STOCK MARKET LIQUIDITY ANALYSIS: EVIDENCE FROM THE ISTANBUL STOCK EXCHANGE

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ABSTRACT

STOCK MARKET LIQUIDITY ANALYSIS: EVIDENCE FROM THE ISTANBUL STOCK EXCHANGE

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The purpose of this thesis is to identify the factors playing a key role in the determination of the Turkish stock market liquidity in *aggregate* terms in a time series context and discuss the joint dynamics of the market-wide liquidity with its selected determinants and the trade volume. The main determinants tested are the level of return, the return volatility and the monetary stance of the Central Bank of the Republic of Turkey. The expected positive relationship between the liquidity and the return is confirmed, while the negative effect of the volatility on liquidity appears one-week later. The behavior of various liquidity variables are also examined around the macroeconomic data announcement dates, during the 2008 financial crisis, and after the tick size change in the Istanbul Stock Exchange (ISE). The time series dynamics between the trade volume, return, volatility and the liquidity are put forward within the Vector Autoregression analysis framework. The GARCH modeling of the return series, which is an input to the liquidity model estimations, is a byproduct of this thesis. It is observed that the return series exhibits volatility clustering, persistence, leverage effects and mean reversion. In addition, while the level of the ISE market return decreased, the volatility of the return increased during the 2008 crisis. Accordingly, EGARCH model assuming normally distributed error terms and allowing a shift in the variance during the crisis period is chosen as the best model.

Keywords: Stock Market Liquidity, GARCH Models, Vector Autoregression.

ÖZ

HİSSE SENEDİ PİYASASI LİKİDİTE ANALİZİ: İSTANBUL MENKUL KIYMETLER BORSASI'NDAN KANITLAR

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Bu tezin amacı, Türk hisse senedi piyasasının toplam likiditesinin belirlenmesinde anahtar bir rol oynayan faktörleri zaman serileri bağlamında ortaya koymak ve toplam piyasa likiditesinin seçilmiş belirleyicileri ve işlem hacmi ile birlikte dinamiklerini tartışmaktır. Test edilen temel belirleyiciler getiri seviyesi, getiri oynaklığı ve Türkiye Cumhuriyet Merkez Bankası'nın parasal duruşudur. Oynaklık ve likidite arasındaki negatif ilişki bir hafta sonra görülürken, likidite ve getiri arasındaki beklenen pozitif ilişki doğrulanmıştır. Çeşitli likidite değişkenlerinin davranışları da makroekonomik verilerin açıklanma tarihleri etrafında, 2008 finansal krizi süresince, ve İstanbul Menkul Kıymetler Borsası'nda (İMKB) fiyat adımı değişikliğinden sonra incelenmiştir. İşlem hacmi, getiri, oynaklık ve likidite arasındaki zaman serileri dinamikleri Vektör Otoregresyon analizi çerçevesinde ortaya konmuştur. Likidite modeli tahminlerine bir girdi olan getiri serisinin GARCH modellemesi bu tezin bir yan ürünüdür. Getiri serisinin oynaklık kümelenmesi, süreklilik, kaldıraç etkisi ve ortalamaya dönme sergilediği gözlemlenmiştir. Ek olarak, 2008 krizi süresince, İMKB piyasa getiri seviyesi düşerken getiri oynaklığı artmıştır. Buna göre, normal dağılan hata terimleri varsayan ve kriz dönemi süresince varyansta kaymaya olanak sağlayan EGARCH modeli en iyi model olarak seçilmiştir.

Anahtar Kelimeler: Hisse Senedi Piyasası Likiditesi, GARCH Modelleri, Vektör Otoregresyon

To My Family

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SYMBOLS	
ADF	Augmented Dickey Fuller Test
CBRT	Central Bank of the Republic of Turkey
GED	Generalized Error Distribution
ISE	The Istanbul Stock Exchange
OLS	Ordinary Least Squares
AIC	Akaike Information Criterion
DX	First differences of variable X
FPE	Finite Prediction Error
$HQIC$	Hannan-Quinn Information Criterion
$ILLIQ$	Illiquidity ratio
$ILLIQSRT$	Square root version of the illiquidity ratio
$LNR100$	Return on the ISE-100 index
LNX	Natural logarithm of the variable X
LR	Liquidity ratio
$LRSQRT$	Square root version of the liquidity ratio
$ONINT$	Overnight interest rate in the interbank money market
$REFFECT$	Relative effective spread
$RESERVE$	A monetary stance variable based on the reserves of the banking sector
$RQUOTED$	Relative quoted spread
SBC	Schwarz Bayesian Criterion
$TLVOLUME$	Value of the number of shares traded in terms of Turkish Lira

$TURNOVER$	Turnover measure
UX	Residuals obtained from regressing the variable X on trend, squared trend, the dummy variables associated with the crisis, tick size change and macroeconomic data announcement
$VLNR100$	Volatility of the return on the ISE-100 index
$VOLUME$	Number of shares traded

CHAPTER 1

INTRODUCTION

In economics, liquidity is used in different contexts and has been attributed several meanings. Basically, three types of liquidity which are intrinsically interrelated can be identified[1]. The first one is macroeconomic liquidity which can be simply measured as the monetary base that is controlled by the Central Bank via the open market operations, reserve requirements and discount rates. The second one is funding liquidity. Funding liquidity is defined as the ability of a firm to settle liabilities on time and is closely related to the extent to which traders can access funding easily[2]. And the third one is financial asset or market liquidity. Sarr and Lybek (2002) differentiated between an asset's market liquidity and a financial market's liquidity. A financial market's liquidity is influenced by the degree of the substitutability of the alternative assets in the market as well. The focus of this thesis is the stock market aggregate liquidity rather than the individual asset liquidity.

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[1] See Nikolaou (2009).

[2] See Drehmann and Nikolaou (2009).

There is no universally accepted definition of the asset or market liquidity. According to Black (1971), an asset is defined as liquid if it takes a short time to sell with a price that is not much less the one if the seller chooses to wait a long time. Further, Black (1971) described a liquid market as a place where (1) bid and ask prices with a small spread between them always exist so that small amounts can be traded immediately, (2) uninformed traders is aware of the fact that it may take a long time to buy and sell large amounts of stocks without having much effect on the current price, (3) the traders with an information that the stock is over or under-priced can trade large amounts of stocks within a short time but at a premium (for buyer) or a discount (for seller) which is positively related to trade volume. This definition, as proposed by Keynes, encompasses the time, transaction costs and volume dimensions of the market liquidity (Fernandez, 1999). In line with this discussion, Kyle (1985) identified three dimensions stressing that the market liquidity is an *elusive* concept: tightness, depth, and resiliency. Tightness basically refers to the difference between the bid and ask prices at a given time. From the point of view of a market maker, the spread between the bid and ask prices represents the compensation for providing liquidity in the market. Hence, this spread is supposed to cover three types of costs, which are generally called as *the components of bid-ask spread*: (1) order processing costs[3], (2) inventory carrying costs[4], and (3) asymmetric information costs[5].

As explained above, large trading volume can be attributed to the informed traders and this can result in price changes larger than the bid-ask spread. With

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[3] See Huang and Stoll (1997).

[4] See Amihud and Mendelson (1980), Demsetz (1968).

[5] See Easley and O'Hara (1987).

this in mind, Kyle (1985) defined the market depth as the extent to which it is able to handle the effects of large volume of trades on prices and measures as the size of order flow necessary to create a given amount of price change. Fernandez (1999) included the existence of counteroffers and the order sizes of the dealers in the depth dimension as well.

Finally, the resiliency refers to how fast the price changes resulting especially from large volumes of uninformed trades dissipate. Due to the difficulty in measuring the resiliency dimension, the tightness and depth dimensions have attracted the most attention while the resiliency dimension is generally overlooked. Dong, Kempf and Yadav (2007) found that there is a weak correlation between resiliency and the other two dimensions and resiliency dimension has a significant impact on stock returns.

Nikolaou (2009) claimed that in periods with low liquidity risk there is a virtuous circle such that the market liquidity helps to the redistribution of the liquidity provided by the Central Bank within the financial system while the funding liquidity ensures the efficient allocation of funding resources among the financial institutions. These interactions work for the sake of the financial stability. Brunnermeier and Pedersen (2008) pointed out that when the funding opportunities for the firms become relatively tight, the willingness of traders to provide market liquidity declines and leads to less market liquidity and higher volatility. This reduction in market liquidity, in turn, has adverse effect on the funding liquidity; hence a vicious circle damaging the financial stability appears as suggested by Nikolaou (2009).

The liquidity analysis both at the individual stock and aggregate level has received the most attention in its relation to the asset pricing. Asset pricing models treat the illiquidity as a risk factor that needs to be compensated for with a premium. This issue is explored both in cross section[6] and time series context[7]. The commonality[8] documented in the cross-sectional liquidity pave the way for further research on the role of aggregate liquidity in explaining the cross-sectional returns. Further, Amihud, Mendelson, and Pedersen (2005) also argued that risk-averse investors should be compensated for the volatility of liquidity as well.

The purpose of this thesis is to identify the factors playing a key role in the determination of the Turkish stock market liquidity in *aggregate* terms rather than on a stock basis in a time series context and discuss the dynamics of the aggregate market liquidity with its determinants. In the next chapter, a literature survey on the liquidity measures and the time series properties of the calculated measures are given. As will be explained in the fourth chapter in which the factors affecting the market liquidity are discussed, the market return and the return volatility are two prominent determinants of market liquidity. As complementary to the chapter four, the third chapter is devoted for discussing the time series properties of the return and choosing an appropriate Generalized Conditional Heteroscedasticity model with the purpose of modeling the volatility of the return series. In the fifth chapter, the dynamics of the market liquidity and the determinants are analyzed within Vector Autoregression framework. Finally, chapter six gives a summary of conclusions of the thesis.

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[6] See Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Pastor and Stambaugh (2003).

[7] See Jones (2002).

[8] See Chordia, Roll and Subrahmanyam (2000), Hasbrouck and Seppi (2001), and Huberman and Halka (2001).

CHAPTER 2

LIQUIDITY MEASURES

In this chapter, a review on the liquidity measures proposed in the literature is provided and besides the basic statistics and correlations among them, the presence of the unit root in the calculated liquidity proxy series is discussed.

2.1. Literature Review

As explained in the introduction chapter, the liquidity measures can be categorized under four headings: (1) transaction cost measures, (2) volume-based measures, (3) price-impact measures, (4) other proxies. Transaction cost measures capture the cost of trading the financial assets. Volume-based measures refer to time and depth dimensions of liquidity concept. Price-impact measures aim to capture the depth dimension. Unfortunately, none of the proposed measures in the literature is able to capture all of the dimensions. In the fourth group that is out of the scope of this thesis, the measures that attempt to combine the several dimensions can be collected.

2.1.1. Transaction Cost Measures

Demsetz (1968) included the bid-ask spread as one of the two components of the transaction costs[9] and explains the existence of the bid-ask spread as the markup paid for providing immediacy in the market. Sellers or buyers cannot guarantee that there is a counterorder at the price they are willing to trade. It may take time a matching order to arrive in the market. If they are not willing to wait, incurring a price concession, they can trade with the market makers who always stand ready to transact. Transaction cost measures are primarily related to the tightness dimension of the liquidity concept. The most widely used transaction cost measure in the literature is the bid-ask spread. There is an inverse relationship between the bid-ask spread and liquidity of the underlying asset or the market.

A multitude of alternative ways of computing the bid-ask spread has been used in the literature. Acker, Stalker and Tonks (2002) differentiated between the quoted spread and inside spread. The quoted spread refers to the difference between the bid and ask prices at which an individual market maker is willing to trade. On the other hand, the inside spread refers to the difference between the highest bid and lowest ask price, with a high probability that they are given by different agents, prevailing in the market at a given point in time. However, the concept of market making is relatively new to the ISE and the stocks included in the ISE-100 Index calculations are not appointed a market maker and traded on a continuous auction basis. In this thesis, restricted by the unavailability of data, the spreads are calculated according to the *inside* definition although the terms quoted and effective spread are used.

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[9] The other component of the transaction costs mentioned in Demsetz (1968) is brokerage fees.

The first one is calculated as the absolute difference between the bid and ask price. This is usually called as *quoted spread*[10] and, for stock i, calculated as,

$$QUOTED_t^i = \left(a_t^i - b_t^i\right)$$

where

$QUOTED_t^i$ = quoted bid-ask spread for stock i at day t
a_t^i = the lowest closing ask price for stock i at day t .
b_t^i = the highest closing bid price for stock i at day t

The second type of spread is called as *relative spread*[11] and calculated in this way:

$$RQUOTED_t = \frac{\left(a_t^i - b_t^i\right)}{m_t^i} * 100$$

where m_t^i is the midpoint of the best bid and ask prices; that is $m_t^i = \left(a_t^i + b_t^i\right)/2$

Similar to the continuously compounded return, Hasbrouck and Seppi (2001) calculated the relative spread as the log differences of the best bid and ask prices. That is;

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[10] This is also called as absolute spread.The examples of studies that use high frequency bid-ask spread meausure include Chordia, Roll and Subrahmanyam (2001), Chordia, Roll and Subrahmanyam (2002), Chordia, Sarkar and Subrahmanyam (2005), Brennan and Subrahmanyam (1996).

[11] This is also called as percentage or proportional spread. The examples include Atkins and Dyl (1997), Chordia, Roll and Subrahmanyam (2001), Brennan and Subrahmanyam (1996).

$$LOGRELQUOTED_t^i = log(a_t^i) - log(b_t^i).$$

The relative spread which is unit-free makes it easier to compare stocks. The pure quoted spread can be used in the individual stock liquidity analysis safely. However, the purpose of this thesis is to analyze the aggregate market liquidity and in order to eliminate the effect of differences in the price of each stock on the aggregate measure the relative counterpart of the quoted spread is preferred. The construction of the relative spread rests on the idea that the higher the price the less costly will be a given spread.

Another closely related type of spread is *effective spread*[12] which is calculated as follows:

$$EFFECTIVE_t^i = 2 * |p_t^i - m_t^i|$$

where p_t^i is the closing price of stock i at day t.

Similar to the quoted spread, the relative counterpart of the effective spread is defined as

$$REFFECT_t^i = \frac{2 * |p_t^i - m_t^i|}{m_t^i} * 100$$

Goyenko, Holden and Trzcinka (2009) used the following log difference specification for the relative effective spread:

$$LOGRELEFFCT_t^i = 2 * |log(p_t^i) - log(m_t^i)|$$

[12] Hasbrouck and Seppi (2001).

Most of the studies that focus on transaction cost aspect use high frequency intra-daily data which is not available for most of the emerging markets and complicate the measure calculation process even if the data is available. A comprehensive review on the data frequency used in the liquidity analysis can be found in Hasbrouck (2009). Acker, Stalker and Tonks (2002) questioned whether the daily closing spreads represent the intraday spread and show that the intraday spread is an unbiased estimator of the closing counterpart. Using daily closing prices rather than the intra-day data makes it possible to study a longer period of time and that is why the closing bid-ask prices are used in this thesis.

The literature on low frequency measures that aim to measure the transaction costs has been expanding at a fairly rapid pace. Under the assumption of market efficiency, Roll (1984) showed that the effective spread can be approximated by the serial covariance of price changes. Holden (2009) extended the Roll measure by integrating the price clustering phenomenon. Lesmond, Ogden and Trzcinka (1999) used a market model approach to estimate the effective spread by assuming non-zero return that indicates informed trading. In addition, relying on the idea that the less liquid stocks tend to have more days with zero-return, they use the proportion of days with zero return as the liquidity proxy.

In this thesis, only $RQUOTED$ and $REFFECT$ are calculated[13] by using the best bid and ask prices waiting at the end of the day.

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[13] The natural logarithm transformation is also applied in order to reach more desirable distributional properties.

2.1.2. Volume-Based Measures

The volume-based proxies generally correspond to the depth and time dimensions[14]. The relation to the depth dimension is obvious. As the total trade volume in a stock market increases, the time required to trade a given number of shares decrease. This is how it is related to the immediacy dimension. There is a positive relationship between volume-based measures and liquidity.

The traditional measure of transactions is the trade volume[15]- that is the number of shares traded for a given period of time. A closely related measure is the value of traded shares[16] which is calculated as the sum of the number of shares traded multiplied by the price of the trade. The third measure is the number of contracts traded[17]. The fourth proxy is turnover. It gives an indication of how many times the outstanding volume of the stock i changes hands. In Wang and Kong (2011), it is calculated as value of the number of shares traded divided by the market capitalization of the stock. Atkins and Dyl (1997) found evidence that the holding period which is calculated as the reciprocal of the turnover is longer for the stocks with higher bid-ask spreads. In this thesis, turnover is calculated as

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[14] See Wyss (2004).

[15] See Lee, Mucklow and Ready (1993), Chordia, Roll and Subrahmanyam (2001), Chordia, Subrahmanyam and Anshuman (2001), Hasbrouck and Seppi (2001).

[16] See Brennan, Chordia, and Subrahmanyam (1998).

[17] See Chordia, Roll and Subrahmanyam (2001), Hasbrouck and Seppi (2001).

$$TURNOVER_t^i = VOLUME_t^i / N_t^i$$

where

$$VOLUME_t^i = \text{the number of shares of stock } i \text{ traded at day } t$$
$$N_t^i = \text{the number of shares outstanding of stock } i \text{ at day } t \quad .$$

In this thesis, $TURNOVER$, $TLVOLUME$ and $VOLUME$ are employed as the volume-based measures. For ease of representation, $TLVOLUME$ and $VOLUME$ are divided by 10^6 and this scaled versions are used in the estimations.

2.1.3. Price-Impact Measures

The price impact measures focus on the relationship between the order flow and the price changes. The literature that aims to measure the price impact can be traced back to Kyle (1985). According to Kyle (1985), large trading volume can be attributed to the informed traders and this can result in price changes larger than the bid-ask spread. Kyle (1985) defined the market depth as the size of order flow required to change prices a given amount. From this point of view, the liquidity proxies presented in this section are related to the depth dimension.

In the literature, several low frequency measures are developed with the purpose of measuring the price impact. The Amivest measure[18] which is also

[18] See Amihud, Mendelson, and Lauterbach (1997), Berkman and Eleswarapu (1998) and Goyenko, Holden and Trzcinka (2009).

called as liquidity ratio (LR) relies on the idea that trading large volumes of shares requires only small changes in prices if the stock is highly liquid. High values of LR indicate higher market depth and the stocks with high market capitalization tend to have a large LR scores misleadingly implying higher liquidity. Amivest measure for stock i on day t is calculated as follows:

$$LR_t^i = \left(TLVOLUME_t^i / \left|R_t^i\right|\right) * 10^{-6}$$

where

R_t^i = the return of stock i on day t
$TLVOLUME_t^i$ = TL value of shares traded of stock i on day t

The presence of outliers in this measure led Hasbrouck (2005) and Wang and Kong (2011) to use the square root version of this proxy. That is,

$$LRSQRT_t^i = \sqrt{\left(TLVOLUME_t^i / \left|R_t^i\right|\right) * 10^{-6}}$$

Hasbrouck (2005) pointed to the importance that the average is calculated after taking the square root of the daily measures.

Amihud, Mendelson and Lauterbach (1997) used the log transformation of the liquidity ratio in analyzing the improvement in liquidity. However, Hasbrouck (2005) did not prefer this form since it is possible this ratio to have a zero value.

Ranaldo (2000) used an alternative version of Amivest measure which is adjusted for the free floating number of shares of the stock, NF_t^i, and concluded that the inability of liquidity measure to incorporate the free floating rate may result in misleading results. The specific form used is

$$ADJUSTEDLR_t^i = \frac{TLVOLUME_t^i / NF_t^i}{\left|R_t^i\right|}.$$

Amihud (2002) proposed the illiquidity ratio which has the nice property that it can be calculated by using daily price and volume data which are easily accessible. Comparing to the high frequency benchmarks, Goyenko, Holden and Trzcinka (2009) concluded that the illiquidity ratio is successful at capturing the price impact. However, Amihud's measure does not treat buyer and seller initiated trades differently. Further, Grossman and Miller (1988) criticized the illiquidity measure in that it cannot differentiate between the price changes caused by the illiquidity and the arrival of new information. For an individual stock i, the illiquidity on day t is given by

$$ILLIQ_t^i = \left(\left|R_t^i\right| / TLVOLUME_t^i\right) * 10^6.$$

The square root transformation proposed for the liquidity ratio can be applied to the illiquidity ratio as well. That is;

$$ILLIQSQRT_t^i = \sqrt{\left(\left|R_t^i\right| / TLVOLUME_t^i\right) * 10^6}$$

This ratio gives the absolute price change in response to the one unit of daily value of shares traded. In other words, the illiquidity measure gives the daily price impact of order flow. Due to the ease of calculation and the importance of the dimension it is intended to capture, Amihud's illiquidity measure is widely used[19] and there are two alternative specifications of this proxy. Brennan, Huh and Subrahmanyam (2011) used share turnover rather than the traded value of shares as the trading activity measure in the denominator and take the natural logarithm in order to decompose the effects of the size and turnover on the asset pricing. That is, the first modified version of Amihud measure for a stock is

$$MODIFIEDILLIQ_t^i = \left|R_t^i\right|/TURNOVER_t^i.$$

The log transformation is

$$MODIFIEDILLIQ2_t^i = log\left(\left|R_t^i\right|/TURNOVER_t^i\right).$$

$ILLIQ$ and LR measures do not distinguish between transitory and permanent price changes. With a specific focus on this, Pastor and Stambaugh (2003) proposed a measure that can be calculated with low frequency data with the reasoning that the order flow will be followed by a partial return reversal and the magnitude of this reversal has an inverse relationship with the stock's liquidity. Another depth measure is the volume of orders waiting for trade at a given price. As there is higher volume of orders, a large volume of trade will not be associated with large price change movements. This high frequency measure is preferred in Chordia, Roll and Subrahmanyam (2001) and Chordia, Sarkar and Subrahmanyam (2005). Due to the simplicity of calculations, $ILLIQ$ and LR measures together with their squared root versions are preferred in this thesis.

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[19] See Acharya and Pedersen (2005), Goyenko and Ukhov (2009), Goyenko, Holden and Trzcinka (2009), Hasbrouck (2009).

2.1.4. Other Proxies

The composite liquidity measure of Chordia, Roll and Subrahmanyam (2001) and the quote slope of Hasbrouck and Seppi (2001) are taken as valuable attempts to combine the tightness and depth dimensions in one measure. However, both require the volume data associated with each bid and ask quotes and this makes the calculations complex even if not impossible.

A multitude of measures is mentioned up to this point. However, an important empirical challenge appears when to decide which measure to use. Goyenko, Holden and Trzcinka (2009) found that the spread proxies[20] calculated by using low frequency data is able to estimate the high frequency counterparts. However, this result does not hold for the price impact proxies[21] but, in any case, $ILLIQ$ is suggested to be the best one among price impact measures. For the Chinese stock market, Wang and Kong (2011) determined the turnover as the best liquidity proxy both in terms of explanatory power in asset pricing models and the proximity to the high frequency benchmarks. Since there is not a consensus on the best liquidity measure and many different specifications are proposed even for the same dimension of the liquidity, nine different measures- four for price impact dimension, two for the tightness dimension, and three volume-based measures- are calculated. The statistical properties of these measures are discussed in the next section.

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[20] The low frequency spread proxies used are Roll, effective tick, Gibbs, Holden, LOT and zeros.

[21] The price impact proxies from low frequency data are Amihud, Amivest and Pastor&Stambaugh measure.

2.2. A Note on the Calculation of $ILLIQ$ and LR

$ILLIQ$ and LR measures require the computation of daily returns. However, defining the return as simply the daily percentage change in price may not be appropriate since some other events other than the magnitude of trade volume may be the reason of large price changes. In these cases, there needs to make some adjustments on the closing prices of individual stocks. The events that deserve adjustment on the closing prices can be listed as follows: cash dividend payment, capital increase through rights offerings and bonus issues. In the absence of new information, if a firm pays cash dividends, the price of the stock drops by the after tax amount of cash dividend per share on the ex-dividend day[22] (Parrino & Kidwell, 2009, Ch.17). This is simply the result of the change in the expected cash flow from holding the stock after the ex-dividend day. Firms may raise capital through rights offerings either by allowing the existing shareholders to use pre-emptive rights or selling the shares only to the new shareholders. In the ISE, the selling price of the new shares, that is subscription price, is generally determined as 1TL but it is also possible to sell at a higher price. The important point is that the market value increases as much as the amount of funds raised, that is the number of new shares issued multiplied by the subscription price. This, in turn, makes the adjustment in the return calculations essential. In the case of bonus issues whether as a result of capital increase from internal resources[23] or stock

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[22] Ex-dividend day is the first day a stock is traded without the right to receive the dividend.

[23] The primary source of the bonus issues is the revaluation fund account which is used for tracing the value of fixed assets on an inflation-adjusted basis. The other sources are share premium, the cost revaluation account, capital gains from the sale of affiliates and real estates (Adaoğlu, 2001).

dividends[24], the market value does not change as the number of shares increases. Hence, proportional to the number of shares, the price of the stock decreases and this requires the closing price to be adjusted for the return calculations.

The ISE publishes monthly returns by using the monthly counterpart of the following formula. However, the ISE does not publish daily returns calculated in this way. Hence, the daily return as used in the liquidity measure calculations is obtained by author's own calculations as follows:

$$R_t^i = \left(\frac{p_t^i * \left(1 + r_t^i + bonus_t^i\right) - \left(p_t^{i,r} * r_t^i\right) + d_t^i - p_{t-1}^i}{p_{t-1}^i} \right) * 100$$

where

R_t^i = return of stock i on day t
p_t^i = closing price of stock i on day t
r_t^i = rights issues ratio of stock i received on day t
$bonus_t^i$ = bonus issues ratio of stock i received on day t
$p_t^{i,r}$ = price of stock i for exercising rights (i.e. subscription price) on day t
d_t^i = amount of net dividends paid on day t for of stock i with a nominal value of 1 YTL

When a stock is not traded on a particular day, the return for that day is set to "MISSING". However, when the stock begins to trade after a suspension, the price no more than 10 days old (since it is not traded on the previous day the

[24] Stock dividend refers to the distribution of new shares to the existing shareholders in proportion to the shares they own. The sources of the stock dividends are retained earnings and distributable profit (Adaoğlu, 2001).

price is zero and this makes return calculation impossible) is used for the purpose of calculating the return on the first trading day after suspension.

2.3. Data

The sample chosen in this thesis spans the period between April 2005 and December 2010. For the period of study, there are 300 weeks. For 2 out of 300 weeks, the value is set to missing since the whole weeks are holidays[25]. So, the number of available observations is 298.

The daily closing prices, best bid and ask prices waiting at the end of the day, and trading activity data for each stock are collected from daily bulletins published on a session basis; the data on the number of outstanding shares are obtained from the files that are used for index calculation purposes by the ISE; and the data on dates, amounts and prices related to the dividends and capital increase (decrease) are collected from the dividend distribution and capital increase (decrease) history files from the web-site of the ISE.

All of the liquidity measures are calculated on a weekly basis. First, the daily measures are calculated for each stock. And then, the weekly measures for each stock are constructed as simply the averages of the daily measures. Finally, the weekly aggregate stock market liquidity measures are calculated as the equally weighted averages of the weekly measures of each stock in the sample. The

[25] The Council of Ministers made the decision that the week 9-13.01.2006 is completely holiday due to the feast of sacrifice. Actually, for the week 15-19.11.2010 there is no such decision and there is only one session hold at 15.11.2010. In order not to cause any outlier effects, this week is excluded from the sample and the return value for this week is also set to missing.

sample of stocks is consisted of the stocks included in the ISE-100 index with the aim of discarding any potential distortions due to the infrequent trading.

2.4. Summary Statistics

Before moving to any type of analysis, it is usual to examine the basic statistics of the series given in Table 1. For the original liquidity measures, the presence of positive skewness is common. Except $LRSQRT$, $TLVOLUME$ and $VOLUME$, all the liquidity measures have excess kurtosis; that is they are leptokurtic. The Jarque-Bera statistics are large enough to reject the null hypothesis of normal distribution for all of the measures. After taking the natural logarithm, the series become closer to the normal distribution with the relative quoted and effective spreads being still skewed to right and leptokurtic. Taking the natural logarithm of the number of shares traded eliminates the positive skewness from the series at the cost of added platykurtosis.

2.5. Correlations

Up to this point, how each proxy is related to the level of the liquidity is described. In this vein, since higher values of LR and volume-based measures, lower values of $ILLIQ$ and spread are associated with higher level of liquidity, LR and volume-based proxies are expected to be negatively correlated to $ILLIQ$ and spread measures while positively to each other.

Next section is a summary of the degree of co-movements among the three classes of liquidity measures. The variable names used refer to the original measures. However, the general pattern applies to the log variables as well.

Table 1 Summary Statistics of the Liquidity Measures and the Natural Logarithm Transformations

VARIABLE	MEAN	ST. DEVIATION	MIN	MAX	SKEWNESS (SK=0)	EXCESS KURTOSIS (KU=0)	JARQUE-BERA (JB=0)
ILLIQ	1.472	1.465	0.217	12.101	3.050 (0.000)	13.393 (0.000)	2689.285 (0.000)
LR	8.943	3.963	2.171	23.507	1.141 (0.000)	1.227 (0.000)	83.332 (0.000)
ILLIQSQRT	0.802	0.345	0.263	2.654	1.691 (0.000)	4.316 (0.000)	373.355 (0.000)
LRSQRT	2.128	0.555	0.896	3.638	0.557 (0.000)	-0.179 (0.533)	15.783 (0.000)
RQUOTED	0.793	0.140	0.460	1.312	1.781 (0.000)	3.896 (0.000)	346.101 (0.000)
REFFECT	0.795	0.142	0.468	1.318	1.783 (0.000)	3.792 (0.000)	336.528 (0.000)
TURNOVER	0.016	0.007	0.005	0.056	1.410 (0.000)	3.696 (0.000)	268.283 (0.000)
TLVOLUME	13.438	5.103	3.390	29.669	0.700 (0.000)	-0.040 (0.890)	24.376 (0.000)
VOLUME	4.278	2.006	1.479	10.926	0.819 (0.000)	-0.125 (0.664)	33.543 (0.000)
LNILLIQ	0.058	0.780	-1.528	2.493	0.387 (0.007)	-0.174 (0.543)	7.830 (0.020)
LNLR	2.101	0.424	0.775	3.157	0.086 (0.545)	-0.187 (0.515)	0.804 (0.669)
LNILLIQSQRT	-0.299	0.385	-1.334	0.975	0.376 (0.008)	0.141 (0.624)	7.261 (0.027)
LNLRSQRT	0.722	0.260	-0.110	1.291	-0.062 (0.663)	-0.242 (0.400)	0.916 (0.633)
LNRQUOTED	-0.246	0.161	-0.776	0.272	0.894 (0.000)	3.470 (0.000)	189.259 (0.000)
LNREFFECT	-0.243	0.162	-0.760	0.276	0.935 (0.000)	3.299 (0.000)	178.519 (0.000)
LNTURNOVER	-4.221	0.415	-5.247	-2.890	0.114 (0.425)	-0.283 (0.325)	1.636 (0.441)
LNTLVOLUME	2.526	0.384	1.221	3.390	-0.145 (0.311)	-0.291 (0.311)	2.097 (0.351)
LNVOLUME	1.347	0.461	0.391	2.391	0.107 (0.455)	-0.954 (0.001)	11.865 (0.003)

Note: The values in parentheses are p-values.

