The Behavior of Istanbul Stock Exchange Market: An Intraday Volatility/Return Analysis Approach.

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ABSTRACT

The study investigates the intraday effect in Istanbul Stock Exchange (ISE) during the latest financial turmoil period of August 2007 to February 2010. We test for the possible existence of the intraday anomalies using both return and volatility equations as empirically applying GARCH(p,q) models. The paper uses a unique data set compiled from 15 minute intraday values of ISE-100 Index that are formed by averaging historical ten second tick data. The paper contributes to the current literature in three distinct features. Firstly, the basic characteristic of unique data used in this research is investigated in details. Secondly, four range based volatility measures namely Garman Klass (GK), Yang-Zhang (YZ), Rogers-Satchell (RS) and Parkinson (PK) are employed to form more precise measures of volatility for intraday data analysis in order to identify the changes in general market sentiment as using open, close, high and low prices. Thirdly, we estimate the relative efficiency of GK, YZ, RS and PK by applying GARCH(p,q) models. Results are quite promising, as indicating that strong opening price jumps are present for daily and morning calculations. They illustrate that YZ estimator has relatively more power in generating tolerable volatility patterns.

Keywords: Volatility, GARCH, Istanbul Stock Exchange

I. INTRODUCTION

Estimating the volatilities of equity prices from historical data has received considerable attention both from academicians and market professionals. Many empirical tests have been made to examine the efficiency of stock markets all over the world as using stock prices, transaction data, volatility and intraday frequency of bid and ask spreads. Wood, McInish, & Ord (1985) found a number of patterns in trading frequency such as number of shares per trade, size of price changes, length of time between trades and the absolute values of price changes. They used minute by minute market return changes to test the normality and autocorrelation and showed that unusually high returns and standard deviations were found at the beginning and at the end of the day. Similar results were found by Harris (1986) as using intraday returns over 15 minute intervals. He showed that there was a significant difference in intraday returns during the first 45 minutes after the market openings. Smirlock & Starks (1986) studied the Dow Jones Industrial Average stock returns on an hourly basis data and they witnessed that Monday mornings provide negative returns on average.

Further evidence for the differences across trading hour returns are intruduced by Jain & Joh (1988). They extended previous studies by including the average daily trading volume for each trading hour. It was found that average daily trading volume was lowest on Monday, increased until Thursday and declined again on Thursday

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and Friday. They results suggest that the average trading volume across six trading hours of the day differ considerably. The first hour has the highest average volume which declined until the fourth hour and increased on the fifth and sixth hours.

Harris L. (1989) extended his previous research and examined transaction prices to further characterize the systematic day-end price rise. He drew attention to the importance of the first and last couple of transactions. McInish & Wood (1990a) have confirmed their earlier study by using 1980-1984 New York Stock exchange data. They find a high variance of returns at the beginning and at the end of the trading day. Evidence of a U-shaped pattern in the variance of price changes by hour of the day is also reported by Foster & Viswanathan (1990) and Gerety & Mulherin (1992).

Lockwood & Linn (1990) extended the previous volatility studies by examining market variance of returns on the Dow Jones Industrial Average for the period 1964-1989. According to their study, return volatility decreases from the opening hour until early afternoon and increases subsequently and is considerably greater for intraday versus overnight periods.

The availability of transactions data since mid 1980s in U.S. exchanges boosted the empirical research in this specific field. Meanwhile similar research results were observed in other markets. The availability of non US equity market intraday transactions data during the 1990s has encouraged the extension of international studies in other national stock exchanges. McInish & Wood (1990b) found that the stocks on the Toronto Stock Exchange showed a U-shaped return and volume pattern. Similar results have been reported for the Stockholm Stock Exchange (Niemayer & P.Sandas 1993), the Australian SEATS trading system (Aitken, Brown, & Walter 1993), the London Stock Exchange (Yadav & Pope 1992), the Tokyo Stock Exchange (Chang, Fukuda, Rhee, & Taakano 1993), and the German Stock Exchange (Lowengrub & Melvin 2002).

According to these empirical results there is a systematic inefficiency and variation in stock prices related to calendar year. However, another stream of research claims that the patterns are a product of market structure. Stoll & Whaley (1990) attributes the greater volatility in NYSE to private information revealed in trading and to temporary price deviations induced by specialists and other traders. Hong & Wang (2000) shows that market closures in U.S. market can affect investors' trading policies and the resulting return generating process. There is evidence from other markets as well. Cyree and Winters (2001) studied the federal funds market in US and found that the reverse-J pattern in intraday returns, variances and volume can be explained by trading stops and the private information is not a necessary condition for the observed pattern. However the authors also state that their results do not state that "private information does not play a role in intraday patterns in other securities markets but rather, that private information is not a necessary condition for the observed intraday pattern". Another study by Akay et.al (2010) about the federal funds market which examines the efficiency of several range-based volatility estimators showed that the range based estimators remove the upward bias created by microstructure noise [1] .Ederington and Lee (1993) examined the impact of

[1] Akay et.al define "microstructure noise" as follows: A time series of security prices has volatility that decomposes into economic volatility and trading process volatility. Trading process process volatility is induced by the mechanics of trading and arises from the use of transaction level data.

scheduled macroeconomic news announcements on interest rate and foreign exchange futures markets and found that the observed intraday and day of the week volatility patterns in these markets are mainly due to the timing of major macroeconomic announcements. The authors also show that when the impacts of these announcements are removed, volatility is basically flat across the trading day and the trading week. Kalev and Pham (2009) examine the impact of the time of the day and day of the week on the patterns of informed investors' trading. They found an inverted U-shaped pattern of investors' intraday trading activities. They suggest that informed traders select an optimum day-of the week to trade that will minimize their transaction costs. They also demonstrate that informed traders use different trading strategies depending on the time of day.

There is still an ongoing debate about the findings of the studies mentioned above. Some consider them to be the fruit of data mining whereas others defend the findings of previous researches and seek to find rational explanations for the irrational results. As a result of these studies there immerged the phenomena called the calendar anomalies. These studies have shown that asset returns vary on different days of the week, months of the year, and turn of the month, before the holidays or even in intraday patterns. These effects have been regarded as evidence against efficient market hypothesis.

