Technology and Financial Crisis:

Economical and Analytical Views

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A volume in the Advances in Finance, Accounting, and Economics (AFAE) Book Series

BUSINESS SCIENCE Reference
An Imprint of IGI Global

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Cover Design: Jason Mull

Published in the United States of America by
Business Science Reference (an imprint of IGI Global)
701 E. Chocolate Avenue
Hershey PA 17033
Tel: 717-533-8845
Fax: 717-533-8661
E-mail: cust@igi-global.com
Web site: http://www.igi-global.com

Library of Congress Cataloging-in-Publication Data

Technology and financial crisis : economical and analytical views / Ali Serhan Koyuncugil and Nermin Ozgulbas, editors.
pages cm
Includes bibliographical references and index.
Summary: "This book investigates financial crises from unique points of view, considering the broader economical implications that a financial crisis can have on one business or on a whole country, and also thoroughly discussing the smaller areas that are affected or contribute to the downfall"--Provided by publisher.
ISBN 978-1-4666-3006-2 (hardcover : alk. paper) -- ISBN 978-1-4666-3007-9 (ebook : alk. paper) -- ISBN 978-1-4666-3008-6 (print & perpetual access : alk. paper) 1. Financial crises. 2. Business cycles. 3. Information technology--Management. I. Koyuncugil, Ali Serhan, 1973- II. Ozgulbas, Nermin, 1968-

HB3722.T42 2013
338.5'42--dc23

2013011229

This book is published in the IGI Global book series Advances in Finance, Accounting, and Economics (AFAE) Book Series (ISSN: 2327-5677; eISSN: 2327-5685)

British Cataloguing in Publication Data
A Cataloguing in Publication record for this book is available from the British Library.

Chapter 18
The Impact of Crises:
Evidence from the Istanbul Stock Exchange

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ABSTRACT

Stock markets are the barometers of an economy. They are very sensitive to the news and can measure economic pressures to forecast economy. They react momentarily to crises that might be triggered by such events as a currency crisis, a debt crisis, a political crisis, or an accounting fraud crisis. According to technical analysts, drastic decreases in stock prices recover from their crash value rapidly since these decreases are realized with low traded values. The overreaction hypothesis affirms that extreme price movements are subsequently adjusted by opposite direction. This chapter analyses these assertions by measuring the impacts of the crises on the Istanbul Stock Exchange (ISE) over the last decade. The duration of the crises and weekly negative abnormal percentage returns in the period of 01.01.2000-31.12.2011 are analyzed using a regression model. In this period, from a total of 621 weeks, 277 weeks have negative returns, 93 of which are identified as negative abnormal returns. The results are statistically significant, and suggest that the duration of the crises is related to the magnitude of negative returns. On the other hand, research shows that the duration of the crisis and traded value are positively correlated. This study offers empirical observations that would be useful for technical analysts and stock investors.

INTRODUCTION

It used to take months for crises to be transmitted from the originating country to other countries. Globalization shortened this period which used to be measured by months to seconds. The first example was the Black Monday on 19 October 1987, when the stock markets in Hong Kong crashed followed by the ones in Europe and the United States. The Black Monday decline was the largest one-day percentage decline with 22.61% in the Dow Jones. This crash is considered as the first systemic stock market shock (Carlson, 2007).

Capital market crashes have become contagious. Evidence suggests that stock market crises are spread globally through asset holdings of international investors (Boyer, Kumagai, & Yuan, 2006). Market reactions tend to follow the behavior of other markets rather than macro data (Kenourgios, Samitas, & Paltalidis, 2011; Khan & Park, 2009). Decoupling markets for crisis are rare and when there is one, it is temporary. Empirical

DOI: 10.4018/978-1-4666-3006-2.ch018

evidence shows that integration among markets is even stronger after the crisis (Yang, Hsiao, Li, & Wang, 2006). Markets are not only integrated in the post-crisis period but also during the pre-crisis period (Oh, Lau, Puah, & Mansor, 2010). Contagion is even more serious for emerging markets. Ülkü (2011) finds that developed markets are highly integrated, while developing markets are more strongly linked to Western markets than their neighbors.

Stock exchanges contribute to the development of capital markets and economies. However, they are fragile, and they react to economic, social and political news. Events may distort the general equilibrium all of a sudden. For instance, a credit rating agency has recently incited a new global turmoil after the AAA downgrade of the United States. The default probability of Greece and the Portugal borrowing rates that rise to record 19.4% create unrest in the countries that use euro. Therefore, the impact of the crisis can be studied by observing stock market behavior, just like using barometers (Hamilton, 1998) to predict market behavior.

