THE RELATIONSHIP BETWEEN PRICE-TRADE VOLUME AND WEATHER EFFECT IN ISTANBUL STOCK EXCHANGE: ASYMMETRIC CAUSALITY TEST ANALYSIS

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Abstract

This research examines the effects of weather on investor choices. For this purpose, 4772 daily data sets, which are in the range of 1987-2006 years, are used. The article investigates the effect on the investor preferences change in temperature by using daily data. Unlike previous studies in the existing literature, negative and positive effects of change in temperature on investors are researched separately. As indicator parameter of behavior of investors, BIST100 price index and total trade volume are used. Thus, the effects of positive and negative shocks happened in temperature change, are examined both as return and trade volume. According to findings, investors react both positive and negative temperature change in same direction. In other word, positive temperature changes can be assumed as a factor increases the trade volume and positive returns in stock market. Similarly, negative temperature changes affect stock market in direction of decreasing trade volume and returns.

Keywords: Weather Effect, Asymmetric Causality, Behavioral Finance, Turkey

JEL Classification: G02, G11, G14

1. Introduction

According to behavioral finance approach, human psychology is a significant factor which can affect investment choices. Mood of investors has a direct impact on risk perception, which is one of the most important factor determining stock market strategy. Thus, the

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mood of investor emerge as determining financial choices by affecting risk perception. Good decisions taken in a good mood and bad decisions taken in a bad mood, actually, reflect the timing and decision-making abilities of investors in stock markets. This fact, also, affect the financial performance of investor.

According to psychology researches, one of the important factors which has an impact on people's mood is temperature. To this, whereas low temperature leads people to act aggressive behaviors; high temperature may cause both apathy and aggressive behaviors. In financial markets, this fact has an impact on risk taking level of investors. Accordingly, aggressive behaviors thought it is caused by low temperature, increases the risk taking level of investors. Then, apathy, caused by high temperature, may lead investors to keep away from risk taking behaviors. Beside of these, temperature changes, which have an impact on risk taking levels, also, affect the expected return level of investor. Accordingly, if accepted that low temperatures lead us aggressive behaviors, it is so natural that high return expectations emerge in response to high risk. However, in high temperatures, a certain return expectation is out of question. Just because, high temperature may not only cause high return but also low returns. Therefore, risk-taking level of investors shows up as one of the determining factors of trade volume processed and return level changes in financial markets.

There are many researches examining the correlations between temperature change and stock market returns. In existing literature, researching return-temperature correlations, it is seen that the factors examined focus on causality relations by using time sequence analyses. Yet, effects of positive and negative shocks are not identical. In current literature, counting temperature, stock market returns and trade volume in just one direction, so that simultaneous positive and negative values taken, may mislead us at the point of which if it provides proper information to explain the changes of ups and downs upon each others properly. In other words, it is once agreed that the effects of both positive and negative direction temperature changes on investor psychology are the same. Yet, psychology researches claim that, this case is not like that, contrary, whose effects are very different from each others. At this point, the most crucial contribution of this research to the current literature is that the effects of negative and positive shocks in temperature in financial markets can be viewed separately. Thus, by forming positive and negative values in question for stock market returns and trade volume, it is researched that if positive and negative changes in temperature provides useful information.

The researches in current literature, once examines the correlations between environmental data and stock market return by using time sequence analysis. This research, then, unlike current literature, is carried out with an asymmetric causality test assuming effects of positive and negative shock are not same. Findings also support that, in developing markets, the researches carried out with current time sequence analyses may provide misleading information and that the effects of positive and negative shocks in financial markets are different from each others. It is thought that this research can contribute to current literature at this particular point. This study has also contribution to making effective predictions in relation to possible responses investors in Turkey will give to the relevant market in the face of temperature changes. In this case, it is thought that this article is significant for the study of weak form market efficiency in Turkey. In this direction, the research consists of four parts. After introduction part, the current literature researches are presented in second part, focused on methodology and data set used in this research in third part. In fourth part, the results are presented. In last part, the research is evaluated in the light of these results.