When we investigate the related literature about the Turkish Stock Exchange, the only detailed research specifically aimed at intraday patterns belongs to Bildik (2001). His findings were also consistent with the results of the previous research in other international studies. Bildik (2001) showed that intraday effects also existed in Istanbul Stock Exchange Market. He used 15 min (also 5 and 1 minute) interval data for the years between 1996 and 1999. He also found that opening and closing returns were large and positive. Volatility was higher at the openings and followed an L shaped pattern. He concluded that the relatively higher mean and standard deviation at the opening sessions was generated by the accumulated overnight information and the closed-market effect (halt of trade). The large day-end returns were affected by the activities of fund managers and speculators for the window-dressing around the close.

This study focuses on analyzing the market behavior of Istanbul Stock Exchange (ISE) during the latest financial turmoil period of August 2007 to February 2010. We test for the possible existence of the intraday anomalies by using both return and volatility equations as empirically applying GARCH(p,q) models. The paper uses a unique data set compiled from 15 minute intraday values of ISE-100 Index that are formed by averaging historical ten second tick data.

The paper contributes to the current literature in three distinct features. Firstly, the basic characteristics of unique data used in this research are investigated in details. Secondly, four range based volatility measures namely GK, YZ, RS and PK are employed to form more precise measures of volatility for intraday data analysis in order to identify the changes in general market sentiment as using open, close, high and low prices. Thirdly, we estimate the relative efficiency of GK, YZ, RS and PK by applying GARCH (p,q) models. Although there are other studies that aim to search different calendar anomalies[1], the research about the intraday effect as a behavior of Istanbul Stock Exchange is very limited.

This paper differs from the previous research in that it explicitly analyzes the intraday effects of the trading hours in Turkey during the latest financial turmoil period of August 2007 to February 2010. Another distinction of this paper is that it analyzes the trading day for three different periods. Daily, morning and afternoon sessions are investigated separately and compared to identify any discrepancies.

The remainder of this paper is organized as follows. The next section provides the necessary background about Istanbul Stock Exchange. Third section describes the intraday data set and the methodology used. Section 4 presents the empirical results and the fifth section analyzes the efficiency of range based volatility measures. The final section provides some concluding remarks.

II. INSTITUTIONAL BACKGROUND OF ISTANBUL STOCK EXCHANGE

Istanbul Stock Exchange (ISE) can be considered as a relatively young stock exchange market when compared to the stock exchanges of developed countries. The history of ISE dates back to 1986. There are 316 listed stocks as of February 1, 2010. Total market capitalization is approximately US$ 316 billion and the average daily volume is around US$ 1.25 billion as of 2009.

There have been major developments in ISE in the last couple of years. For example, very recently, effective as of June 1, 2009, ISE introduced the “Automated Disclosure Platform”, which is an electronic system enabling the companies traded on the ISE to release any information, required to be publicly disclosed in compliance with the respective legislation, as using Internet and electronic signature technologies.

Another development in ISE is the concept of market making. It has been decided that the market making process to be executed through a method named “continuous auction trading method” which will be applied and in the absence of a market maker. Market making operation principles have been determined at the meeting of the Executive Council of the Exchange on February 4, 2009.

Trades are executed automatically in ISE as per "Multiple Price - Continuous Auction" principle based on price and time priority rule via the electronic trading system. Trades are executed in two trading sessions; morning and afternoon sessions. An “Opening Session” based on the Single Price System is organized at the beginning of the morning session. Another change in ISE is about the trading hours.

Effective from October 13 2008, the trading hours in the stock market were rearranged as follows: A preliminary session starts at 09:45 when the bid and ask orders are collected and executed and then the market remain closed until 09:50 when the morning session restarts. The trades are done until 12:30 when the market is closed for the lunch break. The same procedure is held for the afternoon session too. The preliminary session starts at 14:15 just for an instance and then the afternoon session starts at 14:20 which lasts until 17:30 closing time.

Settlement of equities traded is realized by the ISE Settlement and Custody Bank Inc., which is the sole and exclusive central depository and custody company in Turkey. General settlement principle is T+2, which is the second business day following the transaction.

III. DATA ANALYSIS

The dataset consists of 15 minute intraday values of ISE-100 index which is retrieved from the ISE itself. 15 minute intraday values have been formed by averaging historical ten second tick data. In order to capture the overall effect of the recent financial turmoil, we used the sample period between August 1, 2007 and February 22, 2010. This sample period consists of 611 Trading days and the holidays and the days that the markets are closed for other reasons are excluded from the data.

In order to make a comparison with the previous literature, 15-minute mean returns are also calculated with formula (1) and intraday 15-minute volatility is measured with standard deviation formula (2):

$$r_t = \ln\left(p_t / p_{t-1}\right) x\, 100 \qquad (1)$$

$$\sigma_T = \sigma\sqrt{T} \qquad (2)$$

where p_t is the Composite Index at time t and p_{t-1} is the index observed fifteen minutes before. The generalized volatility σ_T for the time horizon T is expressed in Equation 2.

In this paper, we also used volatility estimators to re-evaluate the volatility for ISE 100 Index. In the last 30 years there have been improvements to the classical standard deviation method. Many of these attempts to improve the estimators, such as those developed by Parkinson (1980), Garman & Klass (1980), Rogers & Satchell (1991), Alizahdeh, Brandt and Diebold (2001) and Yang and Zhang (2002), use information on daily trading ranges such as the intraday high and low prices of the assets.

The Parkinson formula for estimating the historical volatility uses both high and low prices. Before Parkinson the diffusion constant, characterizing the random walk, was traditionally estimated using only closing prices. Parkinson (1980) showed that the use of both high and low extreme values provided about 2.5 to 5 time better estimate.

$$\sigma = \sqrt{\frac{Z}{n 4 \ln 2} \sum_{i=1}^{n} \left(\ln \frac{H_i}{L_i}\right)^2} \qquad (3)$$

σ Volatility

Z Number of closing prices in a year

n Number of historical prices used for the volatility estimate

H_i The high

L_i The low

GK estimator uses three price information namely high, low and close prices, to estimate volatility. It is up to eight times more efficient in comparison with the close-to-close volatility estimator, the standard deviation of returns and the PK estimator, which uses only high and low prices (Garman & Klass, 1980). The GK estimator for estimating historical volatility assumes Brownian motion with zero drift and no opening jumps (i.e. the opening = close of the previous period). This assumption creates a shortcoming for the GK estimator. Since stock prices are observable only at discrete time moments, it creates a possible source of bias. In many empirical studies, it is concluded that non-continuous prices bias downward the extreme value and the efficiency of these estimators[2]. The notation for GK is;

$$\sigma = \sqrt{\frac{Z}{n}\sum\left[\frac{1}{2}\left(\ln\frac{H_i}{L_i}\right)^2 - (2\ln 2 - 1)\left(\ln\frac{C_i}{O_i}\right)^2\right]} \tag{4}$$

σ Volatility

Z Number of closing prices in a year

n Number of historical prices used for the volatility estimate

O_i The opening price

H_i The high

L_i The low

C_i The closing price.

