (1984), Lesmond et al. (1999), Corwin-Schultz (2012) and Abdi-Ranaldo (2017) can be counted among these estimators. Roll and Lesmond estimators focus only on closing prices, while Corwin-Schultz estimator estimates spreads by taking into account the daily high and low prices. As another estimator, Abdi-Ranaldo takes its place in the literature as an estimator taking into account both the daily closing prices and the daily high and low prices. In this study, Efficient Discrete Generalized Estimator (EDGE), which was introduced by Ardia et al. (2021), is preferred in the formation of the liquidity proxy variable. This estimator is based on the most comprehensive information set that includes the opening-high-low-closing (OHLC) prices together. Thus, EDGE gives more accurate estimates than the other estimators. Moreover, it can be used in practice independently of low and high frequency data, minimizes small sample upward bias and is robust in the presence of overnight jumps and infrequent trades.

After focusing on the concept of liquidity, EDGE, which is an efficient method used in the creation of the liquidity proxy variable, is introduced with its various aspects, in the next section. Following the explanations about the Financial Stress Indicator, primarily the studies on the factors affecting the liquidity level and then the findings obtained from the articles analyzing the effects of economic crises on the stock exchange liquidity levels of different countries are emphasized. In the data set and econometric method section, the properties of the variables are examined and Han et al.'s Cross-Quantilogram method (2016) is explained. Finally, the findings are interpreted and the answer to the research question is given in the conclusion.

2. The Concept of Liquidity and a New Method in Liquidity Measurement: Efficient Discrete Generalized Estimator (EDGE)

The liquidity levels of financial markets are important in terms of both being a prerequisite for market efficiency and having potential to cause a systemic crisis. In this subsection, the concept of liquidity is emphasized, various methods used in the creation of the liquidity proxy variable are mentioned and finally the EDGE that was put forward in 2021 is examined in all its aspects.

Liquidity is an important property of any financial instrument. The illiquidity of an asset, as measured by the total cost of a transaction, reflects the level of difficulty in trading that asset. The "bid price" known as the highest price at which market participants are willing to buy a certain amount of the asset at a given time and the "ask price" known as the lowest price at which a seller is willing to sell a certain amount of the asset at a given time are in question, for immediate settlement of buyer and seller transactions. An important component of the transaction cost is the difference between the "bid price" and the "ask price". The liquidity of an asset can be measured by this spread which represents the price of liquidity services (Amihud and Mendelson, 1988).

An asset is called "liquid" if it can be fastly bought and sold at a low cost at the current market price. For this reason, illiquidity is associated with the costs of performing a transaction in the capital markets. The illiquidity costs can be broken down into different components. These are called the bid-ask spread, market effect costs, delay-research costs and direct transaction costs (Amihud and Mendelson, 1991).

The market liquidity, on the other hand, is at the center of central banks' financial stability concerns because it is a prerequisite for market efficiency and the sudden disappearance of this liquidity from the markets can turn into a systemic crisis. A perfectly liquid market is an ideal market that always guarantees a single trading price regardless of the volumes traded, but such a market ideal is unlikely to be achieved (Bervas, 2006).

There are "three basic criteria" that allow measuring the degree of market liquidity. These are expressed as the tightness of the bid-ask spread, market depth and market resilience. Of these, the tightness of the spread is measured by the cost of reversing the position in a short time for a standard amount. This tightness is a first-hand measure of transaction costs. Transaction costs are the costs of applying to the market for the resource allocation and the transfer of property rights. Market depth, on the other hand, corresponds to the trade volume executed instantly with no slippage in the best limit prices. Finally, the market resilience criterion shows the rate of return of the prices to the equilibrium after a shock in the transaction flow (Bervas, 2006).

Transaction costs are important for investors, as net gains from investments are affected by them. For this reason, various “bid-ask spread” measures have been introduced at different times in the literature. "Effective trading spreads" can be calculated with the Roll estimator, based only on market closing prices, but two assumptions must be met here. The first is the assumption that the transaction costs of the asset are zero, that is, it is traded in an information efficient market, while the second is the stationarity of the observed price changes (Roll, 1984).

Lesmond et al. have introduced a model that requires daily returns in order to internally estimate the effective transaction costs. The characteristic of the data used in the model and for which transaction costs are calculated is that it allows the existence of zero returns. Zero returns are more common when price movements are infrequent (Lesmond et al., 1999).