2. Literature review

Whether daily weather affects financial market behavior is an interesting question to financial economists and psychologists. There are many results studying the relationship between the stock returns and weather conditions that are thought to affect investor's psychology. On the one hand, there are researches demonstrating a relationship between meteorological events and stock returns. On the other hand, no relationship was found in some of the other researches.

A pioneering work in behavioral finance area analyzing the relationship between meteorological events and stock market returns is documented by Saunders (1993). In this research, the effect of regional weather events on American Stock Exchange and New York Stock Exchange market is investigated from 1927 to 1989. According to the results, cloudiness level is determined to be an important factor that affects the return values. When the weather is %100 cloudy returns are lower than average value. If it is below %20 then returns are higher than average value.

Keef and Roush (2002) study whether temperature, wind and cloudiness have effects on New Zealand stock returns or not. Daily data set between June 1986 and October 2002 has been used. The results support that cloudiness does not effect stock returns. However, the temperature is a little bit effective factor while the wind is stated to be the most powerful variable.

The effect of weather conditions on Spanish market is studied by Pardo and Valor (2003) from January 1981 to May 2000. Daily return values consist of the data set of this study. Return values are divided into groups based on humidity levels and sunny days for the research. According to findings, there is no interaction between weather events and stock prices. Meanwhile, there is no important difference amongst the returns grouped with respect to meteorological events.

Goetzmann and Zhu (2005) investigate whether cloudy and sunny days have any effect on stock buying and selling investors' behaviors in the US or not. The authors document that there is no relationship between the weather events and the investors' behaviors. Moreover, there is no significant difference in trade investors' behavior in sunny or rainy days.

Tufan and Hamarat (2004, 2006) analyze the weather effect in ISE. 3662 daily data sets are used from October/26/1987 to July/26/2002. The results support that cloudy and rainy days do not affect ISE. However, snow days affect ISE.

Cao and Wei (2005) examine whether stock returns are affected by temperature. Analysis is performed for nine different market that are US, Canada, UK, Germany, Sweden, Australia, Japan and Taiwan between the years 1962-2001. The results support a negative correlation between temperature and stock market return.

Shu and Hung (2009) study the wind effect on 18 European market returns between 1994-2004. According to results the temperature and powerful seasonal effects exist on the investigated stocks.

Yoon and Kang (2009) examine whether any relationship between cloudiness, humidity, temperature and returns belong to Korean Stock Market from January/15/1990 to December/13/2006 exist or not. The research documents that weather variables lose their effect with the 1997 financial crisis. Because the reduced effect of the weather events depending on the increased market activities.

The relationship between weather condition variables and stock market volatility is analyzed by Symeonidis, Daskalakis and Markellos (2010). A relationship between the cloudiness and stock market volatility is found in the article.

Floros (2011) analyzes the relationship between the weather conditions and stock returns in Portugal by considering the calendar anomaly. Daily data set between 1995-2007 is used in the study. The results indicate that there is a negative relationship between the temperature and Portugal stock market. However, this effect arises depending on the effect of January and the traded month. Furthermore, a result of having higher stock returns is documented in the first two weeks of the month and in January. It is stated that the low temperature in January causes higher stock returns depending on aggressive risk-taking behavior of the investor.

Nissim, Liran and Eshel (2012) study the relationship between the factors that are temperature, earthquake, wind, daylight and investor's mood on Israeli Stock Exchange. 2295 daily data from September/3/2000 to December/31/2009 is studied in the research. According to the results, perceivable earthquakes are not effective on stock returns while rainy days have negative effect. Temperature and wind effects are observed as mixed.

Tuna (2014) examines the weather effect on ISE for the period between January/11/1987 and December/31/2006. While the research analyzes the relationship between the weather variables and stock returns, at the same time weak-form efficiency test in ISE is applied. The results support that the selected weather variables do not affect ISE. For this reason there is an efficient market in the weak form.