A regression model is used to examine the negative reactions and their duration with XU100 index of Istanbul Stock Exchange over the period 1.1.2000-31.12.2011. The results suggest that the greater the negative reaction, the longer it takes for the index to recover the losses and to return to pre-crisis level. The results neither agree with technical analysts' view that the traded value decreases during the weeks of the crises, nor with the overreaction hypothesis that says that the extreme price movements are subsequently followed by an opposite strong trend. The paper has practical implications. It provides empirical results that would be useful especially for stock analysts and investors to review their strategies for the abnormal negative return periods.

LITERATURE REVIEW

According to the traditional asset pricing theory, co-movement in prices reflects co-movement in fundamentals in an economy with rational investors. However, as the markets are getting more and more globalized, co-movement in prices has taken a worldwide character. The conditions of big markets such as the United States and Europe affect other markets directly. Nation-specific conditions have become of secondary importance. Hence, the traditional belief that a stock market crisis occurs due to long-term cumulative deterioration of the stock market fundamentals is challenging (Kim, Lee, Oh, & Kim, 2009). That is the point technical analysts, who study past market data such as price and volume (Kirkpatrick & Dahlquist, 2006), disagree with fundamental analysts who examine financial statements.

In the context of stock markets, technical analysis is the study of the behavior of stocks in the markets which ignores the fundamental analysis that is conducted by a firm's financial data such as earnings, dividends, investments and so on. Fundamental analysts assert that the operating activities of a firm are separate from the share price of that firm in the stock markets that are shaped by many external forces. The markets are influenced very easily by optimistic or pessimistic news. On the other hand, the firm would probably not be totally influenced by these temporary news, and would continue to carry its operations as before. Thus, the share price may go up or down easily but not necessarily make the real operations of the firm better or worse. On the technical analysts' side, they are not interested in the fundamental data of the firms. One of the reasons is that the reported financial statements belong to the past, which is no more relevant for making decisions about the future. However, market prices include both the past data and the expectations of the future. The market prices have this superior advantage to fundamental data. Technical analysts believe that there are some trends in the market that repeat themselves. Thus, these trends can be determined by analyzing market prices and volumes in order to predict the directions of the prices. The strategies are also different for technical and fundamental analysts. The latter ones concentrate on the firms that promise prosperity in the long run, while technical analysts are interested in when to buy and when to sell to make trading gains in a shorter period of time. In terms of the time needed to perform the analysis, it can be said that technical analysis may be less time-consuming compared to fundamental analysis. One can decide more easily upon the charts and graphs prepared by technical analysts that can be accessed easily through the related Web sites. There are different chart patterns (head and shoulders, cup and handle, double tops and bottoms, triangles, flaps, and so forth) that can be traced through graphs. For instance, Sawin, Weller, and Zvingles (2007) documented that a trading strategy based on head-and shoulders pattern yielded excess return in stock markets. An investor may act according to these patterns. On the other hand, fundamental analysis necessitates at least elementary knowledge of financial table analysis and interpretation skills. Many technical analysts consider Dow Theory as the starting point of modern technical analysis. Although the theory is called by his name, Dow Theory was put forward after the death of Charles Dow, journalist, founder and the first editor of the Wall Street Journal and co-founder of Dow Jones and Company, who himself never used the terminology. One of the classical works on technical analysis was published in 1948 by Edwards and Magee. Levy (1966) contributed by setting the conceptual framework of technical analysis and claimed that technical analysis serves as a complement of fundamental analysis. The way technical analysts look varies from some basic analysis such as price changes, price and volume relationship, moving averages, support and resistance levels to such stochastic or moving average convergence divergence (MACD) indicators (Gorgulho, Neves, & Horta, 2011). Technical analysis may work better when institutional investors have a large trading portion in the market. Institutional investors utilize also technical analysis to decide when to enter and when to exit in order to minimize the losses. They have their pre-established enter and exit price levels so that they can act more rationally compared to individual investors who cannot control their emotions especially during the period of crisis.

In his seminal work on efficient market hypothesis, Fama (1970) affirms that one cannot predict future prices based on the past data, because all the past information has already been priced; otherwise, it would be inconsistent with the weak form of the efficient market hypothesis. Consistent with the efficient market hypothesis, random walk hypothesis (Cootner, 1964; Fama, 1965; Malkiel, 1973) also asserts that stock market prices change according to a random walk, that means that one cannot predict prices. According to the random walk theory, if an investor cannot beat the market, his best strategy would be to buy and hold the stocks for a determined period. Technical analysts refuse this theory and their major argument is one can easily see through the study of graphs, and that there are upward and downward trends for stocks. Lo and Mackinley (2001) show that market can be predicted to a certain level by using about seventy technical indicators.