Corwin and Schultz developed the “High-Low (HL) Spread Estimator” based on daily high and low prices. It is possible to derive the spread estimator, which is a function of the High/Low ratio at the 1-day and 2-day intervals. There are implicit assumptions about the HL estimator. The first of these is the assumption that the stock is traded continuously when the market is open, while the second is the assumption that the stock values do not change when the market is closed. These assumptions cause problems in practice and the estimates of the differential margin of the High/Low price ratio are downwardly biased without adjustment for overnight returns. Also, true high and low prices are not observed for rarely traded stocks and estimates of the high-low spread can be negative (Corwin and Schultz, 2012).

The Abdi-Ranaldo (AR) estimator is a method that allows making bid-ask spread estimates based on the daily closing, high and low prices. AR is an efficient estimator that uses a larger information set, is completely independent of the trade direction dynamics and does not require extra adjustment for non-trading periods as weekends, holidays etc. (Abdi and Ranaldo, 2017).

The “Efficient Discrete Generalized Estimator (EDGE)”, used in this study, is asymptotically unbiased and optimally combines “Opening-High-Low-Closing (OHLC)” prices in order to minimize variance. The EDGE makes two contributions to the literature. The first contribution is the derivation of the ROLL(1984) and Abdi-Ranaldo(2017) estimators with the correction term for rare trading, while the second contribution is the combination of the adjusted estimators in order to minimize EDGE variance, that is, to obtain an efficient estimator (Ardia et al., 2021).

It is possible to obtain fewer negative spread estimates with EDGE than with other estimators by reducing the estimator variance. Another benefit of this estimator is that the method can be applied regardless of low or high frequency data (Ardia et al., 2021). EDGE is derived from various combinations of OHLC prices by calculating the covariance between subsequent price changes. Three steps are followed to obtain the relevant estimator. These steps are listed below (Ardia et al., 2021):

- Spread estimators based on C, CO, CHL, CHLO, O, OC, OHL, OHLC prices can be written as moment conditions and an asymptotic efficient estimator can be obtained with the generalized moments method.
- In the derivation of the EDGE, prior knowledge is taken into account in order to increase the efficiency in small samples.
- The “k estimator” is formed, which takes into account the high (low) prices initiated by the buyer (seller) and is included in the estimator formula.

The EDGE formula can be formally expressed as:

$$S^2 = -4\frac{w_1E[X_1]+w_2E[X_2]}{(1-k\nu_{o=h,l})+(1-\nu_{h=l=c})(1-k\nu_{c=h,l})} \quad \textbf{(1)}$$

In formula (1), $\nu_{o=h,l} = \frac{(\nu_{o=h}+\nu_{o=l})}{2}$ equation is valid. $\nu_{o=h}$ and $\nu_{o=l}$ are the amounts of times the opening price equals the high or low price, respectively. o, h, l, c show logarithmic opening, high, low and closing prices. In addition, $\nu_{c=h,l} = \frac{(\nu_{c=h}+\nu_{c=l})}{2}$ equation is valid in the formula (1) and when $\nu_{c=h}$ and $\nu_{c=l}$ are examined, it is seen that they express the amounts of times when the closing price is equal to the high or low price. $\nu_{h=l=c}$ shows the amount of times the high and low prices are both equal to the previous closing price and "$k = 4w_1w_2$" is valid. The formulas $w_1 = \frac{V[X_2]}{V[X_1]+V[X_2]}$ and $w_2 = \frac{V[X_1]}{V[X_1]+V[X_2]}$ expressed here are the formulas for the weights used in the equality k. The X_1 and X_2 vectors are calculated as follows:

$$\begin{aligned} X_{1,t} &= (\eta_t - o_t)(o_t - \eta_{t-1}) + (\eta_t - c_{t-1})(c_{t-1} - \eta_{t-1}) \\ X_{2,t} &= (\eta_t - o_t)(o_t - c_{t-1}) + (o_t - c_{t-1})(c_{t-1} - \eta_{t-1}) \end{aligned} \quad \textbf{(2)}$$

η_t in equation (2) is calculated as $\eta_t = \frac{(l_t + h_t)}{2}$ and represents the mid-prices (Ardia et al., 2021).