GK study forms the basis of the more recent YZ and RS estimators. In this study four different volatility estimators, GK, PK, YZ and RS, are used in order to compare the findings of the range based volatility measures.

YZ as an extension of the GK uses open, high, low and close prices to estimate volatility. YZ devises an estimator that combines the classical and RS estimators, as showing that it has the minimum variance and is both unbiased and independent of process drift and opening gaps. This extension is a multi-period estimator and allows capturing the effects of opening jumps during the first and second sessions. Most asset markets are closed overnight and during holidays. For ISE, there is also a break at noon for one hour and 45 minutes. Information arriving during these periods when the markets are closed often results in opening prices that differ significantly from the closing price of the prior trading session. This estimator is given by:

$$\sigma = \sqrt{\frac{Z}{n}\sum\left[\left(\ln\frac{O_i}{C_{i-1}}\right)^2 + \frac{1}{2}\left(\ln\frac{H_i}{L_i}\right)^2 - (2\ln 2 - 1)\left(\ln\frac{C_i}{O_i}\right)^2\right]} \tag{5}$$

The third volatility estimator used in the study is RS estimator which significantly outperforms other estimators when the asset process includes a time-varying drift.

The main difference between YZ and RS estimators is that the latter does not account for price jumps and assumes no opening jump. It uses open, close, high and low prices for volatility calculation. In other words, RS historical volatility estimator allows for non-zero drift, but assumes no opening jumps.

$$\sigma = \sqrt{\frac{Z}{n}\sum\left[\ln\frac{H_i}{C_i}\ln\frac{H_i}{O_i} + \ln\frac{L_i}{C_i}\ln\frac{L_i}{O_i}\right]} \tag{6}$$

In this study, we use YZ and RS estimators for three time periods. First, the daily calculations are done as using both estimators. Basically, the daily estimators use the c*lose* value as the yesterday's closing value of ISE 100 Index, *opening* as the opening value of the Index on that specific day, *low* and h*igh* values represent minimum and maximum values for the whole trading day.

Secondly, for the *morning* session or the first session, the daily estimators use the *opening* value as first session's opening value, c*losing* as the closing value of the first session on that specific day, l*ow* and h*igh* values represent the minimum and maximum values for the first session of the trading day.

Similarly, for the *afternoon* session or the second session, the daily estimators use the *opening* value as second session's opening value, c*losing* as the closing value in the second session on that specific day, *low* and h*igh* values represent the minimum and maximum values for the second session of the trading day.

For an empirical test of the volatility estimators 15 minute ISE 100 Index data from August 2007 to February 2010 is used to construct a series of 611 daily observations comprising open, high, low and close prices.

The selected descriptive statistics results for daily prices, morning session and afternoon session are given in Table 1.

Table 1: Descriptive Statistics for Daily-Morning-Afternoon Sessions Using GK, PK, RS & YZ Estimators

	DAILY				MORNING				AFTERNOON			
	GK	PK	RS	YZ	GK	PK	RS	YZ	GK	PK	RS	YZ
Mean	0.040830	0.023021	0.019069	0.001660	0.022404	0.012356	0.011490	0.000912	0.028256	0.015972	0.013060	0.000479
Median	0.034873	0.019167	0.017412	0.000722	0.019786	0.010782	0.010565	0.000392	0.024571	0.013845	0.011553	0.000256
Std. Dev.	0.022049	0.013162	0.011378	0.002800	0.012189	0.006936	0.007276	0.002103	0.015292	0.008972	0.008459	0.000682
Skewness	2.098.104	2.102.223	1.654.673	4.759.365	2.127.553	2.137.640	2.027.551	7.649.159	1.677.090	1.712.205	1.165.917	4.415.013
Kurtosis	1.019.191	9.733.174	9.678.329	3.311.141	1.136.388	1.063.950	1.295.036	8.307.838	7.179.945	7.500.227	5.160.238	2.932.561
Jarque-Bera	1.765.070	1.604.206	1.414.257	25389.68	2.241.873	1.951.127	2.939.253	169211.0	7.312.258	8.141.226	2.572.329	19628.56
Observation	611	611	611	611	611	611	611	611	611	611	611	611

All series have positive skewness implying that the distribution has a long right tail. When RS and YZ methods are compared, the level of skewness is stronger for YZ for all three time periods. Almost all values for kurtosis are high except for RS afternoon value as implying that the distributions are peaked. Furthermore, the Jarque-Bera test rejects normality at the 5% level of significance for all distributions.

Figure 1 shows 15-minute mean return values for ISE 100 Index and Figure 2 shows the Standard Deviation of Intraday 15 Minute Returns. The results are consistent with Bildik (2001) which shows us that stock returns follow a "W" shaped pattern over two separate trading sessions in a day. However, the pattern also creates a minor "W" shape in both sessions but more significantly during the morning session. In other words, there is a "W" shaped pattern for the trading day in general and two minor "W" shaped patterns co-exist for morning and afternoon sessions.

Figure 1: Mean 15-Minute Returns

Opening and closing returns are significantly high both in daily values and morning and afternoon sessions separately.

The volatility of the corresponding returns in each time period is shown in Figure 2.