A number of studies have been also assigned to evaluating the dynamic relationship between variables by using asymmetric Granger causality approach (Chen and Lin (2014); Gozhor (2014); Tiwari (2014); Nguyen, Sousa and Uddin (2015)). Such as Nguyen, Sousa and Uddin (2015) find two-way asymmetric causality between the US equity returns and returns of commodity futures. The effect of inflation, the investment horizons and commodity futures under consideration affect the direction of causality.

Chen and Lin (2014) examine asymmetric causality between foreign exchange and stock markets for six Pacific RIM countries that are Japan, Taiwan, India, South Korea, Singapore and Indonesia. Finally the authors indicate that for the first three countries above there is uni-directional symmetric and asymmetric Granger causality from foreign exchange rates to stock prices.

Gozgor (2014) examines causal relation between economic growth, domestic credit and economic globalization. The empirical results indicate that in seven developing economies there is causality running from domestic credit to economic growth. Additionally, unidirectional causality is found from economic growth to domestic credit in five developed and ten developing countries.

3. Methodology

In traditional Granger (1969) causality test, on future directed predicting of one factor it is tested if second factor provides useful information. For traditional Granger causality test, the series in question should be fixed. In Granger causality analyze, firstly, VAR model is taken as basis, as below. Assuming that all temperature, trade volume and return are integrated variables each can be presented as the following:

$$Y_t = \alpha_{01} + \sum_{i=1}^{p} \alpha_{1i} Y_{t-i} + \sum_{i=1}^{p} \beta_{1i} X_{t-i} + u_{1t} \qquad (1)$$

$$X_t = \alpha_{02} + \sum_{i=1}^{p} \alpha_{2i} Y_{t-i} + \sum_{i=1}^{p} \beta_{2i} X_{t-i} + u_{2t} \qquad (2)$$

In first model, in order to test the hypothesis indicates that X is not the Granger cause of Y, the first model is predicted according to Least Squares Method, then the residual sum of squares of this model is reached. In latter grade, the restricted model below, which there are no lags of X, is predicted according to Least Squares Method and residual sum of squares are obtained.

$$Y_t = \alpha_{01} + \sum_{i=1}^{p} \alpha_{1i} Y_{t-i} + u_{1t} \qquad (3)$$

F test statistic below is obtained, by using residual sum of squares of both restricted and unrestricted model:

$$\frac{(RSS_{rest} - RSS_{unrest})/m}{RSS_{unrest}/(n-k)} \quad (4)$$

Where, m displays constraint number, k is the predicted parameter numbers in unrestricted model. This test statistic taken is compared with F table value in (m, (n-k)) degree of freedom. If, $F_{(critical)}>F_{(table)}$basic hypothesis claims that Y is not Granger cause of X, is rejected.

3.1. Hacker-Hatemi-J Causality Test

In Hacker-Hatemi-J (2006) test, for causality relations between factors, Toda-Yamamoto test is applied however bootstrap critical values are obtained, in case errors are not normal distributed.

In this test, the causality relation between two series is based on a lag(s) augmentation of the vector autoregressive model (VAR) below.

$$Y_t = \alpha + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + u_t \quad (5)$$

where y_t, α and U_t are n-dimensional vectors and A_r is a parameter vector for lag r.

Toda and Yamamoto (1995) propose the following augmented VAR model to test the causality between integrated variables:

$$Y_t = \hat{\alpha} + \hat{A}_1 Y_{t-1} + \cdots + \hat{A}_p Y_{t-p} + \cdots + \hat{A}_{p+d} Y_{t-p-d} + \hat{u}_t \quad (6)$$

where the circumflex above a variable represents its OLS estimate.

