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INVESTOR REACTION TO MARKET SURPRISES ON THE ISTANBUL STOCK EXCHANGE

İSTANBUL MENKUL KIYMETLER BORSASINDA PİYASA SÜRPRİZLERİNE YATIRIMCI TEPKİSİ

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ABSTRACT: This paper examines the reaction of investors to the arrival of unexpected information on the Istanbul Stock Exchange. The empirical results suggest that the investor reaction following unexpected news on the ISE100 is consistent with Overreaction Hypothesis especially after unfavorable market surprises. Interestingly such pattern does not exist for ISE30 index which includes more liquid and informationally efficient securities.

A possible implication of this study for investors is that employing a semi contrarian investment strategy of buying losers in ISE100 may generate superior returns. Moreover, results are supportive of the last regulation change of Capital Market Board of Turkey which mandates more disclosure regarding the trading of less liquid stocks with lower market capitalization.

Key words*:* Istanbul Stock Exchange; Market Efficiency; Overreaction; Uncertain Information Hypothesis; Uncertainty; Abnormal Returns

JEL Classification: G14; G15

ÖZET: *Bu çalışma İstanbul Menkul Kıymetler Borsasına sürpriz bir bilgi gelişi karşısında yatırımcının tepkisini incelemektedir. IMKB100 endeksi için sonuçlar sürpriz bilgi gelişi karşısında yatırımcının davranışının Aşırı Tepki Hipotezi'ne uygun olduğunu göstermektedir. Bu durum özellikle negatif etkisi olan bilgi gelişi sonrası daha belirgindir. Daha likit ve pazar etkinliği fazla olan şirketler grubunu kapsayan IMKB30 endeksi aynı yapıyı göstermemektedir.*

Çalışmanın bir sonucu; endeksteki aşırı düşmeler sonrası IMKB100 endeksine yatırım yapmanın anormal getiri sağlayabileceğidir. Sonuçlar Sermaye Piyasası Kurulu'nun likiditesi ve toplam piyasa değeri düşük olan hisselerin alım satımı için daha fazla bilgi verilmesini zorunlu kılan son değişikliklerini destekler niteliktedir.

Anahtar Kelimeler*: İstanbul Menkul Kıymetler Borsası; Pazar Etkinliği; Aşırı Tepki; Belirsizlik Hipotezi; Belirsizlik; Anormal Getiri*

1. Introduction

In the past three decades the efficient market hypothesis (EMH) has been the most venerable tenet of financial economics and a staple of academic analysis. The EMH suggests that security prices reflect all currently available information. (historical, current and insider information) and securities are efficiently priced at their true values. The crucial assumption of EMH is that investors are rational and therefore information is reflected to the security values unambiguously. If the EMH holds, then it "rules out the possibility of trading systems based only on currently available information that have expected profits or returns in excess of equilibrium expected profit or return (Fama 1970).

In recent years, however, the validity of the EMH has been challenged by behavioral financial economists arguing that the market participants include not only rational economic agents but also "behavioral economic agents," so-called "noise traders," (Kyle 1985, Black 1986). These agent's asset allocation and trading decisions are often driven by irrational and sentimental considerations (Lee, Shleifer and Thaler, 1990 and 1991). Hence, people deviate from the standard decision making model in a number of fundamental areas (Kahneman and Riepe 1998). In addition, some studies claim that increasing presence of these noise traders relative to institutional traders, and the concomitant risks introduced by these unsophisticated traders, result in return anomalies (Kamara, 1997; Lee, Shleifer and Thaler, 1991; and Shleifer, 2000). In this framework, noise traders systematically form expectations based on erroneous interpretations of economic events thereby generating systematic risk, or noise trader risk, which is incorporated into equilibrium security prices.

Furthermore, theoretical models have been proposed in which the presence of noise traders induces rational investors to pursue unexpected favorable feedback strategies, which destabilizes security prices (De Long et al., 1990). These considerations imply that the interaction of multiple classes of investors with heterogeneous beliefs about expected returns for assets result in less-than-optimal equilibrium prices. As a result of this interaction, the arbitrage based theoretical case for the efficient markets is limited as well.

