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M A S T E R ' S T H E S I S

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Abstract

This paper tests for the existence of herding behavior in the Egyptian stock market using daily and monthly data of listed companies on the Egyptian stock Exchange. We follow the methodology of Christie and Huang (1995) and Chang, Cheng, and Khorana (2000) to test for the presence of herding behavior in general, during up and down times (times of stress in the market), and during bearish and bullish market phases. We also split the sample into pre-revolution and post-revolution periods to test the effect of 25th January, 2011 revolution on herding behavior in the market. We found that: ***first***, the Egyptian stock market exhibits herding behavior in general and weak adverse herding in stressful conditions; s***econd***, prolonged effects of adverse herding exist in up markets only and herding behavior is a short-lived phenomenon; ***third***, no evidence of herding behavior during bull and bear markets was noticed; ***fourth***, during the pre-revolution period, in pre-post revolution analysis, herding existed in the Egyptian stock market in general and weak adverse herding existed during times of market stress as well as during bullish market phases, however no evidence of herding behavior during bearish market phases was observed; ***fifth***, interestingly, during post-revolution period, adverse herding exists in all market states; stressful conditions, in general, and during bullish and bearish phases; and ***finally***, after modifying the model for multicollinearity and autocorrelation, **no evidence of herding behavior in the Egyptian stock market in general for all tested periods was recorded**.

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I. Introduction

Herding behavior in financial markets has been an often observed fact. Herding means that investors do not follow rational thinking based on their own evaluation of the market. They rather follow other investors' behavior in buying and selling of stocks. When people herd, they tend to suppress their beliefs and follow others.

On the other hand, when investors refrain from following the market and rationally make informed decisions even during stressful conditions, adverse herding is said to occur in the market.

It is assumed that, in normal conditions, investors would have enough time to collect enough information, think rationally, analyze the market, and make informed decisions. However, in periods of market stress (rising and falling of prices due to extreme market conditions, roomers, economic and/ or political disturbances) investors are more biased towards others' opinions and would rather follow other investors' actions. The fear of huge losses or the thirst for higher than average returns would disturb investors' rational thinking and bias their decisions regarding entering and exiting the market (i.e. buying and selling of stocks). This stress would also decrease the time for proper information gathering and investors would be more likely to react to roomers. Such stress in the market would lead to herding behavior where investors ignore their own opinions in favor of others' views.

Time is not the only constraint that could lead to herd behavior; other reasons could exist as well. Sometimes the information required to make a rational decision may not be available to the public. Even if it is available, the quality, reliability, and credibility of the information may well present a problem to the investors. Analysts' forecasts may also be biased due to low self-confidence or weak forecasting abilities. Finally, portfolio managers' decision making process could also be distorted by their investors' behaviors and beliefs.

Normally, there should be variations in stocks' returns because individual stocks differ in their sensitivity to the market and vary in performance. However, in presence of herding behavior, individual returns are not likely to deviate much from overall market returns where individual investors follow each other's' actions and thus individual returns would be close to the market's average return. This is because most of the market is moving in the same direction – either buying or selling – and thus individual stocks' performance would follow the average performance of the market as a whole.

Herding behavior affects the market because it leads to miss pricing of assets since the decision making process is biased and accordingly risk and return determination.

There are many reasons that could cause herding behavior in financial markets; low trust in available information, information blockage, government intervention, weak regulation, forecasting difficulties, high market volatility, low disclosure requirements, and less educated investors. Thus, herding is assumed to be a characteristic of emerging economies where stock markets are expected to be inefficient.

This paper aims at identifying if herding exists in the Egyptian stock market under normal conditions as well as during times of market stress, and tests for Jan 25th revolution effects on herd behavior in the Egyptian stock market.

Egypt has gone through various market states and varying economic and political conditions. Egypt is also classified as an emerging economy and thus we find it an interesting market for testing for the presence of herding behavior.

We use daily data of 73 listed companies on the Egyptian stock exchange for the period starting Jan 2003 till April 2014 and monthly data of 86 listed companies on the Egyptian stock exchange for the period starting Jan 2000 till April 2014. We also use EGX 30 index as proxy for the market for both frequencies. To test for the revolution effect, we split the sample into two equal data sets. The first set starts Jan 14th, 2008 and ends Jan 24th, 2011 representing the pre-revolution period; and the second starts Mar 23rd, 2011 and ends Apr 15th, 2014 representing the post revolution period.

Through daily data analysis, we found evidence of weak adverse herding in extreme market conditions and evidence of herding behavior in the Egyptian stock market in general. Analyzing monthly data, we found that weak adverse herding exists in the up market conditions only, however it vanishes at the extreme tails of the distribution. We could not find an evidence for herding behavior in the market in general which means that herding behavior is a short-lived phenomenon. We also found no evidence of herding behavior in neither bearish nor bullish market phases in the Egyptian stock market. Splitting the sample we found that during the pre-revolution period, herding behavior existed in general and adverse herding existed during stressful conditions as well as during bullish market phases; however, we found no evidence of herding behavior during bearish market phases in this period. During post-revolution period, we found that adverse herding exists in general, during stressful conditions, and also during bullish and bearish market phases.

When we corrected for multicollinearity and autocorrelation, we found no evidence of herd behavior in the Egyptian stock market in general and neither did we in the pre-post revolution analysis.

The rest of the paper is organized as follows. Section II gives an overview about behavioral finance and its relation to the conventional financial theory, and defines herding behavior, its types, and possible reasons behind its existence among different market participants. Section III gives a brief about the Egyptian stock market, proposed effects of Jan 25th revolution, and how Egypt is proposed to be a fertile environment for herding behavior to exist. Section IV addresses previous literature about herding in different countries. Sections V and VI explain the data and methodology used to test for herding. Sections VII and VIII explain various tests we ran on the model and proposed modifications. Section IX explains the results and section X concludes.

II. Herding and Behavioral Finance

This section presents an overview of the basic elements of behavioral finance in relation to conventional finance theory and their implications, as well as an understanding of the concept of herd behavior and its implications for financial market behavior.

II.1. Behavioral Finance

Investment behavior of market participants in financial markets is captured by two theoretical views: conventional and behavioral finance views. The conventional view of finance and financial market behavior rests crucially on the efficient market hypothesis (EMH) (Shleifer, 2000). In an efficient market setting, asset prices always "fully reflect" all available information that is relevant for price formation (Lindhe, 2012). Since financial assets are considered to be at their fair value, conventional finance argues that active traders or portfolio managers cannot produce superior returns over time that beat the market. Therefore, investors should just own the "entire market" rather than attempting to "outperform the market." Investors therefore cannot pursue active investment strategies to beat the market index in the long run.

Three forms of market efficiency are distinguished: a weak, a semi-strong and a strong form. The weak form of the EMH assumes that prices reflect all past information. The semi-strong form assumes that prices reflect all publicly available information. The strong form of the efficient market hypothesis assumes that all relevant private information is reflected in prices (Fama, 1970).

The EMF is based on two assumptions. On one hand, investor behavior in financial markets is assumed to be rational. However, even if some investors are not rational, prices will not be affected because their trades are random and would cancel each other out. On the other hand, if investors are irrational in similar ways, the EMF assumes that arbitrageurs will eliminate price discrepancies and restore equilibrium prices.

The empirical evidence has been inconclusive. In the 1960s and 1970s, empirical evidence was consistent with the EMH (Shleifer, 2000). However, since the 1980s, empirical findings were not consistent with the conventional efficient market hypothesis. A series of "anomalies" were discovered in financial market behavior, which attracted considerable research. For example, the efficiency of asset prices was not confirmed by the findings of Nicholson (1968) and Basu (1977) who suggested that stocks with high price-to-earnings ratios (PE) are overvalued and stocks with low such ratios are undervalued (see an overview De Bondt, 2008). Moreover, calendar effects were documented (Keim, 1983; Reinganum, 1983), according to which daily abnormal returns distributions in January were found to have large means relative to the remaining eleven months (January effect). Similar anomalies were documented for a single week date (day of the week effect) and other timing intervals. (Lindhe, 2012)

In response to the observed anomalies, conventional finance models based on the EMH were challenged by behavioral finance models. Behavioral finance is a body of theoretical propositions and empirical tests that attempt to explain understanding of the reasoning patterns of investors and the degree to which these influence the decision-making process. Essentially, behavioral finance attempts to explain the what, why, and how of finance and investing, from a human perspective. This new field has been included in financial analysis from a broader social science viewpoint which includes both sociology and psychology. Nowadays, and particularly after the recent international financial crisis, behavioral finance is one of the most important research fields and challenges on the EMH (Shiller, 2003).

An earlier challenge on rational individual behavior is prospect theory (Kahneman and Tversky, 1979). Prospect theory deals with the idea that people do not always behave rationally. This theory holds that there are persistent biases motivated by psychological factors that influence people's choices under conditions of uncertainty. Prospect theory considers preferences as a function of "decision weights", which do not always match with established probabilities. Specifically, prospect theory suggests that decision weights tend to overweigh small probabilities and under-weigh moderate and high probabilities. When confronted with various options to maximize financial investment return, most investors become risk averse when confronted with the expectation of a financial gain.

Behavioral finance analysis rests on two building blocks: the limits to arbitrage and the role of psychology (Barberis and Thaler, 2003). These authors argue that real world arbitrage involves exposure to risks and costs and accordingly arbitrageurs might not interfere to correct a mispricing of an asset in a financial market. This theory contradicts sharply the EMH which is built on the foundation of arbitrageurs' abilities and motivation to correct price discrepancies. They also propose that investment decisions that cannot be explained or predicted by conventional theories can be better explained by psychological studies of investors' behavior.

In addition to the numerous studies of market 'anomalies, in the aftermath of recent financial crises (stock market crash of 1997, Asian crisis of 1997, the dot-com bubble of 2000s, and the financial crisis of 2008), the role of investor psychology in decision-making has been highlighted as an important influence on financial market behavior (De Bondt et al., 2008). Further, the EMH cannot explain many empirical puzzles that exist in the financial markets. For example, financial asset prices often demonstrate excessive tail volatility, fragility and wave-like behavior. Investors in financial markets exhibit unpredictable behavior, with localized and consensus characteristics, which is not necessarily directed by access to and absorption of private information. Thus, the assumption of independent decision-making across all investors is not reasonable. Instead, investors' behavior is shown to be interdependent subject to various influences (Devenow and Welch, 1996). Behavioral finance suggests that investors' psychology, among other non-economic factors, may offer a possible explanation, which could not be offered by the EMH, for the previous stock crashes and empirical puzzles. As a matter of fact, nowadays the tendency of individuals to mimic the actions of other's, i.e. herding, is of particular interest (De Bondt et al, 2008)

II.2. Herding Behavior

Concerns about overall market efficiency are aroused by the empirical findings that asset prices display more volatility than predicted by expected returns or fundamentals (Lux, 1995). In order to provide an explanation of these observed facts, Christie and Huang (1995) argue that the influence of herding behavior in the financial market is a frequently used explanation. The existence of herding behavior has become increasingly interesting especially in the aftermath of several financial crises. Chari and Kehole (2004) argue that financial crises are a result of widespread herding among market participants. Also Devenow and Welch (1996) claim that extensive herding behavior is believed economists and practitioners to take place among investors in various financial markets.

To understand herding, one needs to understand investors' behavior. Various factors could affect the decision making process of investors in financial markets: general market conditions, investors background and education, surrounding economic and political situation, analytical skills, confidence in oneself judgment, fear of making a mistake, time, difficulty of a situation, roomers, analyst forecasts, as well as what other investors do (mimicking). Investors' behavior can be affected by others through different channels: rumors, statements, observed actions, or observed outcomes of an action (Hirshleifer and Teoh, 2003).

Experimental social psychology gives evidence that most individuals would follow decisions made by their group even if they do not fully approve those decisions. In financial markets, investors are said to herd when they suppress their personal decisions in favor of the collective view of the market even when they do not think that this view is right (Christie and Huang, 1995). In other words, if an investor was planning to make a certain investment, but does not invest when s/he becomes aware that other investors are not going to make such an investment, the investor exhibits herd behavior, and vice versa. Thus, for an investor to herd, s/he must be aware of and influenced by other investors' actions (Bikhchandani and Sharma, 2000).

The existence of herding behavior refutes the efficient market hypothesis (EMH): that is the theory that financial markets are efficient in terms of public availability of information and that the current stock prices reflect all the available information (Caparrelli, D'Arcangelis and Cassuto, 2004). This is not only because one of the basic reasons of herding is the lack of information, but also because herding behavior biases the market leading to mispricing of assets. However, not all herding behavior leads to market inefficiency.