Park and Irwin (2007) reviewed the literature whether technical analysis generates economic profitability. Although the technical trading strategies of early empirical studies are not profitable for stock markets, 60% of modern studies yield positive results while 20% show negative results and the rest 20% indicate mixed results. Despite positive results, the research (Park & Irwin, 2007) also draws attention to some problems (data snooping, ex post selection of trading rules or search technologies, and difficulties in estimation of risk and transaction costs) of testing procedures of those empirical research. Technical analysis is performed not only for stock markets but also for other markets. Foreign exchange markets are one of the other markets where technical analysts conduct their work. According to Taylor and Allen (1992), the best method is the technical analysis when trading currencies. For instance, Chang and Osler (1999) found that head-and-shoulder pattern in foreign exchange markets is profitable but not efficient. Similarly, a more recent study (Garcia, Gaytan, & Wolfskill, 2012) concludes that the use of chart observations through technical analysis gives valuable information on the nature of the foreign exchange markets. However, this study affirms at the same time that the strategy followed by the technical analysis does not guarantee an abnormal return for the investor who should construct his own set of rules to generate trades that take advantage.

The interest in technical analysis is multiplied by the use of artificial intelligence (genetic algorithms, fuzzy logic, pattern recognition, neural networks, and machine learning). Zhou and Dong (2004) used a fuzzy logic-based approach to incorporate human cognitive uncertainty in technical analysis. They found this approach as a valuable one that can be used by investors to have future winning trading strategies. Gorgulho et al. (2011), basing on intelligent computation, developed a new approach by genetic algorithms to select the most appropriate technical indicator that outperformed buy and hold, and pure random walk strategies. This approach has been also favorable during the crisis period of 2003-2009 when market crashed to decide on the trading strategies. Another similar study (Lin, Yang, & Song, 2011) using genetic algorithms demonstrates that the system outperformed buy and hold strategies, and profit both in bull and bear markets. However, researchers had to manually select the parameters of the system to attain the results. Therefore, there is not any guarantee that the selected parameters which have worked well for the simulation, would also work well in the real life. Additionally, parameter optimization is also studied and a proposed method improved digital trading by offering a set of close optimum solutions with the constraint of a population size effect, that is, increased population size improved the performance of the system (Papadomou & Stephanides, 2007). Thus, further work is necessitated for more enhanced technical analysis approaches and improving the system with other soft computing techniques.

However, Lo, Mamaysky, and Wang (2000) propose an objective systematic approach to use technical analysis, and found that technical indicators derived from the market data provide incremental information and have some practical value. Another view that supports technical analysis is the irrational behavior of the investors who ignore fundamentals during trading. Although efficient market hypothesis assume that investors are rational, in the real life, the impact of emotions, cognitive errors, irrational preferences, and dynamics of group behavior shape the decisions of the investors (Aronson, 2006). Black (1986) defined this latter situation as noise that makes an investor's observations imperfect. This noise effect causes the markets to be inefficient, but at the same time prevents investors to make profits from these inefficiencies. In a recent study (Bloomfield, O'Hara, & Saar, 2009), it is observed that these noise traders undertake aggressive and unprofitable trading strategies, hence simply generating noise in the market. By acting in this way, these uninformed investors increase transactions but at the same time prevent market to react to new information. As predicted in the behavioral finance literature, noise traders trade too much in ignorance. Thus, behavioral finance may explain excess market volatility and returns, which are the data for technical analysts to forecast the future.

Technical analysis has some shortcomings. First of all, there is not a best indicator (namely, exponential, hull and other moving averages, rate of change, double crossover method, relative or true strength indices, MACD and so on). Analysts should combine more than one indicator that can give conflicting signals among themselves to have a wider angle to make a decision. Secondly, the technical analyst selects subjectively the past period to form its graphs. However, this past period may be 5 days, 20 days or 250 days. Selecting different time period may give totally different buy and sell signals. Thirdly, an analyst has to see the formation of the graph before making a decision. However, by doing so, usually one third of the price movement is missed by the investor. Lastly, relying only on past market prices by disregarding the fundamentals and future outlook may be totally misleading. Prices may fluctuate to unreasonable levels due to macro or emotional reasons. These unrealistic trends would be adjusted themselves.