In recognition of the presence of both "rational economic agents" and "behavioral economic agents" in securities markets, three alternative hypotheses have been proposed in the finance literature. De Bondt and Thaler (1985, 1987) advance the "overreaction hypothesis" (OH) to explain the potential sentimental behavior of market participants and their subsequent deviation from rationality by being overly optimistic or pessimistic in response to the arrival of new information. They argue that investors overreact to unexpected information by setting security prices too high in reaction to good news, and too low in reaction to bad news. Larson and Madura (2001) for the foreign exchange market and Poteshman (2001) for the options market document a similar pattern. The second competing explanation, the "uncertain information hypothesis" (UIH) set forth by Brown, Harlow and Tinic (1988), postulates that investors are not necessarily irrational, but they respond to increased uncertainty caused by unexpected arrival of new information. They, therefore, could initially set security prices below their fundamental values. Subsequent clarifications of the uncertainty result in price reversion to equilibrium levels over time. It is speculated that he prediction of the UIH is consistent with rational investors' reaction to "noise-trader risk," which is priced in equilibrium as an additional risk factor. Securities exposed to such a risk will consequently be underpriced following the arrival of good or bad news. Zhang (2006) models the price movement against uncertainty in information and suggests it as an alternative to what is argued as underreaction. He states that greater information uncertainty should produce relatively higher expected returns following good news and relatively lower expected returns following bad news. The third competing explanation, the "underreaction hypothesis" (UH), predicts that security prices will move in the same direction of the initial change as the information is slowly incorporated into prices initial prices are revised. The literature presents vast amount of evidence in support of underreaction hypothesis.[1] Hong and Stein (1999) suggest a unified theory of overreaction, underreaction and momentum trading.

Appendix 1 provides a graphical illustration of the stock market reaction to unexpected information under the four competing hypotheses outlined above. Panel A displays instantaneous price adjustments to the unexpected arrival of favorable or unfavorable news as proposed by the EMH. Panel B shows a pattern of price reversals following an initial overreaction to good or bad news as posited by the OH. Panel C displays price adjustments consistent with the predictions of the UIH, whereby price adjustments are positive, or at least non-negative, following the arrival of unexpected information. Panel D displays price adjustments consistent with the prediction of UH, where initial price adjustments are followed by revisions in the same direction.

The objective of this paper is to examine investor reaction to surprises on the Istanbul Stock Exchange (ISE hereafter). We examine daily returns of the ISE100 and ISE30 stock indices. ISE100 include those 30 companies that form the ISE30 index. ISE30 companies are likely to be the companies that have the most analysts' coverage. Valuation of stocks with fewer analysts' coverage and less available information is more likely to be affected by overreaction, underreaction or momentum etc. (Hong etal 2000). However, Tetlock (2010) argues that public news coverage helps the diffusion of more information to the price of the security reducing the informational asymmetry. Fang and Peress (2009) suggest that mass media coverage helps to alleviate the informational frictions helping to overcome asymmetric information. Thus, ISE30 index should not reveal significant and persistent deviations from fundamental values for long periods whereas evidence for the deviations due to behavioral reasons would be more explicit for ISE100 index. We examined the daily returns and identified 42 major unexpected events in ISE100 and 23 major unexpected events in ISE30 (identified using a strictly quantitative trigger-point approach) to investigate whether investors' reactions are consistent with the predictions of the efficient market hypothesis (EMH), the overreaction hypothesis (OU), the underreaction hypothesis (UH) or the uncertain information hypothesis (UIH).

Empirical results from this study indicate a significant increase in the volatility of daily returns following the arrival of unexpected news in both markets during the sample period. Furthermore, the findings suggest that increases in volatility of returns following major unfavorable market surprises is associated with increases in returns and favorable market surprises is associated with decreases in the ISE100 index returns, a result consistent with the prediction of the overreaction hypothesis (OH). Nevertheless, reversals of stock prices are not at same degree for good or bad surprises and stronger following the losses. This to some extent could be explained by the "Prospect Theory" suggesting that losses have more emotional impact than an equivalent amount of gains (Kahneman and Tversky 1979). No such pattern is examined in ISE30 index supporting the idea that intense coverage of these securities helps overcoming information asymmetry.
Therefore, we believe that the empirical evidence presented here supports the notion

[1] Abarbanell and Bernard (1992), Jegadeesh and Titman (1993), Ikenberry, Lakonishok, and Vermaelen (1995), Michaely, Womack, and Thaler (1995), and Chan, Jegadeesh, and Lakonishok (1996)

that the presence of "noise trader risk" in the stock market leads rational investors to respond to new information by initially setting security prices above their fundamental their fundamental values. Further clarifications of the deviation result in a reverse adjustments of security prices to their fundamental values.

The rest of the paper is set forth as follows. Section II presents the data and methodology. The empirical results are presented in Section III and Section IV provides the summary and concluding remarks.

2. Data and Methodology

2.1. Data

The data for this study consist of daily closing values for Istanbul Stock Exchange Index adjusted for dividends and stock splits. ISE100 index covers the period of January 5th 1988 to April 21st 2010 and ISE30 index covers the period of January 2nd 1997 to April 21st 2010.