There are two types of herding; spurious herding and intentional herding (Caparrelli, D'Arcangelis and Cassuto, 2004). *Spurious herding* occurs when all investors are exposed to the same information and thus reach the same decision. Their behavior stems from market analysis and personal perspectives. This type of herding is not likely to affect the market since actions are a result of informed decisions. *Intentional herding*, on the other hand, is pure imitation of others, regardless of oneself beliefs. It occurs when investors act against their own judgment and follow other market participants because they doubt their decision making process, they regard other investors as superior, or because they seek conformity. This is the type of herding that we are concerned with because it is assumed to affect the market. The degree of herding varies depending on personal characteristics and context of the situation.

There are several potential reasons for herd behavior in financial markets. The relevant research is growing large. In what follows we shall concentrate on only few important reasons which include imperfect information, concern for reputation, and compensation structures.

Avery and Zemsky, (1998) argue that individuals face similar investment decisions under uncertainty and have private (but imperfect) information about the correct course of action. An investor's private information may be the result of his research effort.

Alternatively, all information relevant to a financial investment can be public but there may be uncertainty regarding the quality of this information. Individuals can observe each other's actions but not the private information that each market player receives. Even if individuals communicate their private information to each other, the idea that "actions speak louder than words" provides justification for this assumption. Only if individuals have some view about the appropriate course of action, then inferences about a market player's private information can be made from the actions chosen (Bikhchandani and Sharma, 2000). Herd behavior may arise in this setting. Moreover, such behavior is fragile in that it may break easily down following the arrival of some new information; and it is idiosyncratic in that random events combined with the choices of the first few players determine the type of behavior on which individuals herd.

Investors who have access to more reliable and credible information are likely to take the lead; those who are less informed are more likely to follow these better informed investors, a phenomenon that is called *"informational cascade"* (Zhou and Lai, 2009). It is obvious then that first movers determine what other investors do. The decision, however, may prove to be wrong for all investors. If this occurs, it is likely that those who made the decision first will reverse it, and if the herd follows, this increases the volatility of the market.

As previously mentioned, the information on which first movers based their actions may be personally collected or publicly available. The differences lie in individual interpretations and confidence in the information. Other investors would not know what type of information first movers were exposed to; they only observe their actions, unless they have an idea on which course of action is appropriate, in which case they could be able to make inferences about the type of information first movers had.

Herding behavior can be exhibited not only by individual investors, but also by financial institutions investing in the market, financial analysts and forecasters, and portfolio managers as well. The actions of all of them could bring a bias causing market unpredictability and increasing inefficiency.

Shu-Fan Hsieh (2013) suggested that individual herding is rather driven by emotions and is likely to disturb the market, but institutional herding is mostly a result of private information and it could speed the price adjustment process.

Financial analysts and forecasters are assumed to herd because of the following:

- ***Concern for reputation****:* forecasters could herd in the fear of losing their reputation in the market. They could provide recommendations that oppose their personal judgments and analysis of the market but in line with other analysts forecasts because they fear that if their recommendations turned out to be wrong they risk their reputation and credibility. Thus, when forecasters are more concerned with their reputation than with providing their accurate beliefs and results, herding occurs.
- ***Forecast ability****:* financial analysts and forecasters can also herd if they do not trust their analytical and forecasting abilities. When analysts doubt their results, they are more likely to herd.
- ***Perceived credibility of other forecasters****:* when opposing forecasts and recommendations come from credible forecasters, others are more likely to herd.
- ***Variance of forecasts****:* when most forecasters agree upon certain recommendations, others who deviate from such opinions are likely to herd in order not to stand alone if things go wrong. However, when variation increases among forecasters, there is less probability of herding behavior to occur.

Cote and Sanders (1997) argue that herding in financial forecasts is affected by forecast ability, reputational concerns, and perceived credibility of other forecasters. However they found no conclusive evidence that variations in forecasts affect herding behavior of financial analysts and forecasters. Scharfstein and Stein (1990) provide another theory of herding based on the reputational concerns of fund managers or analysts. Reputation or career concerns arise because of uncertainty about the ability or skill of a particular manager. If an investment manager and her employer are uncertain of the manager's ability to pick the right stocks, conformity with other investment professionals preserves the uncertainty regarding the ability of the manager to manage the portfolio. This benefits the manager and if other investment professionals are in a similar situation then herding occurs.

Portfolio managers may also exhibit herd behavior when there compensation is linked to the portfolio's performance compared to other investors' and the market benchmark (Maug and Naik, 1996). If this is the case, then the portfolio manager's choices may very well be biased and in most cases this could lead to herding behavior. These authors consider a risk-averse investor whose compensation increases with her own performance and decreases with the performance of a benchmark or a separate group of investors. Both the agent and her benchmark have imperfect, private information about stock returns. The benchmark investor makes her investment decisions first and the agent chooses her portfolio after observing the benchmark's actions. Then, the agent has an incentive to imitate the benchmark in that her optimal investment portfolio moves closer to the benchmark's portfolio. Furthermore, the fact that her compensation decreases if she underperforms the benchmark causes the agent to skew her investments even more towards the benchmark's portfolio than if she were trading on her own account only.

Herding not only increases asset price volatility but it also makes the overall financial system more fragile and subject to substantial destabilization following the occurrence of external shocks (Bikhchandani and Sharma, 2000).

III. The Capital Market in Egypt

Egypt's stock market is an emerging market which is thought to be inefficient due to the lack of sufficient public information, weak market awareness among investors, few financially educated market participants, and low liquidity of the market. Further, Egypt's securities market has suffered from the repercussions of the large swings in the business cycle of the Egyptian economy and the political turmoil of the recent years.

III.1. Market Developments

The Egyptian Exchange (EGX), formerly known as the Cairo and Alexandria Stock Exchange (CASE), comprises both Cairo and Alexandria stock exchanges. The first was officially established in 1883, and the latter followed in 1903. In 1909, the issuance of the first general regulations for stock exchanges was made.

The Egyptian Financial Supervisory Authority (EFSA) is the authority responsible for the supervision of non-bank financial markets and instruments, including the Capital Market, the Derivative Exchange as well as all activities related to Insurance Services, Mortgage Finance, Financial Leasing, Factoring, and Securitization.

The two Exchanges were very active in the 1940's and Alexandria Stock Exchange was ranked the fifth in the World. In 1953, the first law to regulate the market trading after 1952 revolution was issued. In 1980, The Capital Market Authority (CMA) was established. In 1994, the exchange shifted to an automated order-driven system. In October 1996, Misr for Central Clearing, Depository and Registry was established. MCDR is a private company which handles the clearing and settlement operations and also acts as the Central Depository for all securities in Egypt. The main shareholders of MCDR are EGX, banks and member firms.

The Presidential Decree No. 51 for year 1997 re-defined the legal structure of the Exchanges and accordingly both are governed by the same board of directors and share the same trading, clearing and settlement systems. Also in the same year, Cairo and Alexandria Stock Exchange was added to the International Finance Corporation (IFC) Global and Investable Indices.

In 2001, Cairo and Alexandria Stock Exchange was included on the Morgan Stanley Capital International (MSCI) Emerging Market Free Index (EMF) and EMEA and All Country World Index.

On February 1st, 2003, the Egyptian exchange launched the EGX 30 index to include top 30 companies in terms of liquidity and activity. The Index is weighted by market capitalization and adjusted by free float. It is a good representation the market because it is well diversified among different sectors of the economy.

On June 18, 2012, EGX became a founding member of the United Nations Sustainable Stock Exchanges initiative on the eve of the United Nations Conference on Sustainable Development (Rio+20)

Neither the transactions taking place on the stock exchange nor the dividends distributed by the listed companies to shareholders are subject to tax. Moreover, there are not any restrictions precluding foreign participation in the market.

The exchange has normal trading sessions from 10:30 am to 2:30 pm, local time, on all weekdays, except Fridays, Saturdays, and holidays declared by the exchange in advance. (Frequently asked questions: The Egyptian Exchange, 2014), (Wikipedia: The Egyptian Exchange, 2014)

III.2. The Capital market after the Jan. 25th Revolution

Since January 2011, Egypt has become an unstable country economically and politically. The revolution aroused calling for freedom, social justice, and better living conditions has negatively affected the economy in various ways. Three years now and the Egyptians haven't reaped any of what they went out calling for. The average standard of living has decreased, and unemployment rate, poverty, budget deficit, and debt rate have all increased. The political situation in the country has been unclear with many parties struggling to govern. The tourism sector – one of the most important revenue generating sectors in Egypt – has gone through a stagnation phase due to the instability of the security situation. The investment sector has been suffering because the country has lost its attractiveness for both domestic and foreign investors due to the uncertainty in almost all country aspects.

The stock market has also fallen, especially during the revolution, and volatility has extremely increased which decreased the efficiency of the market. Kamal (2014) reported a 16% decrease in the EGX 30 index during the first few days of the revolution before the authorities decided to close the market on Jan 28th, 2011 – to prevent further losses. Ezzat (2012) also reported another fall of 9% after the reopening of the market on March 22nd same year. Ezzat (2012) studied the Egyptian stock market during the political turmoil of 2011 and found that, during the revolution period, all market indices exhibited high standard deviations – implying high volatility of stock returns – where EGX 70 showed the highest volatility. Kamal (2014) tested the market for weak form efficiency and was specifically concerned with the effect of closing the market for almost two months. First, she implied that both market indices, EGX 30 and EGX 100, were sensitive to uncertain conditions. Second, that negative information affected expectations of investors faster than positive information did. Third, that closing the stock market has actually negatively affected the market.

Thus, these significant fluctuations of asset prices and market indices in the Egyptian exchange make the latter a good candidate for analyzing the existence of herding behavior along the empirical lines pursued for other emerging markets. We turn now to the relevant empirical literature on herd behavior. The latter is growing considerably, indicating the persistent interest in this phenomenon.

IV. Literature Review on Empirical Herd Behavior

Herding in financial markets has been regarded by behavioral finance researchers as a behavior that could affect financial asset prices and future returns. Thus, papers were written with the aim of finding whether herding exists in different stock markets and, if it does, whether it affects the market in terms of future returns and volatility.

The empirical investigation of herd behavior in financial markets is divided into two broad parts (Chiang and Zheng, 2010). The first line of research examines co-movement behavior based on measures of dynamic correlations among asset prices. Forbes and Rigobon (2002) study three financial crises (US stock market crash in 1987, Mexican peso devaluation in 1994, and the Asian financial crises in 1997) and analyze the presence of sustainable contagion and interdependence of asset prices during these crises. They find no significant evidence of contagion during these crises periods. Baur and Fry (2004) find that interdependence is of more significance than contagion during the Asian crisis. In contrast, Corsetti et al. (2005) find partial evidence of contagion in their study of the Hong Kong stock market crisis in October 1997 to both emerging and industrial countries. Billio and Caporin (2010) also find some evidence of contagion between the US and the Asian markets. Boyer et al (2006) split emerging market stocks into those which are accessible by foreigners and those that are not, and they find larger co-movement during high volatility periods in accessible stocks' returns, thus highlighting the role of foreign investors. Chiang et al (2007) detect two phases of the crisis: the first phase is characterized by increasing correlation in stock returns, and the second is characterized by consistently higher correlation between stock returns. They argue that in the first phase of the crises the main focus of investors is on local country information causing contagion. As the crisis becomes widely known, investors' decisions tend to converge due to herd behavior, which in turn raises the degree of correlation.

The second line of research focuses on the cross-sectional dispersion in stock returns, which is taken as a measurement for herd behavior. This is also referred to as market-wide herding (Hwang and Salmon, 2004). This line of research was initiated with Christie and Huang (1995), who analyzed the US market and argued that herding among investors is more likely during periods of market stress. The cross-sectional standard deviation of equity returns is used as a measurement for dispersion. A decrease in dispersions during market stress is taken to indicate the presence of herding. Bit no evidence of herding was found in the US stock market. Chang et al (2000) suggested a similar but less stringent method to detect herding in the market. They use the cross-sectional absolute deviation as a measurement for dispersion. Significant evidence of herding was found in emerging countries Taiwan and South Korea, partial evidence of herding was found in Japan, and no evidence of herding was found in the US and Hong Kong markets. Asymmetry of dispersions as a function of the aggregate market return was found across all markets, there is less increase in dispersion during down-market days.