2.5.1. Price Impact vs. Volume-Based Measures

The two price impact or depth measures that are similar in calculation, $ILLIQ$ and LR, are negatively correlated as expected and more interestingly, the square root versions of these measures has a correlation coefficient quite larger than the one for the original series. Generally speaking, the volume-based measures have a positive relationship with each other with $TLVOLUME$ and $VOLUME$ exhibiting the most significant co-movement. It is seen that $ILLIQ$ has a negative correlation with the volume based measures as the most significant with $TURNOVER$. LR is positively related to the volume measures and it is mostly correlated with $TLVOLUME$.

2.5.2. Transaction Cost vs. Volume-Based Measures

There is almost one-to-one linear relationship between $RELQUOTED$ and $RELEFFECT$. Among the three classes of measures, the smallest correlation coefficients are observed between transaction cost and volume-based measures. One thing to note is that spread measures have an inverse linear relationship with $TURNOVER$ and $TLVOLUME$ while a positive one with $VOLUME$.

2.5.3. Transaction Cost vs. Price Impact Measures

There is a positive relationship between spread measures and $ILLIQ$ and a negative one with LR. However, this relationship is stronger with the square root version of LR compared to LR itself. Excluding the within class measures, $ILLIQ$ has the highest correlation coefficients with price impact measures and vice versa. However, this does not hold for LR and $LRSQRT$ which are mostly correlated with the volume-based measures.

2.6. Unit Root Tests

The two most popular unit root tests are the Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) test. The PP and ADF tests differ mainly in how they treat the serial correlation and heteroscedasticity in the innovations. While the ADF test account for the autocorrelation by the inclusion of lagged terms, the PP tests correct for any serial correlation and heteroscedasticity in the errors u_t of the test regression non-parametrically with the help of Newey and West heteroscedasticity and autocorrelation-consistent covariance matrix estimator. However, both of them have their own shortcomings. Cheung and Lai (1997) showed that PP test exhibits poorer performance compared to the ADF test in the presence of positive serial correlation and the proper bandwidth selection can help improve. The literature on the unit root tests has gained another dimension with Perron (1989) who emphasized that ADF test can result in failure to reject the null hypothesis of unit root in the presence of structural breaks even if the series does not contain unit root in fact. Since then, the effect of the structural breaks on the validity of the unit root tests received much attention as a forefront issue. Perron (1989) treated the break date as exogenous while Zivot and Andrews (1992), Perron and Vogelsang (1992), Clemente, Montane and Reyes (1998) let the break date be endogenously determined by the data. Glynn, Perera and Verma (2007) provided a literature review on the unit root tests allowing for structural breaks. In this section, since it is expected

Table 2 Correlations among the Liquidity Measures

a)

	ILLIQ	LR	ILLIQSQRT	LRSQRT	RELQUOTED	RELEFFECT	TURNOVER	TLVOLUME	VOLUME
ILLIQ	1.000								
LR	-0.517 ***	1.000							
ILLIQSQRT	0.944 ***	-0.655 ***	1.000						
LRSQRT	-0.700 ***	0.934 ***	-0.829 ***	1.000					
RELQUOTED	0.683 ***	-0.396 ***	0.657 ***	-0.537 ***	1.000				
RELEFFECT	0.684 ***	-0.394 ***	0.660 ***	-0.538 ***	0.999 ***	1.000			
TURNOVER	-0.468 ***	0.590 ***	-0.526 ***	0.664 ***	-0.213 ***	-0.217 ***	1.000		
TLVOLUME	-0.270 ***	0.822 ***	-0.400 ***	0.750 ***	-0.192 ***	-0.189 ***	0.653 ***	1.000	
VOLUME	-0.075	0.666 ***	-0.199 ***	0.554 ***	0.183 ***	0.185 ***	0.651 ***	0.868 ***	1.000

b)

	LNILLIQ	LNLR	LNILLIQSQRT	LNLRSQRT	LNRELQUOTED	LNRELEFFECT	LNTURNOVER	LNTLVOLUME	LNVOLUME
LNILLIQ	1.000								
LNLR	-0.762 ***	1.000							
LNILLIQSQRT	0.971 ***	-0.798 ***	1.000						
LNLRSQRT	-0.923 ***	0.931 ***	-0.942 ***	1.000					
LNRELQUOTED	0.608 ***	-0.429 ***	0.597 ***	-0.594 ***	1.000				
LNRELEFFECT	0.615 ***	-0.426 ***	0.603 ***	-0.596 ***	0.998 ***	1.000			
LNTURNOVER	-0.645 ***	0.604 ***	-0.616 ***	0.677 ***	-0.253 ***	-0.257 ***	1.000		
LNTLVOLUME	-0.469 ***	0.794 ***	-0.493 ***	0.689 ***	-0.187 ***	-0.183 ***	0.629 ***	1.000	
LNVOLUME	-0.273 ***	0.649 ***	-0.299 ***	0.492 ***	0.172 ***	0.176 ***	0.601 ***	0.881 ***	1.000

Note: ***, **, * represents significance at 1%, 5% and 10%, respectively.

that there may be structural breaks related to the tick size changes and the global financial crisis or even other breaks resulting from unforeseen events, the unit root test allowing two endogenous break date which is proposed by Clemente, Montanes and Reyes (1998) is also implemented besides the classical ADF test. PP test is not implemented due to the presence of positive autocorrelation in the liquidity measures. The Autocorrelation Functions (ACF) are provided in the Appendix B.

2.6.1. Augmented Dickey-Fuller Test

The most general form of the model on which the ADF test is based is as follows:

$$\Delta y_t = \alpha_0 + \alpha_1 trend + \theta y_{t-1} + \sum_{i=1}^{l} \beta_i \Delta y_{t-i} + u_t$$

The terms $\sum_{i=1}^{l} \beta_i \Delta y_{t-i}$ are included in order to capture the ARMA structure inherent in the series. Depending on the properties of the data, the drift term, α_0, and the trend variable can be excluded from the model. However, the test statistic is not identically distributed in all the three cases and Dickey and Fuller (1981) provided different critical values in each case for testing the null hypothesis θ is equal to 0 or, verbally, there is a unit root in the series. The standard model selection criteria Akaike Information (Akaike, 1974), Schwarz Bayesian (Schwarz, 1978) and Hannan-Quinn criteria (Hannan & Quinn, 1979) can be used in order to determine the appropriate lag length. However, the error term u_t is assumed to be homoscedastic and free of serial correlation.

Table 3 ADF Test Results for the Liquidity Proxies

a)	LAGS	ADF STAT	BREUSCH-GODFREY TEST		
			LAG 1	LAG 5	LAG 10
ILLIQ	6	-2.244	1.476	7.707	12.485
LR	5	-0.906	1.272	7.748	8.570
ILLIQSQRT	5	-2.368	0.075	1.990	5.526
LRSQRT	2	-1.759	1.354	6.724	11.633
RQUOTED	6	-1.839	0.419	9.925	16.961
REFFECT	6	-1.793	0.184	5.403	11.850
TURNOVER	1	-4.325 ***	1.766	3.726	10.620
TLVOLUME	2	-3.411 **	0.276	9.643	18.942
VOLUME	2	-2.628 *	0.460	3.827	14.511
LNILLIQ	4	-2.132	1.993	5.171	13.797
LNLR	5	-1.600	0.003	4.564	9.014
LNILLIQSQRT	4	-2.335	3.199	6.388	13.844
LNLRSQRT	2	-2.228	1.290	4.969	7.175
LNRQUOTED	5	-1.012	1.283	4.837	9.725
LNREFFECT	5	-1.079	0.709	2.974	6.677
LNTURNOVER	1	-4.013 ***	2.842	5.493	14.283
LNTLVOLUME	5	-2.950 **	0.852	6.591	10.833
LNVOLUME	5	-2.587 *	1.072	12.295	17.694

b)	LAGS	ADF STAT	TREND	BREUSCH-GODFREY TEST		
				LAG 1	LAG 5	LAG 10
ILLIQ	6	-2.251	-0.390	1.535	7.838	12.475
LR	3	-2.554	2.360 **	0.185	8.057	9.662
ILLIQSQRT	5	-2.485	-0.800	0.108	2.309	5.864
LRSQRT	2	-2.524	1.900 *	0.994	5.554	10.384
RQUOTED	6	-1.577	-0.690	0.513	9.949	17.118
REFFECT	6	-1.540	-0.660	0.247	5.418	12.091
TURNOVER	1	-4.615 ***	1.610	1.558	3.669	10.358
TLVOLUME	1	-6.270 ***	4.360 ***	2.245	9.512	12.341
VOLUME	4	-4.318 ***	3.320 ***	0.051	3.683	7.750
LNILLIQ	4	-2.351	-1.080	2.032	5.132	12.957
LNLR	5	-2.585	2.070 **	0.014	3.084	7.569
LNILLIQSQRT	4	-2.641	-1.280	3.137	5.954	13.193
LNLRSQRT	1	-3.058	1.770 *	2.261	6.110	8.921
LNRQUOTED	5	-0.603	-1.280	1.150	4.588	10.135
LNREFFECT	5	-0.675	-1.240	0.593	2.714	7.096
LNTURNOVER	1	-4.174 ***	1.190	2.781	5.535	14.274
LNTLVOLUME	2	-5.231 ***	3.670 ***	0.349	3.014	10.308
LNVOLUME	2	-4.751 ***	3.720 ***	1.033	3.583	10.764

Note: ***, ** and * indicates significance at 1%, 5% and 10% , respectively.

The ADF test results are given in Table 3. Among the models with only drift term, only $TURNOVER$, $TLVOLUME$, $LNTURNOVER$, $LNTLVOLUME$ and $LNVOLUME$ are able to reject the null hypothesis of unit root at 5% significance level[26]. Among the models containing trend term, in addition to the previously listed variables, the presence of unit root is also rejected for $VOLUME$. For the variables $TURNOVER$ and $LNTURNOVER$, the unit root hypothesis is rejected in models both with and without trend. As it is seen, the coefficient of the trend term is found to be insignificant.

2.6.2. Clemente, Montanes and Reyes Test

Clemente, Montanes and Reyes (1998) proposed two alternative forms depending on the breaks belong to the innovational and additive outlier. In this thesis, only the innovational outlier approach is used. This test basically depends on the iterative estimation of the following model and choosing the break date combination that gives the minimum pseudo t-ratio for testing the hypothesis that the coefficient ρ is equal to 1. Defining BP_{1t} and BP_{2t} as the structural break points, the model to be estimated is

$$y_t = \mu + \rho y_{t-1} + \alpha_1 B_{1t} + \alpha_2 B_{2t} + \beta_1 D_{1t} + \beta_2 D_{2t} + \sum_{i=1}^{l} \Delta y_{t-i} + u_t$$

[26] Before concluding there is unit root or not, the model should be checked for the remaining autocorrelations. The number of the augmenting lags are determined by following this strategy: Beginning with 5 lags, the insignificant lags are dropped from the model. If there is remaining serial correlation, more lags are added to the model. The presence of the remaining serial correlation is checked by using the Breusch-Godfrey test.

where

$$B_{jt} = \begin{cases} 1 \text{ if } t = BP_j + 1 \\ 0 \text{ otherwise} \end{cases} \quad \text{and} \quad D_{jt} = \begin{cases} 1 \text{ if } t > BP_j \\ 0 \text{ otherwise} \end{cases} \quad \text{for } j = 1{,}2.$$

B_{jt} is a pulse variable that intends to capture the temporary effects while D_{jt} is a dummy variable which measures the permanent effect of some event.

The test results are given in Table 4. The test fails to reject the null hypothesis of unit root only LR and implies that all other liquidity measures are stationary around the structural breaks while there is not enough evidence to reject the existence of the unit root in the natural logarithms of the spread measures and LR. Hence, this constitutes supportive evidence on the argument that the failure of the ADF test in rejecting the unit root hypothesis may be attributed to the existence of structural breaks. Then, the determination of these probable structural break points appears as an important issue. Actually for the period of study, there are two important events that may cause a break. The first one is the global financial crisis that started in the U.S. mortgage market and expands to other sectors and countries in a short time period. The second is more a local one and easy to identify. It is the tick size change in the ISE beginning from November 2010. Of course, there may be other structural breaks due to other events that are not identified so far. Hence, with the information in hand, the problem reduces to determining the points caused by the financial crisis.

Cumulative sum (CUSUM) and CUSUM of squares tests are specialized tests that are proposed for determining the appropriate break point. The Clemente, Montanes and Reyes test, in essence, is a unit root test not a structural break test. This test relies on the determination of the optimal break points inherent in the data. Since the existence of any structural change is of importance due to the stationarity considerations at that point, the optimal points identified by the test can be useful for providing insight. Comparing the optimal break points provided in Table 4 may give a sense of the probable points. The illiquidity together with its square root version, spread and the volume variables exhibits break around 35th week of 2008. This date typically refers to the start of the crisis. Determination of the second break point, which is assumed to correspond to the end of the crisis, is more difficult since both there is not much common point between the measures and it is not always easy the identify the end date of crisis exactly. The volume-based measures indicate a break around 20th week of 2010. The spread and depth measures yield closer results. The depth measures indicate a break around 46th week of 2008 while spread measures around 14th week for 2009. Since there is no consensus, two dummy variables corresponding to two adjacent sub-periods between 30th 2008 and 14th week 2009 are used in order to account for the possibility that different measures reflect the effect of the crisis for different time intervals. The details will be given in Chapter 4.

Table 4 Clemente, Montanes and Reyes Test Results for the Liquidity Proxies

a)

	ILLIQ	ILLIQSQRT	LR	LRSQRT	RQUOTED	REFFECT	TURNOVER	TLVOLUME	VOLUME
D1	2.052 ***	0.298 ***	-0.302	-0.125 ***	0.079 ***	0.083 ***	0.004 ***	2.660 ***	1.067 ***
	(7.043)	(5.220)	(-1.021)	(-3.097)	(6.210)	(6.348)	(4.645)	(4.657)	(5.035)
D2	-2.298 ***	-0.361 ***	2.061 ***	0.356 ***	-0.088 ***	-0.092 ***	-0.002 **	-0.467	-0.408 **
	(-7.434)	(-5.912)	(3.796)	(5.188)	(-6.796)	(-6.958)	(-2.550)	(-0.760)	(-1.968)
RHO-1	-0.300 **	-0.213 **	-0.239	-0.253 **	-0.148 **	-0.154 **	-0.334 **	-0.305 **	-0.302 **
	(-6.603)	(-6.181)	(-3.913)	(-5.519)	(-5.661)	(-5.771)	(-6.170)	(-5.829)	(-5.727)
LAGS	6	7	3	2	10	10	4	2	4
BP1	2008w35	2008w34	2008w3	2008w16	2008w36	2008w36	2009w10	2009w11	2008w35
BP2	2008w49	2008w46	2009w17	2009w14	2009w11	2009w11	2010w20	2010w21	2010w22

b)

	LNILLIQ	LNILLIQSQRT	LNLR	LNLRSQRT	LNRQUOTED	LNREFFECT	LTNURNOVER	LNTLVOLUME	LNVOLUME
D1	0.297 ***	0.121 ***	-0.144 ***	-0.085 ***	0.057 ***	0.059 ***	0.165 ***	0.040	0.216 ***
	(4.868)	(4.131)	(-2.898)	(-3.943)	(4.255)	(4.188)	(3.919)	(1.263)	(4.689)
D2	-0.510 ***	-0.237 ***	0.354 ***	0.197 ***	-0.070 ***	-0.073 ***	-0.113 **	0.166 ***	-0.073
	(-6.053)	(-5.559)	(4.959)	(5.700)	(-5.070)	(-4.993)	(-2.156)	(4.330)	(-1.532)
RHO-1	-0.275 **	-0.273 **	-0.310	-0.294 **	-0.095	-0.098	-0.242 **	-0.327 **	-0.270 **
	(-6.769)	(-6.493)	(-4.979)	(-6.390)	(-3.574)	(-3.595)	(-5.669)	(-6.227)	(-5.549)
LAGS	1	1	7	1	10	10	1	2	2
BP1	2007w45	2007w45	2008w32	2008w19	2008w35	2008w36	2009w10	2007w29	2008w35
BP2	2009w10	2009w13	2009w7	2009w14	2009w11	2009w11	2010w20	2009w11	2010w22

Note: Values in the second rows are t-stats. ***, ** and * indicates significance at 1%, 5% and 10% , respectively.

CHAPTER 3

RETURN AND VOLATILITY MODELING

The purpose of this chapter is to model the volatility of the return series. Volatility is defined as the standard deviation of the conditional distribution of the return series (Tsay, 2005). The literature on the return modeling has investigated many different aspects of the return series but despite the diversification the previous studies have documented some common characteristics of the return series for different markets, asset types and periods of study. An appropriate volatility model should be able to fit these regularities which are usually called as *stylized facts*. Hence, volatility modeling requires a good understanding of what kind of regularities the return series can have.

3.1. Stylized Facts of Return Series

Bollerslev, Engle and Nelson (1994)[27], Cont (2001)[28], Engle and Patton (2001)[29] and Poon and Granger (2003)[30] provided comprehensive lists of

[27] The list of empricial regularities is composed of thick tails, volatility clustering, leverage effects, higher volatility following non-trading periods, high association between forecastable

stylized facts of the return series. Kirchler and Huber (2007) provided a complete survey of literature on the most cited stylized facts of the return series with a special emphasis on the leptokurtosis and clustering phenomenon. Further, Terasvirta and Zhao (2006) examined the ability of several GARCH models to capture the most cited stylized facts specifically volatility clustering, high kurtosis, low starting and slow-decaying autocorrelation function and Taylor effect[31].

The most cited regularities in the return series can be summarized as follows: thick tails, negative skewness, absence of autocorrelation, volatility clustering, persistence, leverage effects and mean reversion. Thick tails are identified by positive excess kurtosis; that is the return series is leptokurtic. Also, a large number of studies have shown the return series is negatively skewed (Harvey & Siddique 1999, 2000). Another distributional property of the return series is that the series itself has no serial correlation. However, the squared series has

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events and volatility, negative inverse relation between volatility and serial correlation, commonality in volatility across stocks, weak relationship with economic uncertainty and strong positive relationship with interest rates.

[28] The complete list of the stylized facts is as follows: absence of autocorrelations, unconditional/conditional heavy tails, gain/loss asymmetry, aggregational Gaussianity, intermittency, volatility clustering, slow decay of autocorrelation in absolute returns, leverage effect, volume/volatility correlation and asymmetry in time scales.

[29] They focus on persistence, mean reversion, asymmetric effects, exogenous variables effecting volatility and heavy tails.

[30] They listed fat tails, volatility clustering, mean reversion and asymmetric effects and comovement of volatility across assets and markets.

[31] Taylor (1986) found that the absolute return series exhibits higher autocorrelation higher than the squared series. Further, Ding, Granger and Engle (1993) showed that the autocorrelations are highest when the power is equal to 1 among alternative power transformation of the absolute return series. This is called as the Taylor effect.

significant serial correlation and it is this feature that makes the volatility modeling essential. The observation that “large changes tend to be followed by large changes-of either sign-and small changes tend to be followed by small change” dates back to Mandelbrot (1963) and is called as “volatility clustering”. The identifying characteristic of volatility clustering is periods of tranquility interrupted by periods of turbulence (Kirchler & Huber, 2007). A commonly used tool to detect the volatility clustering behavior is the autocorrelation function of squared return series (Cont, 2001). Persistence is defined as the extent to which the current return affects the volatility in the far future. Leverage effect is first discussed by Black (1976) and can be basically defined as the negative correlation between past returns and future volatility. This inverse relationship stems from changes in the value of the firm and this leads to stock return and volatility changes. If the firm has financial leverage, a drop in firm value results in higher debt-to-equity ratio and in turn this leads to higher volatility. In the case of operating leverage due to fixed costs, the fall in income results in a fall in the firm value and increased volatility since the small fall in income manifests itself as higher fall in profit. Finally, mean reversion implies that high volatility episodes will be followed by a fall (and vice versa) and it will reach a long-run level. The required conditions for mean reversion are the same as stationarity which are stated in section 3.

3.2. Literature Review on the ISE

In the previous section, the regularities the return series have are summarized and brief description for each is provided. Although these facts are cited in most of the studies, they are not rules. The ISE is an emerging market which has seen major developments both in terms of regulations and trading activity since its establishment. Hence, before moving on to the technical analysis, this section is devoted to briefly review the literature on the volatility model estimation for the ISE.

Yavan and Aybar (1998) examined the daily log return series of the ISE index for the years 1986-1996 and concluded that GARCH(1,1) model is successful at describing the volatility behavior of the ISE and adding the estimated conditional variance (standard deviation as well) into the mean equation improves the mean return estimation. While they found no evidence of negative asymmetry effects, they found out that short term dynamics acts as an important determinant of the conditional variance. Similarly, the findings of Payaslıoğlu (2001) did not support existence of leverage effects and among three alternative models- GARCH(1,1)-M, EGARCH(1,1)-M and TGARCH(1,1)-M namely- none of them is proved to be superior in modeling the conditional heteroscedasticity for the period 1990-2000. By using stochastic volatility model, Yalçın (2007) showed the existence of volatility feedback but did not find any significant leverage effect for the period between 1990 and 2006. In contrary to these studies, Akar (2005) showed that the volatility of the daily return series covering the period 1990-2004 reacts differently to the positive and negative shocks by using TGARCH(1,1) model. By using daily ISE return data for the years 1998-2008, Köksal (2009) reported that models which allows for leverage effect has better volatility forecasts and, in particular, EGARCH(2,2) model with the t-distribution assumption for the innovations is the best model in terms of its fit to historical data and forecast performance. In his study for the period 1997-2004, Mazıbaş (2005) observed that there is leverage and asymmetry effects for daily, weekly and monthly data but the models have better forecast performance for the weekly and monthly series. By using weekly data between 1990-2007, Akar (2007) demonstrated that ARCH and GARCH models has inferior forecasts compared to the

Switching ARCH (SWARH) model which is also free of excessive persistence problem.

The stock markets act as a barometer of macroeconomic conditions and this issue received attention in the Turkish stock market literature as well. Between the years 1986 and 2003 by using monthly data, Kasman (2004) found out a significant causal relationship from money supply volatility to ISE return volatility and from return volatility to exchange rate and inflation volatility. Çağıl and Okur (2010) questioned whether the volatility of the ISE returns is affected by the global financial crisis of 2008 and demonstrated that there is an increase in volatility and its persistence for the period 2007-2010 compared to 2004-2007.

3.3. Volatility Models

Volatility modeling literature has evolved along two separate strands: autoregressive conditional heteroscedasticity models which is called as ARCH for convenience (Engle, 1982) and stochastic volatility models (Taylor, 1986). Ruiz (1993) compared these two classes of models empirically. Poon and Granger (2003) provided a comprehensive survey on volatility forecasting. In this thesis, stochastic models are out of consideration and only the extensions of ARCH model are used.

The ARCH model for the return series is composed of two equations: mean and volatility equation. The general formulation for the ARCH model is as follows:

$$\text{Mean equation:} \qquad r_t = c_0 + \sum_{i=1}^{n} c_i X_i + \varepsilon_t$$

$$\text{with } \varepsilon_t = \sqrt{h_t} z_t$$

$$\text{Volatility equation:} \qquad h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$$

where q and n are non-negative integers, X_i are explanatory variables, h_t is the conditional variance of the return series. ε_t is called as the innovation or shock of the market return at time t. $\{z_t\}$ is a sequence of independently and identically distributed random variables with mean zero and variance 1.

The following conditions ensure that the conditional variance of ε_t is positive:

$$\alpha_0 > 0 \text{ and } \alpha_i \geq 0\ \forall i$$

In addition, $\sum_{i=1}^{q} \alpha_i < 1$ is the necessary and sufficient condition for the weak stationarity of the ARCH model.

The structure of the ARCH model implies that a large past squared innovation tends to lead to a large innovation in the later period. This implies the ARCH model and its extensions are able to capture the volatility clustering phenomenon. Also, Engle (1982) showed that ARCH model is able to capture the fat tail phenomenon.

With the aim of allowing the conditional variance to change over time depending on its lags, Bollerslev (1986) proposed the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) which differs from ARCH models only in the volatility equation with the mean equation is common for both of them. The general form for volatility equation for GARCH model can be formulated as follows:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}$$

For GARCH model, Nelson and Cao (1992) showed that the sufficient conditions for the conditional variance of ε_t to be positive are as follows[32]:

$$\alpha_0 > 0\ ,\ \alpha_i \geq 0\ \forall i = 1\ to\ q\ \ ,\ \ \beta_j \geq 0\ \forall\ j = 1\ to\ p$$

The necessary and sufficient condition for covariance stationarity for the general GARCH model is

$$\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1.$$

The condition $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$ ensures the unconditional variance of ε_t is finite. The sum $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$ is commonly used as the measure of the volatility persistence for the general GARCH(p,q) model. The parameters α_i and β_i shows the contribution to the short and long run persistence, respectively. Similar to ARCH model, Bollerslev (1986) showed that GARCH model is able to fit to the leptokurtosis usually observed in the financial data.

One important extension of GARCH model is GARCH-in-the-Mean model (GARCH-M) which is proposed by Engle, Lilien and Robins (1987). This model is developed in order to model the phenomenon that the market return depends on its volatility. The volatility equation for the GARCH-M model is

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[32] For the sufficiency conditions for positive conditional variance to be valid, it is implicitly assumed that ε_{t-i}^2 and $h_{t-j}$are positive for all models mentioned in this study.

the same as the general GARCH model. However, the mean equation differs from the general specification and can be formulated as follows:

$$r_t = c_0 + \sum_{i=1}^{n} c_i X_i + a h_t + \varepsilon_t$$

$$\text{with } \varepsilon_t = \sqrt{h_t} z_t$$

As it is seen from the formulation, the volatility itself enters the mean equation. The coefficient of the variance variable, a, is called as the "risk premium" coefficient. Positive a implies that as the volatility or risk of asset (market) increases the expected return of the asset (market) increases. The conditions for the positivity of the conditional variance and the covariance stationarity are the same as GARCH model.

Another class of models has been invented with the aim of allowing for the asymmetric effects between positive and negative innovations on the volatility. One extension which allows asymmetric effects and has the nice property that the coefficients are not restricted to be positive in order to guarantee the positivity of the conditional variance of ε_t is the Exponential GARCH (EGARCH) model proposed by Nelson (1991). Nelson (1991) modeled the log of the variance rather than the variance itself. The EGARCH model with $N(0,1)$ innovations can be specified as follows:

$$\log(h_t) = \alpha_0 + \sum_{i=1}^{q} \alpha_i \frac{\left(|\varepsilon_{t-i}| - \sqrt{2/\pi}\right)}{\sqrt{h_{t-i}}} + \sum_{i=1}^{q} d_i \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} + \sum_{j=1}^{p} \beta_j \log\left(h_{t-j}\right)$$

The derivation of the EGARCH model for different distributional assumptions can be found in Nelson (1991). With the above parameterization, a negative value for d_i implies that a negative residual tend to increase the variance more than the positive residuals. If $|\beta| < 1$, then EGARCH(1,1) is said to be covariance stationarity. The parameter β is used as the measure of persistence for the EGARCH model[33].

In the asymmetric GARCH models class, there are GJR-GARCH model which is developed by Glosten, Jagannathan and Runkle (1993) and the Threshold GARCH (TGARCH) model. The distinction between GJR-GARCH and TGARCH models is that the latter models the conditional standard deviation and the former models the variance. In this study, only GJR-GARCH will be considered.

The volatility equation of GJR-GARCH model is

$$h_t = \alpha_0 + \sum_{i=1}^{q} (\alpha_i + d_i I_{t-i}) \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}$$

$$\text{with } I_{t-i} = \begin{cases} 1 \text{ if } \varepsilon_{t-i} > 0 \\ 0 \text{ if } \varepsilon_{t-i} \leq 0 \end{cases}$$

where $I_t$is an indicator for positive ε_{t-i}. A negative value for d_i implies that positive shocks tend to decrease the volatility more than negative ones with the same magnitude.

The sufficiency and necessary conditions for the positivity of the conditional variance of ε_t for GJR-GARCH(1,1) model are

$$\alpha_0 > 0, \alpha_1 \geq 0 , \beta_1 \geq 0 \text{ , and } \alpha_1 + d_1 \geq 0.$$

[33] See Su (2010)

Ling and McAleer (2002) found the covariance stationarity condition for GJR-GARCH(1,1) model with a symmetric distribution as $\alpha_1 + \beta_1 + \frac{d_1}{2} < 1$. The $\alpha_1 + \frac{d_1}{2}$ component is defined as the contribution of shocks to the short run persistence, and $\alpha_1 + \beta_1 + \frac{d_1}{2}$ shows the contribution to the long run persistence.

Following the observation that is structural shift in volatility leads to high persistence of shocks which was put forward by Lamoureux and Lastrapes (1990), Hamilton and Susmel (1994) developed Switching ARCH (SWARCH) model in order to improve forecast performance of the model. However, this class of models is not used in this thesis.

An important issue in the volatility modeling is the choice of the assumed marginal distribution for ε_t. In empirical studies, it is generally assumed to follow Gaussian distribution. However, normal distribution is far from being able to capture the well documented skewness and kurtosis in the conditional distribution of the return series (Harvey & Siddique, 1999). In order to account for the kurtosis, the distributions such as generalized error distribution-GED or exponential power distribution (Nelson, 1991) and student's t distribution (Bollerslev, 1987) are widely used. Similarly, for capturing the asymmetries in the return series, the skewed versions of student's t (Hansen, 1994) and GED (Theodossiou, 2000) are widely used in the literature. Further, Li (2007) used exponential generalized beta distribution of second type in order to capture both the skewness and kurtosis simultaneously. Bollerslev and Wooldridge (1992) proved that the Quasi-Maximum Likelihood estimates (QMLE) are consistent provided that the mean and variance equations are correctly specified. Further, they concluded that the loss of efficiency in the QMLE[34] estimates can be substantial compared to the Maximum Likelihood estimates if the error distribution is skewed while it is negligible if the distribution is symmetric. In order to overcome this issue, they provided formulas for standard errors that are valid even if the normality assumption is not satisfied.

3.4. Time Series Properties of the ISE-100 Index Return

For the period between April 2005 and December 2010, the weekly market return is calculated as continuously compounded series by using the ISE-100 price index according to the following formula:

$$LNR100_t = \ln(p_t/p_{t-1}) * 100$$

where

$LNR100_t$ = market return for week t
p_t = closing value of the ISE 100 index at the end of the week (Friday) t

As Table 5 shows, the unconditional distribution of the return series is leptokurtic and negatively skewed as expected[35]. Examining the time plot of

[34] QMLE refers to the Maximum Likelihood estimation in which the log-likelihood function of the normal distribution is maximized but the true distribution is not normal (Bollerslev & Wooldridge, 1992).

[35] See Mazıbaş (2005).

the return series in Figure 1, it is clearly seen that the volatility of the series increases in the second half of the year 2008[36]. This period typically corresponds to the start of the global financial crisis. Hence, the negative skewness present in the data can be attributed to the outliers due to the financial crisis.