2.2. Methodology

Daily changes for ISE100 and ISE30 indices are calculated as follows:

$$R_t = \log(\frac{I_t}{I_{t-1}}) * 100 \tag{1}$$

Where, R_t is the daily percentage changes of stock index or exchange rate on day t, and I_t, I_{t-1} are the closing values of stock index or exchange rate on the days t and $t-1$ respectively. Augmented Dickey-Fuller unit root tests (not reported here) are performed for daily changes in each index, and those tests reject the null hypothesis of a unit root at the 1% level of significance. Therefore, daily stock market returns calculated in Equation (1) are stationary. Summary statistics of daily changes for the stock index are presented in Table 1.

Table 1. Summary Statistics for Daily Changes in the Indexes

INDEX	DAYS	MEAN	MEDIAN	STD DEV.	MAX	MIN
ISE100*	5540	0.204%	0.133%	2.86%	19.45%	-18.11%
ISE30**	3291	0.174%	0.093%	2.96%	19.30%	-18.18%

* Sample period is from 05/01/1988 to 21/04/2010
** Sample period is from 02/01/1997 to 21/04/2010

2.3. Measuring Post-Event Variance

To identify market surprises we use a strictly quantitative "trigger-point" approach.[2] Specifically, we estimated GARCH (p,q) models up to three lags and chose the appropriate model based on Akaike and Schwartz criterion. Results favored GARCH (2,3) models for daily returns in both of the stock indices and include the appropriate number of autoregressive lags necessary in each equation to eliminate any serial correlation in the residuals. From GARCH (2,3) models for the stock returns, we calculate standardized residuals (which can be interpreted as standard deviation units), and use standardized residuals that are different from the mean

[2] This approach identifies market-wide unexpected major events and does not attempt to identify any company-specific, news-specific or event-specific surprises.

standardized residuals at 1% (2.576 standard deviations) significance level to determine major event days for both series. That is, we identify the greatest positive and negative outliers in the standardized residuals for the market index of 5539 daily returns for ISE100 and 3291 daily returns for ISE30 during the sample period.[3]

Table 2. Trigger Points Used to Determine the Events for Each Market

Market	Value of Standardized Residuals	
	Good News	Bad News
ISE100	7.31%	7.31%
No of days	22	20
ISE30	7.62%	7.62%
No of days	13	10

In the process, we identified 22 major unexpected favorable events (or good news), and 20 major unexpected unfavorable events (or bad news) for ISE100 and 13 major unexpected favorable events (or good news), and 10 major unexpected unfavorable events (or bad news) for ISE30. We then track returns during a window of 30 days after each event, resulting in 1260 post-event daily returns for ISE100 stock index and 690 post-event days for the ISE30 stock index. Table 2 displays the positive and negative trigger points used to determine favorable and unfavorable event days for the two indices, along with the number of events (good and bad) for each.

We next investigate whether the arrival of news (favorable or unfavorable) affects the volatility of stock market returns and changes in exchange rates. To do this the variance of all 30-day post-event window periods (for all favorable and unfavorable events) and the variance of non-event days (entire sample period excluding the post-event days) are compared to ascertain whether the volatility of "post-event" days and "non-event" days are equal using a difference-of-variance test. We also conduct a series of difference-of-variance tests to determine whether there is any significant difference between a) post-favorable event volatility and non-event volatility, b) post-unfavorable event volatility and non-event volatility and c) post-favorable event volatility versus post-unfavorable event volatility.

2.4. The Effect of Surprises on Stock Returns

In order to investigate whether investor's response to unexpected surprises are consistent with the predictions of the EMH, OH, UH or UIH we follow a procedure outlined in Brown et al. (1988) and Ajayi and Mehdian (1994). More specifically, we calculate daily post-event abnormal returns for both series and average them cross-sectionally for each day over the 30-day period following each set of favorable or unfavorable events in each series. Finally these 30-day abnormal returns are added together to generate cumulative abnormal returns (CARs) for each class (favorable and unfavorable) of event. Stated formally, the abnormal return for series i on day t (AR_{itd}) for t = 1 to 30, following an unexpected event d, is computed as follows:

[3] To account for the potential leverage effect of negative returns on stock market volatility, we also estimated asymmetric GARCH models for each index. The results indicate that the structure and number of outliers is not sensitive to the underlying GARCH model employed.

$$AR_{itd} = R_{itd} - \overline{R_{i,non}} \tag{2}$$

where $d = 1,\ldots,n$ and n is the number of favorable or unfavorable events in index i.

R_{itd} = Return of series i on day t for event d,

$\overline{R_{i,non}}$ = Mean return of series i for non-event days

The AR_{itd} therefore measures the difference between changes in each series on each of the 30 days following an event and the mean change in the series n-event days.