The methodology of Christie and Huang (1995) and Chang et al (2000) is widely accepted as a measurement for herding and several studies have applied their methods or modified versions of it (Lindhe, 2012). Indeed, Hwang and Salmon (2004) found that herding exists in the United States and South Korea during rising and falling times. However, contrary to common beliefs, they found that herding behavior actually decreased during crisis times. Caparrelli, D'Arcangelis, and Cassuto (2004) found evidence of adverse herding during stress times in the Italian stock market. Caporale, Economou, and Philippas (2008) found that herding exists in Athens stock market during stress times. However they found that herding started to get weaker since 2002 and they attributed this to the Greek equity market institutional and regulatory reforms and foreign institutional investors increased market presence. They also found evidence that herding is a short lived phenomenon. Tan, Chiang, Mason and Nelling (2008) found, using daily data, that herding exists in A and B-shares markets in China but it is more prevalent in A- shares market. Zhou and Lai (2009) studied informational cascades in relation to herding behavior in Hong Kong and found that; first, investors herd more when the market is low. Second, herding occurs in more dominant industries –the financial sector and the property and construction sector in the case of Hong Kong. Third, investors are more likely to herd when selling than when buying stocks. And finally, informational cascades do exist in Hong Kong stock market. Cajueiro and Tabak (2009) found evidence of herding behavior in Japan stock market during bearish times when investors are more likely to herd as proposed by literature. Chiang, Li, and Tan (2010) found that herding exists in A-shares market in China during up and down times but found no evidence of herding in both states in B-shares market. However, using quantile regression analysis – a new method proposed by them – they found evidence of herding behavior in B-shares market during down times. Chang, Chen, and Jiang (2012) used intraday data to test for herding behavior for institutional as well as individual investors in Taiwan stock market and how would herding strategies affect their portfolio returns. They found that herding is stronger among institutional investors, though individual investors gain more profits through herding than institutional investors do. Chen, Yang, and Lin (2012) found that foreign institutional investors herd towards stocks in the same industry in Taiwan using daily data. Balsco, Corredor, and Ferreruela (2012) investigated the impact of herd behavior on Spain's stock market volatility. They suggested that firms with larger market capitalization and high trading volume during down market conditions set the ideal environment for herd behavior to exist. They proposed that because high market capitalization firms provide low search costs and are easy to sell, investors may prefer to herd on such firms. Concerning volatility and herding, they found that high level of herding leads to greater price changes, higher volatility, and sometimes less informative prices. Thus, according to the authors, herding has a direct linear impact on volatility, though not uniform. Prosad, Kapoor, and Sengupta (2012) concluded that no severe herding has been reported in the Indian stock market; however they found that herding exists during bull phases. Saumitra (2012) was the first to use the econometric model with threshold effect proposed by Hansen (2000) and found little evidence for market herding even during stress times in India.

More recently, Bhaduri and Mahapatra (2013) found that herding exists in the Indian stock market however they stated that certain years happen to be more prone to herding behavior than others. Lee, Chen, and Hsieh (2013) used daily data to test for industry herding in China A-shares market and found evidence for herding behavior. Klein (2013) differentiated between turmoil and tranquil trading periods in the United States and Euro area using daily data and found that adverse herding exists during periods of turmoil and crisis (This means that investors act rationally during crisis times). Ahsan and Sarkar (2013) found no evidence for existence of herding behavior in Bangladesh stock market using daily and monthly data of listed companies in Dhaka Stock exchange. Hsieh (2013) used intraday data to test for the existence of institutional as well as individual herding behavior in Taiwan stock market and the effects of such behavior on stock returns. He found that institutional investors tend to herd more than individual investors and they herd more on firms with small market capitalization, however herding by individual investors increase during volatile periods. He suggested that herding among institutional investors is more likely to be driven by information than by behavior and feelings as with individual investors. Yao, Ma, and He (2014) used daily and weekly data to test for the existence of herding behavior in China A and B- shares markets during up and down times. They found that, first, herding exits in both markets during up and down times, however it is more prominent in B-shares market (which contradicts the findings of Tan, Chiang et. al (2008) that herding is stronger in A-shares market). Second, herding is strongest among smallest and largest stocks but mid trading firms do not exhibit significant herding. Finally, they give evidence that herding is a short lived phenomenon and depends on the industry level.

V. Data

The study uses daily price data of 73 companies listed on the Egyptian Stock exchange, ranging from Jan 2003 till April 2014. We chose this period because it includes various market phases: normal phases as well as abnormal ones, such as the 2008 financial crisis, and the pre- and post-Jan 25th revolution. We also use monthly price data of 86 listed companies from Jan 2000 till April 2014 to account for the probability that herding is not a short-lived phenomenon and that it might take time to affect the market as suggested by Christie and Huang (1995). We use EGX 30 index to measure daily and monthly market return for the same periods. All data was extracted from Thomson Reuter's database. For pre-post revolution analysis, we split the sample into two equal data sets; the pre-revolution period starts Jan 14th, 2008 and ends Jan 24th, 2011 and the post-revolution period starts Mar 23rd, 2011 and ends Apr 15th, 2014.

VI. Methodology

The approach taken by the paper is to detect market-wide herding. The latter arises when investors in the market ignore the individual characteristics of assets and, instead, follow the performance of the market. The advantage of this particular method is that it is fairly simple (Lindhe, 2012). However, the disadvantage is that the method is based on subjective beliefs or information guiding the decisions of individual investors following the performance of the market as a whole.

Christie and Huang (1995) suggest that that a suitable measure of the market impact of investor herding is dispersion. As it measures the average proximity of individual returns to the market return, dispersions are bounded from below zero. When individual returns differ from the market return, the level of dispersions increases. Thus, market-wide herding would indicate a decrease in dispersions (Lindhe, 2012). Because investors think differently, individual stocks would normally vary in their performance and sensitivity to market reactions and thus their returns would deviate from overall market return. However, when investors herd around the market, stock returns would not exhibit as much deviation; individual stock returns will cluster around overall market return. Christie and Huang used the cross-sectional standard deviation as a dispersion measure (CSSD). They also proposed that individuals are more likely to follow the performance of the market during stressful market conditions (periods of large market movements). Accordingly, individual returns will not significantly differ from the market return. Thus, the level of dispersions, CSSD, will be lower than during normal market conditions. This comes in contrast to rational asset pricing models were dispersions are assumed to increase during periods of large market movements.

Chang et al (2000) extend the work of Christie and Huang (1995) and present a modified and less strict method to detect herding behavior in the market as a whole. They assumed (as did Christie and Huang) that rational asset pricing models suggest an increase in dispersions during stressful periods in the market and that these models would predict a linear relation between dispersions in individual assets and the market return (i.e. the dispersions are an increasing function of the market return). The authors use CSAD as a measurement of dispersion, which they base on the conditional version of the Capital Asset Pricing Model. They propose that the presence of herding behavior in the market would cause the linear relationship to become non-linear and would decrease the level of dispersions. This means that the dispersions will decrease or at least increase at a less-than-proportional rate with the market return (Chiang and Zheng, 2010). Thus, the method of Chang et al (2000) is better for detecting herding behavior during more normal conditions as well as during periods of market stress.

More specifically, following Christie and Huang (1995) where they measure dispersion by:

$$CSSD_t = \sqrt{\frac{\sum_{t=1}^{N}(R_{i,t} - R_{m,t})^2}{N-1}}$$

Where:

- $CSSD_t$ is the Cross Section Standard Deviation of individual stocks' returns around the markets',
- $R_{i,t}$ is stock i's return at time t,
- $R_{m,t}$ is the average return of the sample at time t, and
- N is the number of companies included in the sample

They propose that herding only occurs in stressful market conditions where people fail to rationalize their decisions and find it easier to follow other investors. They define market stress or extreme conditions where market returns fall at the tails of their distribution.

The regression model is

$$CSSD_t = \alpha + \beta^{up} D_t^{up} + \beta^{down} D_t^{down} + \varepsilon_t \qquad \textbf{(1)}$$

Where:

- α denotes the average dispersion of the sample that is not captured by the dummy variables
- D_t^{down} is a dummy variable that takes the value of 1 if the market index return falls at the lower tail at 96% and 99% of the index distribution and zero otherwise (i.e. when $R_{index} < -2\sigma_{Rindex}$ and $R_{index} < -3\sigma_{Rindex}$)
- D_t^{up} is a dummy variable that takes the value of 1 if the market index return falls at the upper tail at 96% and 99% of the index distribution and zero otherwise (i.e. when $R_{index} > 2\sigma_{Rindex}$ and $R_{index} > 3\sigma_{Rindex}$)

Hypothesis

H_0: $\beta^{down} < 0$ (i.e. herding exists when returns fall at the lower tail of the returns' distribution – down market)

$\beta^{up} < 0$ (i.e. herding exists when returns fall at the upper tail of the returns' distribution – up market)

H_1: $\beta^{down} \geq 0$ (i.e. herding does not exist when returns fall at the lower tail of the returns distribution)

$\beta^{up} \geq 0$ (i.e. herding does not exist when returns fall at the upper tail of the returns distribution)

If the dummies' coefficients are negative and statistically significant at 95% confidence interval, we fail to reject the null hypothesis and conclude that herding exists at stressful market conditions. However, if the coefficients are positive and statistically significant, we reject the null hypothesis and conclude that adverse herding exists in the market during stressful conditions.

We also follow Chang, Cheng and Khorana (2000) in order to account for all market states and not restrict the model to stressful conditions. Because the CSSD can be sensitive to outliers, they measured returns' dispersion by

$$CSAD_t = \frac{\sum_{t=1}^{N} |R_{i,t} - R_{m,t}|}{N}$$

Where:

- $CSAD_t$ is the Cross Section Absolute Deviation of individual stocks' returns around the markets',
- $R_{i,t}$ is stock i's return at time t,
- $R_{m,t}$ is the average return of the sample at time t, and
- N is the number of companies included in the sample

And used the regression model

$$CSAD_t = \alpha + \beta^{down} D_t^{down} + \beta^{up} D_t^{up} + \varepsilon_t \qquad \textbf{(2)}$$

Chang, Cheng, and Khorana (2000) argued that herding would increase the correlation of stock returns and that the linear relationship proposed by the CAPM (Capital Asset Pricing Model) – which normally exists between individual stock return and market return – becomes nonlinear when herding occurs in the market. We use their modified regression model proposed by Lee, Chen, and Hsieh (2013)

$$CSAD_t = \beta_0 + \lambda_1 R_{m,t} + \lambda_2 |R_{m,t}| + \lambda_3 R_{m,t}^2 + \varepsilon_t \qquad \textbf{(3)}$$

Where:

- $R_{m,t}$ is the average return of the sample at time t. This term was added by Lee, Chen, and Hsieh (2013) to consider asymmetric behavior under different market states,

- $\left|R_{m,t}\right|$ is the absolute market return at time t to account for the magnitude and not the direction of the market, and
- $R_{m,t}^2$ captures the nonlinear relationship that would arise due to herding.

A negative, significant $\lambda_3$coefficient would indicate the presence of herding behavior.

Because the relationship between CSAD and market returns can be asymmetric in bull and bear markets, they further separated the up mentioned model into the following two equations to measure herd behavior in bull and bear markets.

Bull market

$$CSAD_t^{Up} = \alpha + \delta_1^{Up}\left|R_{m,t}^{Up}\right| + \delta_2^{Up} R_{m,t}^{Up\,2} + \varepsilon_t \text{ , if } R_{m,t} > 0 \qquad \textbf{(4)}$$

Bear market

$$CSAD_t^{Down} = \alpha + \delta_1^{Down}\left|R_{m,t}^{Down}\right| + \delta_2^{Down} R_{m,t}^{Down\,2} + \varepsilon_t \text{ , if } R_{m,t} < 0 \qquad \textbf{(5)}$$

Negative, significant δ_2^{Up} coefficient would indicate the presence of herding behavior in bullish market and negative, significant δ_2^{Down} coefficient would indicate the presence of herding behavior in bearish market.

VII. Tests for the Model

Although the model proposed by Chang, Cheng and Khorana (2000) has strong foundation in theory and was used by most previous literature, the model has potential shortcomings due to the high level of multicollinearity between the independent variables $\left|R_{m,t}\right|$ and $R_{m,t}^2$ and this decreases the significance of results (Yao et al., 2014). Thus, we ran the following tests to ensure the validity of the model.

VII.1. Normality

In order to test for the null hypothesis of normal distribution for all variables with 99% confidence interval we calculated the Jarque-Bera test. If the P-value is < 0.01, we reject the null hypothesis of "normal distribution" and conclude that the data is not normally distributed. Also we use the Kurtosis – a descriptive statistic for fat tails which shows the probability for extreme events. When kurtosis is greater than 3, the variable does not follow a normal distribution. From the below tables we see that none of the variables used in our regression equations is normally distributed. It is a stylized fact that many financial time series do not follow a normal distribution.