Overreaction hypothesis asserts that when stock prices systematically overshoot, their reversal should be predictable from past data, irrespective of the economic fundamentals. It is claimed that extreme movements will be followed by movements in the opposite direction, and the more extreme the initial movement, the greater the subsequent adjustment (Beaver & Landsman, 1981; Bondt & Thaler, 1985). Stock overreaction hypothesis explains that investors overreact to some bad or good news which will be subsequently reversed. Beaver and Landsman (1981), one of the earliest studies in this filed, introduced the terms of winners and losers to identify two adverse portfolios. The research was not fully conclusive. Bondt and Thaler (1985), using a similar methodology to Beaver and Landsman (1981), found evidence to support overreaction hypothesis. Prior losers portfolio are determined to outperform prior winners portfolio: the losers portfolio has earned about 25% more than the winners portfolio at the end of three years after the portfolio formation. They show that extreme stock changes are reversed in the following periods and conclude that the market is in a weak form of efficiency. Howe (1985) finds that stocks having bad news have significantly higher returns than the market during the 20-week period after the bad event. The results found by Brown and Harlow (1985) demonstrates that the negative events are corrected by investors in the short term. However, longer-term results indicate that investors in the negatively affected firm continue to sell their shares in the following years which point outs that the stocks that are initially marked as losers remain that way in the longer period. Pettengill and Jordan (1999) investigate the winner-loser pattern through firm size and seasonality. They demonstrate that losers have a tendency to become winners but the reverse is not true. Firm size also matters and large-firm returns are more consistent with overreaction hypothesis. They also find similar findings for the January effect which was also found by Bondt and Thaler (1985), which is the prior losers portfolio earns large positive excess returns during January.

Atkins and Dyl (1990) examine common stock prices after a large change in price that occurs during a single trading day. They observe that the abnormal return for the loser portfolio is significantly positive immediately after the large price decrease, but there is no significant price reversal for the winner portfolio immediately after the sharp price increase. They also find the magnitude of the overreaction is small compared to the bid-ask spreads observed for the individual stocks in the sample. They interpret this finding as being consistent with an efficient market. Chopra, Lakonishok and Ritter (1992) find an economically important overreaction effect even after adjusting for size and beta. In portfolios formed on the basis of prior five-year returns, extreme prior losers outperform extreme prior winners by 5 to 10% per year during the subsequent five years. Contrary to Pettengill and Jordan's (1999) findings, their study show the effect of overreaction is considerably stronger for smaller firms than for larger firms. Cox and Peterson (1994) used bid-ask spreads to examine stocks which had more than 10% daily decline. They find significant price reversals related to bid-ask spreads that led them to conclude that there is no evidence consistent with the overreaction hypothesis. Akhigbe, Gosnell, and Harikumar (1998) also used bid-ask spreads to study daily largest percentage gainers and largest percentage losers. The sample indicated significant reversals during the immediate post-announcement period. Their results indicated that the returns during the reversal period are less than the average bid-ask spread during the same time. Major losers, firms with -20 percent to -50 percent event-date abnormal returns, experience price reversals generating returns that are significantly greater than the average bid-ask spread during that period. They interpret this result as consistent with the overreaction hypothesis, contrary to the results of Cox and Peterson (1994). Larson and Madura (2003) identified samples of losers and winners by selecting daily stock price returns in excess of 10% and determined whether these samples overreacted or underreacted. They identified "informed" events, which correspond to announcements in the Wall Street Journal, and "uninformed" events, which are not explained in the Wall Street Journal. For winners, there is overreaction in response to uninformed events but no overreaction on average in response to informed events. This finding suggests that the degree of overreaction to new information depends on whether or not the cause of the extreme stock price change is publicly released.

Ma, Tang, and Hasan (2005) found no evidence of any significant overreaction effect for either the New York Stock Exchange winners or the losers for the stocks with the daily largest percentage change in price. However, they noted significant abnormal returns over two consecutive days right after the event day for the Nasdaq winners and losers. They observed a stronger overreaction effect for the loser stocks.

Ali, Nassir, Hassan, and Abidin (2009) examined a twenty-year period for Malaysia stocks and concluded that arbitrage portfolio does not provide any significant abnormal returns which is not consistent with the overreaction hypothesis. Overreaction is unjustifiable and some time is needed until the proper equilibrium is settled.