We then calculate the mean abnormal return $\overline{AR_{it}}$ for index i on day t as follows:

$$\overline{AR_{it}} = (1/n)\left(\sum_{d=1}^{n} AR_{itd}\right), \quad t = 1.....30 \tag{3}$$

Under the null hypothesis, the abnormal returns will be jointly normally distributed with a zero conditional mean and conditional variance $\sigma^2(AR_{it})$:

$$\sigma^2(AR_{it}) = \sigma_{e_i}^2 + \frac{1}{L}\left[1 + \frac{(R_{mt} - \overline{R}_m)^2}{\sigma_m^2}\right] \tag{4}$$

where L is the estimation period length (i.e. number of days used for estimation) and $\overline{R_m}$ is the mean of the market portfolio. With L large enough, $\sigma^2(AR_{it}) \to \sigma_{e_i}^2$ thus variance of non event days $\sigma_{e_i}^2$ could be used for further tests.

Finally, the *CAR*s are generated by summing up the mean abnormal returns over 30 days as:

$$CAR_{it} = CAR_{i(t-1)} + \overline{AR_{it}}\,, = \sum_{t=1}^{n} \overline{AR_{it}} \quad t= 1\ldots30 \tag{5}$$

We perform a standard t-test as to whether the calculated *CAR*s are statistically different from zero. The t-statistic is stated as:

$$t = \frac{CAR_{iT_2}}{\left[Var\left(CAR_{iT_2}\right)\right]^{1/2}} \tag{6}$$

where $Var\left(CAR_{iT_2}\right) = \sigma_i^2(T_1,T_2) = (T_2 - T_1 + 1)\sigma_{e_i}^2$ and $T_1 = 0$ in our specific case.

According to MacKinlay (1997) an aggregation of results for each index can also be performed across both time and events. In that scenario, the cumulative average abnormal return for each index is defined as:

$$CAAR_i(T_1,T_2) = \frac{1}{d}\sum_{i=1}^{d} CAR_i(T_1,T_2) \tag{7}$$

where d is the number of events.

The variance of $CAAR$ is given by:

$$\mathrm{var}(CAAR(T_1,T_2)) = \frac{1}{N^2}\sum_{i=1}^{N} \sigma_i^2(T_1,T_2) \tag{8}$$

Under the null hypotheses that the abnormal returns are zero.

To assess the statistical significance of the *CAR*s, we perform t-tests of the null hypothesis that the *CAR*s are equal to zero during post-event windows. In addition, graphical representations of *CAR*s over the 30 day window for each class of event in each series are used to determine whether investors' behavior is consistent with EMH, OH, UH, or UIH.

3. Empirical Results

Table 3 displays daily mean returns for non-event days, all post-event days, post-favorable event days, and post-unfavorable event days, along with the sample size for each series. As can be seen, the results show that a) aggregate post-event mean returns are higher than non-event mean returns for ISE100, lower for ISE30; b) mean returns for unfavorable post-event days are higher than mean returns for favorable post-event days for both series.

Table 3. Mean Returns for Non-Event Days and Post-Event Days

Market	Non-Event Days	All Post Event Days	Post Favorable Event Days	Post Unfavorable Event Days
ISE100	0.164%	0.248%	0.074%	0.438%
No of days	4138	1260	660	600
ISE30	0.171%	0.071%	0.012%	0.086%
No of days	2432	667	377	290

Table 4 presents the variance of daily returns for non-event days, all post-event days, favorable post-event days and unfavorable post-event days, along with the sample size for each series.

This table contains two columns of F-statistics. In the penultimate column, the first F-statistic reported for each market is the test-statistic of the null-hypothesis that the variance of post-event returns is equal to the variance of all non-event returns. The second F-statistic is for the test of the null-hypotheses that the variance of returns following favorable events is equal to the variance of returns during non-event days, and the third F-statistic is for the test of the null-hypotheses that the variance of returns in the period following unfavorable events is equal to the variance of returns during non-event days. The second column contains the F-statistics testing the null-hypothesis that the variance of returns following favorable events is equal to the variance of returns following unfavorable events.

Table 4. Variance of Returns for Non-Event Days and Post-Event Days

Market Sample	Days	Variance(%)	F-statistic(a)	F-statistic(b)
1. ISE100				
Non-event Days	4137	5.575	---	---
Post-event Days	1260	6.895	0.809***	
Favorable	660	7.087	0.787***	1.071
Unfavorable	600	6.625	0.841***	
2. ISE30				
Non-event Days	2432	7.834	---	---
Post-event Days	667	5.143	1.523***	
Favorable	377	5.090	1.539***	0.934
Unfavorable	290	5.448	1.438***	

a) The first F-statistic (a) for each stock index is the test statistic of the null hypothesis that the variance of post-event returns is equal to the variance of non-event returns. The second F-statistic (a) is the test statistic of the null hypothesis that the variance of returns after unexpected favorable events is equal to the variance of non-event returns. The third F-statistic (a) is from a test of the null hypothesis that the variance of returns after unexpected unfavorable events is equal to the variance of non-event returns.

b) F-statistic (b) is the test statistic of the null hypothesis that the variance of returns after unexpected favorable events is equal to the variance of returns after unexpected unfavorable events.