Fig. 1 – CSSD Histogram and Statistics

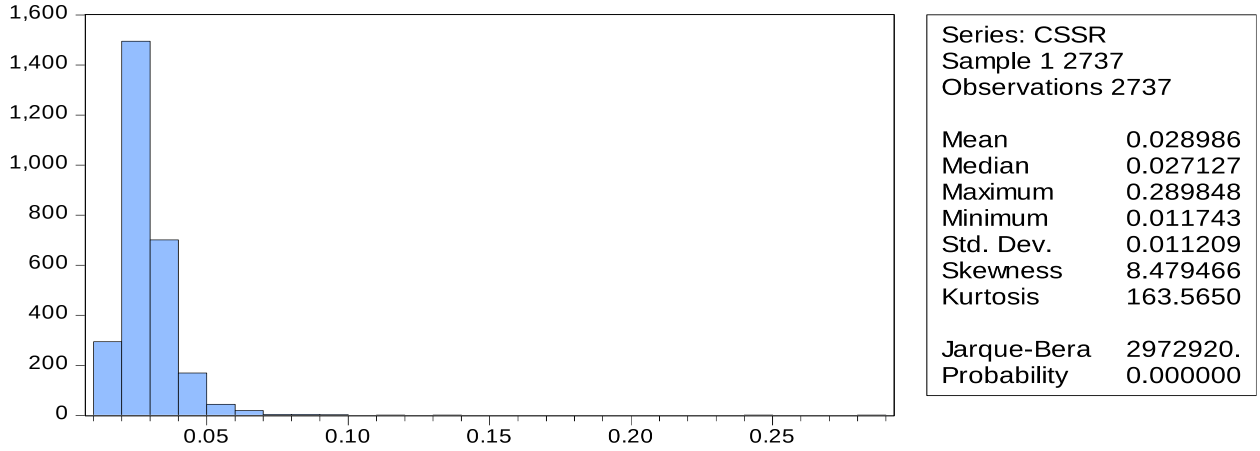


Fig. 2 CSAD Histogram and Statistics

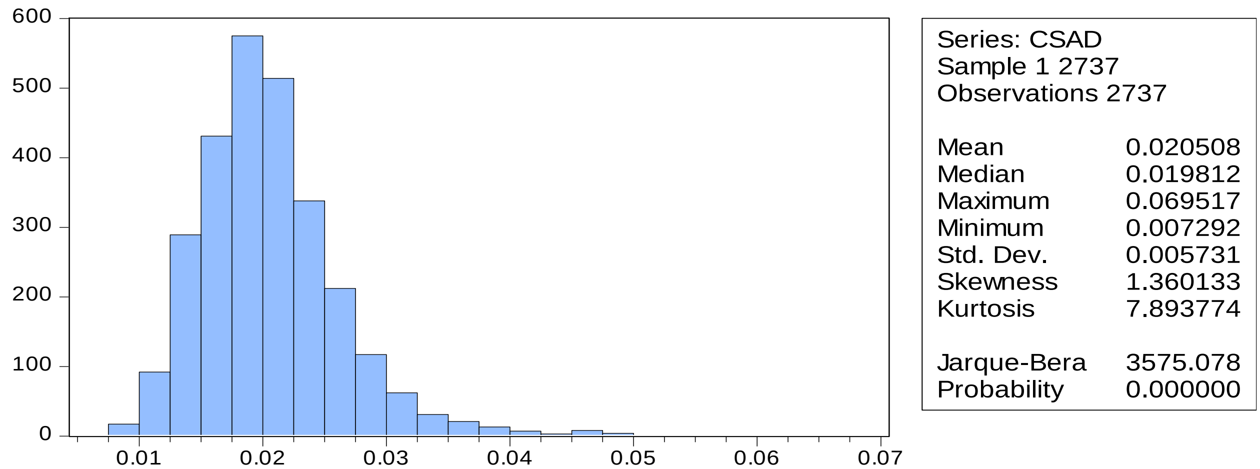


Fig. 3 – EGX 30 Returns Histogram and Statistics

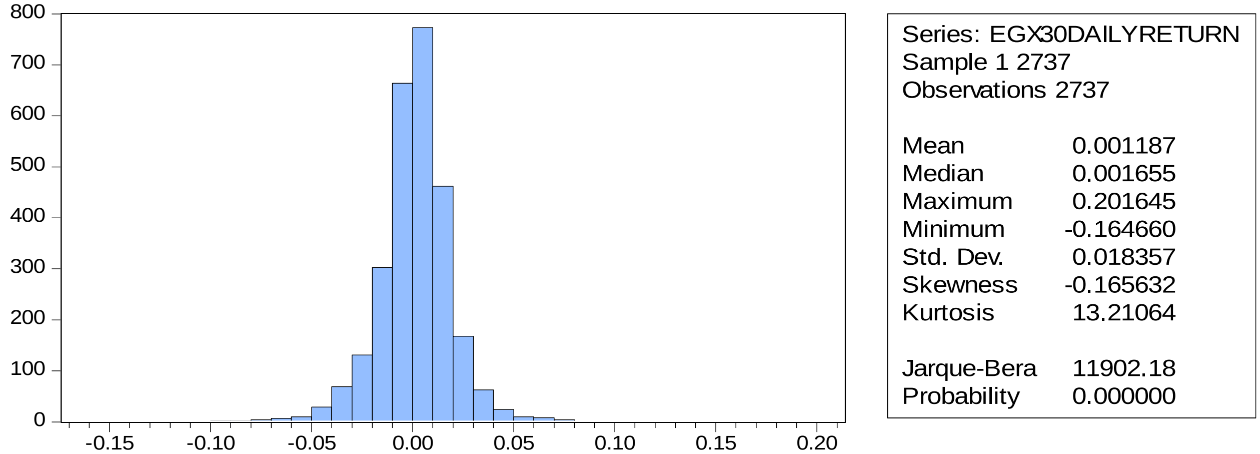


Fig. 4 – EGX 30 Absolute Returns Histogram and Statistics

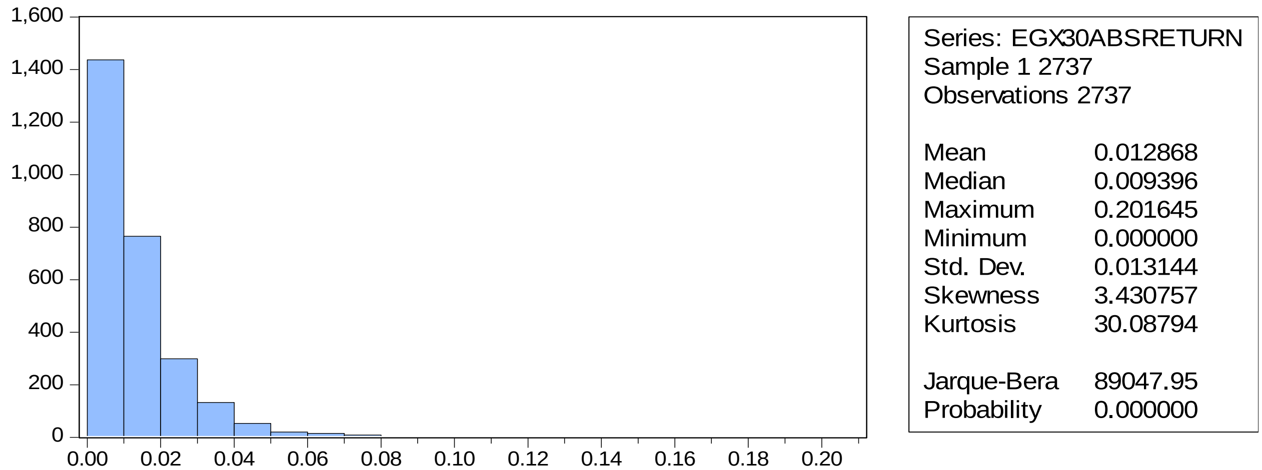
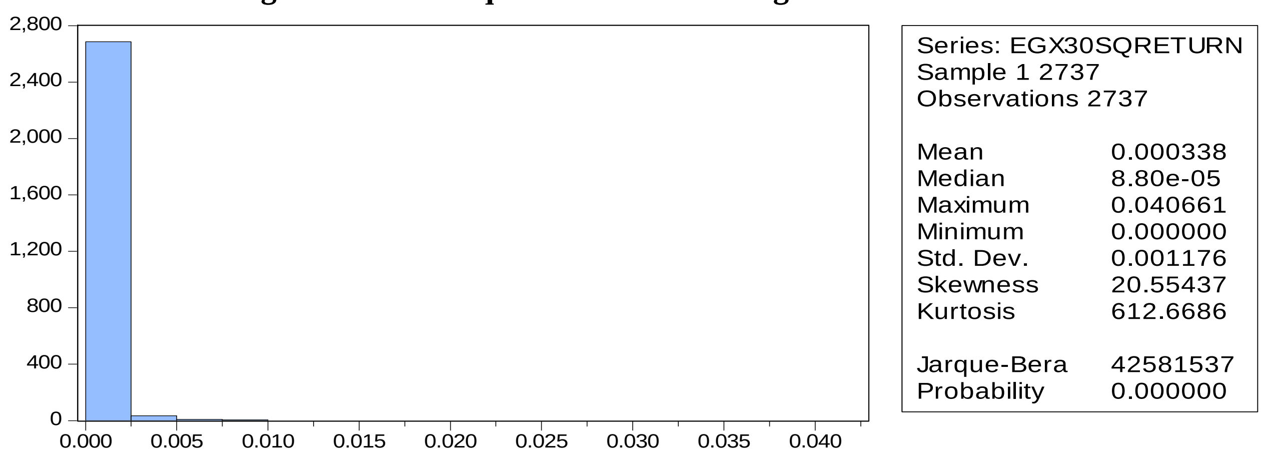


Fig. 5 – EGX 30 Squared Returns Histogram and Statistics



VII.2. Heteroscedasticity

As previously mentioned, multicollinearity may be an issue in the model we will use. Thus, we have tested the model for the presence of heteroscedasticity using White's General Heteroscedasticity test. Under the null hypothesis of homoscedasticity, the sample size n times the R^2 obtained from the auxiliary regression asymptotically follows a Chi-square distribution with degrees of freedom equals to the number of regressors (Gujarati & Porter, 2009). Since the p_{value} χ^2 is < 0.01 we reject the null hypothesis and conclude that the model suffers from heteroscedasticity.

Table 1 – Heteroscedasticity Test Result

Heteroscedasticity Test: White

F-statistic	3.917950	Prob. F(8,2728)	0.0001
Obs*R-squared	31.08980	Prob. Chi-Square(8)	0.0001
Scaled explained SS	116.3974	Prob. Chi-Square(8)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/16/14 Time: 08:32
Sample: 1 2737
Included observations: 2737
Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.83E-05	3.61E-06	7.840879	0.0000
EGX30DAILYRETURN	-3.41E-05	0.000214	-0.159160	0.8736
EGX30DAILYRETURN^2	-2.279640	5.239916	-0.435053	0.6636
EGX30DAILYRETURN*EGX30ABSRETURN	0.003541	0.007127	0.496921	0.6193
EGX30DAILYRETURN*EGX30SQRETURN	-0.000845	0.043008	-0.019647	0.9843
EGX30ABSRETURN	-0.000540	0.000661	-0.817327	0.4138
EGX30ABSRETURN*EGX30SQRETURN	-0.154197	0.420291	-0.366881	0.7137
EGX30SQRETURN	2.310143	5.240010	0.440866	0.6593
EGX30SQRETURN^2	0.031689	1.517316	0.020885	0.9833

R-squared	0.011359	Mean dependent var	2.91E-05
Adjusted R-squared	0.008460	S.D. dependent var	7.98E-05
S.E. of regression	7.94E-05	Akaike info criterion	-16.03961
Sum squared resid	1.72E-05	Schwarz criterion	-16.02016
Log likelihood	21959.21	Hannan-Quinn criter.	-16.03258
F-statistic	3.917950	Durbin-Watson stat	1.527137
Prob(F-statistic)	0.000129		

VII.3. Autocorrelation

We also test for autocorrelation. The null hypothesis is that there is not serial correlation. Since the Durbin-Watson test for first order autocorrelation is 0.6644 which is closer to 0 for n = 2738 and k = 3, we reject the null hypothesis of no autocorrelation at the 5% level and conclude that there is evidence of positive autocorrelation.