The expected values and variances are substituted for their sample counterparts in the estimation stage. The estimated value of S^2 for the EDGE may be negative in small samples. In this case, negative values are trimmed to ensure the non-negativity of the transaction cost estimates. The EDGE produces less negative estimates as an efficient estimator and thus is minimizing small sample upward bias. Also, when b, the probability of a buyer-initiated high price (or the probability of a seller-initiated low price), is in the interval $0 \ll b \ll 1$, the EDGE formula is at least approximately valid even when the bids and asks are not equally probable (Ardia et al., 2021). $0 \ll b \ll 1$ means that b is much greater than zero and much less than one.

In case of larger spreads, EDGE always provides the most precise estimates. This estimator is robust even in the presence of infrequent trades and overnight jumps. It produces unbiased estimates even in the case of illiquid assets or high frequency where only a few trading activities per period are observed. Regardless of the spread sizes, the EDGE provides the most accurate estimates compared to the others (Ardia et al., 2021).

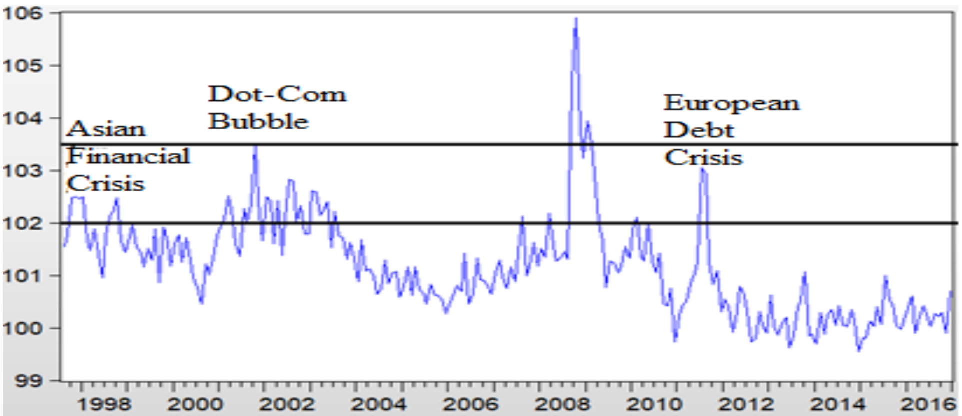
3. Financial Stress Indicator

Five major American newspapers named Boston Globe, Chicago Tribune, Los Angeles Times, Wall Street Journal, Washington Post were founded in the 19th century and have been broadcasting without any interruptions since then. In order to create an indicator about financial stress and to measure financial sensitivity (beliefs and opinions about financial markets), a new financial stress indicator has been put forward, taking into account the period 1889-2016, out of 35 million titles. The fact that daily newspapers are also published on weekends and bank holidays offers in-depth and high-frequency historical coverage. The financial stress indicator (FSI) proposed here is continuous, so not binary (Püttmann, 2018).

Three stages are followed in the calculation of indicator values. First, the new dataset and measurement of financial sensitivity is described. All articles on financial markets are selected using a large 120-word dictionary. Words with positive and negative connotations are determined and the sensitivity content of newspaper headlines is examined based on four sensitivity dictionaries containing 11407 words with positive or negative connotations. Four different indicators are created, one for each of the sensitivity dictionaries. For the main financial stress indicator, the number of articles should be normalized with the length of the newspaper in order for the newspaper language to be interpretable. After the normalization, the averages are taken. Secondly, the accuracy of the financial indicator is tested using 23,000 articles with high size and level of detail, published in the Wall Street Journal, read and labeled by a professional media analysis company experts. Finally, what happened during and after the increasing negative financial sentiment in the American economy is analyzed. The spikes in the indicator graph are followed by various economic and financial problems (Püttmann, 2018).

In the 1997 – 2016, the periods when the negative effects of the Asian Financial Crisis, the Dot-Com Bubble and the European Debt Crisis which causes the financial indicator to take values between 102 and 103.5, began to be felt are shown in Figure 1:

Figure 1 Graph of FSI Variable Containing Crisis Periods



4. Literature

Studies on securities and securities markets (Beber and Pagano 2013; Mishra et al. 2020; Mahfouz and ElShayeb 2022; Blau and Whitby 2018; Li et al. 2018) focus on different factors that affect liquidity. According to the studies examining the short selling effects, it is frequently encountered that short sales have a positive effect on liquidity in different markets. In the studies investigating the news effect on liquidity (Ekinci et al. 2019; Yue et al. 2021; Gorman et al. 2021; D'Souza and Gaa 2004; Jiang and Sun 2015, Dayanandan et al. 2017), it is seen that news has an effect on liquidity. In addition to the studies showing that economic and political uncertainties are related to liquidity, it is concluded that increases in sensitivity have a predominantly positive effect on liquidity, in studies examining the investor sentiments.