Note: Post-event periods contain the days after both favorable and unfavorable events.***, ** and * indicates statistical significance at the 1%, 5% and 10% level respectively.

It can be seen that the F-statistics indicate that the variance of returns following both unfavorable and favorable market surprises (good or bad) is statistically significantly higher than the variance of returns for non-event days for ISE100. These results provide support for the notion that the volatility of ISE100 index returns increases significantly following unexpected events. We observe the opposite relation for ISE30. This result and the descriptive statistics suggest that behavioral agents affect the return of ISE100 whereas ISE30 display a structure that supports the efficient market hypothesis.

The last column of F-statistics in Table 4 indicates that post-event market volatility is not statistically significantly different following favorable or unfavorable events Thus, the difference between post event days volatility and no event days volatility is not specific to the type of the event.

Table 5 displays post-event cumulative average abnormal returns (*CARR*s) along with their corresponding t-values for 1, 2, 3, 4, 5, 10, 20, and 30 days following surprises, while Figure 1 presents the graphs of the *CARR*s over the 30-day post-event windows for each index. The t-values are calculated using Equation (9) to test the null hypothesis that the *CARR*s are equal to zero.

$$t = \frac{CAAR(T_1, T_2)}{(\mathrm{var}(CAAR(T_1, T_2)))^{1/2}} \sim N(0,1) \tag{9}$$

Table 5. Post-Event Cumulative Average Abnormal Returns

Market	Post-Event Day	Favorable Event *CARR*	t-statistics	Unfavorable Event *CARR*	t-statistics
1. ISE100	+1 day	-0.483	-0.67	0.808	1.08
	+2	-0.426	-0.49	1.576	1.72*
	+3	0.246	0.24	1.939	1.84*
	+4	1.261	1.12	2.762	2.34**
	+5	1.080	0.88	3.789	2.93***
	+10	0.222	0.13	5.299	3.03***
	+20	-1.143	-0.50	7.549	3.12***
	+30	-2.682	0.96	8.226	2.80***
2. ISE30	+1 day	0.270	0.25	1.200	0.96
	+2	0.880	0.65	-0.530	0.35
	+3	-0.042	-0.03	-0.611	0.35
	+4	-0.736	-0.42	-0.586	0.30
	+5	-1.820	-0.96	-0.338	-0.16
	+10	-0.574	-0.22	-1.039	-0.35
	+20	-2.908	-0.82	-0.749	-0.19
	+30	-4.612	-1.07	-2.464	-0.50

ISE30 reveals a supportive pattern of the argument of press coverage and related liquidity. As outlined above, the test results of ISE30 are not only important to us alone but also shed light on the interpretation of further results on ISE100. Both the pattern and the insignificance of the statistical results of the *CARR*s of the ISE30 following an “unexpected negative surprise” suggests that investors could not beat the market by taking a specific position in this index. The pattern of the positive unexpected surprises for ISE30 resembles the pattern of same type of events for ISE100. However, the *CARR*s are not statistically different than zero, neither. Overall, insignificant post surprise results support EMH suggesting that ISE30 index which includes securities that are a widely covered in press, highly liquid and traded in large aggregate volumes displays an efficient trading environment.

However, same analysis of ISE100 index which includes (besides the ISE30 stocks) additional 70 securities which are relatively less liquid shares with less information flow reveal different results. It is striking to note that the *CARR*s in Table 5 and the graphs in Figure 1 exhibit a set of identifiable patterns. The *CARR*s of ISE100 index exhibit largely statistically significant increases during the 30 day period following the arrival of an unfavorable market surprise. The corresponding *CARR*s for the favorable events exhibit an opposite pattern of decreases though not statistically significant. The pattern exhibited by the ISE 100 is consistent with the notion that the arrival of unexpected negative information generates market-wide uncertainty, inducing a pessimistic reaction on the part of investors, so that they initially set security prices below their fundamental values. However, further clarification of the uncertainty results in positive price adjustment to their fundamental values as predicted by the Overreaction Hypothesis (OH). Pattern of the ISE100 return following unexpected positive information also supports the OH but the *CARR*s are not statistically different from zero, preventing us from reaching a conclusive result.