The order p of the process is assumed to be known and d is equal to the maximum order of integration of the variables. The k th element of y_t is not Granger-cause of the j th element of y_t if the following hypothesis

H_o: The row j, column k element in A_r equals zero for r=1…p

is not rejected. Here, the parameters for the extra lag(s) are unrestricted in testing for Granger causality.

According to Toda and Yamamoto (1995), this is to guarantee the use of asymptotical distribution theory. The test statistics introduces by Toda-Yamamoto for testing the hypothesis of interest can be written as:

$$Y = \hat{D}Z + \hat{\delta} \quad (7)$$

Let us define the above denotations:

$Y: (y_1, \ldots . . y_T)(nXT)matrix$

$\widehat{D} \coloneqq (\hat{\alpha}, \hat{A}_1, \ldots \ldots . , \hat{A}_p, \ldots \ldots . . \hat{A}_{p+d})(nX(1 + n(p + d))))$

$$Z_t \coloneqq \begin{bmatrix} 1 \\ Y_t \\ Y_{t-1} \\ . \\ . \\ . \\ Y_{t-p-d+1} \end{bmatrix}$$ ((1+n(p+d))X1 matrix for t=1,…,T,

Z: =$(Z_0, \ldots . , Z_{T-1})((1 + n(p + d))XT)\ matrix,$

$\hat{\delta} \coloneqq (\hat{u}_1, \ldots . , \hat{u}_T)(nXT)$

The suggested Wald test statistic by Toda-Yamamoto (1995) to test non-Granger causality of one variable in y_t on another variable in $\square_t$ is written as:

$$\text{MWALD}=(C\beta)'[C((Z'Z)^{-1} \otimes S_U)C']^{-1}(C\beta) \qquad (8)$$

where $\otimes$ is the Kronecker product. Here, β=vec(D) and vec denotes the column-stacking operator. C is a pXn(1+np) indicator matrix with elements ones for restricted parameters and zeros for the rest of the parameters. S_U is the variance-covariance matrix of the unrestricted VAR model estimated as $\frac{\hat{\delta}'_U \hat{\delta}_U}{T-q}$, where q is the number of parameters in each equation of the VAR model.

3.2. Hatemi-J (2012) Asymmetric Causality Test

The idea of transforming data into both cumulative positive and negative changes comes forward from Granger and Yoon (2002). This approach is used to test for cointegration by the authors that is entitled as hidden cointegration.

There are four important cases in Hatemi-J (2012) asymmetric causality analysis: Determining the lag length of the VAR model, determining the added additional lag length to the model, obtaining the critical values for the Wald test statistics and finally change of causality relationship depending on the time.

In Hatemi-J (2012), Hatemi-J extends the article of Granger and Yoon (2002) to causality analysis and refers to it as asymmetric causality testing. According to Hatemi-J (2012), it is asymmetric in the sense which positive and negative shocks may have different causal impacts. It is assumed that the casual relationship between two integrated variables y_{1t} and y_{2t} defined as the following random walk processes:

$$Y_{1t} = Y_{1t-1} + \varepsilon_{1t} = Y_{1,0} + \sum_{i=1}^{t} \varepsilon_{1i} \quad (9)$$

$$Y_{2t} = Y_{2t-1} + \varepsilon_{2t} = Y_{2,0} + \sum_{i=1}^{t} \varepsilon_{2i} \quad (10)$$

where t=1,2,... T, the constants $y_{\{1,0\}}$ and $y_{\{2,0\}}$ are the initial values and the variables ε_{1i} and ε_{2i} signify white noise disturbance terms. Positive and negative shocks are defined as follows:

$$\varepsilon_{1i}^{+} = \max(\varepsilon_{1i}, 0)\,, \varepsilon_{2i}^{+} = \max(\varepsilon_{2i}, 0), \varepsilon_{1i}^{-} = \min(\varepsilon_{1i}, 0), \quad \varepsilon_{2i}^{-} = \min(\varepsilon_{2i}, 0),$$