Table 2 – CSAD on Returns Regression Output

Dependent Variable: CSAD
Method: Least Squares
Date: 04/30/14 Time: 15:52
Sample: 1 2737
Included observations: 2737

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.018272	0.000167	109.6940	0.0000
EGX30DAILYRETURN	-0.005275	0.005626	-0.937600	0.3485
EGX30ABSRETURN	0.194154	0.012854	15.10400	0.0000
EGX30SQRETURN	-0.757249	0.143621	-5.272550	0.0000

R-squared	0.113490	Mean dependent var	0.020508
Adjusted R-squared	0.112516	S.D. dependent var	0.005731
S.E. of regression	0.005399	Akaike info criterion	-7.603622
Sum squared resid	0.079675	Schwarz criterion	-7.594978
Log likelihood	10409.56	Hannan-Quinn criter.	-7.600499
F-statistic	116.6247	Durbin-Watson stat	0.664172
Prob(F-statistic)	0.000000		

VII.4. Stationarity

In order to check whether the independent variables are stationary processes we use the Dickey-Fuller unit root test. The null Hypothesis is that the time series are non-stationary (i.e. have a unit root). The computed ADF test-statistic was found smaller than the critical values for all tested variables at 1%, 5%, and 10% significance. Thus, we reject the hull hypothesis and conclude that all variables are stationary (Appendix A).

VIII. Proposed Modifications

To correct for multicollinearity and autocorrelation, we re-ran the regressions – for the daily data analysis as well as the pre-post revolution analysis – using the modification proposed by Yao et al. (2014) on eq. (3) as follows:

$$CSAD_t = \beta_0 + \lambda_1 R_{m,t} + \lambda_2 |R_{m,t}| + \lambda_3 R_{m,t}^2 + \lambda_4 (R_{m,t} - \bar{R}_{m,t})^2 + \lambda_5 CSAD_{t-1} + \varepsilon_t \quad \textbf{(6)}$$

Where

- $\bar{R}_{m,t}$ is the arithmetic mean of $R_{m,t}$, and
- $CSAD_{t-1}$ is the 1-day lag of the dependent variable $CSAD_t$

These modifications are proposed to remove a large portion of multicollinearity and increase the power of the model (Yao et al, 2014).

IX.Results

IX.1. The Whole Sample

a. Descriptive Statistics

All dependent and independent variables are quantitative, continuous, and measured without error since they come from official sources. The descriptive statistics for the variables used in our tests are shown in the table below.

Table 3 – Daily Data Descriptive Statistics

Daily Data					
CSSD		***CSAD***		***EGX 30 Returns***	
Mean	0.028986395	Mean	0.02050779	Mean	0.001186743
Standard Error	0.000214251	Standard Error	0.000109553	Standard Error	0.00035089
Median	0.027127162	Median	0.019811589	Median	0.001655185
St.Dev	0.011208847	St.Dev	0.00573139	St.Dev	0.018357273
Sample Var.	0.000125638	Sample Var	3.28488E-05	Sample Var.	0.000336989
Kurtosis	160.8608784	Kurtosis	4.90492162	Kurtosis	10.2315598
Skewness	8.484116648	Skewness	1.36087874	Skewness	-0.165720288
Range	0.278104436	Range	0.062224668	Range	0.366305264
Minimum	0.011743067	Minimum	0.007292083	Minimum	-0.164659818
Maximum	0.289847503	Maximum	0.069516751	Maximum	0.201645446
Sum	79.33576341	Sum	56.12982001	Sum	3.248115178
Count	2737	Count	2737	Count	2737
Confidence Level(95.0%)	0.000420111	Confidence Level(95.0%)	0.000214814	Confidence Level(95.0%)	0.000688036

Where the variables are: CSSD is a time series created using the equally weighted cross section standard deviation of stock returns; CSAD is a time series created using the equally weighted cross sectional absolute deviation of stock returns; and EGX 30 is a time series created using the market value weighted index returns. The descriptive statistics show that all our variables have non-zero variance.

The number of observations in the sample is 2737. Average EGX 30 daily return for the period starting Jan 2003 till April 2014 is 0.1187% with a standard deviation of 1.8357%. Maximum return for the period is 20% and the minimum return is -16%. The returns are negatively skewed with kurtosis of 10.23 indicating that many returns fall at the tails of the distribution.

For the same number of observations, the CSSD has a mean of 2.899% and a standard deviation of 1.121%. The CSAD has a mean of 2.051% and a standard deviation of 0.573%. They are both positively skewed.

Table 4 – Monthly Data Descriptive Statistics

Monthly Data					
CSSD		***CSAD***		***EGX 30 Returns***	
Mean	0.13883241	Mean	0.09353682	Mean	0.01572172
Standard Error	0.00476828	Standard Error	0.00278241	Standard Error	0.00746673
Median	0.11912374	Median	0.08465134	Median	0.01517083
St. Dev.	0.06217071	St. Dev.	0.03627816	St. Dev	0.09735428
Sample Variance	0.0038652	Sample Variance	0.0013161	Sample Variance	0.00947786
Kurtosis	2.44427366	Kurtosis	0.91453862	Kurtosis	1.16378953
Skewness	1.43369527	Skewness	1.05899907	Skewness	0.10415198
Range	0.33903423	Range	0.17977197	Range	0.69794147
Minimum	0.05000997	Minimum	0.03476031	Minimum	-0.33189643
Maximum	0.38904421	Maximum	0.21453227	Maximum	0.36604504
Sum	23.6015096	Sum	15.9012597	Sum	2.67269191
Count	170	Count	170	Count	170
Confidence Level(95.0%)	0.00941306	Confidence Level(95.0%)	0.00549275	Confidence Level(95.0%)	0.01474008

The number of observations in the sample is 170. Average EGX 30 monthly return for the period starting Jan 2000 till April 2014 is 1.5722% with a standard deviation of 9.7354%. Maximum return for the period is 36.605% and the minimum return is -33.1896%. The returns are slightly positively skewed with kurtosis of 1.163.

For the same number of observations, the CSSD has a mean of 13.883% and a standard deviation of 6.217%. The CSAD has a mean of 9.354% and a standard deviation of 3.628%. They are both positively skewed as well.

b. Regression Results

1) Daily data

Using the regression model of Christie and Huang (1995) – eq. (1) – we find that both coefficients – β^{up} and β^{down} – are positive and statistically significant at $2\sigma_{Rindex}$ and $3\sigma_{Rindex}$ up and down, suggesting that weak adverse herding exists in extreme market conditions. This contradicts Christie and Huang's theory that markets exhibit herding behavior during stress times. In fact, the results indicate that investors actually refrain from following market consensus and act more rationally during stressful conditions in the Egyptian stock market.

Using CSAD instead of CSSD as proposed by Chang et al. (2000) – eq. (2) – we find that both β^{up} and β^{down} are positive and statistically significant at $2\sigma_{Rindex}$ and $3\sigma_{Rindex}$ which supports the previous result that weak adverse herding exists during stressful market conditions.

Using the modified regression model of Chang, Cheng, and Khorana (2000) – eq. (3) – we find that λ_3 is negative and statistically significant which confirms the nonlinear relationship suggested by Chang et al. (2000) to exist in presence of herding. We thus conclude that herding behavior exists in the Egyptian stock market in general.

However, the explanatory power of these models is weak and, as earlier illustrated; Chang et al.'s model suffers from multicollinearity and autocorrelation problems. Using up mentioned model adjusted for autocorrelation and multicollinearity – eq. (6) – we find that $\lambda_3$is statistically insignificant. Thus we conclude that herding behavior is not evident in the Egyptian stock market in general. The model explanatory power has significantly increased and the calculated Durbin Watson test for autocorrelation has increased as well to 1.6.

2) Bull and Bear Markets – Daily Data

Using equation (4) to test for herding behavior existence in bullish market phase, we find that δ_2^{Up} is statistically insignificant, though negative. Thus, we could not conclude that herding behavior exists during bullish market periods.

Using equation (5) to test for the presence of herding behavior in bearish market phase, we find that δ_2^{down} is positive and statistically insignificant. Thus we conclude that herding does not exist during bearish market periods as well.

3) Monthly data

Using the regression model of Christie and Huang (1995) – eq. (1) – we find that β^{up} is positive and statistically significant but β^{down} is insignificant, though negative, at $2\sigma_{Rindex}$ up and down. This means that weak adverse herding exists in up market conditions only. However, at $3\sigma_{Rindex}$ up and down, both coefficients are statistically insignificant suggesting that no herding is evident in stressful market conditions.

Using CSAD instead of CSSD as proposed by Chang et al. (2000) – eq. (2) – we find that both β^{up} and β^{down} are positive at $2\sigma_{Rindex}$ and $3\sigma_{Rindex}$. However, only β^{up} is statistically significant which supports the previous result that weak adverse herding exists during up market conditions only.

Using the modified regression model of Chang, Cheng, and Khorana (2000) – eq. (3) – we find that λ_3 is positive and statistically insignificant. This comes in agreement with previous literature findings that herding behavior is a short-lived phenomenon.

IX.2. Pre- and Post-Revolution

a) Pre-Revolution Phase

1) Descriptive statistics

As illustrated in Table 5 below, the number of observations in the sample is 749. Average EGX 30 pre-revolution daily return for the period starting Jan 14th, 2008 till Jan 24th, 2011 is -0.044% with a standard deviation of 2.059%. Maximum return for the period is 6.5492% and the minimum return is -16.466%. The returns are slightly negatively skewed with kurtosis of 6.57.

For the same number of observations, the CSSD has a mean of 3.291% and a standard deviation of 1.0712%. The CSAD has a mean of 2.269% and a standard deviation of 0.672%. They are both positively skewed.

Table 5 –Pre-revolution Data Descriptive Statistics

Pre-Revolution					
CSSD		*CSAD*		*EGX30 Returns*	
Mean	0.03289957	Mean	0.02269442	Mean	-0.00043707
Standard Error	0.00039141	Standard Error	0.00024538	Standard Error	0.000752492
Median	0.03136415	Median	0.02182617	Median	0.001069941
Standard Deviation	0.01071199	Standard Deviation	0.0067156	Standard Deviation	0.020594087
Sample Variance	0.00011475	Sample Variance	4.5099E-05	Sample Variance	0.000424116
Kurtosis	4.47038967	Kurtosis	1.49576162	Kurtosis	6.569398935
Skewness	1.52312233	Skewness	1.01155533	Skewness	-1.01227334
Range	0.0795215	Range	0.03863397	Range	0.230151321
Minimum	0.0143965	Minimum	0.01065061	Minimum	-0.16465982
Maximum	0.093918	Maximum	0.04928458	Maximum	0.065491503
Sum	24.6417801	Sum	16.9981208	Sum	-0.32736767
Count	749	Count	749	Count	749
Confidence Level(95.0%)	0.00076839	Confidence Level(95.0%)	0.00048172	Confidence Level(95.0%)	0.001477247

2) Regression results

(i) Daily data

Using the regression model of Christie and Huang (1995) – eq. (1) – we find that both coefficients – β^{up} and β^{down} – are positive and statistically significant at $2\sigma_{Rindex}$ up and down. At $3\sigma_{Rindex}$ we find that both coefficients – β^{up} and β^{down} – are positive, however only β^{down} is significant. Thus, weak adverse herding exists in stressful market conditions and persists at the extreme lower tail of the distribution but vanishes at the extreme upper one.

Using CSAD instead of CSSD as proposed by Chang et al. (2000) – eq. (2) – we find that both coefficients – β^{up} and β^{down} – are positive and statistically significant at $2\sigma_{Rindex}$ up and down. At $3\sigma_{Rindex}$ we find that both coefficients – β^{up} and β^{down} – are positive, however only β^{down} is significant which supports previous result.

Using the modified regression model of Chang, Cheng, and Khorana (2000) – eq. (3) – we find that λ_3 is negative and statistically significant which confirms the nonlinear relationship suggested by Chang et al. (2000) to exist in presence of herding. We thus conclude that herding behavior existed in the Egyptian stock market before the revolution.

However, the explanatory power of these models is weak too and, as previously illustrated; eq. (3) suffers from multicollinearity and autocorrelation problems. Using eq. (6) – we find that $\lambda_3$is statistically insignificant. Thus we conclude herding behavior was not evident in the Egyptian stock market in general before the revolution. The model explanatory power has significantly increased. Also the calculated Durbin Watson test for autocorrelation has increased as well to almost equal 2 which suggests that this model corrects for autocorrelation.

(ii) Bull and Bear markets

Using equation (4) to test for herding behavior existence in bullish market phase, we find that δ_2^{Up} is positive and statistically significant indicating adverse herd behavior in bullish market states. Using equation (5) to test for the presence of herding behavior in bearish market phase, we find that δ_2^{down} is statistically insignificant, though negative. Thus, we found no evidence of herd behavior in bearish market states.

b) Post-Revolution Phase

1) Descriptive statistics

As illustrated in Table 6 below, the number of observations in the sample is 749. Average EGX 30 post-revolution daily return for the period starting Mar 23rd, 2011 and ending Apr 15th, 2014 is 0.0602% with a standard deviation of 1.626%. Maximum return for the period is 7.588% and the minimum return is -9.588%. The returns are slightly negatively skewed with kurtosis of 4.46.

For the same number of observations, the CSSD has a mean of 2.381% and a standard deviation of 0.662%. The CSAD has a mean of 1.6999% and a standard deviation of 0.501%. They are both positively skewed.