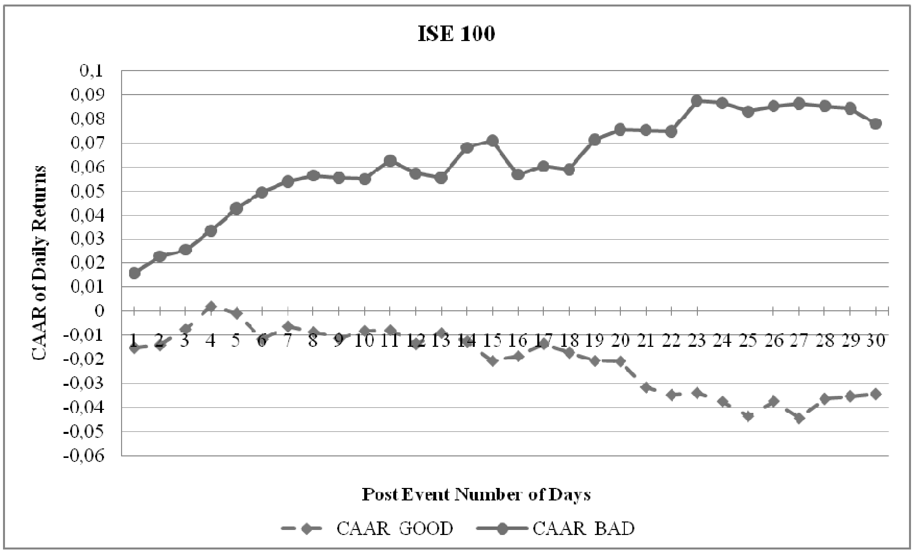


Figure1a. Post-Event Cumulative Average Abnormal Returns of ISE100

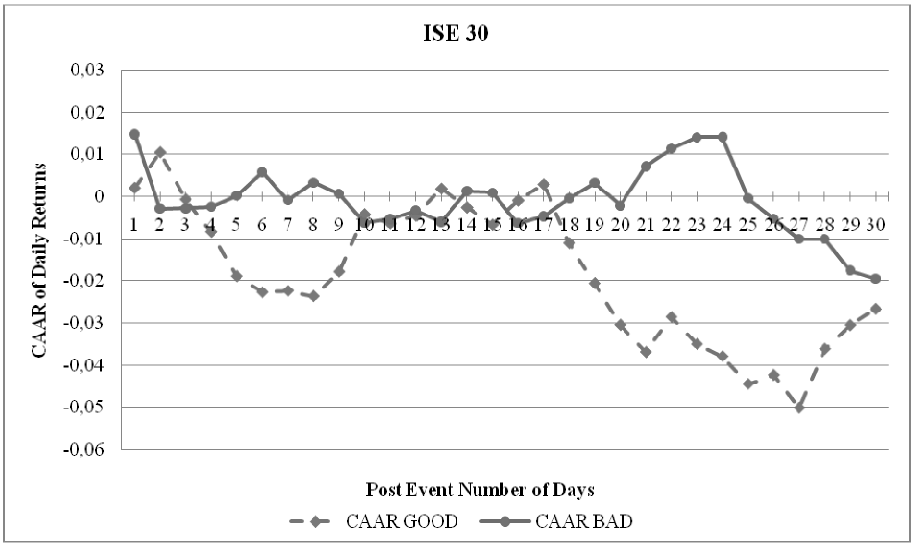


Figure1b. Post-Event Cumulative Average Abnormal Returns of ISE30

Results overall suggest that as we move from a basket of securities (ISE30) to another basket of securities relatively less liquidity and with less press coverage results reveal evidence of the violation of EMH. These patterns certainly allow investors to obtain abnormal returns. In ISE100 case, results suggest that investors could achieve significant abnormal returns by buying current losers.

Finally these results raise the question whether a similar pattern exists at individual security base. Tetlock (2010) provides evidence that is inconsistent with the idea of all inefficiencies being result of behavioral reasons. Therefore the subject deserves further examination. However, evidence of the appearance of such behavioral patterns is interesting, considering the recent regulation change enforced by The

Capital Market Board of Turkey dividing the securities in three groups based on market capitalization in order to overcome manipulation.

4. Summary and Conclusion

This paper examines investor's reaction in the Istanbul Stock Exchange Indices, ISE100 and ISE30 following the arrival of unexpected information during the period from 1988 to 2010. Market surprises are identified for both indices using a strictly quantitative "trigger-point" approach, and cumulative abnormal returns are calculated and traced for a period of 30 days following each favorable and unfavorable event.

The empirical results indicate a significant increase in the volatility of daily changes in both indices following the arrival of unexpected news. Nevertheless ISE30 pattern is consistent with EMH. We believe that it is due to the reason that the securities included in ISE30 are highly liquid, well traded and well covered in press.

In addition, patterns of cumulative abnormal returns indicate changes in ISE100 following good or bad events is consistent with the Overreaction Hypothesis. Yet, significant only on the bad news side, implying that, losses have more impact than an equivalent amount of gains as suggested by "Prospect Theory". Our findings are consistent with the notion that the presence of "noise trader risk" in stock market leads rational investors to respond to new unfavorable information by initially setting security prices below their fundamental values. Further clarifications of the uncertainty result in positive changes as security prices move to their fundamental values.