Considering the studies examining the effects of economic crises on stock market liquidity, which is also the subject of this study, it is seen that there is no consensus. While Engkuchik and Kaya (2012) found that the liquidity level in the Malaysian stock market moved upwards after the start of the 1997 Asian crisis; Khan and Rehman (2020), Hanh (2015), Hammami and Boujelbene (2022) and Rösch & Kaserer (2014) found that the liquidity levels of Pakistan, Taiwan, Tunisia and German stock markets were negatively affected by financial and economic crises, respectively. Kaya and Engkuchik (2017), in their study to test the effect of financial crises on the liquidity levels of various stock markets, concluded that the liquidity level decreased in some of the countries and increased in others. Poon et al. (2013) concluded that in the 2007-08 financial crisis, especially when there were many institutions selling the same stocks, the institutional sell-side herding strategy significantly increased the spread and liquidity risk. Investors following the buy and hold investment strategy, on the other hand, did not affect the stock market liquidity during the crisis, as they had a very low probability of being driven.

5. Data Set and Econometric Method

The descriptive statistics of the monthly data related to the "Liquidity (LIQ)" variable, which consists of the bid-ask spread estimates of BIST100 and the "Financial Stress Indicator Growth (FSIG)" variable for the period "August 1997 to December 2016", are given in Table 1:

Table 1 Descriptive Statistics of the Variables

	Mean	Median	Std. Dev.	Skew.	Kurt.	Jarque-Bera Test Stat.	Obs.
LIQ	0.00143	0.000	0.00295	2.8755	13.205	1332.16***	233
FSIG	-3.53E-05	-9.60E-05	0.00555	0.658	8.214	279.60***	232

Note: ***, **, * represent 0.01, 0.05 and 0.10 significance levels.

The reason why the examined period ended in December 2016 is that the data on the financial stress indicator variable ended in December 2016, that is, it was not calculated as of January 2017. Since the crises, the effects of which were examined in this study, took place before 2016, the fact that the data set ended in December 2016 does not affect the achievement of the study's purpose. According to the descriptive statistics in Table 1, it is observed that the distribution of the LIQ variable, which is formed by the values of the liquidity measure obtained by calculating the transaction costs with the most efficient method, EDGE, is skewed to the right and quite sharp. The shape of the distribution shows that there is a concentration around the values close to zero, and along with this, values far from zero are also present in the values of LIQ. Since the probability of the J-B test statistic is equal to zero, the distribution is not normal.

Although it is seen that the distribution of the FSIG variable is right-skewed, it is closer to the normal distribution compared to the LIQ variable's but since the probability value for the J-B test statistic is still zero, it is detected that the distribution of FSIG is also not normal. The stationarity of the variables are as shown in Table 2:

Table 2 Unit Root Test Results of the Variables

	Test Statistics	Critical Values for $\alpha = 0.05$
ADF Unit Root Test for LIQ	-3.25	-1.942
PP Unit Root Test for LIQ	-10.778	-1.942
ADF Unit Root Test for FSIG	-15.548	-1.942
PP Unit Root Test for FSIG	-23.268	-1.942

According to the ADF and PP unit root test results, the null hypothesis is rejected because all test statistics are more negative than the critical values and it is concluded that both variables are stationary.

In the study, Han et al. (2016)'s "Cross-Quantilogram" method is used. The purpose of this method is to measure the quantile dependence between two stationary variables and to detect the directional predictability, if any. The calculation of the cross-correlations related to quantile-hit processes is seen in formula 3:

$$\rho_\tau(k) = \frac{E\left[\psi_{\tau_1}\left(y_{1t} - q_{1,t}(\tau_1)\right)\psi_{\tau_2}\left(y_{2,t-k} - q_{2,t-k}(\tau_2)\right)\right]}{\sqrt{E\left[\psi_{\tau_1}^2\left(y_{1t} - q_{1,t}(\tau_1)\right)\right]}\sqrt{E\left[\psi_{\tau_2}^2\left(y_{2,\mathrm{t-k}} - q_{2,t-k}(\tau_2)\right)\right]}} \quad \textbf{(3)}$$