Most of the studies in the literature concentrate on the prediction of the next crisis. One of the shortcomings of those studies is that the instability period is shorter in the stock markets relative to the stability period (Kim et al., 2009). However, crises are acute rather than chronic. Markets react to the news immediately. The magnitude of the reaction may point out the severity of the crisis. Thus, instead of forecasting the next crisis, it is worth studying the magnitude and the length of the current crisis.

The duration of a crisis is debatable. It changes depending on how the question is answered. For instance, by evaluating from an economic recession point of view, National Bureau of Economic Research declared that the global financial crisis that began in 2007 and lasted 18 months came to an end on June 2009 (NBER, 2010). People who lost their jobs may interpret the crisis as over when they are re-hired. Politicians are mostly smoothing the effects and duration of crises. However, one way to determine the length of a crisis is the time when the circumstances return to the initial condition or pre-crisis time.

Crises may arise from economic, social and political reasons. The distortion of the economic variables such as inflation, growth, foreign exchange, current account, import export level, debt level, reserves and other economic factors may trigger crises. Currency and debt are the major causes of a crisis. Volatility in the currency market has increased drastically during the last decade. It is true that today the world faces a currency war. The exchange rates change on a daily basis and may behave in a contradictory manner to the news. For instance, the downgrade of the United States made its currency appreciate against Euro and most of the other currencies, while it was expected to depreciate. Although the empirical evidence (Detriagache & Spilimbergo, 2001; Sy, 2004) shows that the currency crisis and debt crisis are linked in the emerging markets; Goldstein, Kaminsky, and Reinhart (2000), Berg, Borensztein, and Pattillo (2004) and other researchers acknowledge that the currency crisis and debt crisis are distinct. Most debt crises are related to currency crises but the reverse is not true, and the currency crises are more frequent (Reinhart, 2002) but defaulting is a more serious issue.

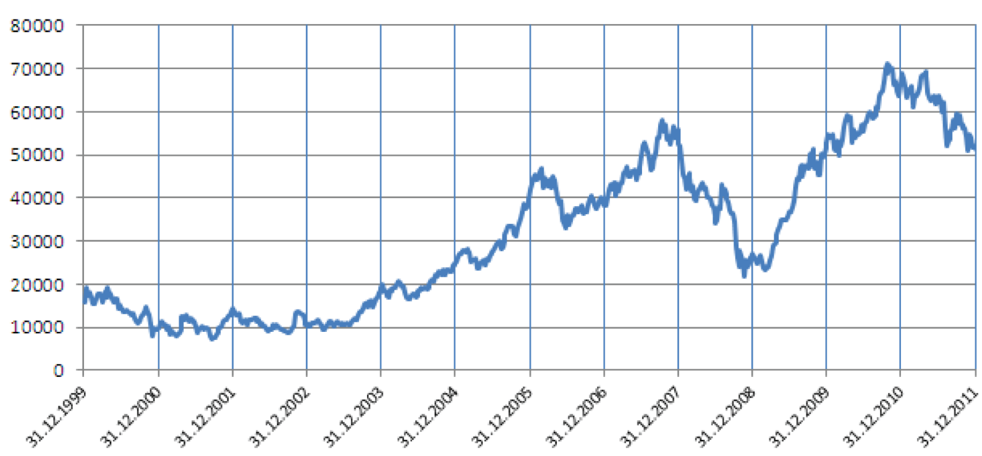
Istanbul Stock Exchange

The capital market in Turkey was established on 26 December 1985, and began its transactions on 3 January 1986. The daily calculation of ISE indices and the requirement of the external audit for the listed companies began a year later. In 1989, foreign investors were allowed to buy and sell all types of securities. Full automation of stock trading commenced in 1994. Today, foreign investment has an important share in the ISE with an equity holding ratio of approximately 62% (CSD, 2011), having the highest ratio hit as 72,63% on 15 October 2007. The highest daily traded value occurred as TL4,93 billion (US$3,08 billion) on 24 February 2011 (ISE, 2011).

Figure 1 presents the ISE XU100 index for the period 31.12.1999-31.12.2011. During the last decade, an upward trend has been witnessed. The end of the year 2002 was marked by the general election that was the beginning of one political party government period. A major downward slope occurred at the end of the year 2007 due to global financial crisis which was triggered by the bankruptcy of Lehman Brothers. The negative impact continued throughout 2008.