Table 5 Summary Statistics of ISE Return (%)

	ORIGINAL SERIES	**RESIDUAL SERIES**
SAMPLE MEAN	0.316	0.000
(MEAN=0)	(0.201)	(1.000)
STANDARD DEVIATION	4.257	4.206
MINIMUM	-19.273	-16.918
MAXIMUM	15.758	16.439
SKEWNESS	-0.434	-0.181
(SK=0)	(0.002)	(0.205)
EXCESS KURTOSIS	2.199	2.416
(KU=0)	(0.000)	(0.000)
JARQUE-BERA	69.414	74.128
(JB=0)	(0.000)	(0.000)

Note: Values in parentheses are p-values.

In order to test the proposition that the skewness in the return series is the result of the outliers caused by the global crisis, the return series is regressed on $CRISIS$ dummy variable. The start and the end dates are determined with the help of Clemente, Montanes and Reyes test.

[36] See Çağıl and Okur (2010).

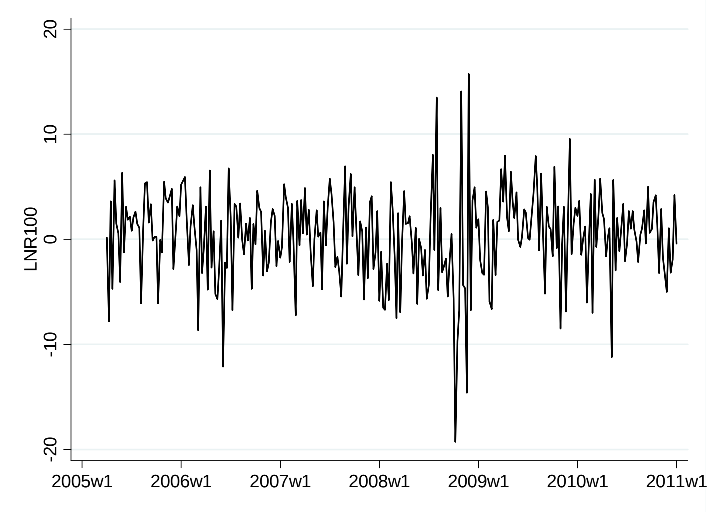

Figure 1 Time Plot of ISE-100 Return (%)

With this purpose the following model is estimated by using the Ordinary Least Squares (OLS) method.

$$\underset{}{LNR100_t} = \underset{(0.251)}{0.478} - \underset{(1.052)}{2.833}\, CRISIS_t + u_t$$

where

$$CRISIS_t = \begin{cases} 1 & \text{if } 2008w30 \leq t \leq 2008w46 \\ 0 & \text{otherwise} \end{cases}$$

and the values in parentheses are standard errors. It is seen that the coefficient of the dummy variable is significant at 1% significance level and negative implying that the return of the ISE-100 index decrease during the period between the end of July and mid-November due to the financial crisis. Further,

Table 5 reveals that the residuals obtained from regressing the return series on the dummy variable is still leptokurtic but symmetric in this case. This result is important in modeling the volatility of the return series.

In the next step, the stationarity property of the series is examined since the concept of volatility can be applied only to the stationary series. Table 6 compares the unit-root models up to 10 lag length based on Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) and presents the associated ADF statistic (Dickey & Fuller 1979, 1981) associated with each model. AIC and SBC in Table 6 are computed according to the following formulas:

$$AIC = T * \ln\left(\frac{RSS}{T}\right) + 2 * k \text{ and } SBC = T * \ln\left(\frac{RSS}{T}\right) + k * \ln(n)$$

where k is the number of parameters, T is the number of observations and RSS is the residual sum of squares.

Table 6 ADF Test Results of ISE Return (%)

	WITH INTERCEPT, NO TREND			WITHOUT INTERCEPT AND TREND			WITH INTERCEPT AND TREND		
m	**AIC**	**SBC**	**T-STAT**	**AIC**	**SBC**	**T-STAT**	**AIC**	**SBC**	**T-STAT**
0	2.902	2.927	-17.651 ***	2.901	2.913	-17.582 ***	2.908	2.946	-17.62406 ***
1	2.889	2.927	-10.788 ***	2.888	2.913	-10.709 ***	2.896	2.946	-10.7688 ***
2	2.901	2.951	-9.002 ***	2.899	2.937	-8.907 ***	2.908	2.971	-8.98747 ***
3	2.914	2.977	-7.798 ***	2.913	2.964	-7.681 ***	2.921	2.997	-7.78322 ***
4	2.921	2.998	-6.921 ***	2.919	2.983	-6.828 ***	2.928	3.018	-6.90983 ***
5	2.938	3.029	-6.157 ***	2.935	3.012	-6.068 ***	2.945	3.048	-6.1509 ***
6	2.946	3.050	-6.176 ***	2.943	3.034	-6.070 ***	2.953	3.070	-6.1678 ***
7	2.938	3.056	-5.388 ***	2.936	3.041	-5.246 ***	2.945	3.076	-5.36575 ***
8	2.941	3.073	-4.810 ***	2.938	3.056	-4.694 ***	2.948	3.093	-4.80082 ***
9	2.950	3.095	-4.882 ***	2.948	3.080	-4.751 ***	2.957	3.116	-4.86956 ***
10	2.962	3.122	-4.400 ***	2.960	3.106	-4.269 ***	2.970	3.143	-4.38826 ***

Note: ***, ** and * denotes significance at 1%, 5% and 10% levels respectively. m refers to the number of augmenting lags in the unit root model.

According to Table 6, the unit root model without constant and trend augmented with 1 lag is the best equation. This result is suggested both by AIC and SBC. The estimation results with standard errors in parentheses are:

$$\Delta LNR100_t = \underset{(0.083)}{-0.887}\, LNR100_{t-1} \underset{(0.058)}{-0.133}\Delta LNR100_{t-1}$$

As the final step of determining the unit root model, it is needed to check for any remaining serial correlations in the model. The ACF given in Figure 2 shows that there is no remaining autocorrelation in the model. Hence, there is no unit root in the return series and it is stationary.

Since the purpose of this section is to determine the appropriate volatility model for the stationary return series, the first step is to check for the serial correlation in the series. From Figure 2, it is observed that there is a minor spike at lag 2. This may be an indication of MA(2) structure but, generally speaking, the autocorrelation coefficients are not significant. Mazıbaş (2005), Çağıl and Okur (2010) used daily series and report significant autocorrelation but this contradictory result can be attributed to the daily data. So, at this stage there seems no need to define an ARMA model for the ISE-100 return series.

As explained before, the dependence present in the return series is the core point of the volatility modeling and this property is investigated by examining the autocorrelation structure of the absolute and the squared series.

From Figure 2, it is observed that absolute return series has significant serial correlation at the first three lags. The visual inspection of the time plot in Figure 3 reveals that there is an increase in the absolute return, hence in volatility, between July and November in the year 2008.

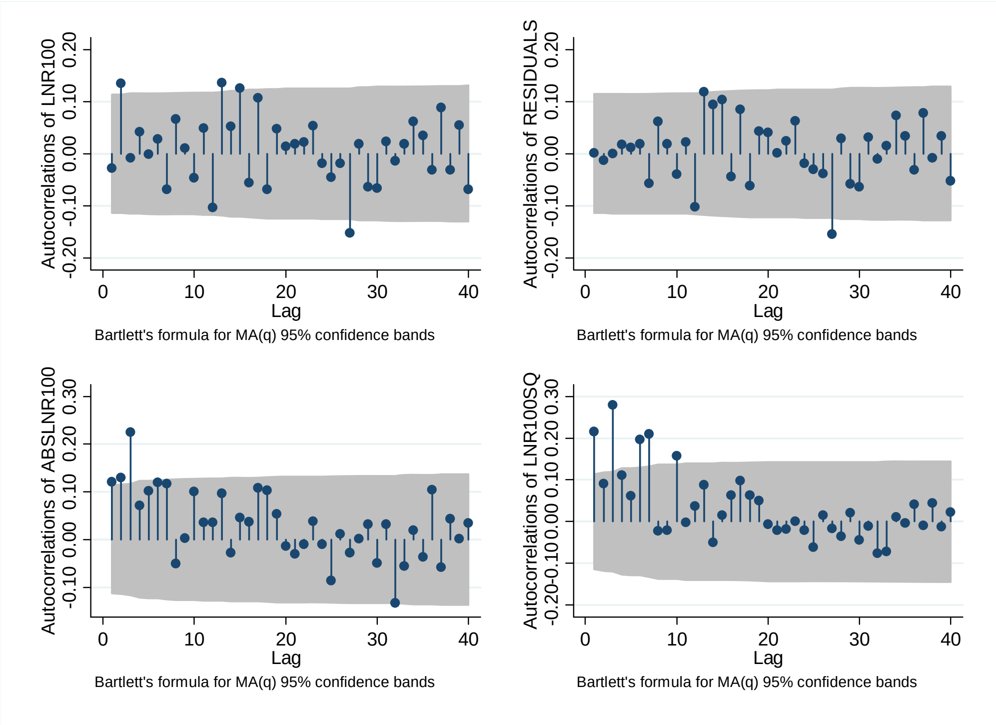

Figure 2 The ACF for the Original, Absolute, Squared Series and Unit Root Model Residuals of ISE-100 Return (%)

The time plot of the squared series in Figure 4 is so similar to that of the absolute one in that there is an apparent increase in the second half of 2008. Not surprisingly, Figure 2 exhibits significant autocorrelation at lags 1, 3, 5, 6, 7 and 10 for the squared series. Lamoureux and Lastrapes (1990) showed that failing to allow for structural shifts in the unconditional variance results in high persistence. With this in mind, these observations that there is a significant increase in the volatility of the Turkish stock market will be tested statistically by adding the crisis dummy variable defined above to the variance equation.

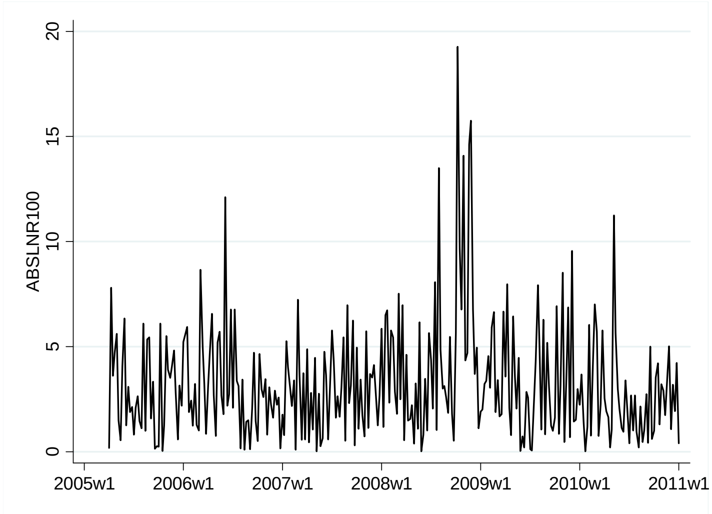

Figure 3 Time Plot of Absolute ISE-100 Return (%)

To sum up; the time plot of the ISE-100 return series does not follow a particular pattern (except decline at the start of the crisis), but the time plots of the absolute and squared return series indicate clustering[37] which is confirmed by the significant autocorrelations for the absolute and squared return series with insignificant ones for the log return series itself.

[37] Volatility clustering is also documented by Yavan and Aybar (1998) and Mazıbaş (2005).

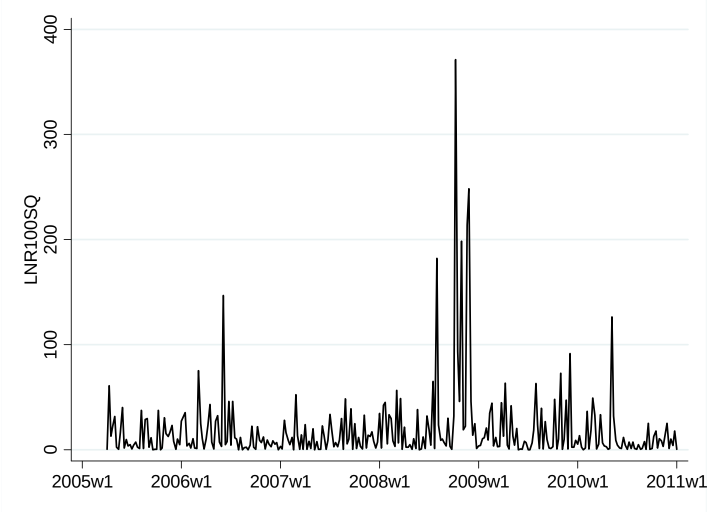

Figure 4 Time Plot of Squared ISE-100 Return (%)

3.5. Volatility Model Estimations

In this section, basically, the estimation results of four types of conditional heteroscedasticity models mentioned in section 3.3 will be presented. However, the models are diversified according to distribution assumption (Gaussian, student's t and GED) and the inclusion of the crisis dummy variable in only the variance and in both the mean and variance equations. Having shown that the inclusion of the crisis dummy variable in the model eliminates the skewness in the unconditional distribution of the log return series, this dummy variable is added to the mean and variance equations in all models in the first group. However, the dummy variable in the mean model is found to have insignificant coefficient in the GARCH model estimations. In the second group, the models are re-estimated without the dummy variable in the mean model. Under the t-distribution assumption, GJR-GARCH(1,1) model yields no convergence result since the likelihood function is not concave. Hence, a total of 23 models will be reported in this section.

The formulations for each type of models are given in section 3.3. The only thing to note is that the only exogenous variable considered in the mean and variance equations is $CRISIS_t$ and c_1 and γ are the corresponding coefficients, respectively. All other things are the same as described before.

Before interpreting the models in Table 7, it is a good practice to check whether the models in hand satisfy the sign restrictions. All GARCH(1,1), with two[38] exceptions, and GARCH(1,1)-M models in all distributional assumptions have negative coefficient for the ARCH terms violating the conditions for the positive variance[39]. The signs and the magnitude of the estimated coefficients for all other models guarantee the positivity of the conditional variance and the covariance stationarity of the model. Covariance stationarity implies that the effect of a shock dissipates over time and the volatility converges back to its long-run level; that is Turkish stock market volatility is mean reverting. Although the volatility process is mean reverting, it takes long time to reach back to the long-run level after a shock disturbs the system; that is the volatility is persistent. The persistence measures for each model are provided in Table 8 and it is seen that GJR model has the lowest persistence for all types of distribution assumption and reaches its minimum at 0.715 with Gaussian innovations. GARCH-M model with the student's t innovations has the highest persistence measure, 0.809.

[38] GARCH(1,1) models, both with dummy and without dummy variable in the mean equation, have positive coeffient for the ARCH term under GED assumption.

[39] In addition, these coefficients are not statistically significant even at 10% level.

A correctly specified GARCH model should have standardized residuals with no serial correlation and no conditional heteroscedasticity. Also, the standardized residuals should obey the assumed marginal distribution in the estimation (Zivot, 2009). The standardized residuals which are the main tool in examining the appropriateness of the model are computed as $\overline{\varepsilon_t} = \varepsilon_t/\sqrt{h_t}$. The statistics related to the standardized residuals are given in Table 8.

The mean models are proved to be appropriate without having remaining serial correlation event at 10% level. Further, the insignificant Ljung-Box Q-statistics at lags 10 and 20 implies that all of the models are able to fully capture the conditional heteroscedasticity of the log return series. One important observation is that the coefficient of the dummy variable in the variance equation is positive and significant supporting the hypothesis that the volatility of the ISE returns increased during the crisis period. However, the evidence on the level of the ISE return is mixed. Except the GARCH-M models under different distributional assumptions, it is seen that the ISE returns decreases during the crisis period but the effect is insignificant in all cases. In addition, the positive risk premium is not confirmed; that is there is no evidence such that the expected return increases as the volatility increases.

Removing the crisis dummy variable from the mean equation leads to improvement in terms of goodness of fit criteria. EGARCH models suggest a negative shock increases the volatility more compared to the positive ones and this asymmetric effect is larger than the effect. This contradicts with the findings of Yavan and Aybar (1998) and Payaslıoğlu (2001) and this contradiction can be attributed to the characteristic of the period of study. The time period they examined corresponds to the very early stages of development of the ISE and can be the result of the associated inefficiency in the market.

Table 7 Volatility Model Estimation Results

MODEL	DISTRIBUTION	MEAN EQUATION			VARIANCE EQUATION						
		c_0	c_1	a	α_0	α_1	β_1	γ	d_1	shape (df)	persistence
GARCH(1,1)	NORMAL	0.485 **	-2.087		1.201 **	-0.009	0.761 ***	1.875 ***			0.752
		[0.236]	[2.586]		[0.575]	[0.039]	[0.147]	[0.323]			
GARCH(1,1)-M	NORMAL	1.815 **	2.770	-0.098 *	1.199 **	-0.019	0.772 ***	1.768 ***			0.753
		[0.824]	[3.207]	[0.054]	[1.768]	[0.029]	[0.136]	[0.310]			
GJR-GARCH(1,1)	NORMAL	0.555 **	-2.511		1.227 ***	0.014	0.797 ***	1.903 ***	-0.157 ***		0.733
		[0.222]	[2.642]		[0.336]	[0.047]	[0.098]	[0.315]	[0.059]		
EGARCH(1,1)	NORMAL	0.598 ***	-1.699		0.613 ***	-0.151 *	0.761 ***	0.450 **	-0.153 **		0.761
		[0.225]	[1.639]		[0.225]	[0.090]	[0.088]	[0.217]	[0.061]		
GARCH(1,1)	GED	0.657 ***	-2.782		0.964	0.001	0.803 ***	1.835 ***		1.617	0.804
		[0.230]	[2.292]		[0.639]	[0.042]	[0.131]	[0.383]		[0.213]	
GARCH(1,1)-M	GED	1.974 **	1.298	-0.097	1.036 *	-0.009	0.799 ***	1.728 ***		1.625	0.790
		[0.910]	[2.974]	[0.061]	[0.536]	[0.030]	[0.116]	[0.343]		[0.212]	
GJR-GARCH(1,1)	GED	0.669 ***	-3.126		1.145 ***	0.019	0.811 ***	1.899 ***	-0.161 **	1.703	0.750
		[0.221]	[2.344]		[0.375]	[0.051]	[0.102]	[0.321]	[0.065]	[0.236]	
EGARCH(1,1)	GED	0.716 ***	-2.701		0.570 **	-0.148	0.776 ***	0.421 *	-0.159 **	1.657	0.776
		[0.221]	[1.642]		[0.236]	[0.101]	[0.093]	[0.216]	[0.068]	[0.233]	
GARCH(1,1)	T	0.579 **	-2.368		0.983 *	-0.002	0.802 ***	1.859 ***		18.963	0.799
		[0.232]	[2.386]		[0.590]	[0.039]	[0.122]	[0.351]		[20.746]	
GARCH(1,1)-M	T	2.033 **	2.337	-0.107 *	1.078 **	-0.013	0.794 ***	1.730 ***		18.092	0.781
		[0.906]	[3.030]	[0.060]	[0.523]	[0.028]	[0.117]	[0.322]		[18.930]	
GJR-GARCH(1,1)	T	0.604 ***	-2.734		1.176 ***	0.016	0.806 ***	1.899 ***	-0.157 **	31.078	0.744
		[0.222]	[2.522]		[0.355]	[0.048]	[0.098]	[0.314]	[0.061]	[58.690]	
EGARCH(1,1)	T	0.660 ***	-2.307		0.566 **	-0.143	0.778 ***	0.418 **	-0.152 **	19.881	0.778
		[0.222]	[1.663]		[0.225]	[0.096]	[0.089]	[0.202]	[0.063]	[27.269]	

Table 7 (continued)

MODEL	DISTRIBUTION	MEAN EQUATION		VARIANCE EQUATION						
		c_0	a	α_0	α_1	β_1	γ	d_1	shape (df)	persistence
GARCH(1,1)	NORMAL	0.464 ** [0.235]		1.157 ** [0.579]	-0.007 [0.039]	0.770 *** [0.141]	1.932 *** [0.335]			0.762
GARCH(1,1)-M	NORMAL	1.241 ** [0.580]	-0.055 [0.035]	1.082 ** [0.527]	-0.015 [0.032]	0.794 *** [0.117]	1.791 *** [0.301]			0.780
GJR-GARCH(1,1)	NORMAL	0.530 ** [0.222]		1.295 *** [0.359]	0.015 [0.050]	0.780 *** [0.110]	1.894 *** [0.311]	-0.159 ** [0.064]		0.715
EGARCH(1,1)	NORMAL	0.557 ** [0.224]		0.617 *** [0.217]	-0.144 [0.092]	0.759 *** [0.085]	0.465 ** [0.198]	-0.147 ** [0.058]		0.759
GARCH(1,1)	GED	0.566 ** [0.234]		1.039 * [0.626]	0.000 [0.042]	0.787 *** [0.137]	1.949 *** [0.385]		1.752 [0.226]	0.787
GARCH(1,1)-M	GED	1.677 ** [0.650]	-0.074 * [0.040]	0.960 * [0.552]	-0.007 [0.032]	0.812 *** [0.111]	1.739 *** [0.344]		1.609 [0.211]	0.805
GJR-GARCH(1,1)	GED	0.578 ** [0.224]		1.274 *** [0.383]	0.018 [0.053]	0.782 *** [0.114]	1.898 *** [0.331]	-0.162 ** [0.068]	1.858 [0.255]	0.719
EGARCH(1,1)	GED	0.621 *** [0.222]		0.599 *** [0.231]	-0.143 [0.098]	0.765 *** [0.091]	0.459 ** [0.210]	-0.150 ** [0.063]	1.816 [0.256]	0.765
GARCH(1,1)	T	0.530 ** [0.233]		1.045 * [0.588]	-0.002 [0.040]	0.788 *** [0.129]	1.952 *** [0.364]		27.093 [38.872]	0.786
GARCH(1,1)-M	T	1.511 ** [0.623]	-0.067 * [0.038]	0.935 * [0.531]	-0.009 [0.031]	0.818 *** [0.104]	1.755 *** [0.321]		16.821 [16.703]	0.809
GJR-GARCH(1,1)	T	NO CONVERGENCE ACHIEVED (FUNCTION NOT CONCAVE)								
EGARCH(1,1)	T	0.589 *** [0.223]		0.597 *** [0.225]	-0.140 [0.096]	0.766 *** [0.088]	0.456 ** [0.201]	-0.146 ** [0.061]	41.252 [107.583]	0.766

Note: The values in brackets are standard errors. ***, ** and * denotes significance at 1%, 5% and 10% levels respectively. The shape parameter is defined for the GED while the degrees of freedom (df) is for the t-distribution.

Table 8 Volatility Model Checking and Selection

	MODEL	DISTRIBUTION	LOG LIKELIHOOD FUNCTION VALUE	AIC	SBC	ST. RES.		SQ. ST.RES.		JARQUE-BERA
						Q(10)	Q(20)	Q(10)	Q(20)	
SHIFT BOTH IN MEAN AND VARIANCE	**GARCH(1,1)**	NORMAL	-829.983	1671.966	1694.149	10.026	24.109	11.561	22.438	9.370
	GARCH(1,1)-M	NORMAL	-829.109	1672.217	1698.097	9.697	24.083	11.015	21.322	8.323
	GJR-GARCH(1,1)	NORMAL	-825.587	1665.174	1691.054	11.920	26.314	12.512	26.540	7.591
	EGARCH(1,1)	NORMAL	-825.320	1664.639	1690.519	11.888	25.675	12.717	27.702	5.256
	GARCH(1,1)	GED	-828.996	1671.992	1697.871	10.414	24.774	11.722	22.571	9.762
	GARCH(1,1)-M	GED	-828.136	1672.271	1701.848	9.977	24.781	10.995	21.785	8.946
	GJR-GARCH(1,1)	GED	-825.033	1666.066	1695.643	12.022	26.360	12.613	26.587	7.807
	EGARCH(1,1)	GED	-824.549	1665.097	1694.674	12.143	25.649	12.864	27.466	5.314
	GARCH(1,1)	T	-829.574	1673.148	1699.028	10.367	24.715	11.827	22.652	9.634
	GARCH(1,1)-M	T	-828.625	1673.250	1702.826	9.852	24.619	10.947	21.418	8.595
	GJR-GARCH(1,1)	T	-825.435	1666.871	1696.448	11.982	26.346	12.657	26.680	7.698
	EGARCH(1,1)	T	-824.993	1665.986	1695.562	12.070	25.677	13.016	27.826	5.401
SHIFT ONLY IN VARIANCE	**GARCH(1,1)**	NORMAL	-830.491	1670.982	1689.468	10.030	24.573	11.486	21.702	8.915
	GARCH(1,1)-M	NORMAL	-829.311	1670.621	1692.804	10.031	24.451	11.611	22.668	8.980
	GJR-GARCH(1,1)	NORMAL	-826.276	1664.553	1686.735	11.866	26.919	12.136	25.419	6.940
	EGARCH(1,1)	NORMAL	-825.869	1663.737	1685.920	11.889	26.219	12.911	27.746	5.217
	GARCH(1,1)	GED	-830.063	1672.126	1694.308	10.188	24.852	11.487	21.557	9.282
	GARCH(1,1)-M	GED	-828.180	1670.360	1696.239	10.158	25.004	11.306	22.470	9.214
	GJR-GARCH(1,1)	GED	-826.145	1666.290	1692.170	11.848	26.867	12.165	25.356	7.004
	EGARCH(1,1)	GED	-825.629	1665.257	1691.137	11.919	26.151	13.082	27.743	5.264
	GARCH(1,1)	T	-830.252	1672.504	1694.686	10.195	24.848	11.568	21.691	9.209
	GARCH(1,1)-M	T	-828.766	1671.532	1697.412	10.189	25.054	11.546	22.742	9.165
	GJR-GARCH(1,1)	T	NO CONVERGENCE ACHIVED (FUNCTION NOT CONCAVE)							
	EGARCH(1,1)	T	-825.777	1665.553	1691.433	11.926	26.190	13.114	27.868	5.301

GJR models also support the existence of the leverage effect; that is, negative shocks are more destabilizing.

The final point is related to the appropriateness of the assumed marginal distribution. However, non-normally distributed errors do not pose a serious problem provided that the mean and variance equations are properly specified and Bollerslev and Wooldridge (1992) robust standard errors can be used for inference purposes. Actually, the null hypothesis of normally distributed innovations cannot be rejected at 1% significance level for most of the models. Bollerslev and Wooldridge (1992) robust standard errors are also computed. Since they do not produce any major difference they are not reported here but available upon request.

The best volatility model selection can be based on several criteria: general model selection criteria such as AIC and SBC, and forecasting performance. In this thesis, AIC and SBC are used in selecting the volatility model that best fits to the historical data. The evaluation of the models based on the forecasting performance is out of the scope of this thesis.

The criteria in Table 8 are computed based on the following formulas:

$$AIC = -2L + 2k$$
$$SBC = -2L + k\ln(T)$$

where L is the value of the likelihood function, k is the number of parameters estimated and T is the number of observations.

Comparing all twenty three model, having confirmed there is no remaining autocorrelation and conditional heteroscedasticity in the model, AIC and SBC choose EGARCH(1,1) under the assumption of Gaussian distribution and without having the crisis dummy in the mean equation. Hence, EGARCH(1,1) model allowing only the volatility shift is determined as the best model. $|\beta_1| = 0.759 < 1$ implies mean reversion of volatility and high persistence of shocks. That is; the return converges to its long run level but at a fairly low pace. As the Jarque-Bera statistic indicates the hypothesis that the standardized residuals of this model are normally distributed cannot be rejected at 5% level. In addition, it provides evidence on the existence of the leverage effect.

3.6. Time Series Properties of the Volatility Variable

As it is clearly stated before, the return volatility variable is used as a determinant of the stock market liquidity and this necessitates determining the best volatility model that can be used to generate appropriate volatility estimates. Since this estimated volatility variable is an important input for the liquidity analysis in the later chapters, this section is devoted to examine the time series properties of the volatility variable which is obtained from the best model determined in the previous section.

The return volatility variable, $VLNR100$, is calculated as the square root of the variance estimates of the EGARCH(1,1) model with the Gaussian innovations.

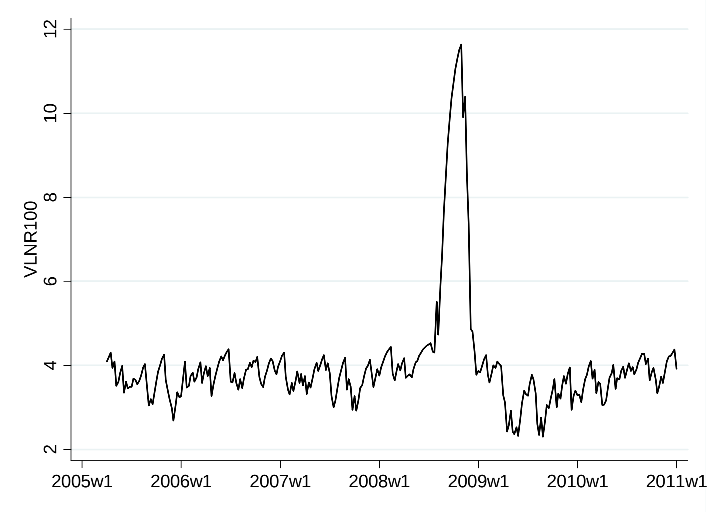

Figure 5 Time Plot of Return Volatility (%)

From Figure 5, it is seen once again that the volatility increase sharply around July-November 2008. Also, the volatility variable exhibits positive skewness and leptokurtosis indicating it is not normally distributed. Further, from Figure 6, it is seen that the autocorrelations are significant up to nine lags. Having confirmed the high persistence in the previous section, presence of serial correlation is no surprise.

Another property to be examined is the existence of unit root. In order to determine the appropriate lag length, a general model containing intercept and ten lags is estimated and compared based on AIC and SBC which are computed according to same formulas as in Table 6. The results are given in Table 10.

Table 9 Summary Statistics of Return Volatility (%)

	VLNR100
SAMPLE MEAN	4.020
(MEAN=0)	(0.000)
STANDARD DEVIATION	1.425
MINIMUM	2.304
MAXIMUM	11.640
SKEWNESS	3.735
(SK=0)	(0.000)
EXCESS KURTOSIS	14.952
(KU=0)	(0.000)
JARQUE-BERA	3468.960
(JB=0)	(0.000)

Note: Values in parentheses are p-values.

Both criteria select the model containing intercept and three lags. The estimation results of the unit model are as follows:

$$\begin{aligned}\Delta VLNR100_t = \underset{(0.064)}{0.232} - \underset{(0.015)}{0.058} VLNR100_{t-1} + \underset{(0.058)}{0.050} \Delta VLNR100_{t-1} + \\ \underset{(0.056)}{0.320} \Delta VLNR100_{t-2} + \underset{(0.059)}{0.147} \Delta VLNR100_{t-3} + u_t\end{aligned}$$

The ACF of the residuals from the volatility unit root model given in Figure 6 indicates absence of remaining serial correlation. Hence, given that the coefficient of $VLNR100_{t-1}$ is significant at 1% significance level, it can be safely argued that there is enough evidence to reject the null hypothesis of unit root in the volatility series.