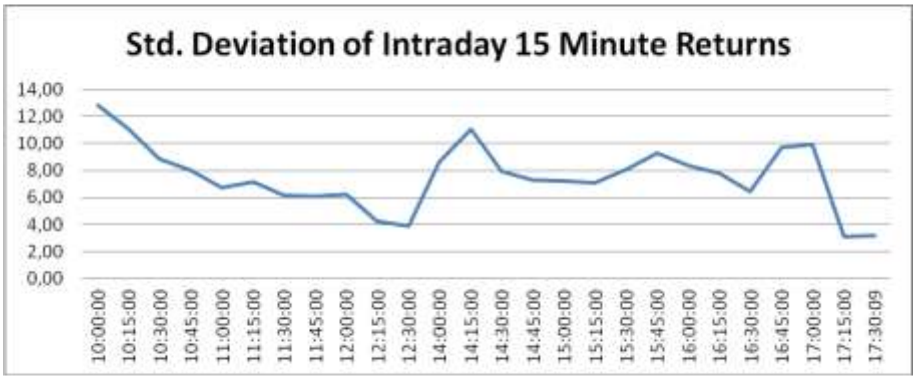

Figure 2: Standard Deviation of Intraday 15 Minute Returns

Figure 2 specifically illustrates the different patterns of volatility of intraday 15 minute returns. The average behavior indicates that right after opening session the standard deviation shows a decreasing trend until the end of the first session. The more significant fluctuations are observed in the afternoon session which is quite rational due to accumulated information flows during the intraday closing time between 12:30 and 14:15.

The results for equations 3, 4, 5, and 6 are presented in Figures 3, 4, 5, and 6 respectively for Parkinson, GK, YZ and RS volatility estimators for three different time periods; daily, morning and afternoon sessions. YZ estimator is clearly a more accurate estimator for estimating volatility in the existence of opening jumps. As it was mentioned earlier, ISE is not continuous and has a break in the midday and also closed overnight. Information arriving during periods when the markets are closed often results in jumps in opening prices that differ significantly from the closing price of the prior trading sessions.

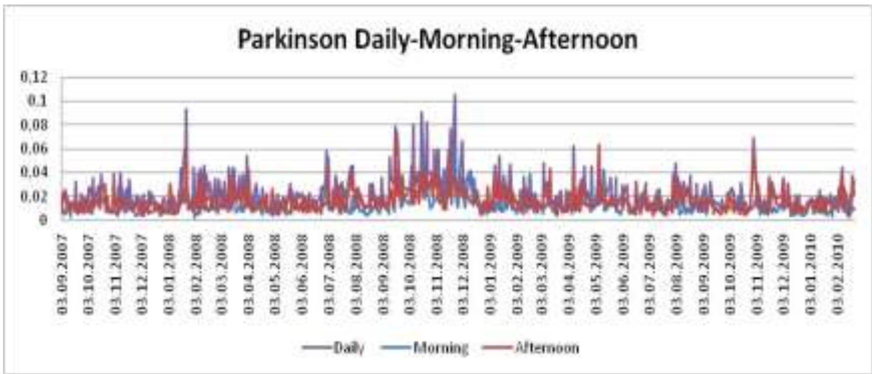

Figure 3: 15-Minute Volatility Using GK

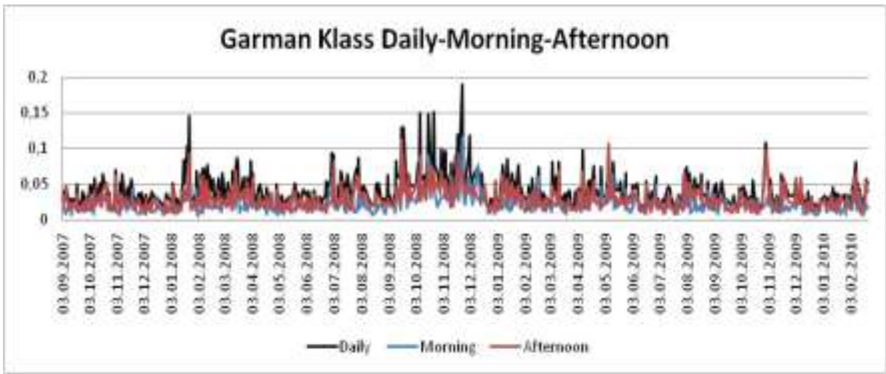

Figure 4: 15-Minute Volatility Using Parkinson

Figure 5: 15-Minute Volatility Using YZ

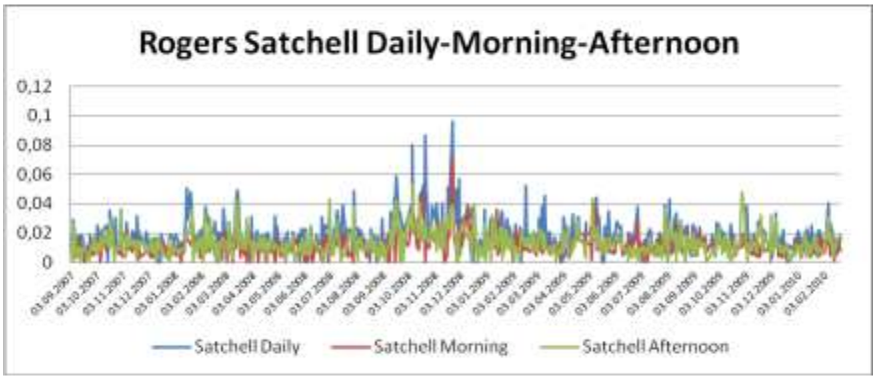

Figure 6: 15-Minute Volatility Using RS

In terms of volatility, due to the fact that there are two opening jumps (morning and afternoon opening jumps) in ISE, YZ estimator is assessed to be a better estimator for estimating volatility in the existence of both opening jumps. Information arriving during periods when the markets are closed often results in opening prices differ significantly from the closing prices of the prior trading sessions.

Once all Asian markets are closed and European markets are near to close, intraday ISE volatility increases throughout the U.S. trading session in local Turkish time. The news effect has clearly impacted the event horizon perceptions of the corporate investors through internal volatility dynamics within the final stages of ISE 100 Index afternoon session. The level of volatility has signaled an upside pattern considerably under the impact of the European markets' opening in the morning session, and again at the American markets' opening significantly. This phenomenon should be assessed as evidence that, despite the already existed knowledge about futures markets, traders in each region prefer to trade in their own time zones and explains the dynamics behind the higher market activity at the beginning and at the end of the regional trading sessions. This indicates a concrete signaling for effective portfolio rebalancing. Volatility from the Asian market affects all other regions; Asia-Europe region volatility spills over to Europe; where Turkey is impacted in terms of intraday volatility due to its regional positioning for the morning session and consecutively Europe region volatility has some effects on America; finally, America region volatility does have a significant spillover effect on European and emerging markets in terms of portfolio flows and market capitalizations. These spillovers might be reasons why there is an intraday "W" shape return pattern and volatility jumps in ISE during the period analyzed.