A possible implication of this study for investors is that implementing a strategy of purchasing ISE100 Index Fund following a bad news may generate abnormal results.

Finally further research is needed on individual stocks as to investigate whether such patterns are more visible for stocks with less market capitalization (i.e. relatively small company shares).

References

ABARBANELL, J.S.; BERNARD, V.L. (1992). Tests of Analysts' Overreaction/ Underreaction to Earnings Information as an Explanation for Anomalous Stock Price Behavior. *Journal of Finance*, Vol. 47 (3), pp 1181-1207

AJAYI, R., MEHDIAN, S. (1994). Rational investors reaction to uncertainty: evidence from the World's major markets. *Journal of Business Finance and Accounting* 21, pp 533-545.

BARBER B.M., ODEAN T. (2008). All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies*, 21 (2): pp.785-818.

BLACK F. (1986), Noise, *Journal of Finance* 41 (3): pp.529-543.

BROWN K.D., HARLOW W.V., TINIC S.M. (1988), Risk aversion, uncertain information, and market efficiency. *Journal of Financial Economics* 22, pp.355-385.

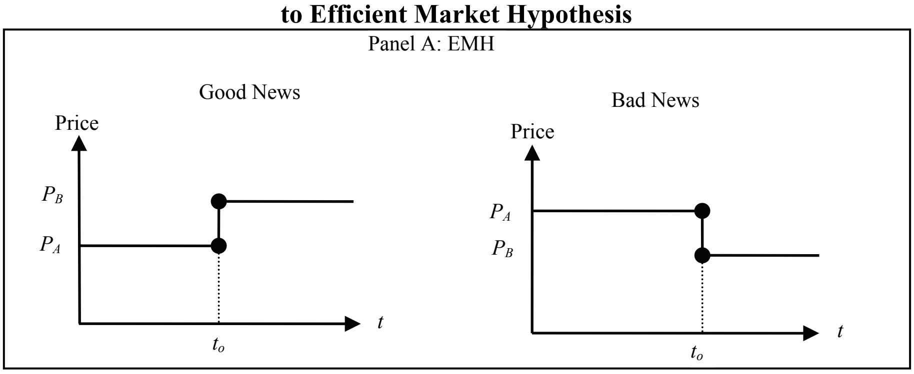
DE BONDT, W.F., THALER R.H. (1985). Does the stock market overreact? *Journal of Finance* 40, pp.793-805.

DE BONDT, W.F., THALER R.H. (1987). Further evidence on investor overreaction and stock market seasonality. *Journal of Finance* 42, pp.557-581.

DELONG, J.B., SHLEIFER, A., SUMMERS, L.H., WALDMAN, R.J. (1990), Unexpected favorable feedback investment strategies and destabilizing rational speculation, *Journal of Finance* 45, pp.379-95.