While k in the formula (3) is an integer and $\tau_1 \& \tau_2$ represent different quantiles; $\{y_{1t} \le q_{1,t}(\tau_1)\}$ and $\{y_{2,t-k} \le q_{2,t-k}(\tau_2)\}$ are two situations whose serial dependence is quantified. The quantile hit can be shown in the form $\{1[y_{it} \le q_{i,t}(.)]\}$ $i = 1,2$ (Han et al., 2016). For the sample equivalent of the cross quantilogram based on the observations $\{(y_t, \mathrm{x}_t) : t \in \mathbb{Z}\}$, the conditional quantile functions of the form $q_{i,t}(\tau_i) = x_{it}^T \beta_i(\tau_i)$ must be estimated first. The optimization problem presented to estimate β_i's is as follows (Han et al., 2016):

$$\hat{\beta}_i(\tau_i) = \underset{\beta_i \in \sim^{d_i}}{\arg\min} \sum_{t=1}^{T} \rho_{\tau_i}\left(y_{it} - x_{it}^T \beta_i\right) \quad \textbf{(4)}$$

The "estimated cross-quantilogram" obtained by solving the minimization problem (4) is seen in (5) (Han et al., 2016):

$$\hat{\rho}_\tau(k) = \frac{\sum_{t=k+1}^{T} \psi_{\tau_1}\left(y_{1t} - \hat{q}_{1,t}(\tau_1)\right)\psi_{\tau_2}\left(y_{2,t-k} - \hat{q}_{2,t-k}(\tau_2)\right)}{\sqrt{\sum_{t=k+1}^{T} \psi_{\tau_1}^2\left(y_{1t} - \hat{q}_{1,t}(\tau_1)\right)}\sqrt{\sum_{t=k+1}^{T} \psi_{\tau_2}^2\left(y_{2,t-k} - \hat{q}_{2,t-k}(\tau_2)\right)}} \quad \textbf{(5)}$$

The "Stationary Bootstrap", analyzed by Politis and Romano (1994), is used in order to obtain confidence intervals valid for large samples and make inferences when the cross-quantilogram method is used. In summary, through the stationary bootstrap method, the standard errors and confidence intervals can be obtained for the parameters (Politis and Romano, 1994).

Lobato's test method (2001) that tests H_0, claiming that a dependent data generating process is uncorrelated, is used to test H_0 that the relevant cross-correlation coefficient is zero at each delay. Since the asymptotic distribution under H_0 is not standard, it is stated that the critical values were calculated based on simulations. Also, it was detected that the test managed the significance level (α) better and the increase in type II error (β) did not reach significant levels in small samples (Lobato, 2001).

The directional predictability from one series to another can also be measured by the cross- quantilogram (Han et al., 2016). For a known quantile level $\tau \in \mathrm{T}$ and delay level p, Ljung -Box test statistic, which can be used when testing the null hypothesis $\left(H_0 : \rho_\tau(1) = ... = \rho_\tau(p) = 0\right)$ showing that all cross-correlations up to the lag p are equal to zero together, is calculated with the formula $\hat{Q}_\tau^{(p)} \equiv T(T+2)\sum_{k=1}^{p}\hat{\rho}_\tau^2(k)/(T-k)$, in order to determine the existence of directional predictability. Here, T represents the number of realizations when $k \in \{1,......,p\}$. If the null hypothesis cannot be rejected, it is concluded that all cross-correlations up to the lag p are together equal to zero. In other case, if the null hypothesis is rejected, it is detected that the cross-correlations up to the lag p are significant together and there is a directional predictability from one variable to the other (Han et al. 2016).