Table 10 ADF Test Results of Return Volatility (%)

	WITH INTERCEPT, NO TREND			WITHOUT INTERCEPT AND TREND		
m	**AIC**	**SBC**	**T-STAT**	**AIC**	**SBC**	**T-STAT**
0	-1.952	-1.927	-2.244	-1.945	-1.932	-0.965
1	-1.958	-1.920	-2.491	-1.946	-1.921	-0.975
2	-2.048	-1.997	-3.426 **	-2.020	-1.982	-1.256
3	-2.061	-1.998	-3.877 ***	-2.023	-1.972	-1.366
4	-2.051	-1.973	-4.056 ***	-2.007	-1.943	-1.436
5	-2.050	-1.960	-3.733 ***	-2.012	-1.935	-1.128
6	-2.039	-1.934	-3.431 **	-2.007	-1.916	-1.043
7	-2.029	-1.911	-3.382 **	-1.999	-1.894	-1.105
8	-2.017	-1.885	-3.358 **	-1.987	-1.868	-1.140
9	-2.026	-1.880	-3.207 **	-1.997	-1.865	-0.879
10	-2.012	-1.852	-3.185	-1.984	-1.837	-0.904

Note: ***, ** and * denotes significance at 1%, 5% and 10% levels respectively. m refers to the number of augmenting lags in the unit root model.

As explained before, the Clemente, Montanes and Reyes test of unit root was helpful in determining the appropriate break points. The results for the return and the volatility are given in Table 10. Both series are found to be stationary around these structural breaks. The two optimal break points are the 30^{th} and 46^{th} weeks of 2008. These dates are taken as the beginning and the ending date for $CRISIS$ dummy variable, respectively. As will be shown in the next chapter, the return level is not significantly affected in the second period proposed by the liquidity measures.

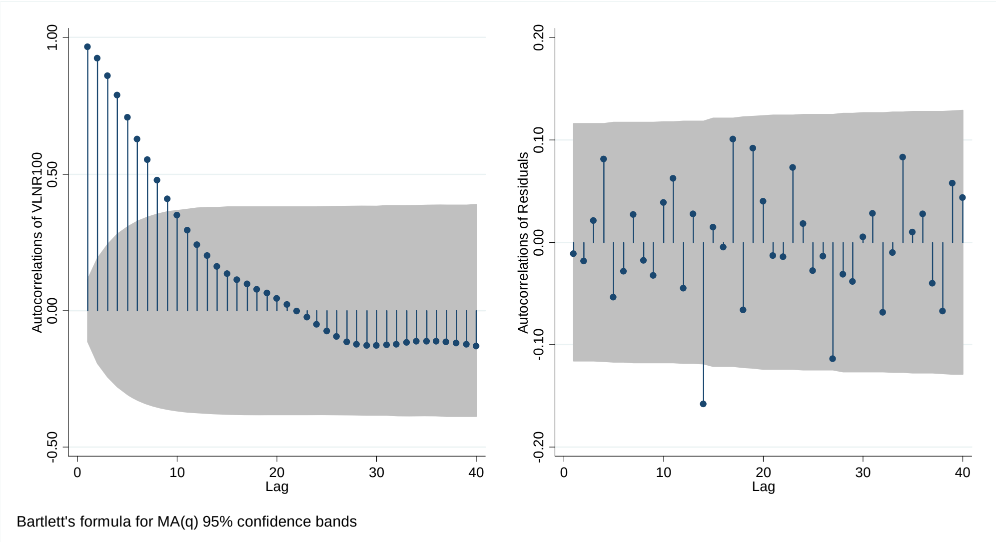

Figure 6 The ACF for the Original Series and Unit Root Model Residuals of Return Volatility (%)

Table 11 Clemente, Montanes and Reyes Test for the ISE Return and Volatility (%)

	LNR100	VLNR100	LNVLNR100
D1	-3.825 ***	1.615 ***	0.238 ***
	(-3.402)	(10.659)	(7.339)
D2	4.616 ***	-1.685 ***	-0.256 ***
	(3.957)	(-10.865)	(-7.622)
RHO-1	-1.205 **	-0.246 **	-0.230 **
	(-6.650)	(-11.556)	(-8.331)
LAGS	11	2	3
BP1	2008w30	2008w31	2008w31
BP2	2008w46	2008w45	2008w45

Note: ***, ** and * denotes significance at 1%, 5% and 10% level respectively.

CHAPTER 4

LIQUIDITY DETERMINANTS

The studies on the cross-sectional determinants of stock-specific bid-ask spread can be traced back to Demsetz (1968). Stoll (2000) used dollar volume, return volatility, market value, closing price and the number of trades in modeling the cross-section of the bid-ask spreads and find a strong relationship which is rarely observed in financial applications. As the volume, number of trades, firm size increases, the risk of holding inventory, and hence bid-ask spread, reduces. Also, the stocks with low price are perceived as riskier implying a negative relation to the spread again. On the other hand, the variance of the stock return gives an indication of the associated risk of an adverse price change. The higher the variance, the higher will be the compensation required for the risk as it is reflected in the bid-ask spread. Besides these determinants that are intrinsically related to the trading characteristic of the individual stock, Tinic (1972) proposed to add some structural variables such as the composition of the market maker's portfolio, the purchasing capacity and the monopoly power of the dealers.

Chordia, Roll and Subrahmanyam (2001) proposed the market return as a plausible candidate determinant for the market liquidity due to its effect on investor expectations allowing an asymmetric effect between rising and falling prices. Odean (1998) found evidence on the existence of the disposition effect; that is investors tend to realize their profits immediately and keep go on with the losing investments. Such a bias in the investor behavior enforces one- way trading pattern tightening the liquidity. This finding encouraged Chordia, Sarkar and Subrahmanyam (2005) to explore the effect of the market return on the market liquidity. In the context of VAR analysis, the findings of Chordia, Sarkar and Subrahmanyam (2005) and Goyenko and Ukhov (2009) supported Chordia, Roll and Subrahmanyam (2001) in that a positive shock to the market return improves liquidity.

Volatility is expressed as a second important determinant of market liquidity. Chordia, Roll and Subrahmanyam (2001) chose and proved the return volatility as one of the time series determinants of market-wide liquidity following the inventory paradigm. The idea is that liquidity is linked to the risk of holding inventory and events that result in order imbalances. The findings of Chordia, Sarkar and Subrahmanyam (2005) are also consistent with this paradigm.

Following the ideas of Kyle (1985), Chordia, Roll and Subrahmanyan (2001) used three dummy variables each corresponding to the announcement dates of Gross Domestic Product (GDP), consumer price index (CPI) and unemployment data in order to account for the information content of trading. This view is also appreciated in this thesis and the hypothesis that the level of the aggregate market liquidity as well as the level of the return and volatility changes at the announcement dates of the macroeconomic data is tested.

Further, Chordia, Sarkar and Subrahmanyam (2005) tested the hypothesis that the monetary stance of the Central Bank (CB) influences the market liquidity. A tightening monetary policy may discourage the trading in the stock market through its effect on the cost of borrowing. Hence, the aggregate stock market liquidity may dry up if the CB takes on a tightening approach. Closely monitoring the financial markets, the CB may announce a loosening of monetary stance in response to reduced liquidity or increased volatility in the markets.

As a measure of the monetary stance, Chordia, Sarkar and Subrahmanyam (2005) used the ratio of the net borrowed reserves[40] to the total reserves which gets higher values as an indication of monetary tightness. Berument, Togay and Sahin (2011) questioned the appropriateness of the non-borrowed reserves[41] as a measure of monetary stance for the Central Bank of the Republic of Turkey (CBRT) which affects the foreign exchange market through its operations. They have two arguments for this. If the CBRT buys foreign exchanges, the total reserves (TR) increases as the non-borrowed reserves (NBR) remain the same. Further, the incomplete sterilization lowers the NBR leading to an even lower NBR/TR ratio. This analysis misleadingly implies that higher liquidity leads to lower NBR/TR ratio. The second argument is that this ratio is converged to 1 due to the CBRT's unwillingness to lend in the past ten years. Following Berument, Togay and Sahin (2011) and using the data from the analytical balance sheet of the CBRT, the monetary stance measure is calculated as follows:

$$RESERVE = \frac{(CBM - CO - OMO) * 100}{OMO + BC + [(FA + DA - BC) - (FL - FXDB + CI + EBF + DNB + YDP)]}$$

[40]Net borrowed reserves are the total borrowings with extended credit and excess reserves subtracted. For a more complete definition, see http://research.stlouisfed.org/.

[41]As the name suggests, the non-borrowed reserves are simply the total reserves with borrowed reserves subtracted. Borrowed reserves includes the credit extended to the banking sector through discount window and liquidty facilities of the Federal Reserve.

where

CBM = Central Bank Money
CO = Cash operations
OMO = Open market operations
BC = Credits to banking sector
FA = Foreign assets
DA = Domestic assets
FL = Total foreign liabilities
$FXDB$ = FX deposits from banking sectors
CI = Currency issued
EBF = Extrabudgetary funds
DNB = Deposits from nonbank sector
YDP = YTL deposits from public sector

Another variable used as a proxy for the monetary stance is the interest rate. Due to the excess liquidity in the banking sector, the policy rate of the CBRT is the overnight borrowing interest rate until the end of 2008 which corresponds to the acceleration of the crisis. With a mixture of several other policy tools, the overnight borrowing rate continued to be the policy rate until when the Monetary Policy Committee determined the interest rate for the repo auctions with one-week maturity as the policy rate due to the shortage of funds in the sector in the meeting held on 18 May 2010. For the period of study, the appropriate interest rate is the simple overnight interest rate in the interbank money market within the CBRT, $ONINT$.

The tick size or the price tick is defined as the minimum allowable amount of change in the stock price. The ISE decided to lower the tick size by taking the attitude of the Federation of European Securities Exchange and the practices of foreign stock exchanges into consideration. Further, the reduction in the transaction costs and the price volatility, the increase in the total depth and trading activity, and the improvement in the liquidity of the small stocks observed after lowering the price ticks in 2003 encourage this decision. Being effective on 01 November 2010, the price ticks that are higher than 1 kurus are lowered by 50%. Tick size constitutes a minimum limit for the bid-ask spread. Harris (1994) predicted that the spread between ask and bid prices and the quotation sizes will decrease whereas the total volume increases following the tick size reduction. The idea is that if the minimum allowable spread, that is tick size, is larger than the spread the dealers willing to quote, the size of the quotes may be larger than the one otherwise displayed. Chordia, Roll and Subrahmanyam (2001) and Chordia, Sarkar and Subrahmanyam (2005) showed evidence of decreased depth and spread following the tick size reduction in June 1997 in the New York Stock Exchange. This hypothesis is also tested for the ISE in this thesis.

4.1. Model Estimations

In the previous sections, the stationarity property of both the liquidity measures and the return and volatility variables examined. The time series properties of the monetary stance variables, $RESERVE$ and $ONINT$, are given in Appendix C. However, the ADF test results fail to reject the unit root hypothesis for most of the liquidity variables. Also, the Clemente, Montanes and Reyes test performed with the assumption of two structural breaks concludes the most of the series are stationary around these break dates which are endogenously determined by the data. At this point, there are two alternatives: the first one is, relying on the ADF test results, to take the first-difference of the series with the aim of making the data stationary. Referring to the potential problem of the existence of unit root, Chordia, Roll, and Subrahmanyam (2001) preferred to use the first difference of the liquidity measures. Highlighting that liquidity measures generally do not contain unit root, Hasbrouck and Seppi (2001) opposed to over-differencing which produces autocorrelation. The second alternative is already used by Chordia, Sarkar, and Subrahmanyam (2005). In order to extract the dynamics in the liquidity explained by order imbalance, return and volatility, Chordia, Sarkar, and Subrahmanyam (2005) adjusted the variables for seasonality, crisis effects and trend. Relying on Clemente, Montanes and Reyes test results, it is expected that eliminating the effects of potential structural breaks due to the crisis, tick size changes, the announcement of the macroeconomic data and removing the trend will help to make the data suitable for the OLS estimation.

The results of following the auxiliary regressions of the liquidity and the determinant variables on the trend and squared trend variable, two crisis dummy variables, tick size change dummy variable, and the dummy variables corresponding to the announcement date of the GDP, CPI and unemployment data are given in Table 12. However, for only the variable $ONINT$, the data announcement and tick size changes are not used for adjustment since the overnight interest rate in the interbank market is just equal to the overnight borrowing rate of the CBRT for the period of study[42] and the CBRT is not supposed to change the policy rate due to such events.

$$y_t = TREND_t + TRENDSQ_t + CRISIS_t + CRISIS2_t + TICK_t + GDP_t + CPI_t + UNEMP_t + u_t$$

where y_t represents the all of the liquidity measures together with the return, return volatility and the monetary stance variable in each case.

[42] The only exception that the interest rate in the interbank market differes from the overnight borrowing rate of the CBRT is 30.06.2008.

As it is already mentioned, two dummy variables are employed in order to measure the effect of the global financial crisis. The first reason for that the Clemente, Montanes, and Reyes test finds different optimal break points for different liquidity measures. In order to account for the possibility that different measures reflect the effect of the crisis at different intervals, the following variables are used:

$$CRISIS_t = \begin{cases} 1 & \text{if } 2008\text{w}30 \leq \text{t} \leq 2008\text{w}46 \\ 0 & \text{otherwise} \end{cases}$$

$$CRISIS2_t = \begin{cases} 1 & \text{if } 2008\text{w}47 \leq \text{t} \leq 2009\text{w}14 \\ 0 & \text{otherwise} \end{cases}$$

In order to eliminate the effect of the tick size change beginning from 01 November 2010, the variable $TICK$ is defined as follows:

$$TICK_t = \begin{cases} 1 & \text{if } 2010\text{w}44 \leq \text{t} \\ 0 & \text{otherwise} \end{cases}$$

The estimation results of the auxiliary regressions are given in Table 12. Both of the crisis dummy variables are found to be significant for the liquidity measures with the exception of $RELQUOTED$, $RELEFFECT$, $VOLUME$, $LNVOLUME$ and $LNTURNOVER$. This refers to a reduction in the depth of the ISE between the end of July 2008 and the beginning of April 2009. $VOLUME$ and $LNTURNOVER$ appear to be unaffected by the crisis while the effects on $RELQUOTED$, $RELEFFECT$, and $LNVOLUME$ are significant between the mid-November 2008 and the beginning of April 2009. On the other hand, the ISE returns are negatively and significantly affected by the crisis between the end of July and the mid-November 2008. Not surprisingly, in the same period, the volatility in the ISE increases.

Table 12 Auxiliary Regressions for the Liquidity Measures and the Determinant Variables

	TREND	TRENDSQ	CRISIS	CRISIS2	TICK	GDP	CPI	UNEMP
ILLIQ	0.022 ***	0.000 ***	2.994 ***	2.312 ***	0.715 *	-0.116	0.188	0.278 *
	[0.002]	[0.000]	[0.274]	[0.254]	[0.421]	[0.237]	[0.147]	[0.152]
ILLIQSQRT	0.012 ***	0.000 ***	0.556 ***	0.434 ***	0.375 ***	0.010	0.126 ***	0.128 ***
	[0.001]	[0.000]	[0.086]	[0.080]	[0.133]	[0.075]	[0.046]	[0.048]
LR	0.084 ***	0.000 ***	-5.094 ***	-5.612 ***	7.711 ***	1.211 *	0.808 **	0.528
	[0.005]	[0.000]	[0.735]	[0.679]	[1.129]	[0.635]	[0.393]	[0.406]
LRSQRT	0.024 ***	0.000 ***	-1.176 ***	-1.280 ***	0.802 ***	0.203	0.302 ***	0.158
	[0.001]	[0.000]	[0.175]	[0.161]	[0.268]	[0.151]	[0.093]	[0.096]
RQUOTED	0.010 ***	0.000 ***	0.035	0.256 ***	-0.034	0.035	0.106 ***	0.077 **
	[0.000]	[0.000]	[0.060]	[0.055]	[0.092]	[0.051]	[0.032]	[0.033]
REFFECT	0.010 ***	0.000 ***	0.037	0.260 ***	-0.029	0.037	0.106 ***	0.077 **
	[0.000]	[0.000]	[0.059]	[0.055]	[0.091]	[0.051]	[0.032]	[0.033]
TURNOVER	0.000 ***	0.000 ***	-0.011 ***	-0.010 ***	-0.001	0.001	0.003 ***	0.001
	[0.000]	[0.000]	[0.002]	[0.002]	[0.003]	[0.002]	[0.001]	[0.001]
TLVOLUME	0.141 ***	0.000 ***	-3.943 ***	-7.467 ***	6.446 ***	0.946	1.683 ***	1.132 *
	[0.007]	[0.000]	[1.088]	[1.005]	[1.671]	[0.939]	[0.582]	[0.601]
VOLUME	0.040 ***	0.000 ***	-0.487	-0.588	0.588	0.248	0.420 **	0.293
	[0.002]	[0.000]	[0.389]	[0.360]	[0.598]	[0.336]	[0.208]	[0.215]
LNILLIQ	0.007 ***	0.000 ***	1.306 ***	1.316 ***	0.440 **	-0.100	-0.040	0.041
	[0.001]	[0.000]	[0.127]	[0.118]	[0.195]	[0.110]	[0.068]	[0.070]
LNILLIQSQRT	-0.001 ***	0.000 **	0.740 ***	0.707 ***	0.115	-0.060	-0.043	0.013
	[0.000]	[0.000]	[0.068]	[0.063]	[0.105]	[0.059]	[0.036]	[0.038]
LNLR	0.025 ***	0.000 ***	-0.902 ***	-0.927 ***	0.882 ***	0.214	0.240 ***	0.150 *
	[0.001]	[0.000]	[0.156]	[0.144]	[0.239]	[0.134]	[0.083]	[0.086]
LNLRSQRT	0.008 ***	0.000 ***	-0.555 ***	-0.595 ***	0.246 **	0.082	0.098 ***	0.040
	[0.000]	[0.000]	[0.064]	[0.059]	[0.099]	[0.056]	[0.034]	[0.036]
LNRQUOTED	-0.004 ***	0.000 ***	0.283 ***	0.494 ***	-0.546 ***	-0.032	-0.055 ***	-0.026
	[0.000]	[0.000]	[0.033]	[0.030]	[0.050]	[0.028]	[0.017]	[0.018]
LNREFFECT	-0.004 ***	0.000 ***	0.285 ***	0.496 ***	-0.535 ***	-0.030	-0.054 ***	-0.026
	[0.000]	[0.000]	[0.033]	[0.031]	[0.051]	[0.029]	[0.018]	[0.018]
LNTURNOVER	-0.059 ***	0.000 ***	0.419	0.498	-1.627 ***	-0.256	-0.605 ***	-0.451 **
	[0.002]	[0.000]	[0.345]	[0.319]	[0.530]	[0.298]	[0.184]	[0.191]
LNTLVOLUME	0.031 ***	0.000 ***	-0.613 ***	-0.910 ***	0.874 ***	0.203	0.343 ***	0.221 **
	[0.001]	[0.000]	[0.178]	[0.164]	[0.273]	[0.154]	[0.095]	[0.098]
LNVOLUME	0.014 ***	0.000 ***	-0.153	-0.158 *	0.255 *	0.108	0.136 ***	0.092 *
	[0.001]	[0.000]	[0.097]	[0.090]	[0.149]	[0.084]	[0.052]	[0.054]
LNR100	0.000	0.000	-2.826 **	-0.374	-1.705	1.397	0.018	-0.053
	[0.007]	[0.000]	[1.092]	[1.009]	[1.677]	[0.943]	[0.584]	[0.603]
VLNR100	0.050 ***	0.000 ***	4.312 ***	-0.009	1.769 ***	0.238	0.535 ***	0.445 **
	[0.002]	[0.000]	[0.365]	[0.337]	[0.560]	[0.315]	[0.195]	[0.201]
RESERVE	0.229	0.005	-40.469	-95.838	-15.826	94.713	-96.605	28.875
	[0.761]	[0.003]	[118.874]	[109.889]	[182.632]	[102.693]	[63.563]	[65.668]
LNVLNR100	0.018 ***	0.000 ***	0.551 ***	-0.102	0.585 ***	0.085	0.198 ***	0.144 **
	[0.001]	[0.000]	[0.114]	[0.105]	[0.175]	[0.098]	[0.061]	[0.063]
LNRESERVE	0.050 ***	0.000 ***	-0.750 **	-1.050 ***	0.627	0.368	0.591 ***	0.337 **
	[0.002]	[0.000]	[0.289]	[0.267]	[0.445]	[0.250]	[0.155]	[0.160]
ONINT	0.252 ***	-0.001 ***	-0.371	-2.045 *				
	[0.006]	[0.000]	[1.158]	[1.073]				

Note: The values in brackets are standard errors. ***, ** and * denotes significance at 1%, 5% and 10% levels respectively.

Another important observation relates to the tick size change. As predicted by Harris (1994), there is a decline in the natural logarithm of the both the quoted and the effective spread implying higher liquidity; and an increase in the TL value of the traded shares together with the natural logarithm of the trade volume, is observed. The price impact measures give inconclusive results. Although the ISE returns are not significantly influenced, the volatility of the returns increased significantly following the tick size change.

The final remark is on the effect of the announcement of the macroeconomic data. The trading activity and the return volatility rise on the CPI week. The evidence on the effect of the CPI data announcement on the liquidity is somehow mixed. The natural logs of the price impact and the transaction cost measures give an indication of significant increase in the liquidity. However, the original spreads rise on that week while the returns are unaffected. The GDP data has a minor impact only on LR. The data on the unemployment has similar effects as the CPI but less significant. The volatility in the ISE rise on the unemployment week as well with the level of the return is unaffected.

The residuals obtained from the above regressions are used as the corresponding liquidity, return, volatility and the monetary stance variables both in the liquidity model estimations and VAR analysis. The prefix "U" on the original variable names indicates they are residuals of the auxiliary regressions and "LN" refers to the natural logarithm of the corresponding variables. The ADF test and the associated autocorrelation test results are given in Table 13. In this case, performance of the ADF test in rejecting the null hypothesis of the unit root improves. This is probably due to the elimination of the structural breaks in the data.

Table 13 ADF Test and Normality Test Results for the Residuals from Auxiliary Regressions

	LAGS	ADF STAT	BREUSCH-GODFREY TEST			JARQUE-BERA
			LAG 1	LAG 5	LAG 10	
UILLIQ	6	-4.900 ***	1.143	8.182	13.806	1593.000 ***
UILLIQSQRT	5	-3.963 ***	2.11	3.336	16.163	127.000 ***
ULR	10	-2.298	0.779	5.327	7.484	3.789
ULRSQRT	3	-2.753 *	0.198	11.132	28.777	6.533 **
URQUOTED	8 (except 6)	-2.850 *	1.404	52.416	62.093	63.440 ***
UREFFECT	8 (except 6)	-2.840 *	0.673	48.026	58.693	63.500 ***
UTURNOVER	8	-2.703 *	0.015	2.267	5.996	23.130 ***
UTLVOLUME	5	-4.307 ***	2.993	8.371	11.53	4.091
UVOLUME	2	-4.074 ***	0.116	5.037	15.523	0.606
ULNILLIQ	1	-6.023 ***	1.144	5.256	9.338	11.050 ***
ULNILLIQSQRT	1	-5.644 ***	0.039	5.071	8.82	7.285 **
ULNLR	8	-1.838	2.688	10.833	20.906	11.310 ***
ULNLRSQRT	1	-3.786 ***	0.251	4.701	22.586	0.080
ULNRQUOTED	1,4,7,8,10	-3.210 **	0.171	5.882	12.333	2.544
ULNREFFECT	1,7,8,10	-3.090 **	0.026	5.669	12.089	3.194
ULNTURNOVER	1,2,3,7	-2.870 *	0.487	6.123	14.059	51.430 ***
ULNTLVOLUME	8	-2.524	2.466	27.31	35.251	20.770 ***
ULNVOLUME	8	-3.018 **	1.469	5.109	8.821	5.434 *
ULNR100	0	-18.351 ***	0.47	2.894	7.283	73.390 ***
UVLNR100	4	-3.654 ***	0.003	4.237	7.739	7.609 **
ULNVLNR100	3	-3.035 **	0.47	9.744	18.581	21.700 ***
URESERVE	1	-18.188 ***	2.381	3.366	7.555	410000.000 ***
ULNRESERVE	8	-2.115	0.791	14.819	27.534	36.030 ***
UONINT	4	-2.624	0.952	2.699	11.908	56.210 ***
DUONINT	3	-4.641 ***	1.383	3.831	14.048	3989.000 ***

Note: ***, ** and * denotes significance at 1%, 5% and 10% levels respectively.

The natural logarithms of both the liquidity and the independent variables are computed and tested for the existence of the unit root and the normality with the aim of determining the appropriate transformation to be used in the liquidity analysis. The square root versions of the price impact measures serve for the same purpose as well. The liquidity measures to be used are $ULNILLIQ$, $ULNLRSQRT$, $ULNRQUOTED$, $ULNREFFECT$ and $ULNTURNOVER$. While the returns are calculated on a continuously compounded basis, the natural logarithms are not preferred for the volatility, $UVLNR100$, and the monetary stance variable, $URESERVE$, due to the non-normality and the existence of unit root, respectively. Finally, the second monetary stance variable, $UONINT$, has unit root and hence, the first difference of this series, $DUONINT$, is preferred in the estimations.

The liquidity model estimation results obtained by OLS are given in Table 14 and Table 15. First of all, the models presented here are dynamic models; that is the various lags[43] of the dependent and the independent variables are also included in the model. This is because the static models, although not reported here, suffer from the existence of autocorrelation. The residuals of all dynamic liquidity models do not contain any remaining serial correlation and ARCH effects and have zero mean. However, they are far from being normally distributed. In the presence of non-normality, the estimates are still unbiased but they are not efficient, that is the coefficient estimates do not have the smallest variance among the linear unbiased estimators, anymore. In performing the t-test and F-test, this fact should be taken into consideration.

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[43]The lag selection procedure applied here does not based on selection criteria such as AIC and SBC. As a first attempt, two lags of dependent and independent variables are included in the models. Then, if there is remaining serial correlation, lags of the dependent variable are added up to 5 lags. If there is still autocorrelation, the insignificant lags are dropped from the model.

The ability of the market return in explaining the market liquidity is not controversial. One percentage point increase in the current and one-week lagged levels of the return leads to about 0.5 percentage point increase in the aggregate liquidity. This significant positive relationship is confirmed by all of the liquidity measures with the only exception of turnover. The case for the return volatility yields more interesting conclusions. The expected negative relationship is found between the current market liquidity and the last week's return volatility. However, there is a significant positive relationship between the current values. Again, the findings of the turnover measure constitute an exception.

Finally, the proxy for the monetary stance of the Central Bank, $RESERVE$, is not found to have significant effects on the price impact and spread measures. The loosening stance of the CBRT is associated with significantly lower TL values of the shares traded and number of shares traded. Further, a positive change in the interest rates in the interbank market which implies tightening monetary policy is associated with significantly narrower spreads and higher trading activity implying higher market liquidity compared to a fall in the interest rates. The results from both monetary stance variables reinforce each other. However, the findings are in contradiction with the expectation that the loosening (tightening) policy leads to higher (lower) market liquidity and trading activity. The contradictory findings can be taken as an evidence for a relationship in the reverse direction; that is the CBRT follows a loosening (tightening) policy in response to decreased (increased) market liquidity and trading activity. This conclusion is supported by the regressions of both monetary stance variables on $ULNR100$, $UVLNR100$ and the various liquidity proxies. The results are given in Appendix D.

Table 14 Liquidity Model Estimation Results with $URESERVE$

	ULNILLIQ	ULNLRSQRT	ULNRQUOTED	ULNREEFFECT	ULNTURNOVER	UTLVOLUME	UVOLUME
L1	0.496807 ***	0.417423 ***	0.583140 ***	0.569071 ***	0.465697 ***	0.561558 ***	0.625305 ***
	[0.056649]	[0.051861]	[0.055401]	[0.055251]	[0.052000]	[0.057766]	[0.050726]
L2	0.214649 ***	0.340736 ***	0.245992 ***	0.253601 ***	0.141921 **	0.127389 **	
	[0.053722]	[0.050722]	[0.055801]	[0.055572]	[0.055321]	[0.056331]	
L3							0.251829 ***
							[0.053861]
L4					0.229648 ***		
					[0.046600]		
L5							-0.087782 *
							[0.050098]
ULNR100	-0.035221 ***	0.012816 ***	-0.003194 ***	-0.003492 ***	0.004476	0.145354 ***	0.044818 ***
	[0.004139]	[0.001624]	[0.000770]	[0.000790]	[0.005080]	[0.038951]	[0.013490]
ULNR100 L1	-0.020722 ***	0.011052 ***	-0.003450 ***	-0.003742 ***	-0.023281 ***	0.081985 *	0.020740
	[0.005183]	[0.001953]	[0.000884]	[0.000908]	[0.006003]	[0.043566]	[0.014926]
UVLNR100	0.041138	0.058403 ***	-0.037107 ***	-0.037795 ***	-0.488995 ***	1.222212 ***	0.315021 ***
	[0.033396]	[0.013245]	[0.006246]	[0.006402]	[0.043490]	[0.299556]	[0.099255]
UVLNR100 L1	0.028352	-0.057171 ***	0.034900 ***	0.033631 ***	0.440634 ***	-0.764969 ***	-0.232557 **
	[0.033705]	[0.013303]	[0.006560]	[0.006686]	[0.051082]	[0.286901]	[0.095773]
UVLNR100 L2	-0.066421 **	0.024436 **	-0.006939	-0.005334	-0.081518 *		
	[0.029241]	[0.011402]	[0.005580]	[0.005707]	[0.042870]		
URESERVE	-0.000027	0.000014	-0.000004	-0.000004	-0.000039	-0.000952 ***	-0.000331 ***
	[0.000037]	[0.000015]	[0.000007]	[0.000007]	[0.000045]	[0.000354]	[0.000121]
CONSTANT	-0.007315	0.002846	-0.001455	-0.001629	0.003711	-0.003780	0.003002
	[0.017532]	[0.006891]	[0.003268]	[0.003352]	[0.021411]	[0.166619]	[0.056898]
BREUSCH-GODFREY AUTOCORRELATION TEST							
LAG 1	1.335	0.016	0.130	0.526	0.005	0.126	1.834
LAG 5	6.510	7.256	7.762	8.087	5.323	9.112	2.848
LAG 10	12.610	33.334 ***	33.416 ***	27.820 ***	12.054	10.701	10.060
LAGRANGE MULTIPLIER ARCH TEST							
LAG 1	2.290	1.177	0.050	0.108	0.113	0.166	0.028
LAG 5	11.220 **	3.678	0.156	0.322	0.481	1.052	9.327 *
LAG 10	16.598 *	18.382 **	5.528	6.791	1.114	2.663	15.096
RESIDUAL DIAGNOSTICS							
SKEWNESS	0.577 ***	-0.749 ***	0.645 ***	0.462 ***	-0.884 ***	0.823 ***	0.659 ***
KURTOSIS	1.494 ***	7.130 ***	24.590 ***	25.045 ***	8.558 ***	1.500 ***	1.253 ***
JARQUE-BERA	43.384 ***	645.802 ***	7377.081 ***	7641.964 ***	916.467 ***	60.385 ***	39.580 ***
MEAN	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ST. ERROR	0.017	0.007	0.003	0.003	0.020	0.158	0.054

Note: The values in brackets are standard errors. ***, ** and * denotes significance at 1%, 5% and 10% levels respectively.