We would like to note that the average equally weighted market portfolio return has actually increased after the revolution, and that the market volatility has decreased. A reason that we propose is that investors, alarmed by the unstable conditions in the country, act slower to information and systematically analyze the market before making entry or exit decisions after the revolution, which decreases the volatility of market return and positively affect the market in general.

Table 6 – Post-revolution Data Descriptive Statistics

Post-Revolution					
CSSD		*CSAD*		*EGX30 Returns*	
Mean	0.02380671	Mean	0.01699297	Mean	0.000602234
Standard Error	0.00024188	Standard Error	0.00018299	Standard Error	0.000594063
Median	0.02260442	Median	0.01610669	Median	0.001228652
St. Dev.	0.00661966	St. Dev.	0.00500799	St. Dev.	0.016258235
Sample Variance	4.382E-05	Sample Variance	2.508E-05	Sample Variance	0.00026433
Kurtosis	6.12424093	Kurtosis	7.02408532	Kurtosis	4.460073121
Skewness	1.79037584	Skewness	1.92357588	Skewness	-0.31213362
Range	0.05245139	Range	0.04053819	Range	0.171772228
Minimum	0.01174307	Minimum	0.00729208	Minimum	-0.09588751
Maximum	0.06419445	Maximum	0.04783027	Maximum	0.075884714
Sum	17.831228	Sum	12.7277359	Sum	0.451072973
Count	749	Count	749	Count	749
Confidence Level(95.0%)	0.00047484	Confidence Level(95.0%)	0.00035923	Confidence Level(95.0%)	0.001166229

2) Regression results

(i) Daily Data

Using the regression model of Christie and Huang (1995) – eq. (1) – we find that both coefficients – β^{up} and β^{down} – are positive and statistically significant at

$2\sigma_{Rindex}$ and $3\sigma_{Rindex}$ up and down, suggesting that weak adverse herding exists in extreme market conditions.

Using CSAD instead of CSSD as proposed by Chang et al. (2000) – eq. (2) – we find that both β^{up} and β^{down} are positive and statistically significant at $2\sigma_{Rindex}$ and $3\sigma_{Rindex}$ which supports previous result that weak adverse herding exists during stressful conditions.

Using the modified regression model of Chang, Cheng, and Khorana (2000) – eq. (3) – we find that λ_3 is positive and statistically significant. We thus conclude that adverse herding behavior exists in the post-revolution Egyptian stock market.

The explanatory power of these models is weak too, as with previous tests and, as previously illustrated; eq. (3) suffers from multicollinearity and autocorrelation problems. Using eq. (6) – we find that $\lambda_3$is statistically insignificant. Thus we conclude herding behavior is not evident in the Egyptian stock market in general after the revolution. The model explanatory power has significantly increased. The calculated Durbin Watson test for autocorrelation has increased as well to almost equal 2 which suggests that this model corrects for autocorrelation.

(ii) Bull and Bear markets

Using equation (4) to test for herding behavior existence in bullish market phase, we find that δ_2^{Up} is positive and statistically significant indicating adverse herd behavior in bullish market states.

Using equation (5) to test for the presence of herding behavior in bearish market phase, we find that δ_2^{down} is positive and statistically significant indicating adverse herd behavior in bearish market states as well.

IX.3. A Note on the Results

We find these results extremely interesting and surprising because, first, we expected that herding behavior would be evident during stressful conditions – as proposed by previous literature – but at the contrary; we found that adverse herding exists in the market suggesting that investors actually act rationally during stressful market times. This could be reasoned by the fact that when investors panic, sometimes they might actually become more precautious and analytical in their decisions and thus, they would not follow the market and count on their personal views. This could be the case in Egypt, especially where most investors assume the low financial education levels of other investors and the inefficiency of the market in general. Thus, investors would actually refrain from following the market which they believe inefficient and accordingly, they might actually exhibit adverse herd behavior as evident by the results.

Second, we rationally expected that herding behavior would exist in the Egyptian stock market after the revolution due to the high uncertainty levels and economic and political disturbance in the country. However, we found that, in fact, adverse herding existed in all market states – in general, during stressful times, and in bullish and bearish market phases – though herding behavior has existed before the revolution in the market in general. The reasons we propose for this behavior are that, first, after the revolution more people became aware of current events and the various risks present in the market and accordingly, a rational investor would analyze the market and make an informed decision regardless of the market trend. Second, investors may have become even more precautious and less adventurous due to the economic and political situation of the country. Finally, low financially educated and irrational investors who were likely to herd previously might have actually exited the market after the revolution in the fear of drastic falls of the market.

Thus, these results indicate that, against the general beliefs; investors in the Egyptian stock market are rational under stressful conditions; and, the 25th Jan revolution has positively affected the rationality of investors in the Egyptian stock market in all states.

X. Conclusion

This paper tests for the presence of herding behavior in the Egyptian stock market. Using daily and monthly data of listed companies on the Egyptian stock market, we used different models to test for herding in the market at different circumstances and during various periods. Specifically, we used Christie and Huang (1995) model to test for herding in stressful conditions, the modified Chang et al. (2000) model to test for herding behavior in general, and their expanded tests to measure herding behavior during bullish and bearish market phases. We also tested for the validity of Chang et al. general model and corrected for multicollinearity and autocorrelation using the model proposed by Yao et al. (2014).

Through daily data analysis, we found evidence of weak adverse herding in extreme market conditions and evidence of herding behavior in the Egyptian stock market in general. Analyzing monthly data, we found that weak adverse herding exists in the up market conditions only, however it vanishes at the extreme tails of the distribution. We could not find an evidence for herding behavior in the market in general which means that herding behavior is a short-lived phenomenon. We also found no evidence of herding behavior in neither bearish nor bullish market phases in the Egyptian stock market. Splitting the sample we found that during the pre-revolution period, herding behavior existed in general and adverse herding existed during stressful conditions as well as during bullish market phases; however, we found no evidence of herding behavior during bearish market phases in this period. During post-revolution period, we found that adverse herding existed in general, during stressful conditions, and also during bullish and bearish market phases.

When we corrected for multicollinearity and autocorrelation, we found no evidence of herd behavior in the Egyptian stock market in general and neither did we in the pre-post revolution analysis.

This paper contributes to literature in three ways. First, this is the first paper that discusses herding behavior in the Egyptian stock market and tests for it. Second, this is also the first to consider for the Jan 25th revolution effects on herding behavior. Finally, we used various models to test for herding behavior in the Egyptian stock market, tested the general model of Chang et al. – which is still being used by different researchers around the world for herding behavior tests – and corrected for its pitfalls using an integration of modifications**.**

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Appendix A – Stationarity Test Results

Table A.1 – CSSD Unit Root test

Null Hypothesis: UNIT_ROOT_CSSD has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-34.22683	0.0000
Test critical values:	1% level	-3.432548	
	5% level	-2.862397	
	10% level	-2.567271	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(UNIT_ROOT_CSSR)
Method: Least Squares
Date: 05/16/14 Time: 12:15
Sample (adjusted): 2 2737
Included observations: 2736 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
UNIT_ROOT_CSSD(-1)	-0.599883	0.017527	-34.22683	0.0000
C	0.017390	0.000545	31.92479	0.0000

R-squared	0.299957	Mean dependent var	5.38E-07
Adjusted R-squared	0.299701	S.D. dependent var	0.012279
S.E. of regression	0.010275	Akaike info criterion	-6.317436
Sum squared resid	0.288655	Schwarz criterion	-6.313113
Log likelihood	8644.253	Hannan-Quinn criter.	-6.315874
F-statistic	1171.476	Durbin-Watson stat	2.232726
Prob(F-statistic)	0.000000		

Table A.2 – CSAD Unit Root test

Null Hypothesis: CSAD has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-19.25880	0.0000
Test critical values:	1% level	-3.432548	
	5% level	-2.862397	
	10% level	-2.567271	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CSAD)
Method: Least Squares
Date: 05/16/14 Time: 08:45
Sample (adjusted): 2 2737
Included observations: 2736 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CSAD(-1)	-0.238968	0.012408	-19.25880	0.0000
C	0.004901	0.000264	18.54676	0.0000

R-squared	0.119457	Mean dependent var	-4.22E-07
Adjusted R-squared	0.119135	S.D. dependent var	0.003963
S.E. of regression	0.003719	Akaike info criterion	-8.349780
Sum squared resid	0.037822	Schwarz criterion	-8.345457
Log likelihood	11424.50	Hannan-Quinn criter.	-8.348218
F-statistic	370.9015	Durbin-Watson stat	2.552463
Prob(F-statistic)	0.000000		

Table A.3 – EGX Returns Unit Root test

Null Hypothesis: EGX30DAILYRETURN has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-44.18234	0.0001
Test critical values:	1% level	-3.432548	
	5% level	-2.862397	
	10% level	-2.567271	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(EGX30DAILYRETURN)
Method: Least Squares
Date: 05/16/14 Time: 09:54
Sample (adjusted): 2 2737
Included observations: 2736 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EGX30DAILYRETURN(-1)	-0.833012	0.018854	-44.18234	0.0000
C	0.000983	0.000347	2.833956	0.0046

R-squared	0.416570	Mean dependent var	-3.71E-06
Adjusted R-squared	0.416356	S.D. dependent var	0.023697
S.E. of regression	0.018103	Akaike info criterion	-5.184709
Sum squared resid	0.896017	Schwarz criterion	-5.180386
Log likelihood	7094.683	Hannan-Quinn criter.	-5.183147
F-statistic	1952.079	Durbin-Watson stat	1.998524
Prob(F-statistic)	0.000000		

Table A.4 – EGX Absolute Returns Unit Root test

Null Hypothesis: EGX30ABSRETURN has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-38.29712	0.0000
Test critical values:	1% level	-3.432548	
	5% level	-2.862397	
	10% level	-2.567271	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(EGX30ABSRETURN)
Method: Least Squares
Date: 05/16/14 Time: 09:56
Sample (adjusted): 2 2737
Included observations: 2736 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EGX30ABSRETURN (-1)	-0.698304	0.018234	-38.29712	0.0000
C	0.008983	0.000335	26.78232	0.0000

R-squared	0.349151	Mean dependent var	-3.71E-06
Adjusted R-squared	0.348913	S.D. dependent var	0.015536
S.E. of regression	0.012536	Akaike info criterion	-5.919739
Sum squared resid	0.429632	Schwarz criterion	-5.915415
Log likelihood	8100.203	Hannan-Quinn criter.	-5.918176
F-statistic	1466.669	Durbin-Watson stat	2.083412
Prob(F-statistic)	0.000000		

Table A.5 – EGX30 Square Returns Unit Root test

Null Hypothesis: EGX30SQRETURN has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-37.56093	0.0000
Test critical values:	1% level	-3.432548	
	5% level	-2.862397	
	10% level	-2.567271	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(EGX30SQRETURN)
Method: Least Squares
Date: 05/16/14 Time: 09:57
Sample (adjusted): 2 2737
Included observations: 2736 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EGX30SQRETURN(-1)	-0.680774	0.018125	-37.56093	0.0000
C	0.000230	2.22E-05	10.38105	0.0000

R-squared	0.340382	Mean dependent var	-9.50E-08
Adjusted R-squared	0.340141	S.D. dependent var	0.001373
S.E. of regression	0.001115	Akaike info criterion	-10.75924
Sum squared resid	0.003399	Schwarz criterion	-10.75492
Log likelihood	14720.65	Hannan-Quinn criter.	-10.75768
F-statistic	1410.823	Durbin-Watson stat	2.010790
Prob(F-statistic)	0.000000		

Appendix B – Regression Results

Daily Data

1. $CSSD_t = \alpha + \beta^{up} D_t^{up} + \beta^{down} D_t^{down} + \varepsilon_t$

At 2σ

Dependent Variable: CSSD
Method: Least Squares
Date: 04/30/14 Time: 15:49
Sample: 1 2737
Included observations: 2737

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.028576	0.000217	131.8336	0.0000
UP95	0.008077	0.001433	5.636555	0.0000
DOWN95	0.008888	0.001331	6.678960	0.0000

R-squared	0.026551	Mean dependent var	0.028986
Adjusted R-squared	0.025839	S.D. dependent var	0.011209
S.E. of regression	0.011063	Akaike info criterion	-6.169309
Sum squared resid	0.334620	Schwarz criterion	-6.162826
Log likelihood	8445.700	Hannan-Quinn criter.	-6.166967
F-statistic	37.28470	Durbin-Watson stat	1.268612
Prob(F-statistic)	0.000000		

At 3σ

Dependent Variable: CSSD
Method: Least Squares
Date: 04/30/14 Time: 15:49
Sample: 1 2737
Included observations: 2737