6. Findings

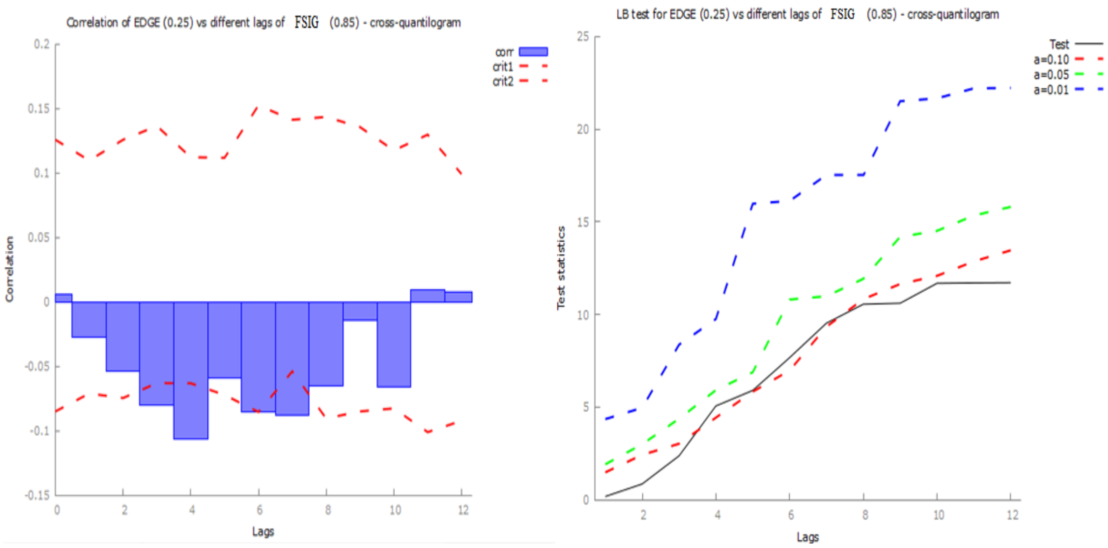
In this section, the possible effect of the growth in the financial stress indicator (FSIG), based on the news headlines in the five major newspapers in the USA for the period August 1997 to December 2016, on the LIQ variable, which is estimated to represent the BIST100 index liquidity level, was analyzed. The possible impact of FSIG on LIQ is examined by dividing the liquidity level into three categories. These categories can be expressed as low, median and high liquidity levels. The low, median and high liquidity levels correspond to the high, medium and low bid-ask spreads, respectively. In the time path graph (Figure 1) of the Financial Stress Indicator variable for the period considered in the study, it is seen that it takes values between 102 and 103.5 during the dates when the Asian Financial Crisis, Dot-Com Bubble and European Debt Crisis felt the negative effects. These values, approximately correspond to the 85th quantile of the variable.

The presence of the directional predictability from three aforementioned crises to the BIST100 liquidity levels indicates that external financial and economic crises are effective in predicting the course of liquidity levels. Detection of such an effect makes it possible to predict the direction of the stock market liquidity level following the external financial and economic crises that may be encountered in the future and to take measures in a way that does not cause a possible systemic crisis. "R program" was used to obtain the LIQ variable and the "Gretl program" was used to generate the Cross-Quantilogram and LB graphs.

The "Cross-Quantilogram" method, which is used to answer the research question, is very useful in terms of robustness and making research possible in different regions of the variable distributions without requiring any distribution conditions. Firstly, considering the 85th quantile of FSIG, which corresponds to the Asian Financial Crisis, Dot-Com Crisis and European Debt

Crisis, the negative effects of these on the high liquidity levels of BIST100 is as seen in Figure 2:

Figure 2 High Liquidity Level Relationship with Different Lags of FSIG at 85th Quantile and LB Test Graph