Table 15 Liquidity Model Estimation Results with $DUONINT$

	ULNILLIQ	ULNLRSQRT	ULNRQUOTED	ULNREEFFECT	ULNTURNOVER	UTLVOLUME	UVOLUME
L1	0.505 ***	0.430 ***	0.584 ***	0.585 ***	0.423 ***	0.561 ***	0.602 ***
	[0.058]	[0.053]	[0.054]	[0.056]	[0.048]	[0.058]	[0.050]
L2	0.197 ***	0.342 ***	0.269 ***	0.274 ***	0.202 ***	0.131 **	
	[0.056]	[0.052]	[0.055]	[0.055]	[0.048]	[0.057]	
L3							0.209 ***
							[0.049]
L4					0.249 ***		
					0.048		
ULNR100	-0.037 ***	0.013 ***	-0.004 ***	-0.004 ***	0.004	0.170 ***	0.047 ***
	[0.004]	[0.002]	[0.001]	[0.001]	[0.005]	[0.039]	[0.014]
ULNR100 L1	-0.017 ***	0.011 ***	-0.004 ***	-0.004 ***	-0.022 ***	0.092 **	
	[0.005]	[0.002]	[0.001]	[0.001]	[0.006]	[0.044]	
ULNR100 L2	0.003			0.001			
	[0.005]			[0.001]			
ULNR100 L3	-0.009 **						
	[0.005]						
UVLNR100	0.057 *	0.056 ***	-0.037 ***	-0.037 ***	-0.487 ***	1.283 ***	0.248 ***
	[0.034]	[0.013]	[0.006]	[0.006]	[0.044]	[0.303]	[0.091]
UVLNR100 L1	0.038	-0.060 ***	0.037 ***	0.039 ***	0.386 ***	-0.807 ***	-0.184 **
	[0.036]	[0.014]	[0.006]	[0.007]	[0.042]	[0.290]	[0.090]
UVLNR100 L2	-0.096 ***	0.028 **	-0.009	-0.010			
	[0.033]	[0.012]	[0.005]	[0.006]			
DUONINT	-0.047	0.026	-0.037 ***	-0.040 ***	0.023	1.020 *	0.045
	[0.063]	[0.025]	[0.011]	[0.011]	[0.077]	[0.565]	[0.192]
DUONINT L1	0.017	0.013			-0.045		
	[0.062]	[0.025]			[0.075]		
DUONINT L2	-0.106 *	0.029			-0.166 **		
	[0.062]	[0.025]			[0.076]		
DUONINT L3	0.132 **	-0.053 **					
	[0.062]	[0.024]					
CONSTANT	-0.003	0.002	-0.002	-0.002	0.001	0.008	0.001
	[0.017]	[0.007]	[0.003]	[0.003]	[0.022]	[0.168]	[0.058]
BREUSCH-GODFREY AUTOCORRELATION TEST							
LAG 1	0.981	0.203	0.002	0.000	0.141	0.028	1.248
LAG 5	6.620	8.507	8.094	9.001	2.999	5.520	3.513
LAG 10	12.272	36.031 ***	39.542 ***	33.873 ***	11.849	7.661	12.941
LAGRANGE MULTIPLIER ARCH TEST							
LAG 1	3.202 *	1.340	0.074	0.218	0.137	0.284	0.160
LAG 5	8.593	4.924	0.543	0.838	0.555	1.967	11.043 *
LAG 10	16.769 *	21.418 **	9.950	11.806	1.980	3.619	14.849
RESIDUAL DIAGNOSTICS							
SKEWNESS	0.499 ***	-0.653 ***	0.469 ***	0.310 **	-0.941 ***	0.793 ***	0.685 ***
KURTOSIS	0.979 ***	5.933 ***	17.153 ***	17.606 ***	8.983 ***	1.324 ***	1.274 ***
JARQUE-BERA	23.301 ***	439.761 ***	3590.503 ***	3775.884 ***	1003.755 ***	51.936 ***	42.417 ***
MEAN	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ST. ERROR	0.016	0.007	0.003	0.003	0.020	0.159	0.055

Note: The values in brackets are standard errors. ***, ** and * denotes significance at 1%, 5% and 10% levels respectively.

CHAPTER 5

VECTOR AUTOREGRESSION ANALYSIS

In the previous section, the factors that help to determine the market liquidity are discussed. However, there are reasons to expect there are relationships running in the reverse direction as well.

The extant literature has focused on the ability of the liquidity to predict stock returns both in market-wide and individual stock level. The studies that try to explore whether the liquidity of a stock has an influence on its expected return can be traced back to Amihud and Mendelson (1986). The early examples of these studies including Amihud and Mendelson (1986) and Brennan and Subrahmanyam (1996) focused on the cross-sectional and stock specific aspects and provide evidence on that a higher level of current liquidity is associated with lower future returns. As the transaction costs, either resulting from inventory[44] or adverse selection[45] considerations, incurred by the investors when they sell their shares increases with the level of illiquidity, they

[44] See Demsetz (1968), Stoll (1978), Amihud and Mendelson (1980), and Grossman and Miller (1988).

[45] See Kyle (1985), and Easley and O'Hara (1987).

will discount the stock in hand by more resulting in lower price and, hence, higher expected return. This straightforward rationale on how liquidity affects the expected return is successful at explaining the cross-sectional results and has been confirmed by many empirical studies[46]. In their theoretical study, Baker and Stein (2004) approached this explanation cautiously in interpreting the time series variation.

Chordia, Roll and Subrahmanyam (2000), Hasbrouck and Seppi (2001), and Huberman and Halka (2001) documented commonality in the individual stock liquidity and these findings pave the way for further research on the role of aggregate liquidity in explaining the cross-sectional returns[47]. Pastor and Stambaugh (2003) showed that market wide liquidity is a risk factor that affects the prices of the stocks. This issue is explored in time series context as well. According to Acharya and Pedersen (2005) and Amihud (2002), in the case that the liquidity is persistent, a high level of illiquidity in the current period leads to even higher illiquidity forecasts in the next period and higher expected returns[48]. Further, a positive shock to illiquidity which predicts higher illiquidity in the coming period directs investors to drop current prices with the aim of obtaining higher return implying a negative contemporaneous relation[49]. The cross-sectional analyses of Chordia, Subrahmanyam and Anshuman (2001) revealed that there is not only negative relationship between the level of liquidity and expected returns but also a negative one between the volatility of

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[46] Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Brennan, Chordia, and Subrahmanyam (1998).

[47] See Acharya and Pedersen (2005), Pastor and Stambaugh (2003).

[48] See Amihud (2002) and Jones (2002).

[49] See Amihud (2002), Chordia, Roll, and Subrahmanyam (2001).

the trading volume and turnover, which are liquidity proxies indeed, and the expected returns.

It is also possible to construct a relationship between liquidity and volatility in the reverse direction as well. It is well documented that illiquid stocks are expected to have higher returns which implies lower current prices. Also, it is true that stocks with low price tend to have higher volatility. Combining these two arguments, Fujimoto and Watanabe (2006) reached the conclusion that higher illiquidity leads to higher volatility. However, Goyenko and Ukhov (2009) found evidence of only one way causality from volatility to liquidity. In the literature, there is no consensus on how to measure return volatility. Chordia, Roll and Subrahmanyam (2001) and Chordia, Roll and Subrahmanyam (2002) used absolute returns while Goyenko and Ukhov (2009) constructed the return volatility variable as the standard deviation of daily returns. To the best of author's knowledge, there is no study that uses ARCH/GARCH approach in the liquidity analysis context.

The theoretical relationship between the trade volume and the liquidity is generally examined in a cross sectional context in the literature. Accordingly, in a market with a high level of trading activity the spreads are expected to be narrower (Lee, Mucklow & Ready, 1993). In the time series context, Easley and O'Hara (1992) expected a positive relation between the trade volume and bid-ask spreads due to asymmetric information while Harris and Raviv (1993) put forward the cases in which liquidity (spreads) responds positively (negatively) to large volumes. The findings of Lee, Mucklow and Ready (1993) supported the views of Easley and O'Hara (1992). However, Chordia, Roll and Subrahmanyam (2001) provided evidence supporting Harris and Raviv (1993).

5.1. Vector AutoRegression Analysis

The Vector Auto Regression (VAR) model which is popularized by Sims (1980) is a useful tool, particularly, in exploring the causal structure of several series and the impacts of unexpected shocks or innovations to specified variables on the remaining variables with the help of the impulse response functions and forecast error variance decompositions.

In this chapter, the dynamics between the market return, return volatility, aggregate market liquidity and the trading activity are investigated. Since the effect of the monetary stance is found to be insignificant for most of the cases, it is not included in the VAR analysis. In addition, in the previous chapter the trade volume and the value of shares traded are taken as the liquidity proxies. However, trade volume and the TL/dollar value of the shares are also taken as the measure of the trading activity in the literature[50]. Hence, the variable $UVOLUME$ is incorporated into the VAR analysis as a measure of trading activity. Once again, the data set employed in this section is the same as in Chapter 4. That is; the residuals of the auxiliary regressions implemented in Chapter 4 are used due to the stationarity considerations.

VAR model of order p has the general form

$$\mathbf{Y}_t = \mathbf{c} + \mathbf{\Pi}_1 \mathbf{Y}_{t-1} + \mathbf{\Pi}_2 \mathbf{Y}_{t-2} + \cdots + \mathbf{\Pi}_{\mathrm{p}} \mathbf{Y}_{t-p} + \mathbf{u}_t$$

where $\mathbf{Y}_t$ and $\mathbf{c}$ are K-dimensional vectors, $\mathbf{\Pi}_i$ are coefficient matrices, and $\mathbf{u}_t$ is an K-dimensional white noise process**;** that is

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[50] See Amihud and Mendelson (1986), Hasbrouck (1991), Chordia, Roll, and Subrahmnayam (2001).

$$E(\mathbf{u}_t) = 0,\ \ E(\mathbf{u}_t\mathbf{u}_t') = \mathbf{\Sigma}\ \text{ and } E(\mathbf{u}_t\mathbf{u}_s') = 0 \text{ for } t \neq s\ .$$

The matrix $\mathbf{\Sigma}$ contains all the information about the contemporaneous relationship between the variables. Further, in empirical studies, $\mathbf{u}_t$ is assumed to be multivariate normal. The stability of the above system is guaranteed if the following matrix

$$\mathbf{F} = \begin{pmatrix} \mathbf{\Pi}_1 & \mathbf{\Pi}_2 & \dots & \mathbf{\Pi}_K \\ \mathbf{I}_K & 0 & \dots & 0 \\ 0 & \ddots & 0 & \vdots \\ 0 & 0 & \mathbf{I}_K & 0 \end{pmatrix}$$

has eigenvalues with modulus less than 1.

Model selection criteria may be used for determining the lag length of the VAR model. For this purpose, p may be chosen such that a selection criterion is minimized. The most common ones of these criteria are Finite Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC) and Hannan-Quinn criterion ($HQIC$).

Following Lütkepohl (2005), the aforementioned model selection statistics up to ten lag length for all of the five liquidity measures are provided in Table 16. For $LNILLIQ$, AIC, FPE and $HQIC$ indicates the two lag system is superior while SBC chooses the more parsimonious one. However, two-lag and three-lag specifications contain remaining serial correlation. In order to eliminate this, four-lag specification is preferred. With the same reasoning, the appropriate lag structure of the VAR system for each measure is determined relying on the highest lag length chosen by at least two criteria. The four-lag VAR system is used for all of the liquidity proxies. The eigenvalues of the VAR system are less than 1 in modulus and are provided in the Appendix E.

Table 16 VAR Model Lag Selection Statistics

	LAGS	LNILLIQ	LNLRSQRT	LNTURNOVER	LNRQUOTED	LNRELEFFECT
FPE	1	0.500	0.083	0.835	0.018	0.019
	2	0.411 *	0.058	0.536	0.014	0.015
	3	0.415	0.061	0.536	0.015	0.015
	4	0.419	0.056 *	0.450 *	0.013 *	0.014 *
	5	0.429	0.057	0.458	0.014	0.015
	6	0.458	0.061	0.490	0.014	0.015
	7	0.475	0.062	0.492	0.015	0.016
	8	0.477	0.061	0.513	0.015	0.016
	9	0.480	0.061	0.463	0.014	0.015
	10	0.476	0.061	0.480	0.014	0.015
AIC	1	-0.723	-2.521	-0.210	-4.036	-3.992
	2	-0.918 *	-2.877	-0.654	-4.275	-4.226
	3	-0.909	-2.833	-0.654	-4.252	-4.208
	4	-0.900	-2.905 *	-0.828 *	-4.361 *	-4.307 *
	5	-0.878	-2.893	-0.812	-4.312	-4.253
	6	-0.813	-2.835	-0.745	-4.280	-4.225
	7	-0.778	-2.814	-0.742	-4.241	-4.187
	8	-0.775	-2.834	-0.701	-4.213	-4.165
	9	-0.771	-2.838	-0.806	-4.301	-4.242
	10	-0.782	-2.835	-0.772	-4.319	-4.247
HQIC	1	-0.637	-2.436	-0.125	-3.951	-3.907
	2	-0.748 *	-2.707 *	-0.483	-4.105 *	-4.056 *
	3	-0.654	-2.578	-0.398	-3.997	-3.952
	4	-0.559	-2.565	-0.488 *	-4.021	-3.967
	5	-0.452	-2.467	-0.386	-3.886	-3.828
	6	-0.302	-2.325	-0.234	-3.769	-3.714
	7	-0.182	-2.218	-0.146	-3.645	-3.591
	8	-0.094	-2.153	-0.020	-3.532	-3.483
	9	-0.005	-2.072	-0.040	-3.535	-3.476
	10	0.070	-1.984	0.080	-3.467	-3.396
SBC	1	-0.510 *	-2.309	0.002	-3.824	-3.780
	2	-0.494	-2.453 *	-0.230 *	-3.851 *	-3.802 *
	3	-0.273	-2.197	-0.017	-3.616	-3.571
	4	-0.051	-2.057	0.020	-3.513	-3.459
	5	0.183	-1.832	0.249	-3.252	-3.193
	6	0.460	-1.563	0.527	-3.007	-2.952
	7	0.707	-1.329	0.743	-2.756	-2.703
	8	0.922	-1.137	0.996	-2.516	-2.468
	9	1.138	-0.929	1.103	-2.392	-2.333
	10	1.339	-0.714	1.349	-2.197	-2.126

Note: ***, ** and * denotes significance at 1%, 5% and 10% levels respectively.

The estimation results of the four-lag VAR system for each of the five liquidity measures are given in Appendix E.

The three main dynamic analyses, namely Granger causality tests, impulse response functions, and forecast error variance decompositions are performed in the next sections.

5.1.1. Granger causality

Granger causality can be described as follows: A variable y_1 is said to Granger-cause y_2 if y_1 well predicts y_2; otherwise it is said that y_1 fails to Granger-cause y_2. One should keep in mind that this notion has nothing to do with the true causality between y_1 and y_2 since it is related only with the ability of y_1 to forecast y_2. Wald statistic which has a Chi-Square distribution with the degrees of freedom equals to the number of restrictions can be used to test the linear coefficient restrictions revealed by Granger non-causality (Lütkepohl, 2005).

The Wald statistics are provided in Table 17. The data suggest evidence on the Granger causality from the ISE returns to the price impact and turnover measures of liquidity. However, this does not hold for the spread measures. In the reverse direction for which there is a great deal of discussion in the literature, the results are disappointing. Only the liquidity ratio and the turnover measures are able to predict the ISE-100 returns. Actually, there is no Granger causality from trading activity and volatility[51] to the market return as well.

[51] For the VAR system estimated for the natural logarithm of the turnover measure, it is found that the volatility helps to predict the level of returns.

Table 17 Granger Causality Wald Test Results

a)

EQUATION	EXCLUDED VARIABLE	CHI SQUARE
UVOLUME	UVLNR100	6.339
UVOLUME	ULNR100	5.280
UVOLUME	ULNILLIQ	6.602
UVOLUME	ALL	13.902
UVLNR100	UVOLUME	12.455 **
UVLNR100	ULNR100	99.029 ***
UVLNR100	ULNILLIQ	10.756 **
UVLNR100	ALL	153.960 ***
ULNR100	UVOLUME	3.124
ULNR100	UVLNR100	2.269
ULNR100	ULNILLIQ	6.410
ULNR100	ALL	13.839
ULNILLIQ	UVOLUME	1.889
ULNILLIQ	UVLNR100	10.806 **
ULNILLIQ	ULNR100	16.958 ***
ULNILLIQ	ALL	31.293 ***

b)

EQUATION	EXCLUDED VARIABLE	CHI SQUARE
UVOLUME	UVLNR100	5.067
UVOLUME	ULNR100	5.896
UVOLUME	ULNLRSQRT	7.771
UVOLUME	ALL	15.101
UVLNR100	UVOLUME	11.257 **
UVLNR100	ULNR100	96.583 ***
UVLNR100	ULNLRSQRT	22.368 ***
UVLNR100	ALL	171.180 ***
ULNR100	UVOLUME	4.727
ULNR100	UVLNR100	4.628
ULNR100	ULNLRSQRT	13.944 ***
ULNR100	ALL	21.564 **
ULNLRSQRT	UVOLUME	6.299
ULNLRSQRT	UVLNR100	33.570 ***
ULNLRSQRT	ULNR100	9.588 **
ULNLRSQRT	ALL	52.386 ***

c)

EQUATION	EXCLUDED VARIABLE	CHI SQUARE
UVOLUME	UVLNR100	8.955 *
UVOLUME	ULNR100	7.117
UVOLUME	ULNTURNOVER	13.946 ***
UVOLUME	ALL	21.430 **
UVLNR100	UVOLUME	28.651 ***
UVLNR100	ULNR100	123.710 ***
UVLNR100	ULNTURNOVER	60.524 ***
UVLNR100	ALL	227.750 ***
ULNR100	UVOLUME	5.618
ULNR100	UVLNR100	10.799 **
ULNR100	ULNTURNOVER	8.766 *
ULNR100	ALL	16.256
ULNTURNOVER	UVOLUME	13.927 ***
ULNTURNOVER	UVLNR100	3.689
ULNTURNOVER	ULNR100	8.305 *
ULNTURNOVER	ALL	34.652 ***

Table 17 (continued)

d)

EQUATION	EXCLUDED VARIABLE	CHI SQUARE
UVOLUME	UVLNR100	6.115
UVOLUME	ULNR100	7.590
UVOLUME	ULNRQUOTED	6.822
UVOLUME	ALL	14.128
UVLNR100	UVOLUME	14.723 ***
UVLNR100	ULNR100	106.840 ***
UVLNR100	ULNRQUOTED	47.669 ***
UVLNR100	ALL	208.690 ***
ULNR100	UVOLUME	2.612
ULNR100	UVLNR100	5.742
ULNR100	ULNRQUOTED	4.448
ULNR100	ALL	11.827
ULNRQUOTED	UVOLUME	2.241
ULNRQUOTED	UVLNR100	27.212 ***
ULNRQUOTED	ULNR100	2.195
ULNRQUOTED	ALL	34.353 ***

e)

EQUATION	EXCLUDED VARIABLE	CHI SQUARE
UVOLUME	UVLNR100	6.010
UVOLUME	ULNR100	7.496
UVOLUME	ULNREFFECT	5.963
UVOLUME	ALL	13.247
UVLNR100	UVOLUME	14.774 ***
UVLNR100	ULNR100	104.980 ***
UVLNR100	ULNREFFECT	46.060 ***
UVLNR100	ALL	206.300 ***
ULNR100	UVOLUME	2.568
ULNR100	UVLNR100	5.766
ULNR100	ULNREFFECT	5.037
ULNR100	ALL	12.432
ULNREFFECT	UVOLUME	2.917
ULNREFFECT	UVLNR100	24.990 ***
ULNREFFECT	ULNR100	2.800
ULNREFFECT	ALL	33.540 ***

Note: ***, ** and * denotes significance at 1%, 5% and 10% levels respectively.

Although the level of the return cannot be predicted with the variables considered, the trade volume, the bid-ask spreads, depth and the level of the returns is successful at predicting the volatility of the market return both individually and jointly. The return volatility exhibits highly significant bi-directional causality only with the depth and tightness measures. Finally, the trading activity as measured by the number of shares traded helps predict only the turnover measure of the liquidity, and turnover is the only liquidity proxy that Granger causes the trading volume. As mentioned previously, there is Granger causality from trading activity to the return volatility. However, this relation is unidirectional with the exception of VAR system for the turnover measure.

5.1.2. Impulse response functions (IRF)

A stable VAR system can be written in moving average form as follows:

$$\mathbf{Y}_t = \boldsymbol{\mu} + \mathbf{u}_t + \sum_{i=1}^{\infty} \boldsymbol{\psi}_i \mathbf{u}_{t-i}$$

where

$$\boldsymbol{\psi}_i = \textstyle\sum_{j=1}^{i} \boldsymbol{\psi}_{i-j} \boldsymbol{\Pi}_i \ .$$

The (j, k)th element of the matrix $\boldsymbol{\psi}_i$ which is given by

$$\psi_{jk}^{i} = \frac{\partial y_{j,t+i}}{\partial u_{k,t}} = \frac{\partial y_{j,t}}{\partial u_{k,t-i}}, \;\; j,k = 1,\dots,K$$

is called as the impulse-response function and gives the amount of change in the jth element of after i periods as a result of one unit increase in the kth element of assuming all other things being equal. However, the presence of contemporaneous correlations among innovations, that is $\boldsymbol{\Sigma}$ is not diagonal, prevents one to use this interpretation since the assumption *all other things being equal* is not valid anymore. The method to be used is the orthogonalization of the innovation terms. Beginning with a matrix $\mathbf{P}$ such that $\boldsymbol{\Sigma} = \mathbf{PP'}$, the VAR system in moving average representation can be rewritten as

$$\mathbf{Y}_t = \boldsymbol{\mu} + \sum_{i=0}^{\infty} \boldsymbol{\psi}_i \mathbf{PP'} \mathbf{u}_{t-i}$$

$$\mathbf{Y}_t = \boldsymbol{\mu} + \sum_{i=0}^{\infty} \boldsymbol{\Theta}_i \boldsymbol{\eta}_{t-i}$$

where $\boldsymbol{\Theta}_i = \boldsymbol{\psi}_i \mathbf{P}$ and $\boldsymbol{\eta}_t = \mathbf{P'} \mathbf{u}_t$.

The orthogonal impulse response function of y_j with respect to η_k is, by definition, the plot of θ_{jk}^{i} against i where θ_{jk}^{i} is (j,k)th element of $\boldsymbol{\Theta}_i$.

Sims (1980) proposed to use the Cholesky decomposition of $\boldsymbol{\Sigma}$ as a solution to the problem of choosing an appropriate matrix $\mathbf{P}$. This method imposes recursive causal ordering on the dynamics of the model. For the three variable case, the ordering such that y_1, y_2 and y_3 has the restrictions that y_3 is affected by y_1 and y_2 but does not affect y_1 and y_2; and y_2 is affected by y_1 but not vice versa. Unless there are theoretical reasons to choose one ordering to another, the particular ordering is somehow arbitrary and it is usual practice to check whether the results are robust to the ordering. Pesaran and Shin (1998) proposed g*eneralized impulse response functions* which are invariant to the ordering of the variables.

Chordia, Sarkar and Subrahmanyam (2005) argued that it is the order flow that leads the market participants to take action and the stock prices and the liquidity are influenced sequentially. However, the specific sequence of the impact on the return, volatility and the liquidity is ambiguous. Chordia, Sarkar and Subrahmanyam (2005) and Goyenko and Ukhov (2009) documented that the results are not affected by the ordering and prefer to present the results of the ordering such that trading activity[52], volatility, return and liquidity. This is the ordering used in this thesis and the results are given in Figures 8-12. However, this ordering prevents us to study the contemporaneous effect of the liquidity shock on the return level since the liquidity variable is placed after the return and the Cholesky decomposition places the restriction that the liquidity does not affect the return. In order to test this hypothesis, another class of VAR equations with the ordering such that trading activity, volatility, liquidity and return is estimated and the corresponding results are given in Figure 7.

Due to the potential correlation between the innovations, the orthogonalized impulse-response functions with the fifty two period forecast horizon are presented in Figures 7-12. A unit of orthogonalized positive shock to the market return is contemporaneously associated with higher aggregate market

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[52] Trading activity is not included in Goyenko and Ukhov (2009). Also, Goyenko and Ukhov (2009) and Chordia, Sarkar and Subrahmanyam (2005) include the bond market counterparts of these variables. However, the ordering of the other variables are as given.

liquidity. In for about ten weeks at most, this positive effect completely dissipates. The expected contemporaneous decrease in the return in response to a positive shock to illiquidity is confirmed and this effect lasts for about next three weeks. As a response to the one percentage point increase (in orthogonalized terms) in the return volatility, there is a contemporaneous improvement in the market liquidity except the illiquidity and turnover measure. After one-week, an increase in the spread and lower depth is predicted. Further, though the illiquidity measure predicts a contemporaneous reduction in depth, the effect is higher on the following week. A positive shock to the trading activity leads to higher depth and turnover and this effect lasts for about fifteen week. However, the effect on the transaction costs is relatively weak. On the other hand, the higher level of trading activity is associated with higher levels of contemporaneous market return. Further, increased return volatility leads to lower returns in the next three weeks with the highest decrease in the current period.

The effect of the liquidity shocks on the market volatility is somehow mixed. On the other hand, higher depth and turnover implying higher liquidity and the higher spreads implying lower liquidity in the current week both tend to lead to higher volatility at least three up-coming weeks. Further, higher levels of return lead to lower volatility in the following weeks. More interestingly, a positive shock to the trading activity leads to higher volatility in the current period while a stronger decrease beginning from the following week.

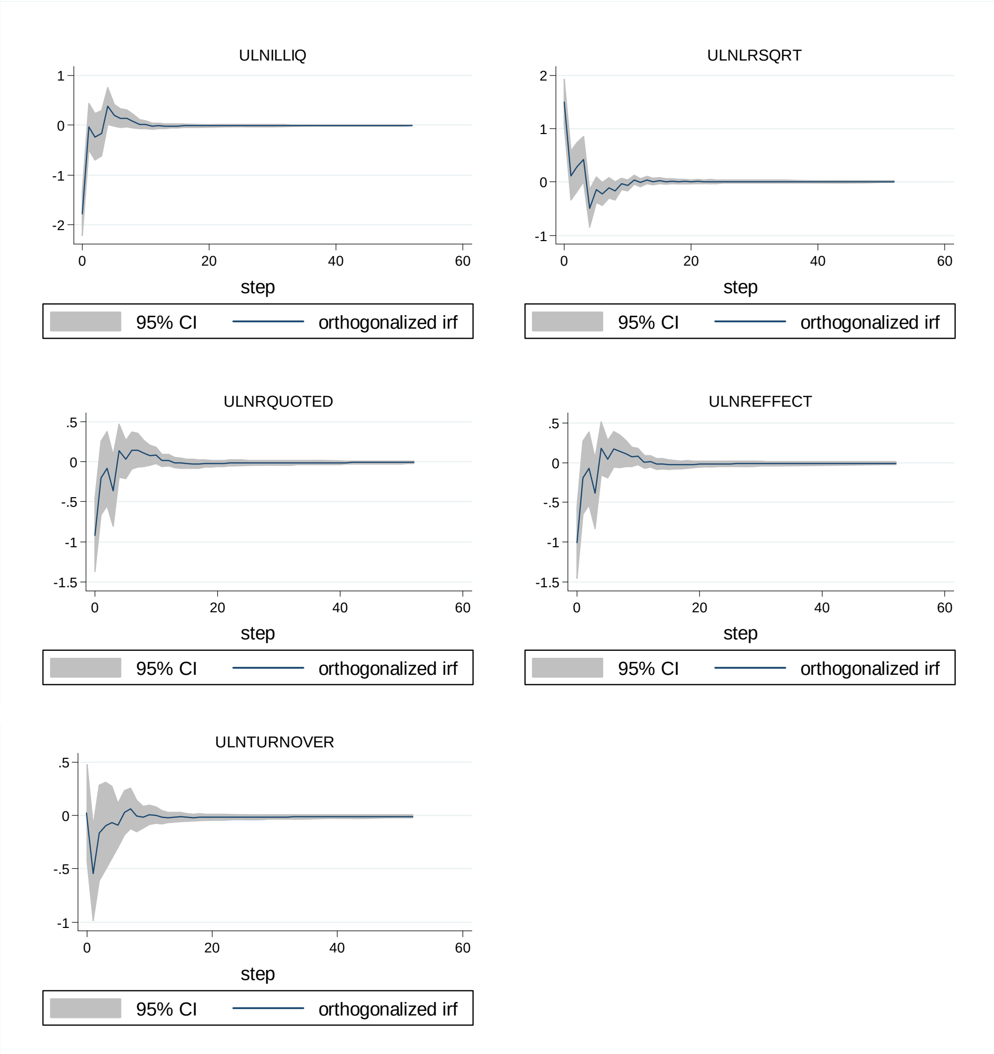
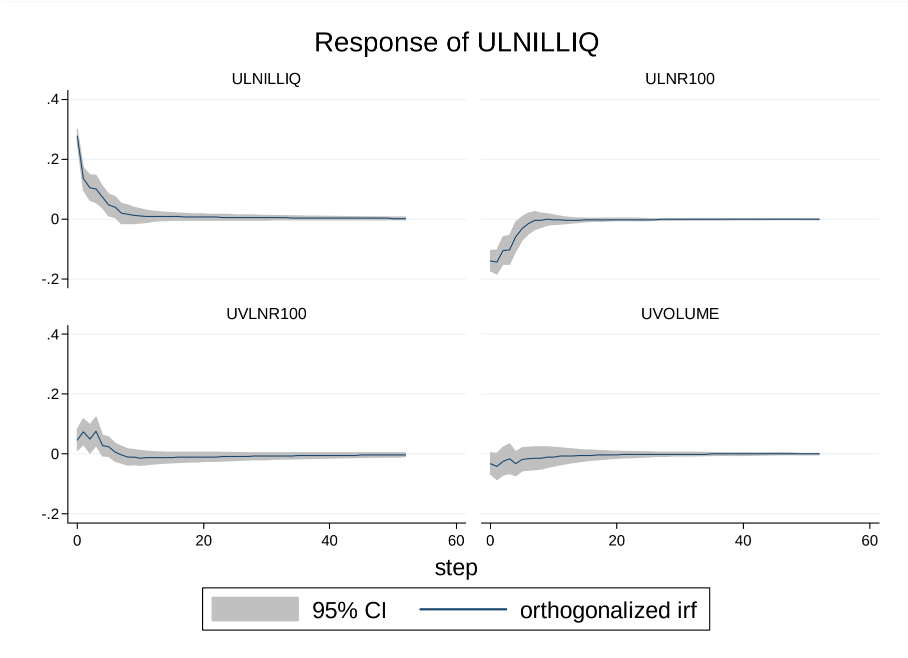