respectively. Therefore, it can be expressed $\varepsilon_{1i} = \varepsilon_{1i}^{+} + \varepsilon_{1i}^{-}$ and $\varepsilon_{2i} = \varepsilon_{2i}^{+} + \varepsilon_{2i}^{-}$. Equation 9 and 10 can be rewritten as the following:

$$Y_{1t} = Y_{1t-1} + \varepsilon_{1t} = y_{1,0} + \sum_{i=1}^{t} \varepsilon_{1i}^{+} + \sum_{i=1}^{t} \varepsilon_{1i}^{-} \quad (11)$$

$$Y_{2t} = Y_{2t-1} + \varepsilon_{2t} = y_{2,0} + \sum_{i=1}^{t} \varepsilon_{2i}^{+} + \sum_{i=1}^{t} \varepsilon_{2i}^{-} \quad (12)$$

Finally, the positive and negative shocks of each variable can be defined in a cumulative form as

$$Y_{1t}^{+} = \sum_{i=1}^{t} \varepsilon_{1i}^{+}\,, Y_{1t}^{-} = \sum_{i=1}^{t} \varepsilon_{1i}^{-} \quad (13)$$

$$Y_{2t}^{+} = \sum_{i=1}^{t} \varepsilon_{2i}^{+}\,, Y_{2t}^{-} = \sum_{i=1}^{t} \varepsilon_{2i}^{-} \quad (14)$$

In Hacker and Hatemi-J (2006) bootstrap Granger causality test, in order to detect the causality between variables, Toda-Yamamoto causality test (1995) is applied, however the bootstrap critical values are obtained with Monte Carlo simulation in case the errors are not normal distributed. However, the lack side of this model is that cannot distinguish the positive and negative shocks. In this context, in asymmetric causality test developed by Hatemi-J (2012), in case there is existence of asymmetric information in financial markets and are heterogeneous participants, because the participants do not give similar reactions to same identical positive and negative shocks, the results of this test may be fallacious. In this context, Hatemi-J (2012) causality test is the positive and negative shocks' decomposed form of Hacker and Hatemi-J (2006) bootstrap Granger causality test.

So, this method is pretty available for those researches at which financial time sequences are used.

4. Data

4772 daily data set are used in the range of November/2/1987- December/29/2006 dates. Cause of using daily data is to find out the effects of change in temperature as clear as possible. In other word, it is aimed to prevent the problem of insufficient data taken from weekly, 15 days and monthly data. BIST 100 Return Index and total trade volume data were used in research. BIST 100 Return Index and total trade volume data are taken from the official website of Istanbul Stock Exchange. Temperature data, then, are taken from The Ministry of Turkey Forestry and Water Affairs, Meteorology General Office. Effects of temperature are examined for both BIST 100 Index and total trade volume separately. All analyses are carried out on raw data. Basic statistical values about variables used in research are presented in Table 1.

Table1

Summary Statistics

	MEAN	STD. DEV.	MINIMUM	MAXIMUM
BIST 100	7797.599	11135.44	3.62	47728.5
TRADEVOLUME	79535.50	134245.4	0.011	1014475.25
TEMPERATURE	14.56243	7.355954	-4.5	32

Basic statistical values of stock return index, trade volume and temperature values are presented in Table 1. All these time sequences are basic. Temperature ranges between -4.5 and 32. In the light of these ranges, the maximum values of the BIST100 Return Index and trade volume are 47728.5 and 1014475.25, respectively. Further, the minimum values of the BIST100 Return Index and trade volume are 3.62 and 0.011, respectively.

When analyzing data E-Views for Granger causality test, Gauss for Hatemi-J bootstrap (2006) and Hatemi-J (2012) asymmetric causality tests are used (Gauss codes are taken from Hatemi's website).

5. Empirical Analysis

5.1. Granger Causality Analysis

Initially, Granger causality test is applied on selected variables. Results taken are presented in Table 2.