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.028826	0.000214	134.5227	0.0000
UP99	0.009000	0.002632	3.419023	0.0006
DOWN99	0.013198	0.002438	5.412934	0.0000

R-squared	0.014678	Mean dependent var	0.028986
Adjusted R-squared	0.013957	S.D. dependent var	0.011209
S.E. of regression	0.011130	Akaike info criterion	-6.157186
Sum squared resid	0.338701	Schwarz criterion	-6.150704
Log likelihood	8429.110	Hannan-Quinn criter.	-6.154844
F-statistic	20.36342	Durbin-Watson stat	1.231737
Prob(F-statistic)	0.000000		

2. $CSAD_t = \alpha + \beta^{down} D_t^{down} + \beta^{up} D_t^{up} + \varepsilon_t$

At 2σ

Dependent Variable: CSAD
Method: Least Squares
Date: 05/04/14 Time: 21:10
Sample: 1 2737
Included observations: 2737

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.020187	0.000109	185.5507	0.0000
UP95	0.006413	0.000719	8.917070	0.0000
DOWN95	0.006870	0.000668	10.28637	0.0000

R-squared	0.062065	Mean dependent var	0.020508
Adjusted R-squared	0.061379	S.D. dependent var	0.005731
S.E. of regression	0.005553	Akaike info criterion	-7.547965
Sum squared resid	0.084296	Schwarz criterion	-7.541482
Log likelihood	10332.39	Hannan-Quinn criter.	-7.545622
F-statistic	90.45670	Durbin-Watson stat	0.585457
Prob(F-statistic)	0.000000		

At 3σ

Dependent Variable: CSAD
Method: Least Squares
Date: 05/04/14 Time: 21:11
Sample: 1 2737
Included observations: 2737

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.020396	0.000109	187.3094	0.0000
UP99	0.006900	0.001338	5.159017	0.0000
DOWN99	0.008716	0.001239	7.034894	0.0000

R-squared	0.026904	Mean dependent var	0.020508
Adjusted R-squared	0.026192	S.D. dependent var	0.005731
S.E. of regression	0.005656	Akaike info criterion	-7.511163
Sum squared resid	0.087456	Schwarz criterion	-7.504680
Log likelihood	10282.03	Hannan-Quinn criter.	-7.508821
F-statistic	37.79488	Durbin-Watson stat	0.522512
Prob(F-statistic)	0.000000		

3. $CSAD_t = \beta_0 + \lambda_1 R_{m,t} + \lambda_2 |R_{m,t}| + \lambda_3 R_{m,t}^2 + \varepsilon_t$

Dependent Variable: CSAD
Method: Least Squares
Date: 04/30/14 Time: 15:52
Sample: 1 2737
Included observations: 2737

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.018272	0.000167	109.6940	0.0000
EGX30DAILYRETURN	-0.005275	0.005626	-0.937600	0.3485
EGX30ABSRETURN	0.194154	0.012854	15.10400	0.0000
EGX30SQRETURN	-0.757249	0.143621	-5.272550	0.0000

R-squared	0.113490	Mean dependent var	0.020508
Adjusted R-squared	0.112516	S.D. dependent var	0.005731
S.E. of regression	0.005399	Akaike info criterion	-7.603622
Sum squared resid	0.079675	Schwarz criterion	-7.594978
Log likelihood	10409.56	Hannan-Quinn criter.	-7.600499
F-statistic	116.6247	Durbin-Watson stat	0.664172
Prob(F-statistic)	0.000000		

4. Modified CSAD on returns

Dependent Variable: CSAD
Method: Least Squares
Date: 05/16/14 Time: 13:52
Sample: 1 2737
Included observations: 2737

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.115219	0.068662	1.678075	0.0934
EGX30DAILYRETURN	-11.64491	7.715600	-1.509269	0.1313
EGX30ABSRETURN	0.141835	0.011138	12.73443	0.0000
EGX30SQRETURN	326.6791	216.7530	1.507149	0.1319
RM_RAV2	-327.1673	216.7521	-1.509408	0.1313
CSADT_1	0.251121	0.007980	31.46875	0.0000

R-squared	0.349726	Mean dependent var	0.020508
Adjusted R-squared	0.348536	S.D. dependent var	0.005731
S.E. of regression	0.004626	Akaike info criterion	-7.912060
Sum squared resid	0.058443	Schwarz criterion	-7.899094
Log likelihood	10833.65	Hannan-Quinn criter.	-7.907375
F-statistic	293.7539	Durbin-Watson stat	1.656933
Prob(F-statistic)	0.000000		

5. Bull Market

Dependent Variable: CSAD
Method: Least Squares
Date: 05/09/14 Time: 11:09
Sample: 1 2737
Included observations: 2737

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019825	0.000134	148.4976	0.0000
EGX30_UP_ABS	0.105239	0.013763	7.646558	0.0000
EGX30_UP_SQ	-0.325722	0.169854	-1.917656	0.0553

R-squared	0.029622	Mean dependent var	0.020508
Adjusted R-squared	0.028912	S.D. dependent var	0.005731
S.E. of regression	0.005648	Akaike info criterion	-7.513960
Sum squared resid	0.087212	Schwarz criterion	-7.507478
Log likelihood	10285.85	Hannan-Quinn criter.	-7.511618
F-statistic	41.72975	Durbin-Watson stat	0.513155
Prob(F-statistic)	0.000000		

6. Bear Market

Dependent Variable: CSAD
Method: Least Squares
Date: 05/09/14 Time: 11:11
Sample: 1 2737
Included observations: 2737

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019965	0.000126	158.8046	0.0000
EGX30_DOWN_ABS	0.081549	0.015740	5.181161	0.0000
EGX30_DOWN_SQ	0.401857	0.227650	1.765245	0.0776

R-squared	0.043943	Mean dependent var	0.020508
Adjusted R-squared	0.043243	S.D. dependent var	0.005731
S.E. of regression	0.005606	Akaike info criterion	-7.528828
Sum squared resid	0.085925	Schwarz criterion	-7.522345
Log likelihood	10306.20	Hannan-Quinn criter.	-7.526485
F-statistic	62.83074	Durbin-Watson stat	0.559125
Prob(F-statistic)	0.000000		

Monthly Data

1. $CSSD_t = \alpha + \beta^{up} D_t^{up} + \beta^{down} D_t^{down} + \varepsilon_t$

At 2σ

Dependent Variable: CSSD
Method: Least Squares
Date: 04/30/14 Time: 16:08
Sample: 1 170
Included observations: 170

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.136758	0.004768	28.68195	0.0000
UP95	0.088454	0.030901	2.862530	0.0047
DOWN95	-0.000554	0.043439	-0.012750	0.9898

R-squared	0.046792	Mean dependent var	0.138832
Adjusted R-squared	0.035376	S.D. dependent var	0.062171
S.E. of regression	0.061061	Akaike info criterion	-2.736393
Sum squared resid	0.622653	Schwarz criterion	-2.681055
Log likelihood	235.5934	Hannan-Quinn criter.	-2.713938
F-statistic	4.098914	Durbin-Watson stat	1.075044
Prob(F-statistic)	0.018288		

At 3σ

Dependent Variable: CSSD
Method: Least Squares
Date: 04/30/14 Time: 16:09
Sample: 1 170
Included observations: 170

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.138057	0.004782	28.86856	0.0000
UP99	0.104583	0.062169	1.682236	0.0944
DOWN99	0.027272	0.062169	0.438674	0.6615

R-squared	0.017726	Mean dependent var	0.138832
Adjusted R-squared	0.005963	S.D. dependent var	0.062171
S.E. of regression	0.061985	Akaike info criterion	-2.706356
Sum squared resid	0.641639	Schwarz criterion	-2.651019
Log likelihood	233.0403	Hannan-Quinn criter.	-2.683901
F-statistic	1.506862	Durbin-Watson stat	1.070620
Prob(F-statistic)	0.224602		

2. $CSAD_t = \alpha + \beta^{down} D_t^{down} + \beta^{up} D_t^{up} + \varepsilon_t$

At 2σ

Dependent Variable: CSAD
Method: Least Squares
Date: 05/09/14 Time: 14:58
Sample: 1 170
Included observations: 170

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.091972	0.002762	33.30370	0.0000
UP95	0.057780	0.017897	3.228427	0.0015
DOWN95	0.017421	0.025160	0.692409	0.4896

R-squared	0.060899	Mean dependent var	0.093537
Adjusted R-squared	0.049652	S.D. dependent var	0.036278
S.E. of regression	0.035366	Akaike info criterion	-3.828639
Sum squared resid	0.208877	Schwarz criterion	-3.773301
Log likelihood	328.4343	Hannan-Quinn criter.	-3.806184
F-statistic	5.414778	Durbin-Watson stat	0.926391
Prob(F-statistic)	0.005266		

At 3σ

Dependent Variable: CSAD
Method: Least Squares
Date: 05/09/14 Time: 15:00
Sample: 1 170
Included observations: 170

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.092847	0.002766	33.56460	0.0000
UP99	0.080365	0.035961	2.234793	0.0268
DOWN99	0.036874	0.035961	1.025383	0.3067

R-squared	0.034787	Mean dependent var	0.093537
Adjusted R-squared	0.023228	S.D. dependent var	0.036278
S.E. of regression	0.035854	Akaike info criterion	-3.801214
Sum squared resid	0.214684	Schwarz criterion	-3.745876
Log likelihood	326.1032	Hannan-Quinn criter.	-3.778758
F-statistic	3.009402	Durbin-Watson stat	0.897857
Prob(F-statistic)	0.052004		

3. $CSAD_t = \beta_0 + \lambda_1 R_{m,t} + \lambda_2 |R_{m,t}| + \lambda_3 R_{m,t}^2 + \varepsilon_t$

Dependent Variable: CSAD
Method: Least Squares
Date: 04/30/14 Time: 16:10
Sample: 1 170
Included observations: 170

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.085736	0.005351	16.02266	0.0000
EGX30RETURN	0.042961	0.028454	1.509860	0.1330
EGX30ABSRETURN	0.049358	0.101252	0.487479	0.6266
EGX30SQRETURN	0.351056	0.374745	0.936788	0.3502

R-squared	0.087213	Mean dependent var	0.093537
Adjusted R-squared	0.070717	S.D. dependent var	0.036278
S.E. of regression	0.034972	Akaike info criterion	-3.845296
Sum squared resid	0.203024	Schwarz criterion	-3.771512
Log likelihood	330.8501	Hannan-Quinn criter.	-3.815355
F-statistic	5.286888	Durbin-Watson stat	0.874625
Prob(F-statistic)	0.001659		

Pre-revolution

1. $CSSD_t = \alpha + \beta^{up} D_t^{up} + \beta^{down} D_t^{down} + \varepsilon_t$

At 2σ

Dependent Variable: PREREV_CSSD
Method: Least Squares
Date: 05/13/14 Time: 05:55
Sample: 1 749
Included observations: 749

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.032215	0.000390	82.63052	0.0000
PREREV_UP96	0.012762	0.002619	4.872835	0.0000
PREREV_DOWN96	0.011419	0.002031	5.621244	0.0000

R-squared	0.067292	Mean dependent var	0.032900
Adjusted R-squared	0.064792	S.D. dependent var	0.010712
S.E. of regression	0.010359	Akaike info criterion	-6.297895
Sum squared resid	0.080055	Schwarz criterion	-6.279395
Log likelihood	2361.562	Hannan-Quinn criter.	-6.290766
F-statistic	26.91083	Durbin-Watson stat	0.794043
Prob(F-statistic)	0.000000		

At 3σ

Dependent Variable: PREREV_CSSD
Method: Least Squares
Date: 05/13/14 Time: 06:00
Sample: 1 749
Included observations: 749

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.032696	0.000387	84.53269	0.0000
PREREV_UP99	0.009030	0.007455	1.211197	0.2262
PREREV_DOWN99	0.022353	0.004316	5.179464	0.0000

R-squared	0.036470	Mean dependent var	0.032900
Adjusted R-squared	0.033886	S.D. dependent var	0.010712
S.E. of regression	0.010529	Akaike info criterion	-6.265383
Sum squared resid	0.082700	Schwarz criterion	-6.246884
Log likelihood	2349.386	Hannan-Quinn criter.	-6.258254
F-statistic	14.11806	Durbin-Watson stat	0.688988
Prob(F-statistic)	0.000001		

2. $CSAD_t = \alpha + \beta^{down} D_t^{down} + \beta^{up} D_t^{up} + \varepsilon_t$

At 2σ

Dependent Variable: PREREV_CSAD
Method: Least Squares
Date: 05/13/14 Time: 05:59
Sample: 1 749
Included observations: 749