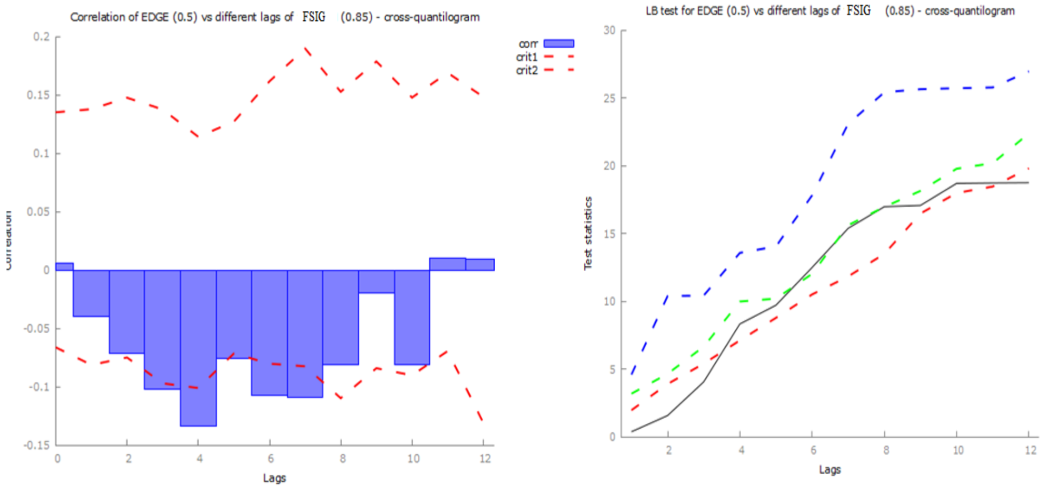


In the left graph, the purple bars extending beyond the confidence limits indicated by the red dashed lines represent significant effects. Since the bars are pointing downwards, these effects are observed to be negative. In the right graph, the jointly significance of the bars at different lags is tested. It is observed that the BIST100 liquidity level increased through a decrease in the bid-ask spreads and this effect occurs between the 3rd and 7th months following the negative effects of the crises. This indicates that the mentioned crises have a temporary positive effect on high liquidity levels. Here, it is determined that there is no instantaneous liquidity increase since the negative effects of the crises started to be felt, but the liquidity-increasing effect lasts for 3-4 months from the following third month.

The cross-correlations starting from the first four lags to the first eight lags are jointly significant at the 0.10 significance level. LB test graph indicates that the crises have a causality effect on the high liquidity levels, that is, after an external crisis, the direction of change in the high liquidity level can be predicted.

At the median liquidity level, the impact of the negative effects of the crises on liquidity can be analyzed with the help of Figure 3:

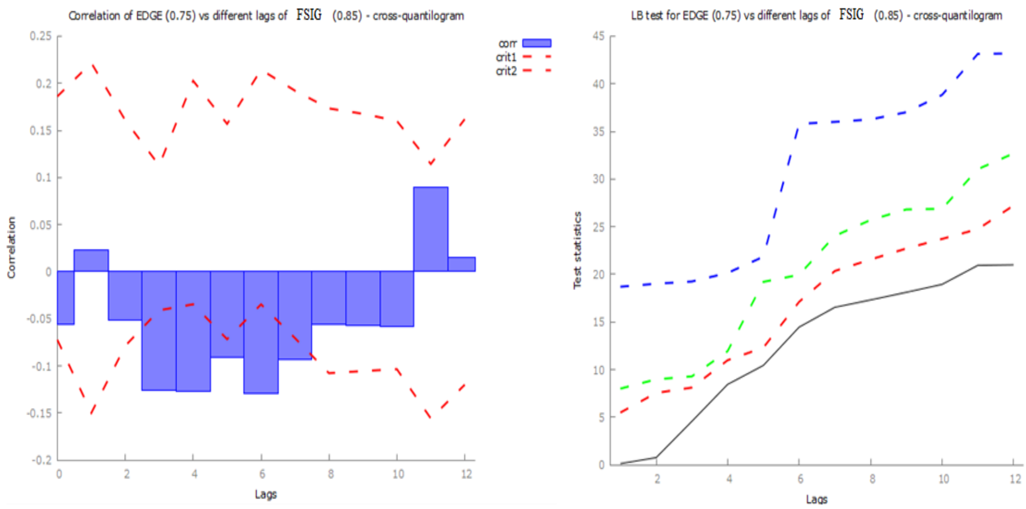
Figure 3 Median Liquidity Level Relationship with Different Lags of FSIG at 85th Quantile and LB Test Graph



In Figure 3, it is stated that the crises have an increasing effect and this positive effect of the crises on the median liquidity level is more pronounced and significant than the effect on the high liquidity level pertaining to BIST100. As can be seen from the graphs, there is no simultaneous increase since the negative effects of the relevant crises began to be felt and the positive effect lasted for 3-4 months starting from the third month.

According to the LB test graph, the jointly significance of the bars at different lags increases up to 0.05 significance level. This shows that, at the medium level, external economic and financial crises have a causal effect on the direction of BIST100 liquidity level.

Figure 4 Low Liquidity Level Relationship with Different Lags of FSIG at 85th Quantile and LB Test Graph



Finally, Figure 4 shows that there are more pronounced and significant liquidity-increasing effect on the BIST100 liquidity level in the period when the bid-ask spreads are high but here, too, it is seen that this effect is temporary.

When the jointly significance is analyzed with the help of the LB test graph, the cross-correlation coefficients are jointly insignificant even at the 0.10 significance level. This shows that, at the low liquidity level, external economic and financial crises have not a causal effect on the direction of BIST100 liquidity level.