Table 2

Granger Causality Test Result

Null Hypothesis	Chi-sq	Prob.
Temperature Δ (BIST100) is not Granger cause	12.09122	0.0600
Temperature Δ (Trade Volume) is not Granger cause	6.163430	0.4051

** Δ displays first difference of the series.*

According to the results taken, in %5 significance level the hypothesis is rejected. In other mean, temperature is not Granger cause for BIST100 Return Index. So, explaining the change in return, temperature variable does not provide helpful data. Similarly, temperature is not also Granger cause for trade volume. So, explaining the change in trade volume, temperature variable does not provide helpful data.

5.2. Hacker and Hatemi-J (2006) Causality

Before applying bootstrap causality test suggested by Hacker and Hatemi-J (2006), it is required to truly determine the stability level and lag of model of variables. Yet, the model on which the causality is tested need to be added addition lag as much as variable's stability level. To this, Hacker and Hatemi-J Bootstrap causality test results are presented in Table 3.

Table 3

Hacker and Hatemi-J Bootstrap Causality

Causality Direction	Test Statistics	Bootstrap Critical Values		
		%1	%5	%10
Temp. > Trade Volume	607.687*	24.427	18.880	16.169
Temp. > Return	5746.925*	19.734	13.480	11.066

** displays %1 significance level.*

As we can see in Table 3, according to the results of Hacker and Hatemi-J bootstrap causality test (2006), test statistics are bigger than bootstrap critical values. So, it is seen that there is a causality relationship between temperature and both trade volume and returns. To support this finding taken from the research, examining the correlation in question are carried out with Hatemi-J (2012) Asymmetric causality test for both positive and negative shocks.

Table 4

Hatemi-J Asymmetric Causality Test Results

Causality Direction	Test Statistics	Bootstrap Critical Values		
		% 1	% 5	% 10
Temp. > Return (+)	184.866*	11.858	6.750	5.096
Temp. > Return (-)	168.843*	15.676	9.625	7.562
Temp. >Trade Volume (+)	2825.834*	14.461	9.801	7.879
Temp. > Trade Volume (-)	2835.250*	14.116	9.656	7.852

** displays %1 significance level*

According to the results of Hatemi-J (2012) Asymmetric causality test presented in Table 4, it is seen that there is causality from temperature to return in both positive and negative shocks. There is also causality from temperature to trade volume for both positive and negative shocks. Thus, the positive changes in temperature affect both stock market return and trade volume in positive direction. Same fact is also valid for negative direction changes.

6. Conclusions

The effects of negative and positive shocks happen in temperature values on trade volume and stock market returns are examined. Research period is between 1987-2006 years, and analyses are carried out with daily data. According to the results of the research, positive change in temperature provide useful data in direction to that trade volume and return level also increase. Similarly, negative change in temperature provide useful data in direction to that trade volume and return level also decrease. This data taken is opposite to the theory about temperature and investor behaviors which conflict with many former researches in literature like Cao and Wei (2005). At the end of this research, it is ended up claiming that, unlike many researches focusing on that there is a negative correlation between temperature and return, is a positive correlation between them. This case also support that there is a positive correlation between temperature and stock market return in developing financial markets.

According to behavioral finance, in cold weather investors act aggressively and take more risks. Yet, after this research with empirical applications carried out in such one of the developing stock markets Istanbul Stock Exchange it is reached that as temperature decreases trade volume and return levels also decreases. So, investors tend to be less risk-taking as temperature decreases.

Similarly, as temperature rises both return and trade volume also rises. In this case, in developing markets, it can be viewed as investors tend to be more risk-taking with temperature rising. In behavioral finance, whereas there is no certain thing about the position of investors when temperature rises, it is known that when temperature decreases investors tend to be more risk taking. The research carried out in Istanbul Stock Exchange, one of the developing markets, whereas the results taken have parallel values with temperature risings, support that the contrary happens in low temperatures.

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