Another possible factor that might have effects on the price movements is the contagion effect. Volatility transmission in a global market dynamic across different regions is mainly explained by intraregional volatility. It is common knowledge that many financial data series such as exchange rates and stock returns exhibit volatility clustering and different patterns of volatility transmission. Investors in a particular market show a biased behavior that has reacted rapidly and efficiently to information transferred from other similar markets, they might still prefer to trade in their home markets. King and Wadhwani (1990) concludes that trading in one market has an influence on other market price movements as well. Chan et al. (1996) study about dually listed companies showed that the daily volatility of the European stocks traded in US market accrues in the mornings when compared to similar American stocks. On the other hand, there are also contradictory studies about the intra-day patterns which claims contrary results to the contagion models. It is also possible for ISE to be effected by the trading patterns and volatility of US and European markets[3].

IV. MODELING VOLATILITY AND EMPRICAL RESULTS

Modeling and forecasting volatility has been the subject of many empirical and theoretical issues. There are several motivations of this research for the line of “the efficiency” of the econometric model. Volatility is often used as a “pure” measure of the risk of the financial assets. In this perspective, researchers use volatility estimation and its forecasting results to price the related assets.

This section takes GK study forms of YZ and RS estimators and models them in a GARCH(p,q) family. We, particularly, are interested in the relative explanatory power of volatilities obtained from econometric models and derived forms of YZ and RS.

Table 2 shows the empirics of the model presented as

$$Y_t = f(Y_{t-1}, YZ, RS, GK, PAR) \tag{7}$$

where Y is the return from ISE100 index defined earlier. The lag values of Y are used as exogenous variables. YZ, RS, GK, and PAR are related indicators of volatilities. All these indicators using the highest and lowest points of a daily price series is a function of the volatility observed during the day and can provide improved volatility estimates. Although, these range-based volatility estimators can be applied to any interval, the reliability of the estimate is dependent on the sampling frequency (Akay, 2010). Very distinctive part of the model lies in its data source. Our data is divided mainly into three groups and reflected in Equation 7. We run twelve separate regressions, three for each variable that cover morning and afternoon sessions in the same day, along with the data covering whole day. The endogenous variable in the first four models is the difference between returns in the morning session at time t and the afternoon sessions at time t-1. This difference may capture the jumps in the morning session that might be resulted from the news affects accumulated during the corresponding breaks.

Second set of regressions (5), (6), (7), and (8) are the volatility models where the endogenous variable is the difference between the returns in the morning session and the day–end at time t-1. Similarly, return differences between afternoon and morning sessions in the same day are presented in (9), (10, (11), and (12).

We begin our analysis by indicating that all regression models are stationary. This feature improves the predictive power of the model and its parameters. The results in Table 2 clearly illustrate that YZ, RS, GK, and PAR measure of volatilities have mixed results having different magnitudes and the directions of the causation. First set of regressions are all positive with YZ and RS are statistically significant. Although, GK and PAR have positive effect on the return differences they are statistically insignificant. Second set of results capture the effects of the volatilities on the return differences between morning and the previous whole day. The parameters have the same pattern having positive impacts with YZ and RS are statistically significant results.

Regressions of the differences in the return on the same day reveal a different picture. Now, the negative effects of the volatilities of return differences are in the same picture. All the range-based volatilities are statistically significant results at the %1 level of significance. These findings indicate that the accumulated news and related variables overnight have positive impact on the return. The volatilities that may capture the news effects during the session breaks within the same day have inverse impact on the related return variable. The results may support the view of Lockwood & Linn (1990) volatility study where return volatility decreases from the opening hour until early afternoon and increases subsequently and is considerably greater for intraday versus overnight periods. Along the same line, these results may also support the findings of Bildik (2001) that the opening and closing returns are large and positive; volatility is higher at the openings and follows an L shaped pattern and the relatively higher mean and standard deviation at the opening sessions was generated by the accumulated overnight information and the closed-market effect (halt of trade) [4].

Table 2. Regression Results from the Related Volatility Estimators

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	-0.02**	-0.003	0.0078	-0.002	-0.019	-0.002	-0.004	-0.0006	-0.02**	-0.01	0.03**	0.02**
	(-1.98)	(-0.56)	(-0.69)	(-0.21)	(-2.88)	(-0.71)	(-0.64)	(-0.08)	(-2.59)	(-1.86)	(3.09)	(2.88)
AR(1)	-0.72**	-0.71**	-0.71**	-0.71**	-0.23**	-0.36**	-0.24**	-0.37**		-0.28		
	(-4.73)	(-5.88)	(-5.98)	(-6.00)	(-2.20)	(-9.64)	(-2.29)	(-9.81)		(-0.88)		
MA(1)	0.58**	0.58**	0.57**	0.57**	-0.15					0.25		
	(3.33)	(4.10)	(4.11)	(4.11)	(-1.46)					(0.81)		
MA(3)									-0.11	-0.11	-0.11	-0.12
									(-2.70)	(-2.67)	(-2.92)	(-2.97)
rs_morning	2.37**				1.75**							
	(2.01)				(3.31)							
rs_afternoon									-2.10**			
									(-3.37)			
yz_morning		6.82**				3.59*						
		(2.62)				(1.89)						
yz_afternoon										-29.74**		
										(-3.92)		
gk_morning			0.48				0.23					
			(1.09)				(0.77)					
gk_afternoon											-1.27**	
											(-3.78)	
par_morning				0.43				0.08				
				(0.55)				(0.15)				
par_afternoon												-2.05**
												(-3.57)

Note: Endogenous variables in
(1), (2), (3) and (4): return_morning – return_afternoon(t-1)
(5), (6), (7) and (8): return_morning – return_daily(t-1)
(9), (10), (11) and (12): return_afternoon – return_morning
** siginificance at %5 significance level
* siginificance at %10 significance level

Table 3, 4, and 5 are obtained from the GARCH model. The GARCH model allows the conditional variance to be dependent upon previous own lags, so that the conditional variance equation in the simple case of

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 . \quad (8)$$

This GARCH (1,1) model is based on the assumption that forecasts of variance changing in time depend on the lagged variance of the asset. An unexpected increase or decrease in the return at time *t* will generate an increase in the expected variability in the next period[5]. Table 3, as a variant of the approach presented in Table 2, gives the pure results from GARCH-M model including the mean equation in the form of:

$$Y_t = \gamma_0 + \gamma_1 Y_{t-1} + \gamma_2 \sigma_t + u_t \quad (9)$$

Where the errors may follow MA(q) terms for the stationarity of the model. The estimates given in Table 3 is the realized set of results that is going to be used as benchmark for testing the relative efficiency of range-based volatilities that will be elaborated below. GARCH-M results in Table 3 illustrates that the variance (or standard deviation) of the model does not have statistically significant effect on the return differences while GARCH model illustrates a highly significant parameter estimates.