Figure 7 Orthogonalized Impulse-Response Functions of the Return in Response to Innovations to Liquidity Measures



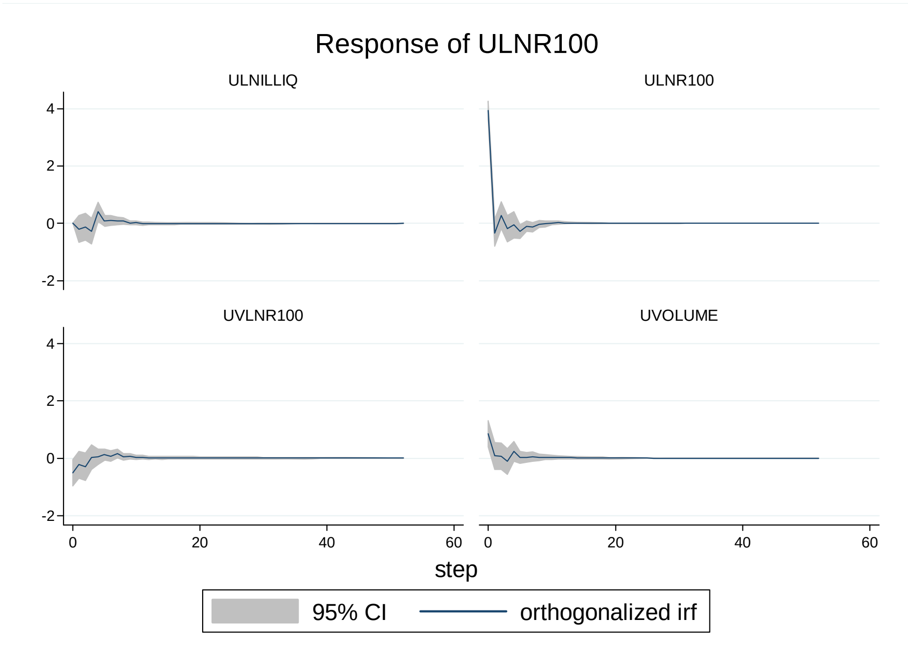
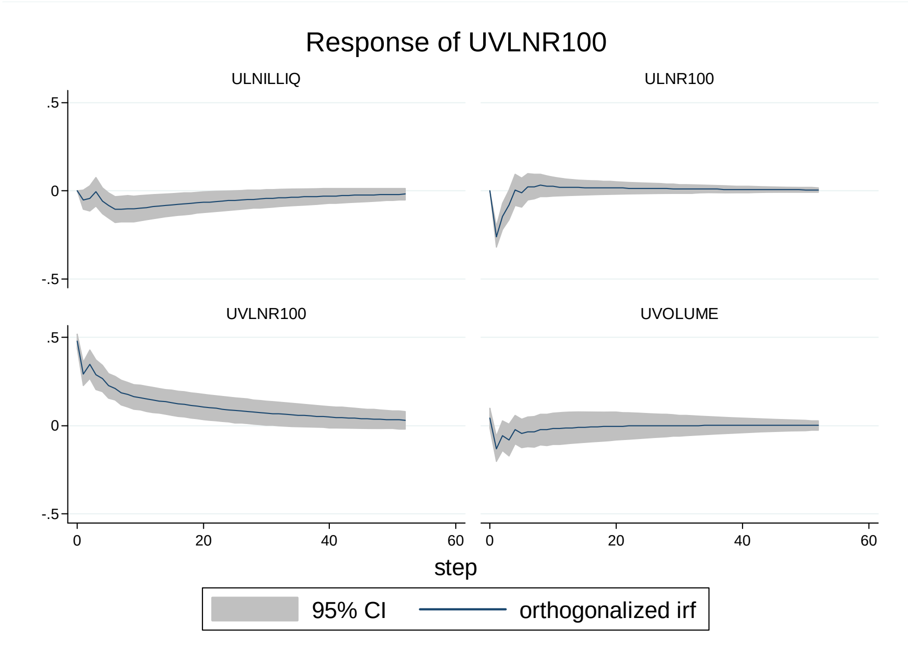


Figure 8 Orthogonalized Impulse-Response Functions from VAR System with $ULNILLIQ$



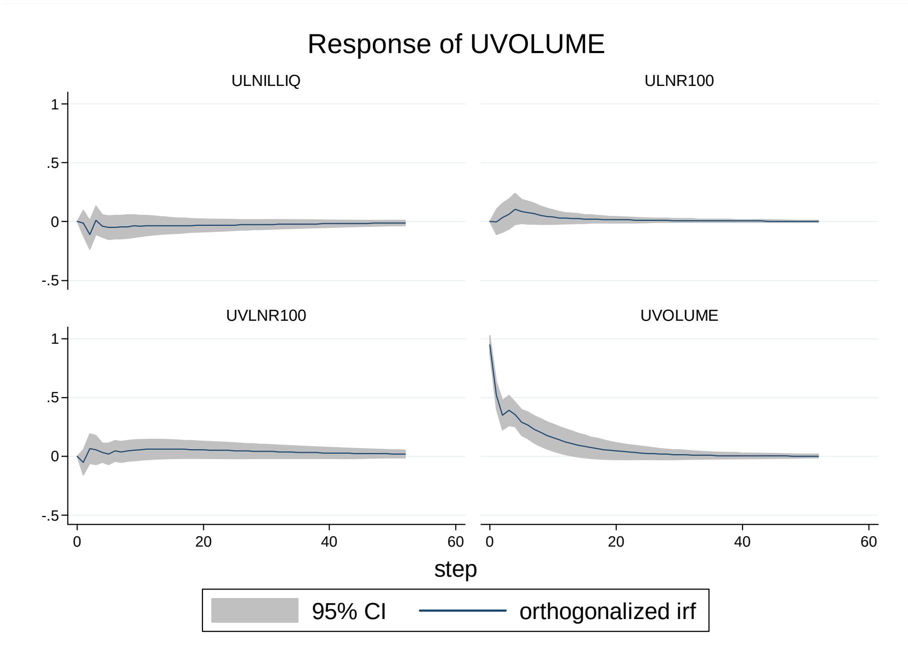
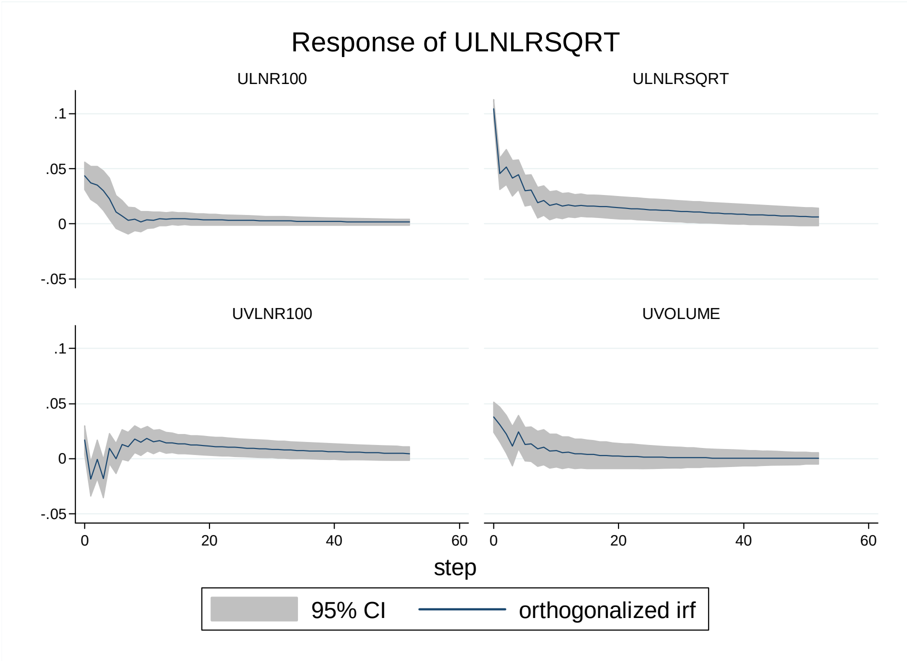


Figure 8 (continued)



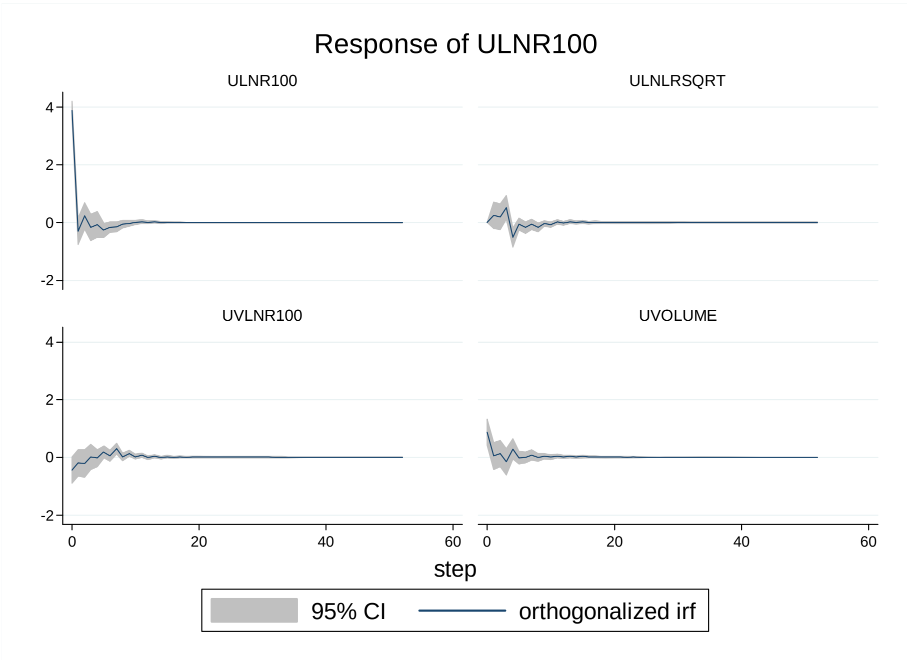
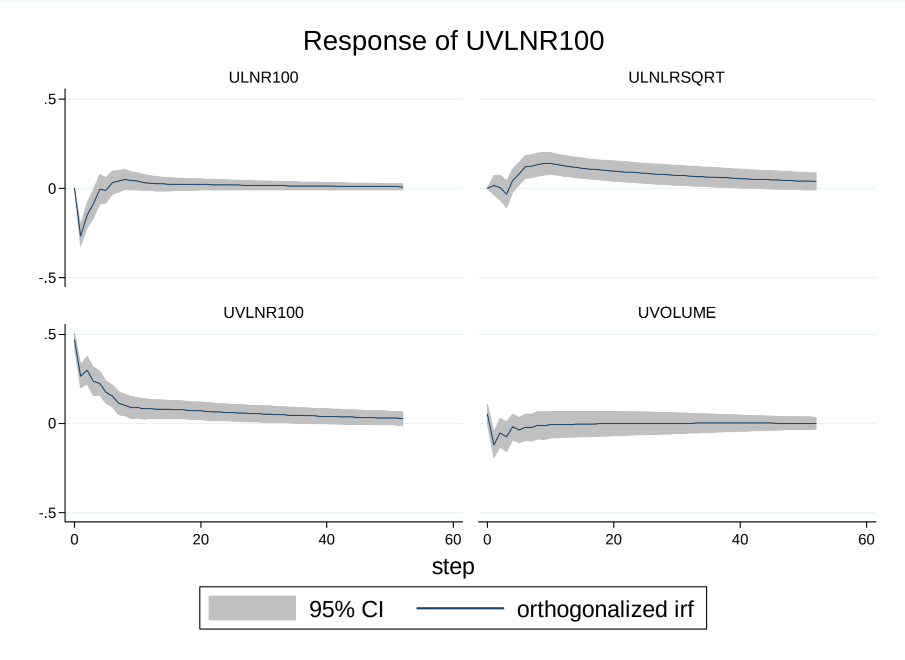


Figure 9 Orthogonalized Impulse-Response Functions from VAR System with $ULNLRSQRT$



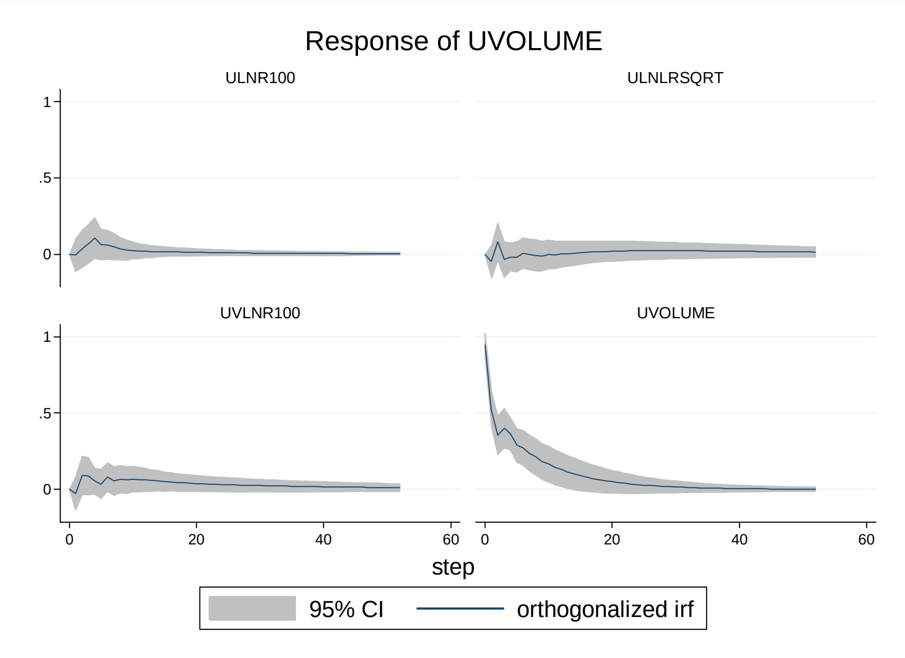
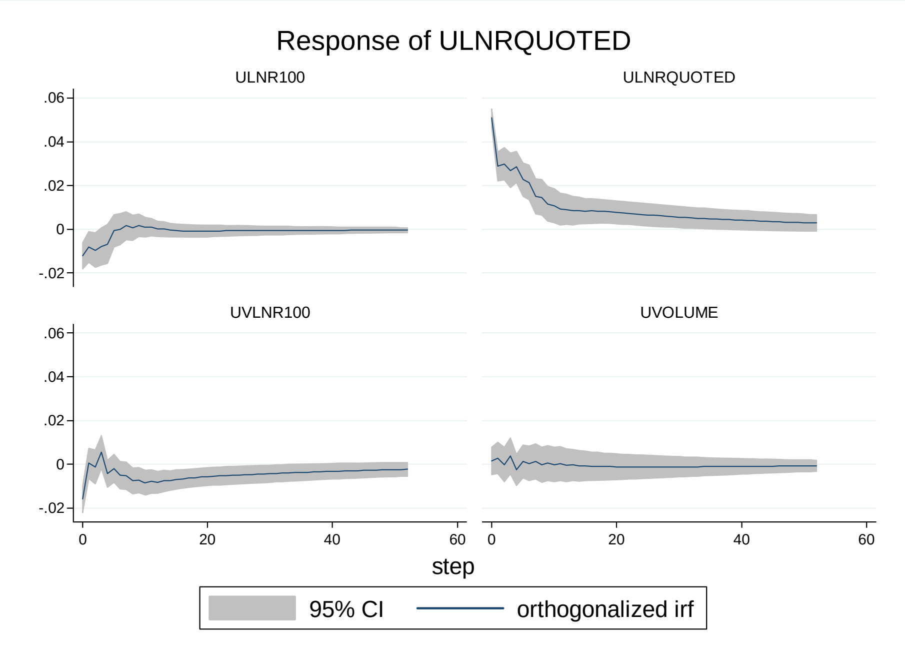


Figure 9 (continued)



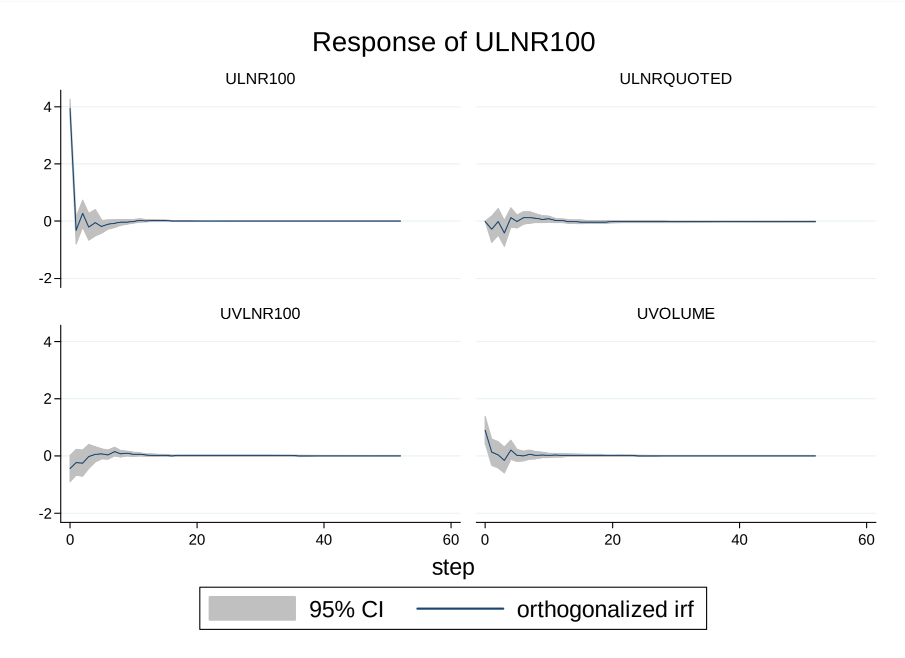
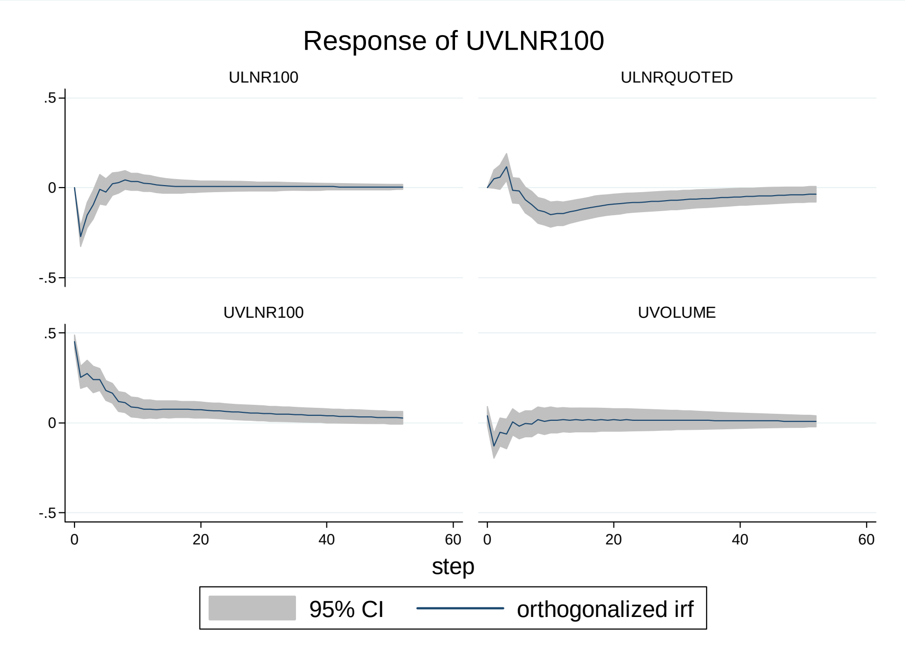


Figure 10 Orthogonalized Impulse-Response Functions from VAR System with $ULNRQUOTED$



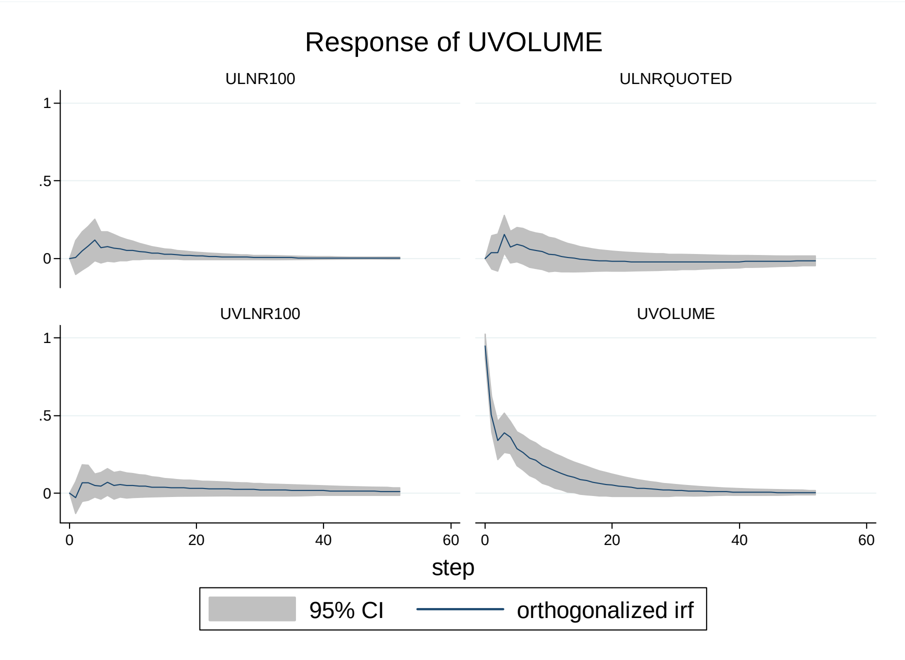
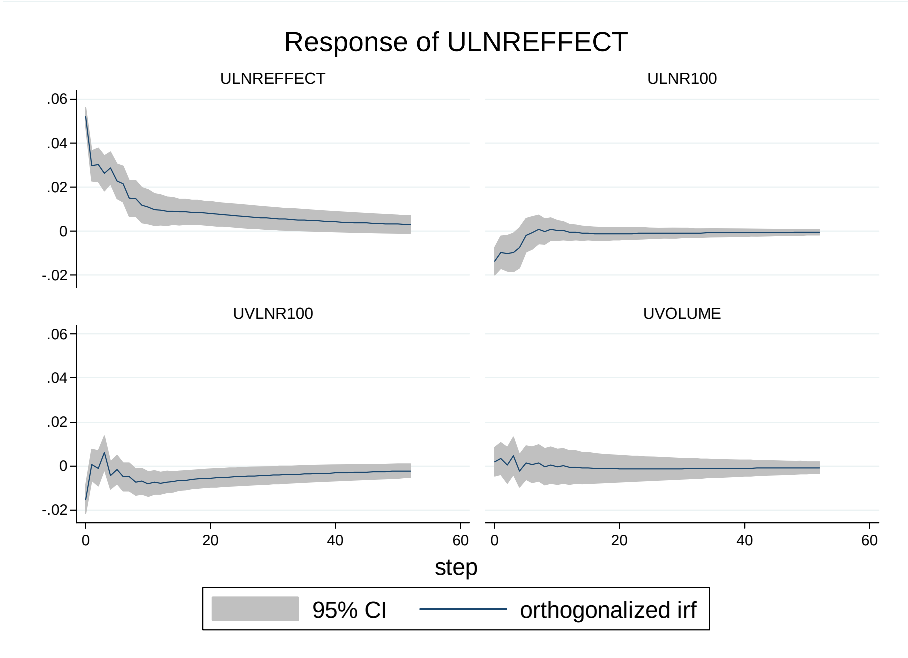


Figure 10 (continued)



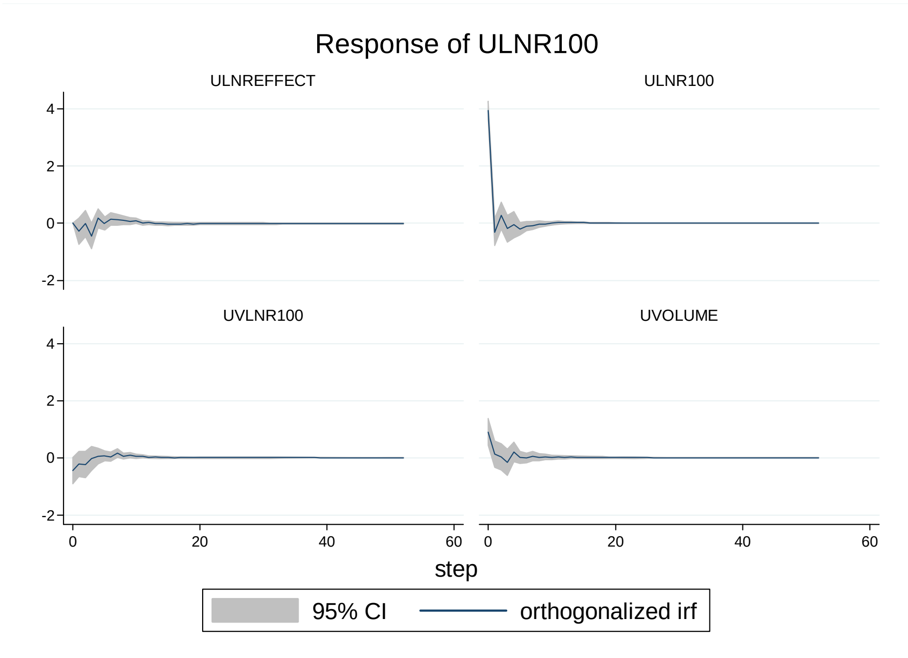
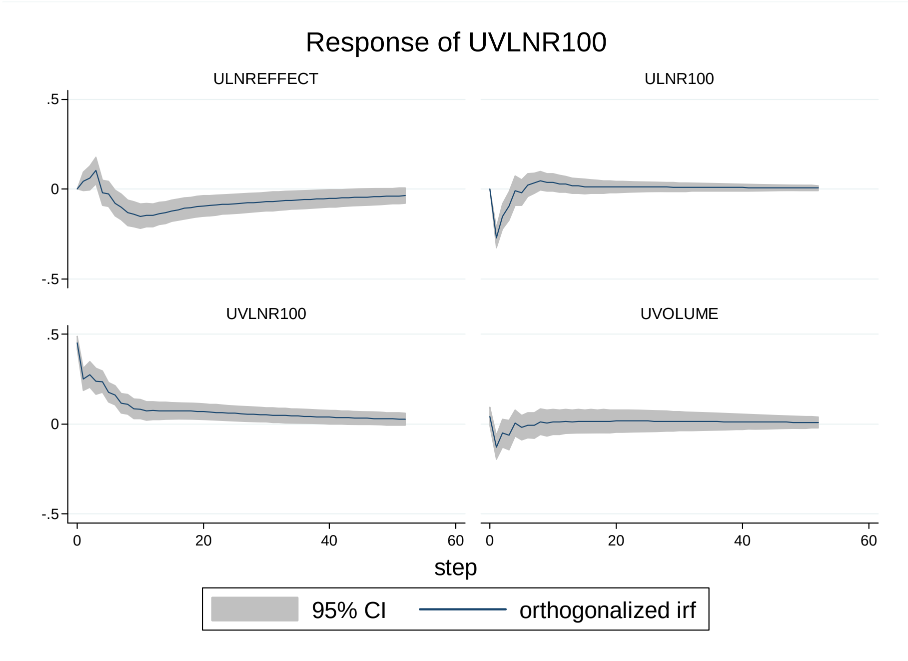


Figure 11 Orthogonalized Impulse-Response Functions from VAR System with $ULNREFFECT$



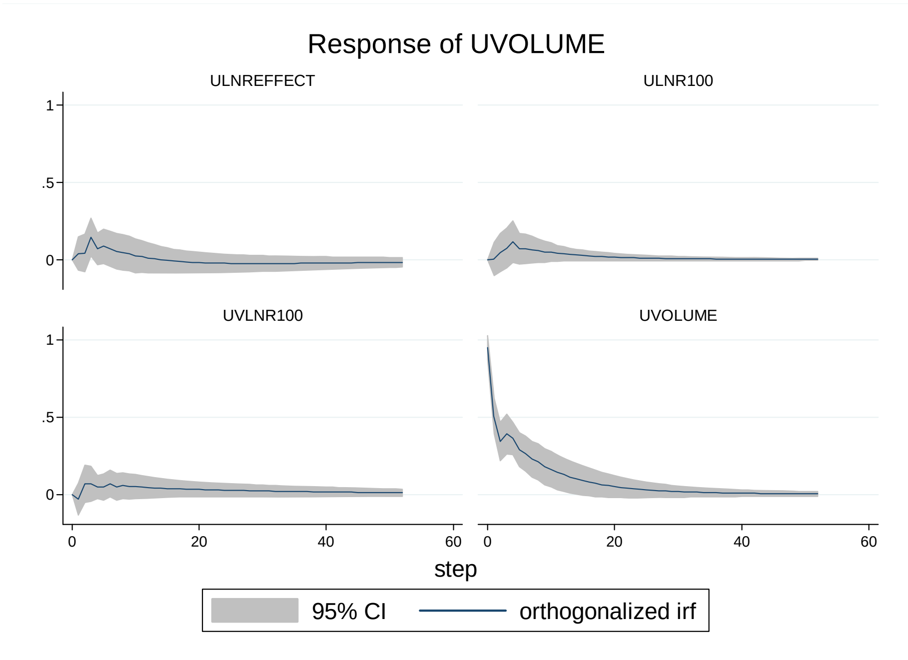
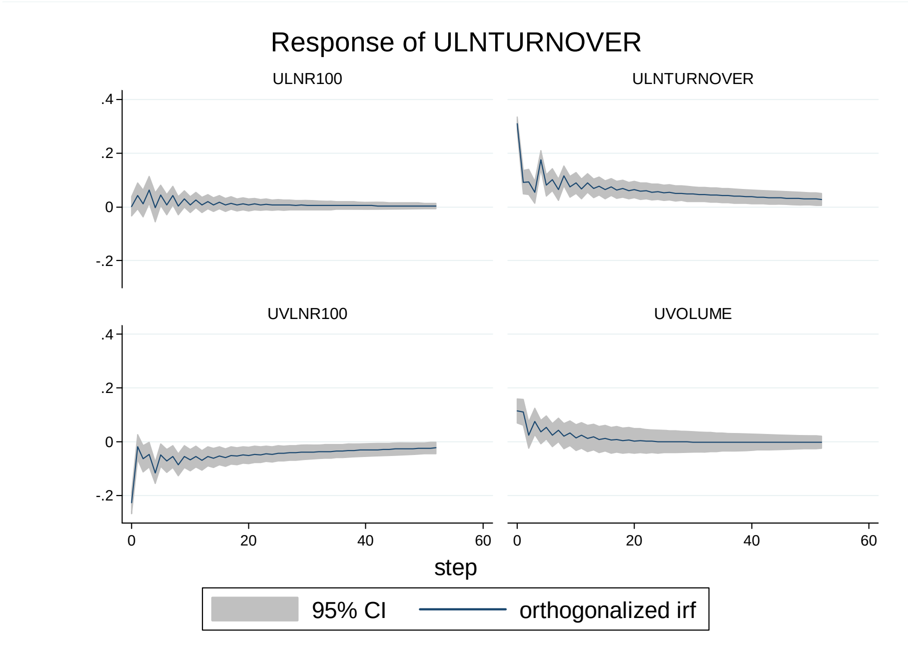


