ESSAYS ON PRICE OVERREACTION AND PRICE LIMITS IN EMERGING MARKETS: THE CASE OF THE EGYPTIAN STOCK EXCHANGE

by

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Abstract

The main objective of this thesis is to investigate the short and long–term overreaction phenomenon in the Egyptian stock market. In addition, the thesis investigates links between stock market regulatory policies (price limits and circuit breakers) and the profitability of contrarian strategies. Finally, the study examines the effect of regime switch – from strict price limits to circuit breakers – on the volatility spillover, delayed price discovery and trading interference hypotheses.

Using data from the Egyptian stock exchange, I find that a panel data approach adds a new dimension to the existing models, offers interesting additional insights and reveals the importance of the role of unobservable firm-specific factors in addition to observable factors in the analysis of the overreaction phenomenon. Moreover, portfolios based on unobserved factors i.e. management quality, corporate governance and political connections of board members, significantly outperform traditional portfolios based on size. Results also show evidence of genuine long-term overreaction phenomenon in the Egyptian stock market as the contrarian profits of the arbitrage portfolio cannot be attributed to the small firm effect, formation period length, and stability of time varying factor or seasonality effect. Finally, switching from a strict price limit to a circuit breakers regime increases stock price volatility and disrupts the price discovery mechanism in the Egyptian stock market.

Dedication

To my wife, my children (Salma, Youssef and Mostafa), my mother and the soul of my father.

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I alone take full responsibility for any errors and inaccuracies found in this thesis.

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Chapter 1 Introduction and Motivation

1.1 Introduction and background

The research on Behavioural Finance (BF) is concerned with the psychological interpretations of investor behaviour in stock markets. BF focuses on the cognitive psychology that links financial economics with the human decision making process. The main research findings of the BF show that investors interpret information differently and irrationally, and this leads to uninformed decisions. Therefore investors sometimes behave in an unpredictable and biased manner. Behavioural Finance puts much weight on the behaviour of investors that leads to stock market anomalies, Subrahmanyam (2007).

In other words, BF tries to introduce a better interpretation for the existing financial econometrics models by taking into account human emotions and cognitive errors. Research findings on BF find that human flaws are predictable and consistent; therefore analysing investor psychology might offer superior investment opportunities Stracca (2004).

The overreaction phenomenon is one of the consequences of taking human emotions in consideration when analysing investors' behaviour in stock markets. In addition, the overreaction phenomenon is considered the most recent market anomaly added to the long list of traditional market anomalies, i.e. day of the week, January effect and low P/E ratio. It is worth mentioning that many non-traditional financial anomalies have been added to the literature over time, e.g.the excessive volatility of stock prices (Shiller 1981), long-term price reversal (De Bondt and Thaler, 1985), and short-term trends (momentum) Jegadeesh and Titman (1993).

Keynes (1936) is considered the first to observe the overreaction phenomenon. Keynes argues that daily variability of profits does influence markets and causes excessive reaction. The appropriate reaction to information can be defined in the light of Bayes' rule (1980). However, Tversky and Kahneman (1974) (TK) introduced the representativeness heuristic theory (RHT) in which people tend to underweight more distant past information and overweight recent information. In addition, TK argue that they usually judge the probabilities of an event compared with a well known probability distribution of other events or previous experiences or beliefs.

Arrow (1982) finds results consistent with the RHT and concludes that all securities and futures markets can be characterised by excessive reaction to the recent information. Dreman (1982) and Basu (1977) also find evidence of the P/E anomaly as they find that stocks with low P/E ratio outperform those of high P/E ratio and earn abnormal risk-adjusted returns. In addition, Dreman (1982) provided a behavioural interpretation of PE/ratio hypothesis; he argued that stocks with low P/E ratios are underpriced due to investor pessimism as the result of announcements of poor earnings or other bad news.

Barberies, Schleifer and Vishny (1998) introduce the model of investment sentiment in which they provide an alternative interpretation to the under and overreaction phenomena. They differentiate between the size of the shocks or signals and their weights (importance). They argue that underreaction occurs if investors focus too much on the importance (weight) of the signal while the overreaction occurs when investors focus too much on the size (strength) of the shocks. On the other hand, (Daniel, Hirschleifer and Subrahmanyam (1998) introduced amodel of biased self-attribution in which they argue that individual investors are over confident and subject to self-attribution bias when public information is found in line with prior information. This leads to rapid overreaction to the predicted signals.

George and Hwang (2007) argue that the systematic mistakes of irrational investors in responding to new information are the main determinant of the overreaction hypothesis. These mistakes may result from the biased self-attribution theory of Daniel et al. (1998) or investors' beliefs about the expected price behaviour in response to good or bad news (George and Hwang, 2007). Therefore investors may interpret and react to the new information arriving in the market differently; this leads to two contradictory investment behaviours, namely, price continuation or price reversals.

On the other hand, the efficient market hypothesis (Fama, 1976) assumes that stock prices reflect all information available instantly, and prices follow a random walk with no trend and therefore abnormal profits are impossible; however in reality, investors tend to overreact to new information, in particular to positive and negative shocks. This suggests that stock price trends are predictable and investors can achieve abnormal returns.

The dilemma, therefore, is whether stock prices are predictable and valuation errors are systematic or not. If this is so we have therefore a potential conflict between the Market

Efficiency and the Behavioural Finance views. The former assumes that stock prices follow random walk and equilibrium will be restored in the longer run in the event of temporary fluctuations in stock prices. Therefore the true price is the present value of the future dividends stream associated with it. However, the latter assumes that prices are highly influenced by investors' psychological makeup (optimistic or pessimistic). This pushes prices to unexpected levels in both directions. Therefore the true stock price is the expected price based on the psychological makeup of investors.