Table 3. Results from GARCH-M Model

		Mean Equation	
	(1)	**(2)**	**(3)**
Constant	-0.02	-0.015	0.01
	(-0.73)	(-0.87)	(0.59)
σ_t	0.17	0.13	-0.15
	(0.76)	(0.84)	(-0.62)
AR(1)	-0.72**	0.24**	
	(-4.99)	(-2.04)	
MA(1)	0.62**	-0.12	
	(3.74)	(-1.04)	
MA(3)			-0.11**
			(-2.61)
		Variance Equation	
	(1)	**(2)**	**(3)**
Constant	0.001**	0.0003**	0.004**
ω	(2.20)	(2.31)	(3.52)
ε_{t-1}^2 (α)	0.08**	0.06**	0.16**
	(2.92)	(3.50)	(3.51)
σ_{t-1}^2 (β)	0.86**	0.91**	0.61**
	(19.02)	(37.28)	(6.65)

Note: t-values are in paranthesis. Endogenous variables:
(1) return_morning – return_afternoon(t-1)
(2) return_morning – return_daily(t-1)
(3) return_afternoon – return_morning

** siginificance at %5 significance level
* siginificance at %10 significance level

These results may suggest that range-based volatility measures may be substituted for the classical measure of the variation. In other words, variance differences at the beginning and at the end of the trading day along with between the sessions may be better presented by the range-based volatility measures.

The estimated parameter values given in Table 4 indicate another dimension of the volatility efficiency. In particular, we include the related RS, YZ, GK, and PAR measures of range-based volatility in the variance equation portion of the GARCH model to see the explanatory power of these measures on the volatility of the model. The same set of twelve regression models have been run again. Again for all the models estimated, we first satisfy the stationary conditions. The GARCH portion of the model gives promising results for all range-based estimates. For all twelve regressions, we obtain statistically significant results at the %1 level of significance with having different magnitudes, though.

Table 4. Regression Results from GARCH Model including RS and YZ Mesures.

						Mean Equation						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Constant	-0.001	-0.0008	0.003	0.004	-0.002	-0.0001	0.001	0.002	0.0004	0.002	0.001	0.001
	(-0.24)	(-0.19)	(0.82)	(1.08)	(-0.73)	(-0.64)	(0.78)	(1.07)	(0.10)	(0.70)	(0.28)	(0.38)
AR(1)		-0.66**	-0.51**	-0.47**	-0.14	-0.35**	-0.10	-0.33**	0.40	0.54	0.46	0.61**
		(-3.84)	(-2.53)	(-2.29)	(-1.20)	(-9.21)	(-1.14)	(-10.52)	(1.02)	(1.62)	(1.30)	(2.36)
MA(1)	-0.59**	0.55**	0.40*	0.35	-0.22*		-0.25**		-0.40	-0.57*	-0.51	-0.66**
	(-3.52)	(2.90)	(1.83)	(1.62)	(-1.88)		(-2.82)		(-1.02)	(-1.72)	(-1.43	(-2.69)
MA(3)									-0.07	-0.02	-0.03	
									(-1.90)*	(-0.83)	(-0.88)	
						Variance Equation						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Constant ω	-0.001*	0.0012**	-0.0055**	-0.005**	-0.0016**	0.0008**	-0.003**	-0.003**	0.0001	0.001*	-0.004**	-0.004**
	(-1.65)	(2.14)	(-4.40)	(-4.56)	(-3.76)	(2.14)	(-7.17)	(-7.61)	(0.17)	(1.66)	(-5.99)	(-6.85)
ε^2_{t-1} (α)	0.017	0.05*	-0.023	-0.02	0.005	0.037	0.03	0.009	0.077**	-0.02	0.03	0.019
	(0.47)	(1.71)	(-0.81)	(-0.79)	(0.20)	(1.15)	(1.09)	(0.28)	(2.51)	(-1.15)	(0.94)	(0.56)
σ^2_{t-1} (β)	0.62***	0.68**	0.23**	0.23**	0.67**	0.53**	0.03	0.12	0.56**	0.16**	0.21**	0.27**
	(7.78)	(9.60)	(2.10)	(2.25)	(11.46)	(6.96)	(0.40)	(1.51)	(8.03)	(2.20)	(2.23)	(3.03)
rs_morning	0.68**				0.46**							
	(6.19)				(9.25)							
rs_afternoon									0.45**			
									(6.19)			
yz_morning		4.76**				5.94**						
		(3.69)				(4.69)						
yz_afternoon										31.68**		
										(8.25)		
gk_morning			0.84**				0.58**					
			(8.83)				(11.41)					
gk_afternoon											0.58**	
											(10.69)	
par_morning				1.54**				1.03**				
				(8.31)				(11.77)				
par_afternoon												0.97**
												(10.70)

Note: Endogenous variables in
(1), (2), (3) and (4): return_morning – return_afternoon(t-1)
(5), (6), (7) and (8): return_morning – return_daily(t-1)
(9), (10), (11) and (12): return_afternoon – return_morning
** siginificance at %5 significance level
* siginificance at %10 significance level

The results have some implications. As in the previous cases, YZ has greater effect on the volatility of the model in magnitude. Even though the effects of all other range-based estimates on the variance of the model do not vary too much for all cases, YZ differs significantly. The effect of YZ is much greater once the model covers the return differences within two sessions within the day. Given the fact that the data cover the period that is financially unsound, we expect that return volatility decreases from the opening hour until early afternoon and increases subsequently and is considerably greater for intraday versus overnight periods. In other words, the news effect and the speculative actions within the day may be greater than that of overnight periods.