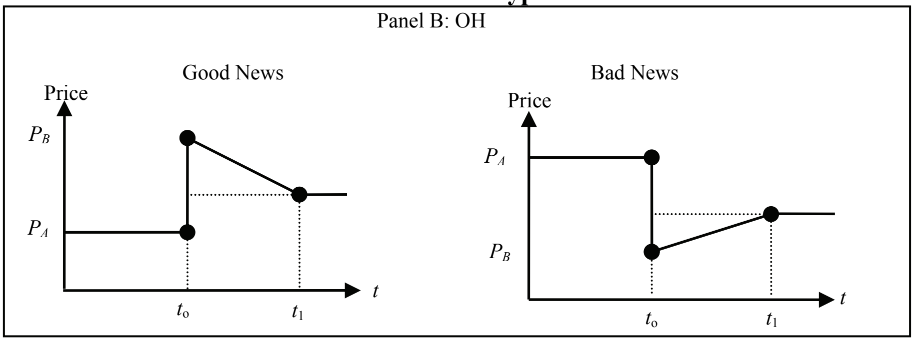
FAMA, E. (1970), Efficient capital markets: a review of theory and empirical work. *Journal of Finance,* 25, pp.383-417.
FANG, L., PERESS, J. (2009) Media coverage and cross-section of stock returns. *Journal of Finance*, 64 (5), pp.2023-2052.
HONG, H., STEIN J.C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance,* 54, pp.2143-2184.
HONG, H., LIM, T., STEIN, J.C. (2000). Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance,* 55 (1), pp.265–295.
JEGADEESH, N. TITMAN, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance*, 48 (1), pp. 65-91
KAHNEMAN, D., TVERSKY, A. (1979). Prospect theory: an analysis of decision under risk, *Econometrica.* 47(2), pp.263-292.
KAHNEMAN, D., RIEPE M.W. (1998). Aspects of investor psychology. *The Journal of Portfolio Management* 24 (4), pp.52-65.
KAMARA, A. (1997). New evidence on the Monday seasonal in stock returns. *Journal of Business*, 70, pp.63-84.
KYLE, A.S. (1985). Continuous auction and insider trading. *Econometrica,* 53 (6), pp.1315-1335.
LARSON, S.J., MADURA, J. (2001). Overreaction and under reaction in the foreign exchange market. *Global Finance Journal.* 12 (2), pp.153-177.
LEE, C.M., SHLEIFER, A., THALER, R.H. (1990). Anomalies: closed-end mutual funds. *Journal of Economic Perspectives.* 4, pp.153-164.
LEE, C.M., SHLEIFER, A., THALER, R.H. (1991). Investor sentiment and the closed-end fund puzzle. *Journal of Finance,* 46, pp.75-110.
MACKINLAY, A.C. (1997). Event studies in economics and finance. *Journal of Economic Literature*. 35 (1), pp.13-39.
NG, L., FEI, W. (2006). Revealed stock preferences of individual investors: evidence from Chinese equity markets. *Pacific Basin Finance Journal,* 14 (2), pp.175-192.
POTESHMAN A.M. (2001). Underreaction, overreaction, and increasing misreaction to information in the options market. *Journal of Finance*, 56 (3), pp.851-876.
RUBACK, R.S. (1982). The effect of discretionary price control decisions on equity values. *Journal of Financial Economics,* 10, pp.83-105.
SHLEIFER, A. (2000). *Inefficient markets: an introduction to behavioral finance*, London: Oxford University Press.
TETLOCK P.C. (2010). Does public financial news resolve asymmetric information? *Review of Financial Studies.* 23 (9), pp.3520-3557.
ZHANG, X. F. (2006) Information Uncertainty and Stock Returns. *Journal of Finance*, 61 (1), pp. 105-136.

Appendix 1a. Market Reaction to Unexpected Good and Bad News According to Efficient Market Hypothesis

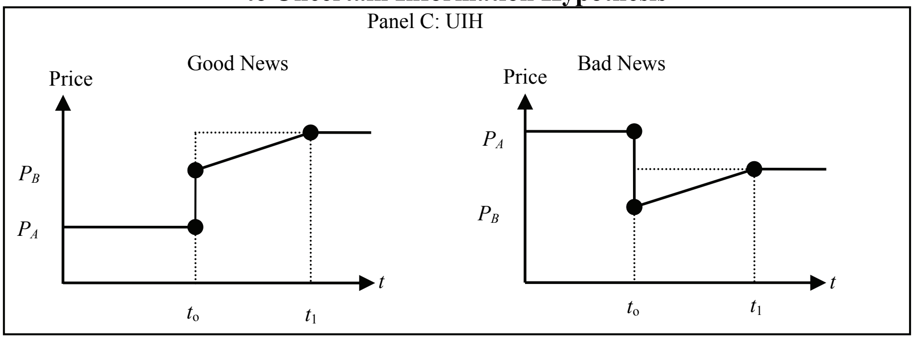


P_A = price before the news
P_B = price after the news

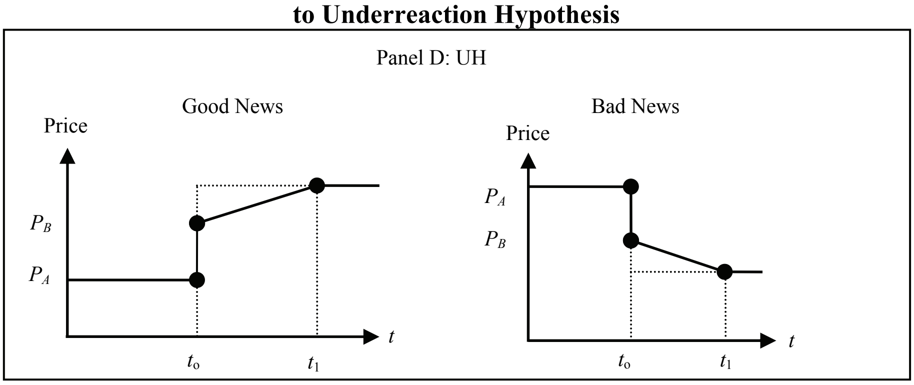
Appendix 1b. Market Reaction to Unexpected Good and Bad News According to Overreaction Hypothesis



Appendix 1c. Market Reaction to Unexpected Good and Bad News According to Uncertain Information Hypothesis



Appendix 1d. Market Reaction to Unexpected Good and Bad News According to Underreaction Hypothesis



P_A = price before the news
P_B = price after the news