Figure 11 (continued)



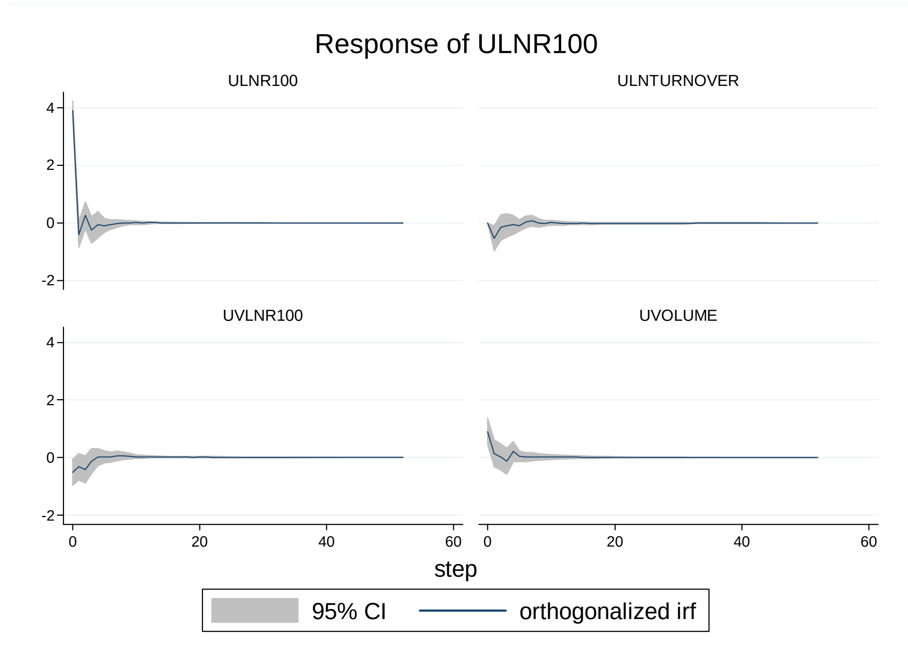
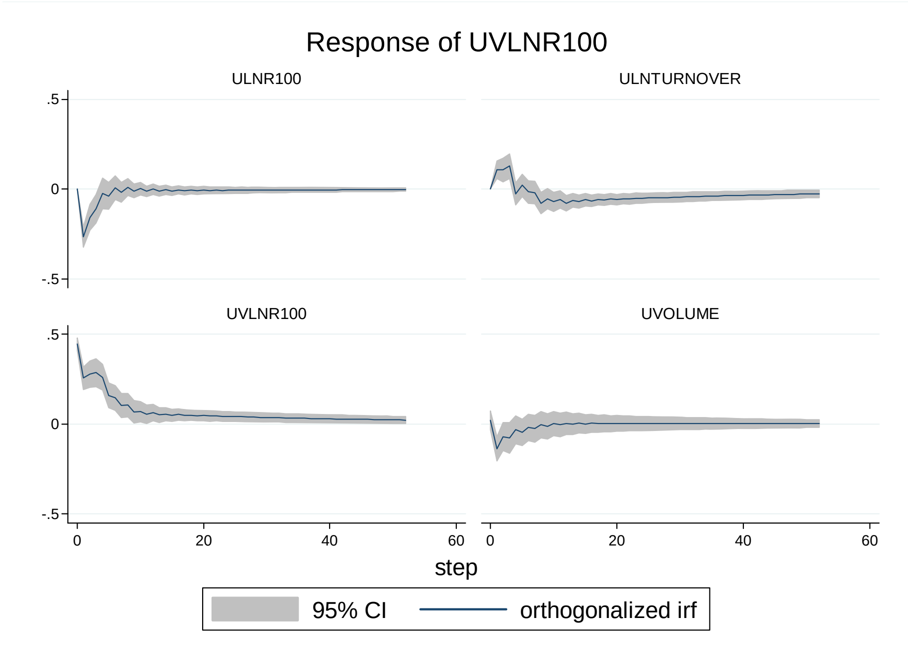


Figure 12 Orthogonalized Impulse-Response Functions from VAR System with $ULNTURNOVER$



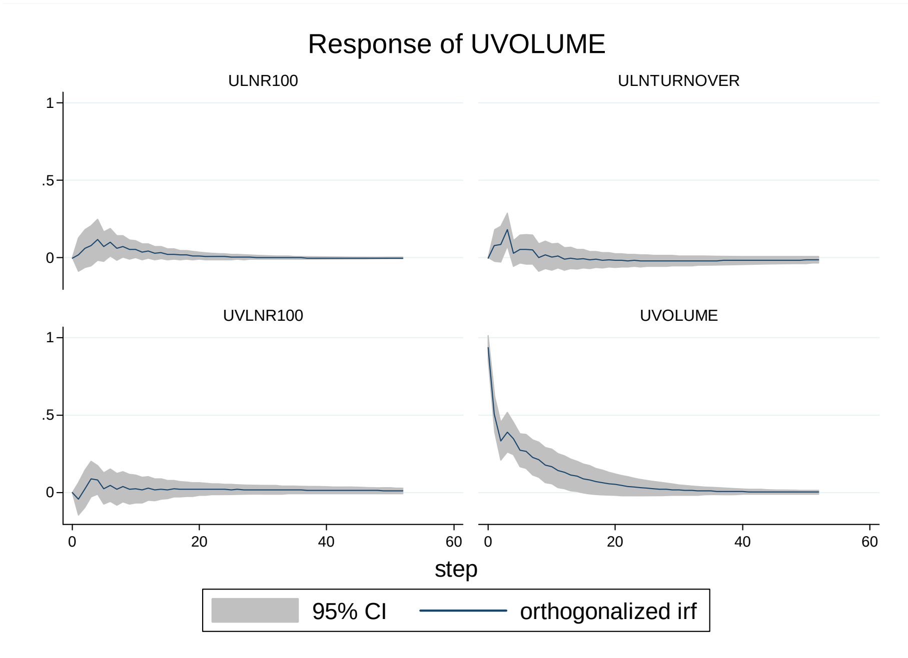


Figure 12 (continued)

5.1.3. Forecast Error Variance Decompositions

The forecast error variance decomposition which is also called as *innovation accounting* aims to find out the portion of the variance of the forecast error in h period forecast of y_j due to the innovation in variable k. In order to discriminate between the individual contributions of each shock to the forecast error variance, again the orthogonalization is applied. Hence, the h-period forecast error for variable j has the form

$$y_{j,T+h} - y_{j,T+h|T} = \sum_{i=0}^{h-1} \theta_{j1}^{i} \eta_{1,T+h-i} + \cdots + \sum_{i=0}^{h-1} \theta_{jK}^{i} \eta_{K,T+h-i}$$

Due to the orthogonalization, the variance of the forecast error is given by

$$\mathrm{var}\left(y_{j,T+h} - y_{j,T+h|T}\right) = \sigma_{\eta_1}^2 \sum_{i=0}^{h-1} \left(\theta_{j1}^{i}\right)^2 + \cdots + \sigma_{\eta K}^2 \sum_{i=0}^{h-1} \left(\theta_{jK}^{i}\right)^2$$

The kth component in the above equation gives how much the shock to variable y_k contributes to the h-period forecast error variance of y_j. Then, the portion of the forecast error variance which is caused individually by η_k can be calculated as

$$FEVD_{j,k}(h) = \frac{\sigma_{\eta_k}^2 \sum_{i=0}^{h-1} \left(\theta_{jk}^{i}\right)^2}{\sigma_{\eta_1}^2 \sum_{i=0}^{h-1} \left(\theta_{j1}^{i}\right)^2 + \cdots + \sigma_{\eta K}^2 \sum_{i=0}^{h-1} \left(\theta_{jK}^{i}\right)^2}$$

Similar to the impulse-response functions, the different ordering of the variables may lead to different forecast error variance decompositions. The ordering is the same as in the impulse response analysis. The results are given in Table 18.

The forecast error variance of the liquidity measures are largely due to the own shocks. The proportion of explained by own liquidity shocks declines at longer forecast horizons and ranges between 58% and 75% for the depth and the turnover measure. However, this proportion increases for the spread measures and ranges between 86% and 89%. The second largest contributor to the liquidity forecast error variance is the return shock while the magnitude of this proportion shows a great deal of variation among the different measures. For the illiquidity measure, the proportion that can be attributed to the return shocks increases from 20% to 30% as moving from 1-period to 8-period forecast, while it is about only 7% for the spread measures. As in most of the analysis documented so far, the variance decomposition analysis yields unique results for the turnover measure. About 30% of the forecast error variance can be attributed to the volatility and about 13% is explained by the trading activity with the return has the smallest proportion. The case for the forecast error variance of the market return is more straightforward. 90% of the variation is explained by own shocks while 5% by the trading activity. More interestingly, 99% of the 1-period forecast error variance for the return volatility is determined by the own shocks. However, for the longer period forecasts this ratio falls to about 75% as the contribution of the level of the return rises to 15%. Finally, the forecast error variance of the trading activity explained by its own shocks is about 95% for short and long forecast periods as well. The proportion of the shocks coming from the other variables increases at longer horizons with, generally, 2% from shocks related to the level of return.

Table 18 Forecast Error Variance Decompositions

a)

	RESPONSE OF UVOLUME				RESPONSE OF UVLNR100				RESPONSE OF ULNR100				RESPONSE OF ULNILLIQ			
STEP	UVOLUME	UVLNR100	ULNR100	ULNILLIQ	UVOLUME	UVLNR100	ULNR100	ULNILLIQ	UVOLUME	UVLNR100	ULNR100	ULNILLIQ	UVOLUME	UVLNR100	ULNR100	ULNILLIQ
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	1.000	0.000	0.000	0.000	0.008	0.992	0.000	0.000	0.044	0.016	0.940	0.000	0.010	0.022	0.196	0.771
2	0.998	0.002	0.000	0.000	0.048	0.776	0.169	0.006	0.044	0.018	0.935	0.002	0.019	0.053	0.276	0.652
3	0.984	0.005	0.001	0.010	0.041	0.788	0.163	0.008	0.044	0.023	0.930	0.003	0.020	0.060	0.299	0.621
4	0.981	0.007	0.004	0.009	0.046	0.799	0.148	0.007	0.044	0.023	0.925	0.008	0.019	0.080	0.313	0.588
5	0.974	0.007	0.010	0.009	0.042	0.814	0.133	0.011	0.047	0.023	0.913	0.017	0.023	0.080	0.313	0.584
6	0.969	0.007	0.014	0.010	0.041	0.817	0.123	0.019	0.047	0.024	0.912	0.017	0.024	0.081	0.312	0.583
7	0.965	0.008	0.017	0.011	0.040	0.814	0.115	0.031	0.047	0.024	0.911	0.018	0.025	0.081	0.310	0.585
8	0.962	0.008	0.019	0.012	0.039	0.810	0.110	0.042	0.047	0.026	0.909	0.018	0.026	0.080	0.309	0.585

b)

	RESPONSE OF UVOLUME				RESPONSE OF UVLNR100				RESPONSE OF ULNR100				RESPONSE OF ULNLRSQRT			
STEP	UVOLUME	UVLNR100	ULNR100	ULNLRSQRT	UVOLUME	UVLNR100	ULNR100	ULNLRSQRT	UVOLUME	UVLNR100	ULNR100	ULNLRSQRT	UVOLUME	UVLNR100	ULNR100	ULNLRSQRT
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	1.000	0.000	0.000	0.000	0.012	0.988	0.000	0.000	0.047	0.012	0.941	0.000	0.098	0.019	0.131	0.752
2	0.997	0.001	0.000	0.002	0.046	0.767	0.187	0.001	0.047	0.014	0.935	0.004	0.124	0.032	0.170	0.674
3	0.985	0.007	0.001	0.007	0.041	0.769	0.189	0.001	0.047	0.017	0.929	0.007	0.122	0.026	0.191	0.661
4	0.978	0.011	0.004	0.007	0.046	0.772	0.180	0.003	0.048	0.016	0.912	0.023	0.113	0.036	0.203	0.649
5	0.971	0.012	0.011	0.006	0.043	0.788	0.164	0.005	0.052	0.016	0.894	0.038	0.120	0.035	0.199	0.646
6	0.969	0.012	0.013	0.006	0.042	0.788	0.155	0.015	0.052	0.018	0.893	0.038	0.121	0.034	0.195	0.651
7	0.965	0.015	0.014	0.006	0.041	0.777	0.147	0.035	0.051	0.018	0.891	0.039	0.122	0.037	0.188	0.653
8	0.963	0.016	0.015	0.006	0.040	0.762	0.143	0.055	0.051	0.023	0.886	0.039	0.122	0.040	0.185	0.653

c)

	RESPONSE OF UVOLUME				RESPONSE OF UVLNR100				RESPONSE OF ULNR100				RESPONSE OF ULNTURNOVER			
STEP	UVOLUME	UVLNR100	ULNR100	ULNTURNOVER	UVOLUME	UVLNR100	ULNR100	ULNTURNOVER	UVOLUME	UVLNR100	ULNR100	ULNTURNOVER	UVOLUME	UVLNR100	ULNR100	ULNTURNOVER
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	1.000	0.000	0.000	0.000	0.002	0.998	0.000	0.000	0.050	0.016	0.934	0.000	0.082	0.322	0.000	0.596
2	0.993	0.002	0.000	0.006	0.054	0.720	0.195	0.031	0.050	0.021	0.912	0.017	0.138	0.284	0.009	0.568
3	0.984	0.002	0.003	0.011	0.051	0.703	0.198	0.047	0.049	0.031	0.902	0.018	0.132	0.285	0.009	0.574
4	0.954	0.007	0.007	0.032	0.051	0.703	0.180	0.066	0.050	0.031	0.900	0.019	0.149	0.276	0.028	0.547
5	0.945	0.010	0.015	0.030	0.048	0.731	0.162	0.060	0.052	0.031	0.897	0.019	0.128	0.279	0.023	0.570
6	0.942	0.010	0.017	0.030	0.049	0.736	0.157	0.058	0.052	0.031	0.897	0.019	0.132	0.274	0.029	0.565
7	0.936	0.011	0.022	0.030	0.048	0.744	0.152	0.056	0.052	0.031	0.897	0.020	0.127	0.276	0.027	0.569
8	0.935	0.011	0.024	0.031	0.048	0.746	0.150	0.056	0.052	0.031	0.896	0.020	0.129	0.277	0.032	0.562

Table 18 (continued)

d)

	RESPONSE OF UVOLUME				RESPONSE OF UVLNR100				RESPONSE OF ULNR100				RESPONSE OF ULNRQUOTED			
STEP	UVOLUME	UVLNR100	ULNR100	ULNRQUOTED	UVOLUME	UVLNR100	ULNR100	ULNRQUOTED	UVOLUME	UVLNR100	ULNR100	ULNRQUOTED	UVOLUME	UVLNR100	ULNR100	ULNRQUOTED
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	1.000	0.000	0.000	0.000	0.008	0.992	0.000	0.000	0.049	0.012	0.939	0.000	0.001	0.084	0.050	0.865
2	0.998	0.001	0.000	0.001	0.050	0.741	0.202	0.007	0.050	0.015	0.931	0.005	0.003	0.065	0.055	0.878
3	0.992	0.004	0.002	0.002	0.045	0.737	0.206	0.013	0.049	0.018	0.928	0.005	0.002	0.052	0.062	0.884
4	0.969	0.007	0.006	0.019	0.045	0.730	0.191	0.035	0.050	0.018	0.917	0.015	0.004	0.050	0.064	0.882
5	0.958	0.008	0.014	0.020	0.041	0.755	0.173	0.032	0.052	0.018	0.914	0.016	0.005	0.046	0.062	0.887
6	0.951	0.009	0.016	0.024	0.039	0.766	0.164	0.031	0.052	0.018	0.913	0.016	0.005	0.043	0.058	0.895
7	0.944	0.011	0.019	0.026	0.037	0.769	0.157	0.036	0.052	0.018	0.913	0.017	0.004	0.043	0.054	0.898
8	0.940	0.012	0.020	0.027	0.036	0.763	0.153	0.047	0.052	0.020	0.910	0.018	0.005	0.045	0.053	0.897

e)

	RESPONSE OF UVOLUME				RESPONSE OF UVLNR100				RESPONSE OF ULNR100				RESPONSE OF ULNREFFECT			
STEP	UVOLUME	UVLNR100	ULNR100	ULNREFFECT	UVOLUME	UVLNR100	ULNR100	ULNREFFECT	UVOLUME	UVLNR100	ULNR100	ULNREFFECT	UVOLUME	UVLNR100	ULNR100	ULNREFFECT
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	1.000	0.000	0.000	0.000	0.008	0.992	0.000	0.000	0.049	0.012	0.939	0.000	0.001	0.074	0.060	0.865
2	0.998	0.001	0.000	0.001	0.051	0.741	0.203	0.005	0.050	0.014	0.931	0.005	0.004	0.056	0.068	0.872
3	0.991	0.004	0.002	0.003	0.045	0.736	0.206	0.012	0.049	0.018	0.929	0.005	0.003	0.045	0.074	0.877
4	0.970	0.007	0.005	0.017	0.046	0.732	0.192	0.030	0.050	0.017	0.917	0.016	0.006	0.045	0.079	0.869
5	0.960	0.008	0.014	0.019	0.041	0.756	0.175	0.028	0.052	0.017	0.912	0.018	0.006	0.042	0.077	0.875
6	0.953	0.009	0.016	0.022	0.040	0.766	0.166	0.028	0.052	0.018	0.912	0.018	0.006	0.039	0.072	0.883
7	0.947	0.011	0.018	0.024	0.038	0.767	0.159	0.036	0.052	0.018	0.911	0.019	0.006	0.040	0.068	0.887
8	0.944	0.012	0.020	0.025	0.037	0.759	0.155	0.049	0.052	0.019	0.909	0.020	0.006	0.042	0.066	0.887

Note: The ordering of the variables is such that trading activity, volatility, return and liquidity. ***, ** and * denotes significance at 1%, 5% and 10% levels respectively.

CHAPTER 6

CONCLUSIONS

The focus of this thesis is on the aggregate market liquidity in the ISE. However, the return volatility modeling is an important input in the liquidity analysis so that it deserves a separate chapter. Hence, the conclusions of the thesis should be divided into two main parts. The first set of results comes from the volatility modeling chapter which is devoted to determine the best fitting volatility model for the log returns in the Turkish stock market. The analyses confirmed that the weekly log return series of the ISE-100 index has negative skewness and leptokurtosis and exhibits volatility clustering, high persistence, leverage effects and mean reversion. GARCH(1,1)-M model fails at the covariance stationarity test stage under different distributional assumptions; in other words the existence of positive risk premium is not confirmed. Under the assumption of normally distributed innovations, the EGARCH(1,1) allowing for only volatility shift between the end of July and mid-November 2008 is found to be most appropriate one according to both AIC and SBC. The most striking implications of this model are that the negative shocks tend to increase the volatility more compared to the positive ones and the volatility of the ISE returns increased due to the global crisis. Due to the proven structural shift and high persistence in the volatility process, although not tested in this study, it is worth to consider SWARCH as an important alternative tool in future studies that aims to model the ISE return volatility.

Due to the global financial crisis, a reduction in the depth is observed between the end of July 2008 and the beginning of April 2009. On the other hand, the spreads react a bit more lately. The negative effect on the return level and volatility is relatively short lived until mid-November 2008. Following the tick size reduction trading activity and volatility increased without a significant impact on returns. The announcement of the data on the CPI is associated with higher trading activity and the return volatility while the effect on liquidity is conclusive. The positive relationship between the return and liquidity is confirmed. Further, the volatility affects the market liquidity with one-week delay. In addition, there is an evidence on that the higher trading activity and lower transactions costs are followed by the tightening policy of the CBRT.

Granger causality from the liquidity to the return is found only for the liquidity ratio and the turnover. Also, there is evidence on the bi-directional causality between the volatility and the depth and tightness measures. There is no Granger causality between the spread and price impact measures and the trading activity in either direction. The shocks to return has positive effects on market liquidity for about ten weeks. Further, the expected contemporaneous decrease in the return in response to a positive shock to illiquidity is confirmed. Positive shocks to trading activity are found to be associated with increased depth and return. The contribution of the shocks to the market return in explaining the forecast error variance of the market liquidity increases as the forecast horizon gets longer for the depth measures while it is relatively stable for the spread measures. The contribution of the market liquidity in explaining the forecast error variance of the return ranges from 2% to 4%.

Most of the studies in the liquidity analysis area use high frequency intra-day price and volume data. In this thesis, daily data are employed and this may prevent one to explore the dynamics of liquidity associated especially with trading activity and return. To the best of author's knowledge, there is a lack of studies focusing on the Turkish stock market liquidity using high frequency data. Further, the relationship between the volatility of the liquidity and the asset pricing in a multivariate GARCH framework, which is out of the scope of this thesis, stands as a fruitful area of research both for the ISE and the other stock exchanges.

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APPENDIX A

TIME PLOTS

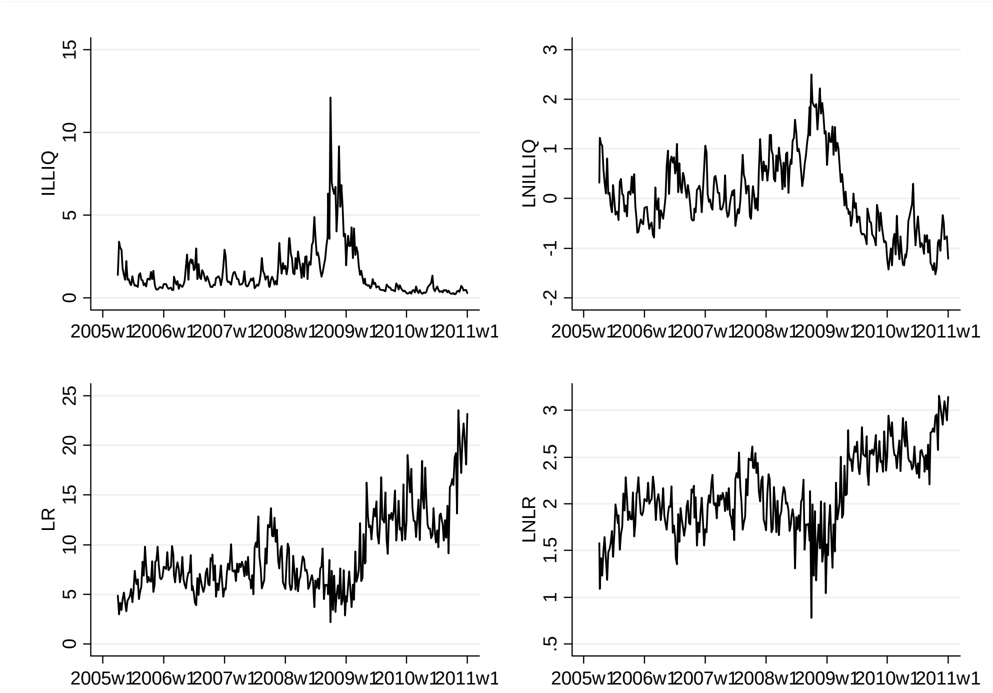
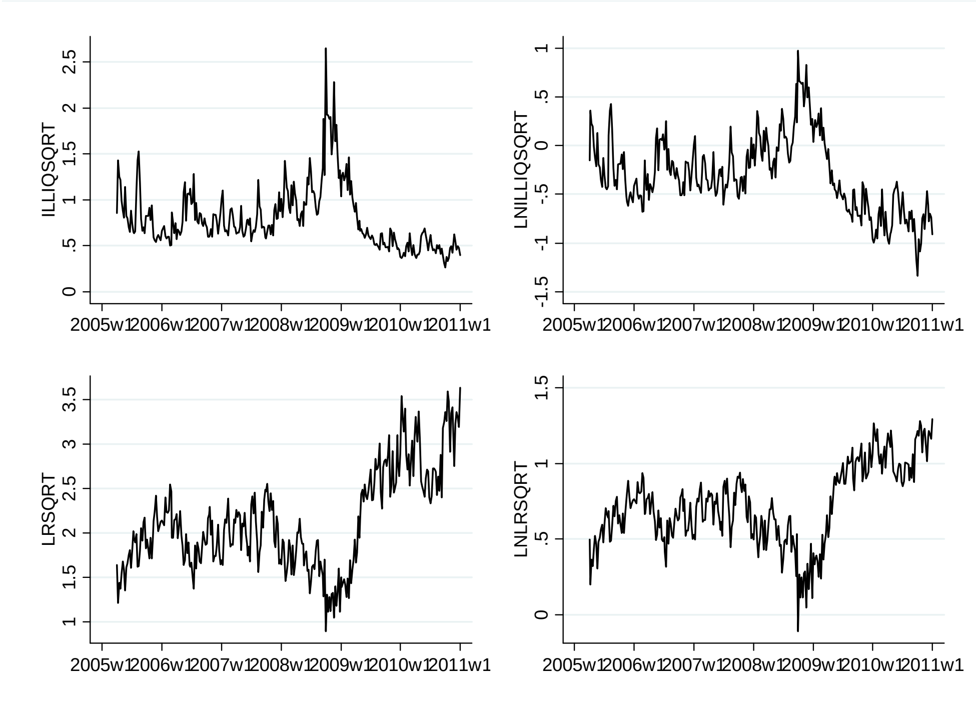


Figure 13 Time Plots of Liquidity Measures



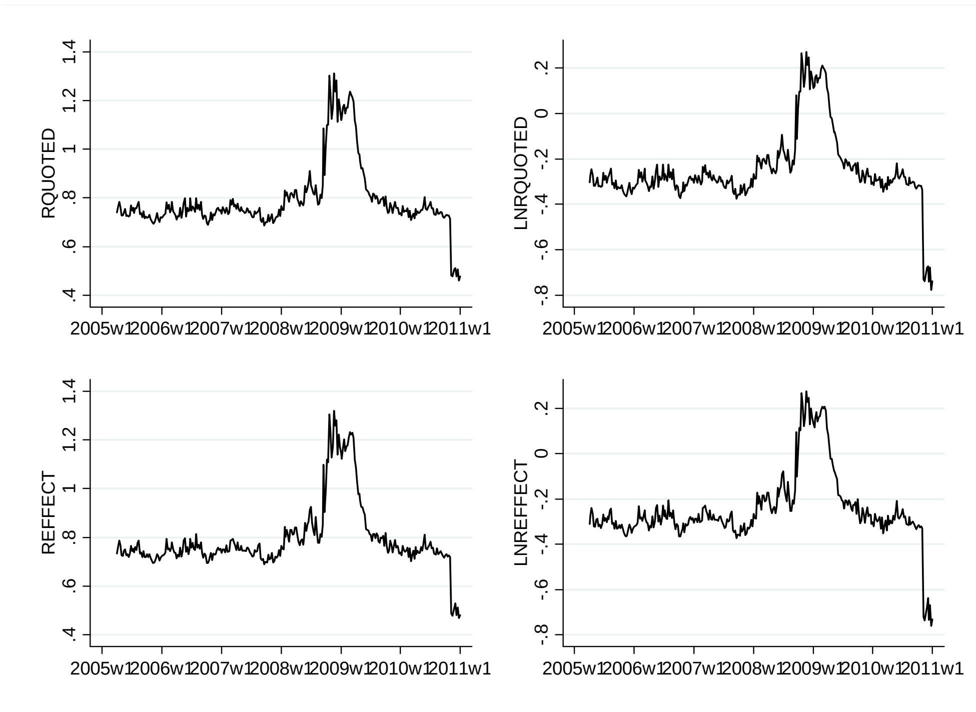


Figure 13 (continued)

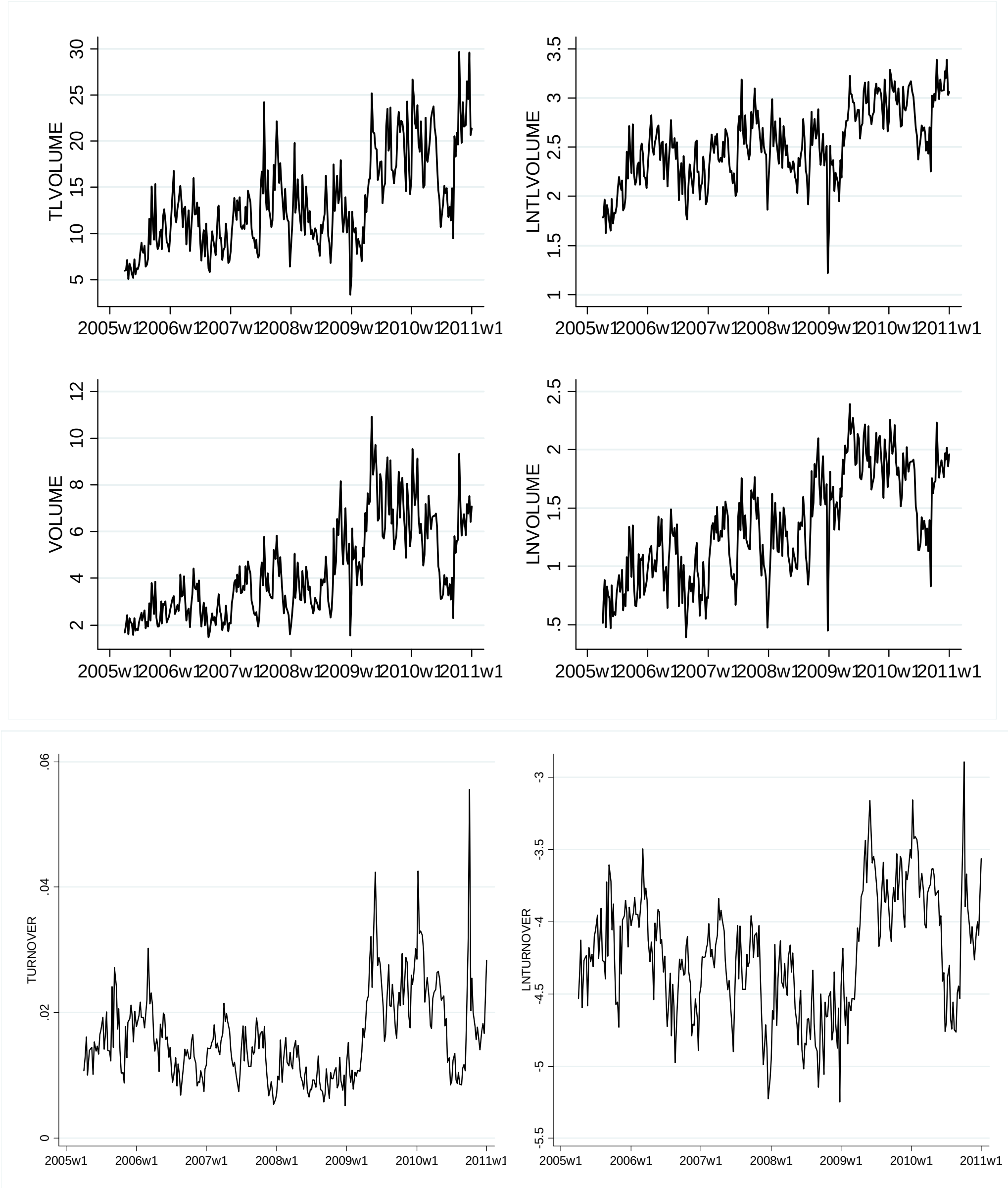


Figure 13 (continued)