Although we see the explanatory power of the range-based volatilities, one may concern about the day-of-the week effects on the volatility of the model simply because of the market structure of ISE. Considering that the settlements take place at the day T+2, buying on Thursdays and Fridays simply extends the transaction to T+4 (adding the weekend) as allowing the investors to earn a-two-extra-day interest in repo market. This could well create an upward market on Thursdays and Fridays (buying takes place) and a downward market on Mondays and Tuesdays as selling will probably take place on these two days. Table 5 illustrates such a set of regression results from the same GARCH models. The day dummies, representing the days of a week, are included in each model to capture the remaining jumps in the volatility of models. We pay particular attention to variance equation again[6].

Table 5. Regression Results from GARCH Model including RS and YZ Mesures and Day-of-the Week Effect.

Mean Equation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	-0.0006	-0.001	0.003	0.003	-0.001	-0.003	0.001	0.001	0.0003	0.002	0.001	0.002
	(-0.14)	(-0.30)	(0.79)	(0.84)	(-0.609	(-1.26)	(0.72)	(0.84)	(0.08)	(0.58)	(0.39)	(0.56)
AR(1)	-0.45**	-0.65**	-0.46**	-0.44**	-0.17	-0.32**	-0.12	-0.33**	0.34	0.54*	0.59**	0.53
	(-1.97)	(-4.53)	(-2.08)	(-1.99)	(-1.59)*	(-9.21)	(-1.31)	(-11.77)	(0.85)	(1.65)	(2.31)	(1.63)
MA(1)	0.32	0.54**	0.34	0.32	-0.18		-0.23**		-0.35	-0.57*	-0.64**	-0.56*
	(1.31)	(2.67)	(0.23)	(1.38)	(-1.69)		(-2.53)		(-0.86)	(-1.75)	(-2.64)	(-1.74)
MA(3)									-0.08**	-0.03		-0.03
									(-2.03)	(-0.91)		(-0.88)

Variance Equation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant ω	-0.006**	0.0001	-0.005**	-0.007**	-0.004**	0.0008	-0.003**	0.001	-0.001	0.001	-0.004**	-0.005**
	(-2.88)	(0.61)	(-3.53)	(-11.59)	(-6.01)	(0.93)	(-6.77)	(0.70)	(-0.61)	(1.62)	(-2.78)	(-3.94)
ε^2_{t-1} (α)	0.01	0.05*	-0.02	-0.03	-0.003	0.06	0.01	-0.01	0.097**	-0.02	0.03	0.08
	(0.45)	(1.72)	(-0.87)	(-1.46)	(-0.12)	(1.54)	(0.41)	(-0.40)	(2.93)	(-1.01)	(0.88)	(0.23)
σ^2_{t-1} (β)	0.59**	0.68**	0.23**	0.23**	0.53**	-0.01	0.09	0.15	0.51**	0.15**	0.20**	0.41**
	(6.99)	(9.26)	(2.19)	(2.80)	(7.24)	(-0.51)	(1.02)	(1.38)	(6.32)	(1.96)	(2.00)	(5.72)
rs_morning	0.78**				0.59**							
	(6.13)				(8.34)							
rs_afternoon									0.45**			
									(4.80)			
yz_morning		4.74**				13.70**						
		(3.46)				(7.59)						
yz_afternoon										31.13**		
										(7.86)		
gk_morning			0.85**				0.59**					
			(8.24)				(11.13)					
gk_afternoon											0.59	
											(8.83)	
par_morning				1.68**				0.94**				
				(9.01)				(9.00)				
par_afternoon												0.87**
												(10.19)
Dmon	0.005*	0.001	0.0005	0.001	0.002**	0.002**	-0.0007	-0.006**	-0.0008	-0.001	-0.0002	-0.0006
	(1.71)	(0.51)	(0.285)	(1.00)	(2.28)	(2.00)	(-0.93)	(-2.10)	(-0.30)	(-0.92)	(-0.11)	(-0.31)
Dtue	0.003	-0.002	0.0007	0.001	0.003**	0.001	0.0005	-0.005**	0.003	-0.000007	-0.0004	0.0005
	(1.28)	(-0.76)	(0.44)	(1.38)	(3.54)	(1.53)	(0.26))	(-1.98)	(1.27)	(-0.04)	(-0.28)	(0.30)
Dwes	0.004	0.001	-0.0005	0.0002	0.003**	0.004**	-0.0005	-0.005**	0.001	-0.0006	-0.0002	0.0009
	(1.54)	(0.48)	(-0.26)	(0.14)	(2.70)	(2.39)	(-0.67)	(-2.11)	(0.37)	(-0.40)	(-0.13)	(0.58)
Dthur	0.008**	-0.0008	0.0009	0.001	0.006**	0.003**	-0.0004	-0.005**	0.005*	-0.001	-0.0001	0.001
	(2.38)	(-0.24)	(0.48)	(0.75)	(4.15)	(2.54)	(-0.59)	(-2.33)	(1.78)	(-0.82)	(-0.07)	(0.56)

Note: Endogenous variables in
(1), (2), (3) and (4): return_morning – return_afternoon(t-1)
(5), (6), (7) and (8): return_morning – return_daily(t-1)
(9), (10), (11) and (12): return_afternoon – return_morning

** siginificance at %5 significance level
* siginificance at %10 significance level

The results show that the magnitude and the signs of range-based volatility measures do not change significantly once dummies are included. Dummies may capture the volatility effects of the day-of-the-week in different aspects. Comparing these twelve regression models, dummies are revealing a more prominent status in the second set of results from (6) to (8), excluding the model (7) in Table 5. These results illustrate, in general, that return differences from the previous whole day enhance the explanatory power of the day-dummies. Most of the dummies in Table 5 from equation (5) to (8) are statistically significant at 1% level of significance. There are few issues to emphasize. First, dummies may help capturing the anomalies along with range-based estimates of volatilities. In other words, they are complementary measures to these volatility indicators. Second, inclusion of dummies enhances the explanatory power of the range-based estimators provided that the dummies are statistically significant. Additionally, results may be the indicators of the news effects due to the reason that the return differences are expressed in the form of "morning at time t and the previous whole-day".[7]

V. EFFICIENCY OF RANGE-BASED VOLATILITIES

In this section, we follow path of the pioneering study done by Akay, et. al. (2010). We have focused exclusively on all of the range-based volatility measures to determine whether the method we apply provides volatility estimates consistent with the theoretical volatility of the Istanbul Stock Exchange Market. As in Akay (2010), to examine the efficiency of range-based volatility estimators, we take the GARCH estimates as a benchmark measure of realized volatility and compare its RMSE (Root-Mean-Square-Errors) with that of range-based volatility measures. Specifically, total 12 regressions of returns explained above are run to obtain the standard deviation in the following from:

$$r_t = \alpha_0 + \alpha_1 \sigma_t + \varepsilon_t$$

Where, r is the return differences defined above, ε is the error term, and σ is the range-based volatility measures (YZ, RS, GK, and PAR). We estimate additional 12 regression models to obtain ARCH and GACRH components of each measure as in Equation (8). Table 6 shows the results of RMSE calculated from these ARCH/GARCH components of such regression equations.