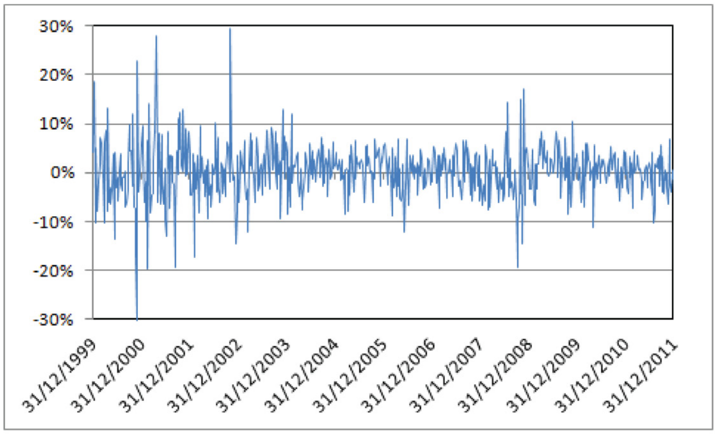
Figure 2 presents the weekly returns of the ISE XU100 index for the same period. Graphical presentation shows that the extreme returns occurred during the first half of the decade. On 24 November 2000 and 01 December 2000, the index decreased by 15.8% and 26.2% respectively as overnight interest rates rose to thousands percent due to liquidity shortages in the money markets. On 23 February 2001, a weekly decrease of 17.9% occurred when Turkey witnessed a currency crisis and Turkish Lira depreciated. The collapse of the Twin Towers on 11 September 2001 caused a weekly decrease of 17.6%. The economic crisis that was witnessed in February 2001 led to the change of the currency regime: crawling-peg cur-

Figure 1. ISE XU100 weekly closings



Note. This figure represents the weekly closing of the ISE XU100 Index for the period 31.12.1999-31.12.2011.

Figure 2. ISE XU100 weekly returns



Note. This figure represents the weekly returns of the ISE XU100 Index for the period 31.12.1999-31.12.2011.

rency regime was substituted with the floating currency exchange rate regime. The economic and political uncertainties continued until the coalition government led to the general election in November 2002 when Ak Party won the elections and formed the government alone. Figure 2 shows that the variation has an upward trend for the period 2002-2007. After this period, extreme fluctuations occurred during the global crisis that affected 2008.

METHODOLOGY

Research Design

This study differs from the previous research in some aspects. Firstly, the index is selected instead of individual stocks. This gives the opportunity to eliminate stock specific behaviors that misguide the researcher. Secondly, most of the researchers examine daily changes which are not always a true sign to determine as the point of a crisis. A daily overreaction may be easily reversed in the following day. Thus, a weekly change is a better estimate to conclude that a serious event has occurred to be identified as a turning point. Thirdly, most of the researchers subjectively determined certain periods (one month, one year, five years and so on) to assess the performance of their winners and losers portfolio. This target period is selected to measure the performance in the context of the investment strategy. However, the subjective timing may give totally contradictory results for these studies. In this study, the real duration of the negative abnormal changes are examined which give evidence about the duration of the crisis. Furthermore, a regression model is used to analyze whether the magnitude of the duration of crisis is related to the magnitude of the abnormal declines.

The study includes the ISE XU100 index for the period 01.01.2000-31.12.2011, and calculates weekly negative returns for the index as follows:

$R_t=[(lnI_t)-(lnI_{t-1})]*100$

where R_t represents return on the ISE XU100 index at period t, I_t and I_{t-1} represent the values of the ISE XU100 index at period t and period $t-1$. The return metric used is the natural logarithmic of the index weekly closing value obtained from ISE Web site. The study also examined the daily negative returns but the results of the linear regression were not significant. One important reason may be that some overreactions are temporary; that is, these overshootings are reversed in the same intensity the followings days. Hence, examining weekly returns are healthier in the sense that they signal more about the permanent character of the impact of the crisis.

The abnormal returns are determined in the following way. The weekly negative returns are put in order from the largest (closest to zero) to the smallest, and divided into three equal groups. There are 277 total negative observations and the last group with 93 observations is defined as the negative abnormal returns. This last group comprises the values less than the 0.048 (that is, a weekly negative change of 4,8%) which is determined as the cut-off point. The duration of the crisis is measured by the time between the pre-crisis index value and the date the index reaches the pre-crisis value again. There are two observations for which the duration is not completed (that is, the index has not yet reached the pre-crisis values) as of the period 31.12.2011; thus, these are removed from the sample, leaving 90 observations in the sample. Additionally, two observations presenting extreme values from both sides of the sample list were removed. These four observations which are dropped from the sample are replaced consecutively from the ranked list. The new cut-off value is 0.047.