APPENDIX B

AUTOCORRELATION FUNCTIONS

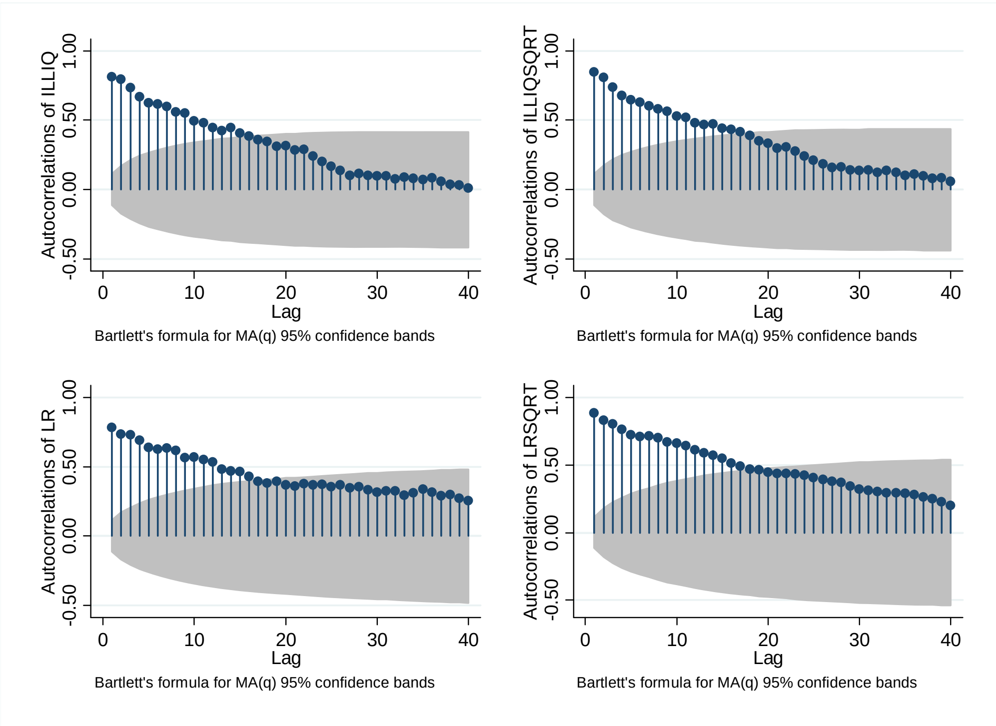


Figure 14 The ACFs of Liquidity Proxies

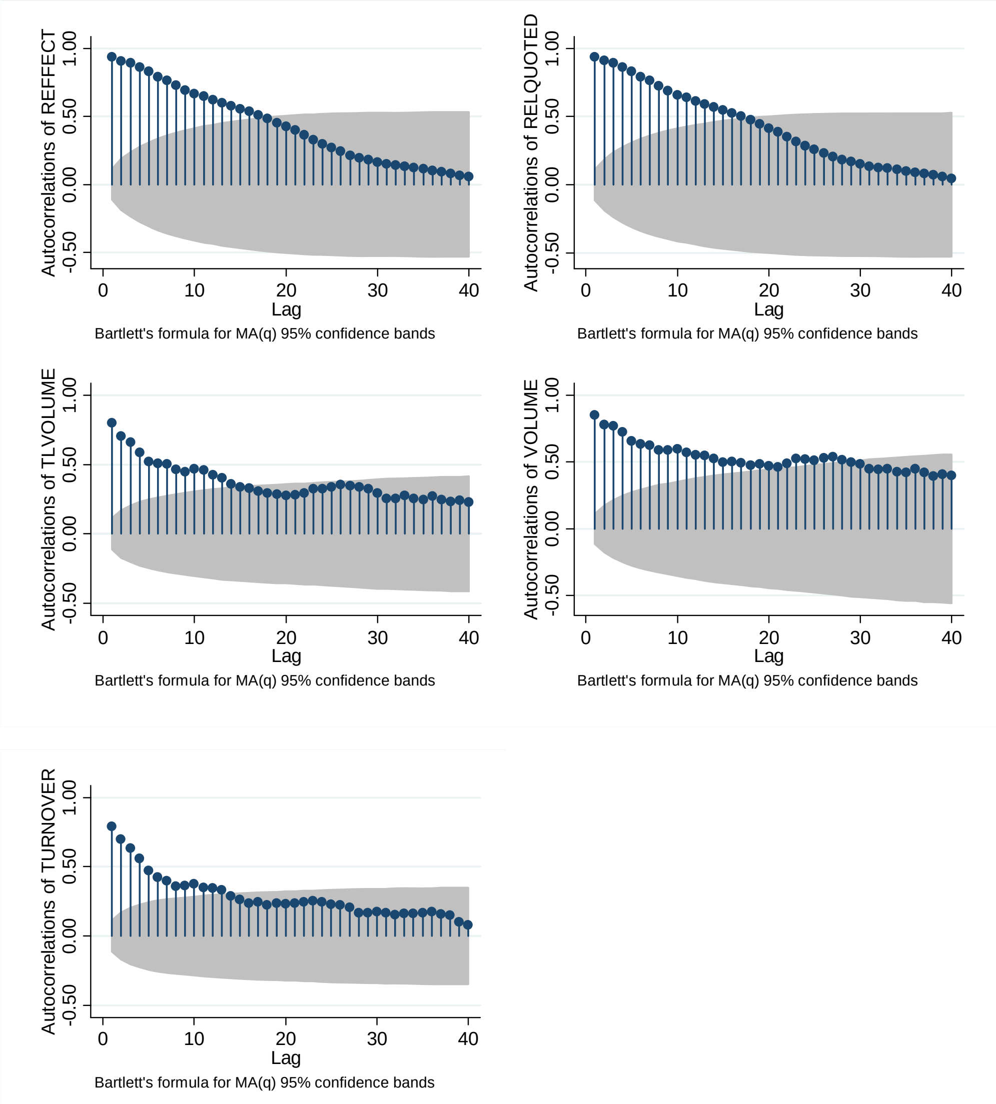


Figure 14 (continued)

APPENDIX C

MONETARY STANCE VARIABLES

Table 19 Basic Statistics of Monetary Stance Variables

	RESERVE	ONINT
SAMPLE MEAN	160.021	12.952
(MEAN=0)	(0.000)	(0.000)
STANDARD DEVIATION	478.318	4.470
MINIMUM	-6682.327	1.500
MAXIMUM	2873.710	17.500
SKEWNESS	-9.006	-0.744
(SK=0)	(0.000)	(0.000)
EXCESS KURTOSIS	145.081	-0.768
(KU=0)	(0.000)	(0.007)
JARQUE-BERA	265378.977	35.035
(JB=0)	(0.000)	(0.000)

Note: The values in parentheses are p-values.

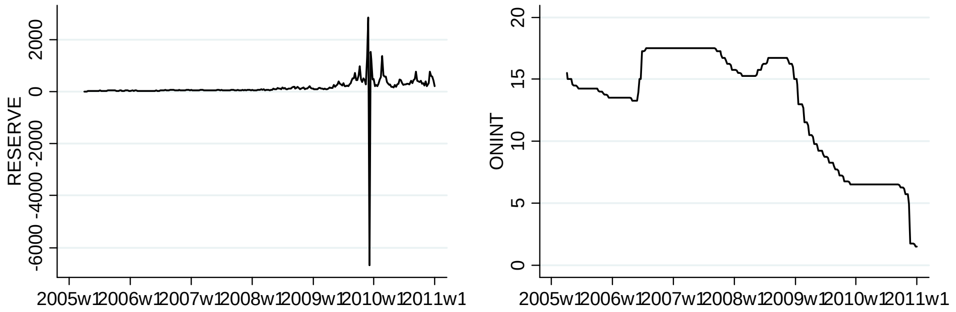


Figure 15 Time Plots of Monetary Stance Variables

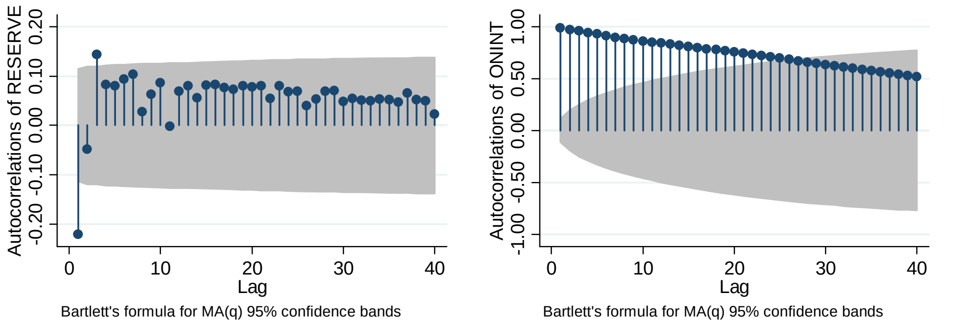


Figure 16 ACFs of Monetary Stance Variables

APPENDIX D

MONETARY STANCE REGRESSIONS

Table 20 Regressions of $URESERVE$

	ULNILLIQ	ULNLRSQRT	ULNRQUOTED	ULNREEFFECT	ULNTURNOVER	UTLVOLUME	UVOLUME
L1	-0.431 ***	-0.429 ***	-0.430 ***	-0.430 ***	-0.426 ***	-0.414 ***	-0.417 ***
	[0.059]	[0.059]	[0.059]	[0.059]	[0.059]	[0.060]	[0.059]
L2	-0.309 ***	-0.310 ***	-0.307 ***	-0.307 ***	-0.303 ***	-0.288 ***	-0.289 ***
	[0.062]	[0.062]	[0.062]	[0.062]	[0.062]	[0.062]	[0.062]
L3	-0.096	-0.099 *	-0.092	-0.092	-0.090	-0.080	-0.077
	[0.059]	[0.059]	[0.059]	[0.059]	[0.059]	[0.059]	[0.059]
ULNR100	-12.765 **	-12.951 **	-11.248 *	-11.255 *	-10.541 *	-7.653	-8.243
	[6.259]	[6.174]	[6.021]	[6.026]	[5.971]	[6.097]	[6.050]
ULNR100 L1						-3.417	-4.237
						[6.767]	[6.714]
UVLNR100	18.286	-2.809	-1.132	-0.807	-13.045	37.977	37.407
	[19.135]	[21.380]	[22.463]	[22.465]	[32.814]	[46.002]	[44.986]
UVLNR100 L1						-30.837	-28.129
						[43.844]	[43.053]
LIQUIDITY PROXY	-77.185	209.373 *	-316.948	-306.705	-36.044	-17.029 *	-57.661 **
	[55.244]	[122.426]	[247.995]	[245.152]	[35.288]	[9.015]	[25.606]
LIQUIDITY PROXY L1						21.633 **	75.807 ***
						[8.808]	[25.207]
CONSTANT	2.449	-0.332	1.024	1.121	1.477	4.165	4.544
	[25.499]	[25.589]	[25.657]	[25.659]	[25.744]	[25.510]	[25.345]
				BREUSCH-GODFREY AUTOCORRELATION TEST			
LAG 1	1.680	2.668	1.740	1.776	1.086	1.044	2.016
LAG 5	3.118	3.835	3.727	3.788	3.670	2.038	3.896
LAG 10	8.274	9.526	8.678	8.749	8.428	7.913	11.455
				LAGRANGE MULTIPLIER ARCH TEST			
LAG 1	27.983 ***	28.817 ***	28.207 ***	28.199 ***	27.748 ***	25.616 ***	25.652 ***
LAG 5	27.975 ***	28.891 ***	28.262 ***	28.256 ***	27.784 ***	25.539 ***	25.543 ***
LAG 10	27.101 ***	27.997 ***	27.377 ***	27.371 ***	26.914 ***	24.812 ***	24.814 ***
				RESIDUAL DIAGNOSTICS			
SKEWNESS	-6.288 ***	-6.168 ***	-6.239 ***	-6.241 ***	-6.213 ***	-6.323 ***	-6.288 ***
KURTOSIS	109.217 ***	107.978 ***	108.822 ***	108.859 ***	108.277 ***	107.194 ***	106.173 ***
JARQUE-BERA	145541.509 ***	142229.047 ***	144476.075 ***	144574.439 ***	143034.708 ***	140292.201 ***	137646.155 ***
MEAN	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ST. ERROR	24.451	24.409	24.464	24.467	24.490	24.253	24.131

Note: The values in brackets are the standard errors. Each column represents the liquidity proxy used in the models rather than the dependent variable. The dependent variable is $URESERVE$.

Table 21 Regressions of $DUONINT$

	ULNILLIQ	ULNLRSQRT	ULNRQUOTED	ULNREEFFECT	ULNTURNOVER	UTLVOLUME	UVOLUME
L1	0.076	0.074	0.066	0.070	0.059	0.083	0.073
	[0.059]	[0.059]	[0.058]	[0.058]	[0.058]	[0.058]	[0.059]
L2	0.164 ***	0.162 ***	0.142 **	0.139 **	0.155 ***	0.160 ***	0.171 ***
	[0.059]	[0.059]	[0.058]	[0.058]	[0.058]	[0.058]	[0.059]
L3	0.111 *	0.108 *	0.107 *	0.105 *	0.113 *	0.121 **	0.117 **
	[0.059]	[0.059]	[0.058]	[0.057]	[0.058]	[0.058]	[0.059]
L4	0.240 ***	0.235 ***	0.260 ***	0.261 ***	0.236 ***	0.244 ***	0.250 ***
	[0.058]	[0.058]	[0.057]	[0.057]	[0.058]	[0.058]	[0.059]
ULNR100	-0.008 *	-0.008 *	-0.012 ***	-0.012 ***	-0.009 **	-0.012 ***	-0.012 ***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
ULNR100 L1			-0.007	-0.007			-0.007
			[0.005]	[0.005]			[0.004]
UVLNR100	-0.006	0.005	-0.067 **	-0.069 **	0.044 **	-0.048 *	-0.056 *
	[0.013]	[0.014]	[0.032]	[0.032]	[0.021]	[0.026]	[0.029]
UVLNR100 L1			0.076 **	0.078 ***		0.050 *	0.051 *
			[0.029]	[0.029]		[0.026]	[0.028]
LIQUIDITY PROXY	0.044	-0.118	-0.677 **	-0.758 ***	0.066 ***	0.015 **	0.029 *
	[0.037]	[0.082]	[0.289]	[0.282]	[0.023]	[0.006]	[0.017]
LIQUIDITY PROXY L1			0.935 ***	1.007 ***		-0.019 ***	-0.025
			[0.280]	[0.272]		[0.006]	[0.016]
CONSTANT	-0.005	-0.004	-0.003	-0.003	0.000	-0.006	-0.006
	[0.017]	[0.017]	[0.016]	[0.016]	[0.017]	[0.016]	[0.017]
BREUSCH-GODFREY AUTOCORRELATION TEST							
LAG 1	1.570	1.664	1.408	1.348	0.467	1.308	0.219
LAG 5	5.353	5.507	4.332	4.309	4.793	3.372	6.193
LAG 10	14.529	14.521	5.206	5.097	10.765	12.653	15.338
LAGRANGE MULTIPLIER ARCH TEST							
LAG 1	0.381	0.346	0.838	0.783	0.233	0.347	0.353
LAG 5	9.829 *	9.914 *	10.918 *	10.703 *	8.878	10.726 *	8.837
LAG 10	14.473	14.183	15.114	14.832	12.760	16.170 *	14.445
RESIDUAL DIAGNOSTICS							
SKEWNESS	0.177	0.170	0.857 ***	0.935 ***	0.280 *	0.458 ***	0.267 *
KURTOSIS	22.530 ***	22.872 ***	22.810 ***	22.875 ***	22.721 ***	22.404 ***	22.778 ***
JARQUE-BERA	5987.083 ***	6170.027 ***	6169.509 ***	6211.582 ***	6091.258 ***	5928.573 ***	6121.578 ***
MEAN	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ST. ERROR	0.016	0.016	0.016	0.015	0.016	0.016	0.016

Note: The values in brackets are the standard errors. Each column represents the liquidity proxy used in the models rather than the dependent variable. The dependent variable is $DUONINT$.

APPENDIX E

VAR RESULTS

Table 22 VAR Estimation Results

a)

	UVOLUME				UVLNR100				ULNR100				ULNILLIQ				CONST.
	LAG1	LAG2	LAG3	LAG4	LAG1	LAG2	LAG3	LAG4	LAG1	LAG2	LAG3	LAG4	LAG1	LAG2	LAG3	LAG4	
UVOLUME	0.551 ***	0.041	0.194 ***	0.015	-0.104	0.289 **	-0.023	-0.091	-0.002	-0.013	0.029	0.029 *	-0.043	-0.380 *	0.492 **	-0.166	-0.011
	[0.060]	[0.069]	[0.069]	[0.061]	[0.116]	[0.135]	[0.137]	[0.114]	[0.016]	[0.018]	[0.018]	[0.017]	[0.201]	[0.222]	[0.219]	[0.188]	[0.058]
UVLNR100	-0.105 ***	0.068 *	-0.021	0.042	0.551 ***	0.358 ***	-0.004	0.027	-0.073 ***	-0.014	0.028 ***	0.020 **	-0.184 *	-0.023	0.134	-0.161 *	0.001
	[0.031]	[0.035]	[0.035]	[0.031]	[0.059]	[0.069]	[0.069]	[0.058]	[0.008]	[0.009]	[0.009]	[0.009]	[0.102]	[0.113]	[0.111]	[0.095]	[0.030]
ULNR100	0.191	-0.115	-0.132	0.317	-0.516	-0.194	0.520	0.224	-0.110	-0.008	-0.128	0.005	-0.709	-0.260	-0.694	1.955 **	0.075
	[0.259]	[0.297]	[0.298]	[0.260]	[0.500]	[0.582]	[0.587]	[0.489]	[0.068]	[0.079]	[0.079]	[0.074]	[0.862]	[0.955]	[0.942]	[0.806]	[0.250]
ULNILLIQ	-0.015	0.024	-0.001	-0.015	0.086 **	-0.047	0.030	-0.079 **	-0.019 ***	0.000 *	-0.003	0.005	0.487	0.144	0.100	-0.028	-0.005
	[0.020]	[0.023]	[0.023]	[0.020]	[0.039]	[0.045]	[0.046]	[0.038]	[0.005]	[0.006]	[0.006]	[0.006]	[0.067]	[0.074]	[0.073]	[0.063]	[0.019]

Table 22 (continued)

b)

	UVOLUME				UVLNR100				ULNR100				ULNLRSQRT				CONST.
	LAG1	LAG2	LAG3	LAG4	LAG1	LAG2	LAG3	LAG4	LAG1	LAG2	LAG3	LAG4	LAG1	LAG2	LAG3	LAG4	
UVOLUME	0.570 ***	0.012	0.207 ***	0.031	-0.038	0.185	0.110	-0.160	0.004	-0.002	0.028	0.037 **	-0.452	1.234 **	-1.108 **	0.038	-0.004
	[0.062]	[0.071]	[0.072]	[0.063]	[0.120]	[0.141]	[0.142]	[0.112]	[0.015]	[0.018]	[0.018]	[0.017]	[0.520]	[0.567]	[0.558]	[0.490]	[0.058]
UVLNR100	-0.098 ***	0.052	-0.011	0.013	0.495 ***	0.318 ***	0.026	0.010	-0.070 ***	-0.012	0.023 **	0.016 *	0.171	0.016	-0.219	0.829 ***	-0.007
	[0.031]	[0.036]	[0.036]	[0.032]	[0.060]	[0.071]	[0.071]	[0.056]	[0.008]	[0.009]	[0.009]	[0.009]	[0.260]	[0.283]	[0.279]	[0.244]	[0.029]
ULNR100	0.082	-0.073	-0.310	0.536 **	-0.602	-0.130	0.198	0.616	-0.103	-0.025	-0.144 *	-0.018	2.453	1.319	3.525	-7.365 ***	0.074
	[0.263]	[0.304]	[0.307]	[0.269]	[0.511]	[0.600]	[0.603]	[0.476]	[0.064]	[0.077]	[0.077]	[0.073]	[2.211]	[2.407]	[2.371]	[2.080]	[0.247]
ULNLRSQRT	0.014 *	-0.018 **	-0.003	0.008	-0.051 ***	0.035 *	-0.016	0.046 ***	0.005 **	-0.002	0.000	-0.002	0.434 ***	0.308 ***	0.021	0.074	0.001
	[0.008]	[0.009]	[0.009]	[0.008]	[0.015]	[0.018]	[0.018]	[0.014]	[0.002]	[0.002]	[0.002]	[0.002]	[0.066]	[0.072]	[0.071]	[0.062]	[0.007]

c)

	UVOLUME				UVLNR100				ULNR100				ULNTURNOVER				CONST.
	LAG1	LAG2	LAG3	LAG4	LAG1	LAG2	LAG3	LAG4	LAG1	LAG2	LAG3	LAG4	LAG1	LAG2	LAG3	LAG4	
UVOLUME	0.503 ***	0.034	0.162 **	0.094	0.043	0.145	0.293	-0.334 **	0.005	0.014	0.023	0.040 **	0.256	0.071	0.298	-0.528 **	-0.005
	[0.063]	[0.072]	[0.073]	[0.064]	[0.153]	[0.192]	[0.192]	[0.136]	[0.014]	[0.017]	[0.017]	[0.017]	[0.168]	[0.191]	[0.184]	[0.160]	[0.058]
UVLNR100	-0.139 ***	0.079 **	-0.021	0.094 ***	0.673 ***	0.151	0.157 *	-0.196 ***	-0.068 ***	-0.004	0.015 *	0.023 ***	0.345 ***	-0.071	0.021	-0.445 ***	-0.012
	[0.030]	[0.034]	[0.035]	[0.030]	[0.073]	[0.092]	[0.091]	[0.065]	[0.007]	[0.008]	[0.008]	[0.008]	[0.080]	[0.091]	[0.087]	[0.076]	[0.028]
ULNR100	0.508 *	-0.270	-0.227	0.266	-1.713 **	0.040	0.477	0.388	-0.101 *	-0.044	-0.130 *	-0.029	-1.746 **	0.272	0.526	-0.053	0.009
	[0.273]	[0.312]	[0.315]	[0.277]	[0.661]	[0.834]	[0.832]	[0.589]	[0.061]	[0.074]	[0.074]	[0.074]	[0.726]	[0.825]	[0.795]	[0.692]	[0.251]
ULNTURNOVER	0.068 **	-0.057 *	0.038	-0.072 ***	0.122 *	-0.089	-0.042	0.028	0.010 *	0.009	0.012	-0.009	0.297 ***	0.173 **	0.039	0.440 ***	0.011
	[0.027]	[0.031]	[0.031]	[0.027]	[0.065]	[0.082]	[0.082]	[0.058]	[0.006]	[0.007]	[0.007]	[0.007]	[0.072]	[0.082]	[0.079]	[0.068]	[0.025]

Table 22 (continued)

d)

	UVOLUME				UVLNR100				ULNR100				ULNRQUOTED				CONST.
	LAG1	LAG2	LAG3	LAG4	LAG1	LAG2	LAG3	LAG4	LAG1	LAG2	LAG3	LAG4	LAG1	LAG2	LAG3	LAG4	
UVOLUME	0.532 ***	0.049	0.177 **	0.034	-0.029	0.207	0.093	-0.151	0.004	0.011	0.035 **	0.034 **	0.768	-0.044	2.111 *	-1.972 **	0.001
	[0.061]	[0.069]	[0.070]	[0.061]	[0.124]	[0.148]	[0.147]	[0.113]	[0.014]	[0.017]	[0.017]	[0.017]	[1.075]	[1.252]	[1.254]	[1.064]	[0.058]
UVLNR100	-0.097 ***	0.070 **	-0.029	0.064 **	0.529 ***	0.262 ***	0.103	-0.054	-0.066 ***	-0.006	0.024 ***	0.022 ***	0.957 *	-0.176	0.913	-2.964 ***	-0.007
	[0.029]	[0.033]	[0.033]	[0.029]	[0.060]	[0.071]	[0.070]	[0.054]	[0.007]	[0.008]	[0.008]	[0.008]	[0.515]	[0.600]	[0.601]	[0.510]	[0.028]
ULNR100	0.278	-0.199	-0.096	0.226	-0.794	-0.021	0.041	0.759	-0.099	0.004	-0.103	-0.038	-5.618	2.784	-5.644	6.929	0.056
	[0.262]	[0.298]	[0.301]	[0.262]	[0.535]	[0.638]	[0.634]	[0.486]	[0.062]	[0.073]	[0.073]	[0.071]	[4.633]	[5.395]	[5.404]	[4.585]	[0.252]
ULNRQUOTED	0.002	-0.001	0.003	-0.005	0.021 ***	-0.005	0.006	-0.024 ***	0.000	0.001	0.001	0.001	0.565 ***	0.248 ***	0.042	0.041	-0.001
	[0.004]	[0.004]	[0.004]	[0.004]	[0.007]	[0.009]	[0.008]	[0.007]	[0.001]	[0.001]	[0.001]	[0.001]	[0.062]	[0.072]	[0.072]	[0.061]	[0.003]

e)

	UVOLUME				UVLNR100				ULNR100				ULNREFFECT				CONST.
	LAG1	LAG2	LAG3	LAG4	LAG1	LAG2	LAG3	LAG4	LAG1	LAG2	LAG3	LAG4	LAG1	LAG2	LAG3	LAG4	
UVOLUME	0.531 ***	0.050	0.179 **	0.033	-0.034	0.219	0.079	-0.144	0.004	0.011	0.036 **	0.034 **	0.789	0.025	1.790	-1.770 *	0.000
	[0.061]	[0.069]	[0.070]	[0.061]	[0.124]	[0.147]	[0.147]	[0.112]	[0.015]	[0.017]	[0.017]	[0.017]	[1.053]	[1.219]	[1.213]	[1.037]	[0.059]
UVLNR100	-0.098 ***	0.069 **	-0.027	0.063 **	0.516 ***	0.279 ***	0.089	-0.047	-0.066 ***	-0.006	0.025 ***	0.021 ***	0.851 *	-0.004	0.641	-2.797 ***	-0.007
	[0.029]	[0.033]	[0.033]	[0.029]	[0.060]	[0.071]	[0.070]	[0.054]	[0.007]	[0.008]	[0.008]	[0.008]	[0.505]	[0.585]	[0.582]	[0.497]	[0.028]
ULNR100	0.277	-0.195	-0.093	0.220	-0.753	-0.029	0.002	0.787	-0.098	0.006	-0.103	-0.041	-5.347	2.857	-6.248	7.551	0.059
	[0.262]	[0.298]	[0.300]	[0.262]	[0.534]	[0.632]	[0.630]	[0.484]	[0.063]	[0.073]	[0.073]	[0.071]	[4.528]	[5.241]	[5.215]	[4.457]	[0.252]
ULNREFFECT	0.002	-0.001	0.003	-0.006	0.020 ***	-0.005	0.006	-0.023 ***	0.000	0.001	0.000	0.001	0.570 ***	0.235 ***	0.026	0.063	-0.001
	[0.004]	[0.004]	[0.004]	[0.004]	[0.007]	[0.009]	[0.009]	[0.007]	[0.001]	[0.001]	[0.001]	[0.001]	[0.062]	[0.072]	[0.072]	[0.061]	[0.003]

Table 23 Eigenvalues and the Stability Test of the VAR Systems

ULNILLIQ		ULNLRSQRT		ULNTURNOVER		ULNRQUOTED		ULNREFFECT	
EIGENVALUE	MODULUS	EIGENVALUE	MODULUS	EIGENVALUE	MODULUS	EIGENVALUE	MODULUS	EIGENVALUE	MODULUS
0.962	0.962	0.972	0.972	0.977	0.977	0.971	0.971	0.971	0.971
0.880	0.880	0.888	0.888	0.887	0.887	0.882	0.882	0.880	0.880
0.680	0.680	-0.743	0.743	-0.849	0.849	0.734 + 0.247i	0.775	0.719 + 0.248i	0.761
0.597 + 0.306i	0.671	0.649 + 0.302i	0.716	0.027 + 0.747i	0.747	0.734 - 0.247i	0.775	0.719 - 0.248i	0.761
0.597 - 0.306i	0.671	0.649 - 0.302i	0.716	0.027 - 0.747i	0.747	-0.743	0.743	-0.746	0.746
-0.651 + .046i	0.653	-0.673	0.673	0.597 + 0.167i	0.620	-0.447 + 0.502i	0.672	-0.447 + 0.4931i	0.665
-0.651 - .046i	0.653	-0.447 + .472i	0.650	0.597 - 0.167i	0.620	-0.447 - 0.502i	0.672	-0.447 - 0.4931i	0.665
-0.400 + 0.458i	0.608	-0.447 - .472i	0.650	-0.397 + 0.410i	0.570	0.077 + 0.567i	0.572	-0.585	0.585
-0.400 - 0.458i	0.608	0.147 + 0.621i	0.638	-0.397 - 0.410i	0.570	0.077 - 0.567i	0.572	0.100 + 0.574i	0.582
0.151 + 0 .552i	0.572	0.147 - 0.621i	0.638	-0.164 + 0.532i	0.556	-0.564	0.564	0.100 - 0.574i	0.582
0.151 - 0 .552i	0.572	0.628	0.628	-0.164 - 0.532i	0.556	-0.039 + 0.562i	0.564	-0.047 + 0.571i	0.573
-0.121 + 0.556i	0.570	-0.104 + 0.615i	0.624	-0.427	0.427	-0.039 - 0.562i	0.564	-0.047 - 0.571i	0.573
-0.121 - 0.556i	0.570	-0.104 - 0.615i	0.624	0.377 + 0.131i	0.399	-.0183 + 0.370i	0.413	-0.169 + 0.367i	0.405
-0.124 + 0.385i	0.404	-0.130 + 0.352i	0.375	0.377 - 0.131i	0.399	-.0183 - 0.370i	0.413	-0.169 - 0.367i	0.405
-0.124 - 0.385i	0.404	-0.130 - 0.352i	0.375	-0.048 + 0.289i	0.293	0.349 + 0.155i	0.382	0.343 + 0.072i	0.350
0.053	0.053	0.093	0.093	-0.048 - 0.289i	0.293	0.349 - 0.155i	0.382	0.343 - 0.072i	0.350

Table 24 LM Test for Autocorrelation in the VAR Analysis

LAGS	ULNILLIQ	ULNLRSQRT	ULNTURNOVER	ULNRQUOTED	ULNREFFECT
1	23.361	25.422 *	22.657	17.838	17.139
2	12.934	23.592 *	16.875	15.664	14.306
3	27.919 **	31.973 **	16.800	18.534	19.426
4	16.080	26.056 *	19.864	13.255	14.139
5	13.069	14.347	14.972	25.976 *	24.237 *
6	15.618	15.325	15.549	11.365	10.819
7	25.528 *	23.202	20.072	13.411	12.631
8	26.364 **	30.719 **	23.919 *	40.763 ***	44.122 ***
9	19.704	23.072	30.158 **	33.875 ***	28.818 **
10	20.199	25.435 *	12.693	12.062	10.227