Table 6. Relative Efficiency of the Estimators by comparing the RMSEs, using Garch-Based Measure as the benchmark of Realized Volatility

Garch – Based Measure	RS - volatility	YZ - volatility	GK - volatility	PK – volatility
0.139	0.028	0.042	0.076	0.023
0.113	0.023	0.042	0.059	0.018
0.133	0.034	0.029	0.011	0.038

Note: the rows correspond to the RMSE of the regression equations:

(return_morning – return_afternoon(t-1));
(return_morning – return_daily(t-1)); and
(return_afternoon – return_morning), respectively.

Table 6 illustrates that all the range-based measures are more efficient than GARCH measure of volatility measures since their RMSE are smaller. In the first and the second sets of regressions PK is the most efficient. It is the least efficient volatility measure for the last group of models. The last group contains the intraday return differences and GK is seen as the most efficient, PK is the least efficient measure of volatility among the range-based measures.

Following Akay (2010) we may state that this may occur for two reasons: one methodological and the second as a result of the nature of the market. Recall that the GK method uses the open and closing observations as well as high and low observations, whereas the Parkinson method only uses the high and low values. The first possible explanation is the method by which we obtained the open and close observations employed in this article as explained in the data section. Second, Bali and Weinbaum (2005) examine the S&P 500 index futures and three exchange rates. In these markets, the previous trade and thus the open tend to have more information because the markets are homogeneous. Additionally, there is also evidence from federals funds market (Cyree & Winters, 2001), exchange rate markets (Ederington and Lee, 1993) and other stock markets, e.g. Australian stock markets (Kalev and Pham, 2009) that the observed patterns are rational responses to market structure and/or information arrivals. This market structure may result in that inter-day sessions create more heterogenous environment than intra-day information flow. This suggests that PK volatility measures should work better in the first two settings as seen in Table 6. Whatever the format of return equation, range based volatilities are more efficient compared to those of the conventional measure.

The findings support the view that range-based measures reduce the effect of microstructure noise. As in Akay (2010), we suggest that range-based methods not only reduce such a noise but also are able to categorize the different volatility measures along with the regular one.

VI. CONCLUSION

This study shows an analytical approach regarding the dynamics of Turkey’s ISE 100 Index intraday return and price volatility during the financial turmoil period of August 2007 to February 2010.

This paper contributes to the literature on the financial market and its behavior in three dimensions. First, we use a unique data on return in the ISE market. Second, the behavior of ISE market is investigated by applying four different measures of volatility; YZ, RS, GK, and PK. Third, we test the relative efficiency of these volatility measures by establishing realized volatility as a benchmark.

The empirical results are consistent with the previous literature and there is a “W” shape pattern for the trading day in general and two minor “W” shape patterns exist for morning and afternoon sessions. It is also observed that on average trading risk is the highest at the start and end of the day.

Estimated results illustrate that all range-based volatility measures have some explanatory power on ISE market volatility. The findings are relevant for establishing the accuracy and relevance of the extreme value volatility estimate. We show that these measures are also highly efficient relative to benchmark ARCH/GARCH estimates. This supports the view in the literature that range-based volatility measures reduce the effect of microstructure noise.

These results comply with the mainstream research in this area. We find strong evidence that economic volatility and trading process volatility can be decomposed and investigated simultaneously using open, close, high, and low values within the daily trading sessions. The measures investigated cover these types of information and decomposition.

Further research should test and compare the YZ estimator with other developing and developed security markets.

Notes

1. For detailed information: Demirer & M. Baha (2002), Aydoğan & Booth (2003), Bildik (2004)
2. See Wiggins (1991), Edwards (1988), Beckers (1983).
3. There is also a third set of factors which base their explanation on behavioral factors. According to behavioral finance literature psychology of investors and markets in general might have an effect in forming intraday price movement and patterns. Mean reversion, price reversals, noise traders in financial markets, herding and informational cascades and some other behavioral factors can be an explanation for the observed intraday anomalies in ISE in this study.
4. LeBaron (1992) finds that the daily serial correlation of index returns is inversely related to the conditional volatility of index returns. Both the capital gain return of the S&P index and the total return of the value-weighted index from the Center for Research in Security Prices (CRSP) file exhibit this pattern. (1) LeBaron argues that the empirically inverse relation between serial correlation and conditional volatility is important for understanding asset price behavior and that it may enhance theoretical models of market microstructure, learning, and information dissemination. He suggests that simple nontrading, specialist interventions, and news accumulation, each of which can cause index serial correlation, may be related to conditional volatility. (2) Thus, the relation between the two measures may be a function of economic factors
5. Using the GARCH model it is possible to interpret the current fitted variance as a weighted function of a long term average value information about volatility during the previous period and the fitted variance from the model during the previous period.
6. For all the set of regression models in Table 2-5, we run additional regression equation where the mean equation covers the day dummies. We eliminated one of the dummies to avoid the perfect multicollinearity problem. Almost all the results show that day-of the week effects are statistically insignificant. The results are expected for the period of data we cover in the analysis. In other words, day-of the week effect does not have explanatory power on the mean return differences when the time period is financially unstable.
7. Thursday has some special implications in Turkish Stock Exchange Market. Once the portfolio investors decide to buy additional assets from the market on

Thursdays, the payments are delayed until coming Monday. This may well change the behavior of the return model particularly for the financially unstable periods because 4 to 5 days payment delay may provide additional opportunities for the investors who are closer to market information set relative to others.

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