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.022203	0.000242	91.93547	0.0000
PREREV_UP96	0.009850	0.001622	6.071563	0.0000
PREREV_DOWN96	0.007808	0.001258	6.204833	0.0000

R-squared	0.089434	Mean dependent var	0.022694
Adjusted R-squared	0.086993	S.D. dependent var	0.006716
S.E. of regression	0.006417	Akaike info criterion	-7.255781
Sum squared resid	0.030717	Schwarz criterion	-7.237281
Log likelihood	2720.290	Hannan-Quinn criter.	-7.248652
F-statistic	36.63547	Durbin-Watson stat	0.493731
Prob(F-statistic)	0.000000		

At 3σ

Dependent Variable: PREREV_CSAD
Method: Least Squares
Date: 05/13/14 Time: 06:00
Sample: 1 749
Included observations: 749

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.022585	0.000244	92.65128	0.0000
PREREV_UP99	0.005921	0.004698	1.260249	0.2080
PREREV_DOWN99	0.011746	0.002720	4.318508	0.0000

R-squared	0.026348	Mean dependent var	0.022694
Adjusted R-squared	0.023738	S.D. dependent var	0.006716
S.E. of regression	0.006635	Akaike info criterion	-7.188793
Sum squared resid	0.032845	Schwarz criterion	-7.170293
Log likelihood	2695.203	Hannan-Quinn criter.	-7.181664
F-statistic	10.09378	Durbin-Watson stat	0.369535
Prob(F-statistic)	0.000047		

3. $CSAD_t = \beta_0 + \lambda_1 R_{m,t} + \lambda_2 |R_{m,t}| + \lambda_3 R_{m,t}^2 + \varepsilon_t$

Dependent Variable: PREREV_CSAD
Method: Least Squares
Date: 05/13/14 Time: 06:02
Sample: 1 749
Included observations: 749

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019204	0.000366	52.44577	0.0000
EGX30_R	0.020384	0.011524	1.768796	0.0773
EGX30_RABS	0.264815	0.026930	9.833443	0.0000
EGX30_RSQ	-0.867239	0.326130	-2.659184	0.0080

R-squared	0.195203	Mean dependent var	0.022694
Adjusted R-squared	0.191962	S.D. dependent var	0.006716
S.E. of regression	0.006037	Akaike info criterion	-7.376586
Sum squared resid	0.027149	Schwarz criterion	-7.351920
Log likelihood	2766.532	Hannan-Quinn criter.	-7.367081
F-statistic	60.23292	Durbin-Watson stat	0.679593
Prob(F-statistic)	0.000000		

4. Modified CSAD on returns

Dependent Variable: PREREV_CSAD
Method: Least Squares
Date: 05/16/14 Time: 13:46
Sample: 1 749
Included observations: 749

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004260	0.000473	9.007512	0.0000
EGX30_R	0.568967	0.292870	1.942729	0.0524
EGX30_RABS	0.085841	0.016789	5.112927	0.0000
EGX30_RSQ	643.7580	334.9926	1.921708	0.0550
_R_RAV__2	-643.9107	334.9888	-1.922186	0.0550
CSADT_1	0.766451	0.020907	36.65944	0.0000

R-squared	0.714408	Mean dependent var	0.022694
Adjusted R-squared	0.712486	S.D. dependent var	0.006716
S.E. of regression	0.003601	Akaike info criterion	-8.407273
Sum squared resid	0.009634	Schwarz criterion	-8.370274
Log likelihood	3154.524	Hannan-Quinn criter.	-8.393015
F-statistic	371.7232	Durbin-Watson stat	2.475766
Prob(F-statistic)	0.000000		

5. Bull Market

Dependent Variable: PREREV_CSAD
Method: Least Squares
Date: 05/13/14 Time: 06:10
Sample: 1 749
Included observations: 749

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.022068	0.000303	72.89602	0.0000
EGX30_UPR_ABS	-0.029727	0.049776	-0.597204	0.5506
EGX30_UPR_SQ	4.891375	1.176218	4.158562	0.0000

R-squared	0.087640	Mean dependent var	0.022694
Adjusted R-squared	0.085194	S.D. dependent var	0.006716
S.E. of regression	0.006423	Akaike info criterion	-7.253813
Sum squared resid	0.030778	Schwarz criterion	-7.235313
Log likelihood	2719.553	Hannan-Quinn criter.	-7.246684
F-statistic	35.83006	Durbin-Watson stat	0.477903
Prob(F-statistic)	0.000000		

6. Bear Market

Dependent Variable: PREREV_CSAD
Method: Least Squares
Date: 05/13/14 Time: 06:12
Sample: 1 749
Included observations: 749

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.021825	0.000284	76.76599	0.0000
EGX30_DOWNR_ABS	0.117512	0.028368	4.142382	0.0000
EGX30_DOWNR_SQ	-0.055184	0.334054	-0.165195	0.8688

R-squared	0.056358	Mean dependent var	0.022694
Adjusted R-squared	0.053828	S.D. dependent var	0.006716
S.E. of regression	0.006532	Akaike info criterion	-7.220100
Sum squared resid	0.031833	Schwarz criterion	-7.201600
Log likelihood	2706.927	Hannan-Quinn criter.	-7.212971
F-statistic	22.27698	Durbin-Watson stat	0.441009
Prob(F-statistic)	0.000000		

Post-revolution

1. $CSSD_t = \alpha + \beta^{up} D_t^{up} + \beta^{down} D_t^{down} + \varepsilon_t$

At 2σ

Dependent Variable: POSTREV_CSSD
Method: Least Squares
Date: 05/13/14 Time: 06:22
Sample: 1 749
Included observations: 749

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.023252	0.000230	101.3038	0.0000
POSTREV_UP96	0.015015	0.001598	9.396566	0.0000
POSTERV_DOWN96	0.008641	0.001326	6.517535	0.0000

R-squared	0.146264	Mean dependent var	0.023807
Adjusted R-squared	0.143976	S.D. dependent var	0.006620
S.E. of regression	0.006125	Akaike info criterion	-7.349006
Sum squared resid	0.027983	Schwarz criterion	-7.330507
Log likelihood	2755.203	Hannan-Quinn criter.	-7.341877
F-statistic	63.90340	Durbin-Watson stat	0.769870
Prob(F-statistic)	0.000000		

At 3σ

Dependent Variable: POSTREV_CSSD
Method: Least Squares
Date: 05/13/14 Time: 06:27
Sample: 1 749
Included observations: 749

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.023506	0.000224	104.7704	0.0000
POSTREV_UP99	0.021991	0.002316	9.494850	0.0000
POSTREV_DOWN99	0.023882	0.003528	6.768621	0.0000

R-squared	0.153408	Mean dependent var	0.023807
Adjusted R-squared	0.151138	S.D. dependent var	0.006620
S.E. of regression	0.006099	Akaike info criterion	-7.357409
Sum squared resid	0.027749	Schwarz criterion	-7.338909
Log likelihood	2758.350	Hannan-Quinn criter.	-7.350280
F-statistic	67.58992	Durbin-Watson stat	0.715688
Prob(F-statistic)	0.000000		

2. $$CSAD_t = \alpha + \beta^{down} D_t^{down} + \beta^{up} D_t^{up} + \varepsilon_t$$

At 2σ

Dependent Variable: POSTREV_CSAD
Method: Least Squares
Date: 05/13/14 Time: 06:27
Sample: 1 749
Included observations: 749

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.016510	0.000169	97.54416	0.0000
POSTREV_UP96	0.012466	0.001178	10.57920	0.0000
POSTERV_DOWN96	0.007940	0.000978	8.121079	0.0000

R-squared	0.188871	Mean dependent var	0.016993
Adjusted R-squared	0.186696	S.D. dependent var	0.005008
S.E. of regression	0.004516	Akaike info criterion	-7.958222
Sum squared resid	0.015217	Schwarz criterion	-7.939723
Log likelihood	2983.354	Hannan-Quinn criter.	-7.951093
F-statistic	86.85286	Durbin-Watson stat	0.800274
Prob(F-statistic)	0.000000		

At 36

Dependent Variable: POSTREV_CSAD
Method: Least Squares
Date: 05/13/14 Time: 06:29
Sample: 1 749
Included observations: 749

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.016753	0.000168	99.85263	0.0000
POSTREV_UP99	0.016641	0.001732	9.608160	0.0000
POSTREV_DOWN99	0.021188	0.002639	8.030233	0.0000

R-squared	0.172818	Mean dependent var	0.016993
Adjusted R-squared	0.170600	S.D. dependent var	0.005008
S.E. of regression	0.004561	Akaike info criterion	-7.938624
Sum squared resid	0.015518	Schwarz criterion	-7.920125
Log likelihood	2976.015	Hannan-Quinn criter.	-7.931495
F-statistic	77.92841	Durbin-Watson stat	0.702281
Prob(F-statistic)	0.000000		

3. $CSAD_t = \beta_0 + \lambda_1 R_{m,t} + \lambda_2 \left|R_{m,t}\right| + \lambda_3 R_{m,t}^2 + \varepsilon_t$

Dependent Variable: POSTREV_CSAD
Method: Least Squares
Date: 05/13/14 Time: 06:30
Sample: 1 749
Included observations: 749

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.014854	0.000276	53.73762	0.0000
POSTREV_EGX30_R	0.017772	0.009630	1.845411	0.0654
POSTREV_EGX30_R ABS	0.145601	0.028482	5.112067	0.0000
POSTREV_EGX30_R SQ	1.628575	0.485085	3.357298	0.0008

R-squared	0.279625	Mean dependent var	0.016993
Adjusted R-squared	0.276724	S.D. dependent var	0.005008
S.E. of regression	0.004259	Akaike info criterion	-8.074207
Sum squared resid	0.013514	Schwarz criterion	-8.049541
Log likelihood	3027.791	Hannan-Quinn criter.	-8.064702
F-statistic	96.39461	Durbin-Watson stat	0.894302
Prob(F-statistic)	0.000000		

4. Modified CSAD on Returns Model

Dependent Variable: POSTREV_CSAD
Method: Least Squares
Date: 05/16/14 Time: 13:37
Sample: 1 749
Included observations: 749

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005273	0.000411	12.83989	0.0000
POSTREV_EGX30_R	-0.083943	0.316049	-0.265601	0.7906
POSTREV_EGX30_R ABS	0.049293	0.020185	2.442085	0.0148
POSTREV_EGX30_R SQ	74.02133	262.6075	0.281871	0.7781
_R_RAV__2	-71.43820	262.6216	-0.272019	0.7857
CSADT_1	0.617991	0.022101	27.96252	0.0000

R-squared	0.650353	Mean dependent var	0.016993
Adjusted R-squared	0.648000	S.D. dependent var	0.005008
S.E. of regression	0.002971	Akaike info criterion	-8.791715
Sum squared resid	0.006559	Schwarz criterion	-8.754715
Log likelihood	3298.497	Hannan-Quinn criter.	-8.777457
F-statistic	276.4001	Durbin-Watson stat	2.431327
Prob(F-statistic)	0.000000		

5. Bull Market

Dependent Variable: POSTREV_CSAD
Method: Least Squares
Date: 05/13/14 Time: 06:32
Sample: 1 749
Included observations: 749

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.016476	0.000217	75.95176	0.0000
POSTREV_EGX30_UP_R ABS	-0.012013	0.033946	-0.353895	0.7235
POSTREV_EGX30_UP_RS Q	4.538678	0.740614	6.128268	0.0000

R-squared	0.144526	Mean dependent var	0.016993
Adjusted R-squared	0.142232	S.D. dependent var	0.005008
S.E. of regression	0.004638	Akaike info criterion	-7.904993
Sum squared resid	0.016048	Schwarz criterion	-7.886493
Log likelihood	2963.420	Hannan-Quinn criter.	-7.897864
F-statistic	63.01534	Durbin-Watson stat	0.647947
Prob(F-statistic)	0.000000		

6. Bear Market

Dependent Variable: POSTREV_CSAD
Method: Least Squares
Date: 05/13/14 Time: 06:33
Sample: 1 749
Included observations: 749

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.016525	0.000208	79.42598	0.0000
POSTREV_EGX30_DOWN_RABS	0.022730	0.030976	0.733792	0.4633
POSTREV_EGX30_DOWN_RSQ	2.551420	0.590459	4.321078	0.0000

R-squared	0.097315	Mean dependent var	0.016993
Adjusted R-squared	0.094895	S.D. dependent var	0.005008
S.E. of regression	0.004764	Akaike info criterion	-7.851275
Sum squared resid	0.016934	Schwarz criterion	-7.832776
Log likelihood	2943.303	Hannan-Quinn criter.	-7.844147
F-statistic	40.21157	Durbin-Watson stat	0.675707
Prob(F-statistic)	0.000000		