In order to investigate the relationships between the crisis measured as negative abnormal returns and the impact of these crisis measured as the duration in days, the equation (1) is used.

$$\mathrm{D}_{t+\tau} = \alpha_0 + \alpha_1|\mathrm{R}_t| + \alpha_2\mathrm{TV}_t + \alpha_3\mathrm{TQ}_t + \alpha_4\mathrm{NC}_t + \varepsilon_t \quad (1)$$

where D_{t+z} is the duration of the crisis measured in natural logarithm of days of the crisis at time $t + \tau$, τ is the time between the day of the crisis and the day the ISE XU100 index returned to its value on the day of the crisis; $|R_t|$ is the return measured by the absolute number of the natural logarithm of the negative abnormal return of the ISE XU100 index at time t; traded value (TV_t) is measured by the natural logarithm of the total traded value which occurred during the week at time t; traded quantity or volume (TQ_t) is measured by the natural logarithm of the total traded volume in terms of nominal value which occurred during the week at time t; number of contracts (NC_t) is the number of the contracts signed during the week at time t, and ε_t is an error term. A logarithmic transformation is used to make variation constant across levels of the series in order to deal with heteroscedasticity.

The end of the crisis is defined as the point when the level of output returns to the previous trend, which is identified by the value of the ISE XU100 index. When the daily closing value of the index is equal or greater than the index value of the crisis, it is concluded that the crisis has ended.

RESULTS

Descriptive Statistics

Table 1 represents the descriptive statistics for the variables included in the analyses. The mean for duration (D) is 3.97 and for return (R) is 7.81 percent. The mean for traded value, traded quantity and number of contracts are 31.24, 29.91 and 22.73 respectively. Return is between 4.71 and 19.77 percent with a median of 6.77 percent.

Table 2 presents the Pearson correlations among test variables. The results show that there is a significant positive association between D and R variables. It signifies that when the weekly index declines are high, the duration of the crisis takes a longer time, and vice versa. R is correlated with TV and TQ, and this relationship shows that the larger the decline of the index, the greater the transactions are in terms of traded value and quantity. This correlation indicates that investors sell their stocks irrespective to the price level, which contradicts with the view of techni-

Table 1. Descriptive statistics

Variables	Mean	Std.Dev.	Median	Minimum	Maximum
D	3.97	1.51	3.85	1.61	7.20
R	7.81	3.37	6.77	4.71	19.77
TV	31.24	0.77	31.35	29.78	32.74
TQ	29.91	1.02	30.15	28.02	31.61
NC	22.73	0.37	22.74	21.99	23.67

Note. n = 93. D is the natural logaritm of the duration of the crisis in days. R is the absolute value of the abnormal negative returns expressed in percent. TV is the natural logarithm of the weekly total transaction volume in the ISE. TQ is the natural logarithm of the weekly total quantity in the ISE. NC is the natural logarithm of the weekly total number of the contracts signed in the ISE.

Table 2. Correlation between variables

	R	TV	TQ	NC
D	.141 **	.058	-.078	.013
R		-.154 **	-.155 **	-.074
TV			.885 *	.924 *
TQ				.752 *

Note. n = 93. *, ** significant at the .1 and 10 percent levels (one-tailed test), respectively.

Table 3. Regression results

Variables	Coefficient	Std. Error	t-Value	Significance
Constant	16.423	11.038	1.488	.140
R	8.519	4.495	1.895	.061
TV	2.870	.770	3.728	.000
TQ	-1.190	.334	-3.559	.001
NC	-2.955	1.133	-2.608	.011

Note. Dependent variable: duration of the crisis (D). R^2 =.17, F =4.354, significance level =.003.

cal analysts that traded volume decreases during the crisis period. As it can be estimated, TV, TQ and NC variables are correlated significantly at the 0.001 level among themselves.

The results of the equation (1) are presented in Table 3. The main interest of the study is to investigate the relationship between the duration and return as well as the duration and the volume of the transactions. Thus, the low R-square is not of great concern for the analysis. The sign of the coefficient R shows that there is a significant positive relationship between the duration of the crisis and the negative abnormal returns. When weekly negative abnormal returns are high, the duration of the crisis is also high, and when weekly negative abnormal returns are low, the duration is also low.

The coefficient of traded value (TV) is positive while the ones of the traded quantity (TQ) and number of contracts (NC) are negative, significantly different from zero, and are related to the duration of the crisis.

Ali et al. (2009) found that the overreaction behavior decreases during the post crisis period. One explanation might be that the investors have understood the importance of the situation and they shape their trading strategy. This supports the findings in this study that a crisis period has its own characteristics which are not just repeating patterns.