If all the findings are evaluated together, it is concluded that the Asian Financial Crisis, Dot-Com Crisis and European Debt Crisis have a liquidity-increasing aspect at all liquidity levels. This result shows that stock market investors can exit the market without facing major losses and bankruptcies in the face of external crises. So, a stock market-based crisis will not occur in the form of infecting the entire financial sector and then the economy in general.

In addition, the crisis periods taken into account through the FSIG variable play a role in predicting the direction of the LIQ variable, at high and medium liquidity level. In periods when liquidity is at low level, it is concluded that crises have a positive effect on the liquidity level, but because the cross-correlation coefficients are not jointly significant, the crisis periods are not effective in predicting the direction of LIQ.

7. Conclusion

In the study, it is aimed to determine the effect of Asian Financial Crisis, Dot-Com Crisis and European Debt Crisis on different liquidity levels of BIST100 index through financial stress indicator by using monthly data for the period of August 1997 – December 2016. Descriptive statistics for the LIQ and FSIG variables show that the distribution of both variables is not normal. As a result of the stationarity tests, it is concluded that both variables are stationary.

All three crises, the effects of which were examined, coincide with the slice where the financial stress indicator takes values between 102 and 103.5. The 85th quantile of the financial stress indicator is taken into account to represent this interval. The LIQ variable, which consists of the bid-ask spread estimation values, is evaluated in three different quantiles. While the 25th quantile is chosen to represent the segment where the bid-ask spreads are low, that is, the liquidity level is high, the 50th and 75th quantiles correspond to the median and high bid-ask spreads, that is, the median and low liquidity levels, respectively.

According to the findings obtained from the cross-quantilograms, it is observed that external financial and economic crises have a temporary liquidity-increasing effect at all quantile levels of BIST100. This prevents investors from experiencing great losses in the face of external crises, prevents bankruptcies and a systemic crisis that may affect the entire economy. As another finding, while the stock market liquidity is at the high and median level, that is, the stock market is operating under good and normal liquidity conditions, an increase in the liquidity level can be predicted in case of any financial or economic external crisis. In the periods when high bid-ask prices are realized, such a conclusion cannot be reached since the causality effect cannot be determined. However, it can still be said that external crises may cause increases in the liquidity level, albeit temporarily.

After an overall assessment, it is thought that financial investors in BIST100 generally follow the buy&sell strategy under normal and good market liquidity conditions and trading accelerates from high liquidity to low liquidity level in the event of an external crisis. In other words, it is seen that the segment in which external crises cause the greatest decrease in the transaction costs corresponds to the periods of high transaction costs. There is an inverse proportion between the BIST100 liquidity level and the magnitude of the liquidity-increasing effect of the external crises. It is thought that behind this result lies the higher tendency of investors to flee from low-liquidity to high-liquidity markets.

The reason behind this increase at the median and high liquidity level is the fact that investors who follow a buy-sell strategy dominate the stock market and they tend to move faster in the face of a crisis they may encounter, sell their assets and exit the market quickly. Moreover, it appears that the investors in BIST100 follow buy&hold strategy by necessity, at low liquidity level in the market. In the face of an external crisis, a stronger liquidity increase at a low liquidity level is an indication that investors are waiting for an opportunity to exit the market. In summary, apart from strategies followed, the higher tendency of investors to flight to liquidity during external crisis periods is also considered as another factor that may have an impact on the increase, especially at low liquidity level.

The increase in the median and high liquidity level is predictable. However, although crises have a liquidity-increasing effect at low liquidity level, this effect is not predictable. The crises cannot predict the direction of the movement in the liquidity level during low liquidity periods.

In the process of comparing the findings obtained from this study with the findings in the literature, it is seen that the financial and economic crises sometimes have positive and sometimes negative effects on the liquidity levels of different countries' stock exchanges. So, there is no consensus in the literature when it comes to the effects of the crises on the stock market liquidity. While getting the impression that the differences in the effects on different liquidity levels are mainly due to the differences in the strategies followed by the investors and the flight to liquidity, it is thought that the differences in the investor sentiments of different countries are important in the differentiation of the crisis effects on the stock market liquidity levels.

In a future study, the question about the existence of the directional predictability from a domestic financial or economic crisis, such as the 2001 and 2018 crises, to the stock market liquidity level, especially in the period when the stock market is at a low liquidity level, is an important question to be answered in order to prevent a crisis originating from a possible flight-to-liquidity phenomenon.

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