Overall, the results of the study show that the duration of the crisis is positively and significantly associated with the magnitude of the crisis measured by the weekly negative returns. The findings are in parallel with Fernandez-Izquierdo and Lafuente (2004) who conclude that the effects of great shocks do not disappear quickly. The greater the stock market crash, the longer it takes the index to reach its pre-crisis level. Stock investors should review their buy and sell strategy during crisis period in the light of the empirical findings of this study.

CONCLUSION

The pace of globalization and technological advancements coupled with risk appetite make crises inevitable. Studies and different methods try to anticipate the next crisis, but crises have contingent and contagious character. Any unforeseen event may trigger a crisis. Therefore, it might be more fruitful to study the duration of the crisis instead of estimating its timing. One best way to observe crises is through stock markets which react momentarily to the news. According to technical analysts, crashes in stock markets are recovered in the same manner, because the traded volume is low during the crashes that enable quick returns. The overreaction hypothesis asserts that extreme movements are reversed by extreme opposite movements.

The main objective of this paper is to investigate whether the duration of the crisis is related to the stock market negative returns. The results of this study suggest that the duration of the crises depend on the magnitude of the crises. The greater the negative return of the ISE XU100 index is, the longer the stock market index takes to reach its initial or pre-crisis level. The findings may contribute to analysts and stock investors to shape their stock trading strategies.

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KEY TERMS AND DEFINITION

Crisis: A moment of crisis is considered to be an undesired period that negatively affects the life of a person, firm, country or even the world. The crises damage the reputation (or credibility) of those they affect. It becomes imperative for the one who believes he is in the crisis period to find the ways to end it in order to restore his relations by returning to pre-crisis period.

Decoupling: In finance literature, decoupling is used to point a market that behaves differently from another or from the rest. In a global world of today, it is predicted that markets show the same patterns as each other. However, due to different reasons, one market may exhibit a contradictory pattern from others.

Efficient Market Hypothesis: The efficient market hypothesis states that one cannot consistently achieve returns over the average market returns since prices already reflect all the information. Efficient market hypothesis that says one cannot predict stock market prices oppose both fundamental analysts and technical analysts. However, efficient market hypothesis is blamed for the

2000s financial crises. Even Fama (1970), who developed the hypothesis, admitted that "poorly informed investors could theoretically lead the market astray" and that stock prices could become "somewhat irrational" as a result.

Fundamental Analysis: Fundamental analysis is concerned with the financial statements of an entity. In the case of a firm, major financial statements are the balance sheet and income statement. In the case of a country, balance of payments is an important statement that shows whether the country is in a deficit or surplus position, and that indicates the cause of this imbalance. By analyzing the statements, one can predict about the future. One important disadvantage of the fundamental analysis is that the data which is analyzed belongs to past results that can be no more valid for the current period. Thus, fundamental analysis differs itself from the technical analysis that is concerned with the market prices that is supposed to reflect all the past and future information.

Stock Market Overreaction Hypothesis: Overreaction is the instance when humans respond to a situation strongly than it is appropriate. This excessive behavior usually stems from a misevaluation of the situation or a mass movement. A declaration of a CEO or a politician may be misinterpreted and cause a sharp decline of a share price or a rising of interest level. The results of these overreactions may end by overshooting (going beyond an acceptable limit) the prices. However, the stock market overreaction hypothesis states that these overreactions are not rational and would be reversed soon after people would reconsider the situation. This permits to construct an investment strategy by buying at the overshooted prices and selling when the market returns to its normal conditions. The study that integrates the human behavior and the investors' financial decision-making is called behavioral finance.

Systemic: A systemic event affects all the elements of the system in question. For instance, when there is a currency risk in a country, all of the banks operating in that country are exposed to the risk. When there is a case of a global credit or default risk for the banking industry, this time, all the banking industries in the worldwide suffer from this situation. This risk is also called market risk and cannot be diversified. Globalization process and technological development increase the interdependence on a world scale so the events have taken a systemic character.

Technical Analysis: Technical analysis is a disciple for predicting the trend of prices through the study of past market data, especially stock prices and transaction volumes. Those who perform technical analysis believe that studying market prices instead of fundamental data has a superior advantage, because all the past and future information have already been reflected in the stock prices. They examine the reaction of investors that are not always rational. Investors show a collective behavior which makes price movements repeat themselves. Thus, technical analysts utilize these patterns by the help of computer-based techniques.