De Bondt and Thaler (1985) were the first to empirically examine the overreaction hypothesis in the finance literature. They built on the reasoning of Dreman (1982) and discovered a new stock market anomaly based on the Tversky and Kahneman's representativeness theory (1974).

De Bondt and Thaler (1985) argue that price reversals can be predicted in the US using only past return data (3-5 years) in case of systematic price overshoot. Therefore stock returns are predictable and this implies violation of the weak-form market efficiency. They formulate two main testable hypotheses; the first hypothesis, "large stock price movements will be followed by price reversals in the opposite direction" (the directional effect of Brown and Harlow, 1988) and the second hypothesis, "the larger the initial price movements the greater the subsequent reversals" (the magnitude effect). This means that stock returns exhibit negative serial correlation over the longer horizon and therefore investors may earn abnormal returns by exploiting this long-term mispricing. This suggests a clear violation of market efficiency. Fama (1976) formulated the efficient market condition as in equation 1

$$E(\tilde{R}_{it} - E_m(\tilde{R}_{it} \mid F^m_{t-1}) \mid F_{t-1}) = E(\tilde{u}_{it} \mid F_{t-1}) = 0 \qquad (1)$$

Where $\tilde{R}_{it}$ is the return on security *i*, F_{t-1} is the complete set of information at time t-1 and $E_m(\tilde{R}_{it} \mid F^m_{t-1}) \mid F_{t-1})$ is the expected return on stock (i) based on the complete set of information arriving in the market F^m_{t-1}. $E(\tilde{u}_{it} \mid F_{t-1})$ is the estimated residual portfolio returns given a complete set of information arriving in the market. The efficiency condition is therefore that the expected returns on Winners equals the expected returns on Losers and equal to zero; therefore investors cannot beat the market by constructing a portfolio based on the past return; arbitrage profits are zero. De Bondt and Thaler (1985) (DT) formulate this condition as in equation (2)

$$E(\tilde{u}_{Wt} \mid F_{t-1}) = E(\tilde{u}_{Lt} \mid F_{t-1}) = 0 \qquad (2)$$

By contrast, the Overreaction hypothesis of DT is "*Loser portfolios constructed using past information (stock returns) outperform those of Winners"*. In particular, they expect residuals to satisfy the following relationship[1]:

$$E(\tilde{u}_{Wt} \mid F_{t-1}) < 0 \;\; and \;\; E(\tilde{u}_{Lt} \mid F_{t-1}) > 0 \qquad (3)$$

[1] Losers are defined as stocks with poor performance (negative stock returns) in the previous period earn positive risk-adjusted abnormal returns in the subsequent period in US. However Winners are defined as stocks that perform better (positive stock returns) in the previous period earn negative risk-adjusted abnormal returns in the subsequent period. (DeBondt and Thaler (1985 and 1987).

In other words, abnormal returns to Winners are expected to be negative and those to Losers, positive. If the market is efficient, trading strategies based on Loser-Winner anomaly cannot achieve abnormal returns (after transaction costs) given the available set of information F_{t-1}^{m} between market participants (Jensen 1978). Therefore, if the efficient market hypothesis holds, the difference between excess returns on Winners and Losers is zero as in equation 4. However, if the overreaction hypothesis holds, we would expect positive excess returns based on the Losers–Winners anomaly as in equation 5 (see Dissanaike, 1997).

$$\overline{R}_{L,T} - \overline{R}_{W,T} = 0 \qquad (4)$$

$$\overline{R}_{L,T} - \overline{R}_{W,T} > 0 \qquad (5)$$

Where $\overline{R}$ is the cumulative average excess return during test period T. $\overline{R}_{L,T}$ and $\overline{R}_{W,T}$ are the average returns on the loser and winner's portfolios respectively.

De Bondt and Thaler (1985) find that past Losers outperform past Winners by 24.6% in the US, and therefore they recommend selling Winners short and buying Losers as a profitable strategy. They argue that the overreaction phenomenon causes past Losers to be underpriced and past Winners to be overpriced. In addition, they find evidence that the overreaction effect is asymmetric and most of the cumulative average abnormal residuals (16.6%) are realised in January. De Bondt and Thaler (1985) concluded that the market prices are predictable and deviate from their fundamental due to investors' overreactive behaviour and this suggests a clear violation of the Weak Form market efficiency (stock prices reflect past information).

Fama (1998), on the other hand, argues that long-term overreaction phenomenon is quite sensitive to the methodology of modelling excess returns (i.e. Cumulative Abnormal Returs-CARs or Buy and Hold-BAH). In addition, the abnormal returns sometimes disappear when using particular models (CAPM, market model and market-adjusted return) or when using a particular statistical approach Fama (1998)[2]. This suggests that the existence of the long–term overreaction might be attributable to chance; this argument is consistent with the EMH Fama (1998).

1.2 Research objectives and motivation

Emerging stock markets –by contrast with developed markets — are characterised by excess volatility and lower efficiency (Fama, 1998). Therefore investors and fund managers in particular have been trying to exploit market imperfection to achieve abnormal returns by creating trading rules or exploiting market anomalies. The overreaction phenomenon is regarded as one of the newly added anomalies to the existing list of stock market anomalies (De Bondt and Thaler, 1985). The existing body of the literature has extensively investigated the overreaction phenomenon and how to achieve abnormal returns in developed markets; however, few studies have been conducted on emerging markets.

The main objective of this thesis is to investigate the short and long–term overreaction phenomenon in the Egyptian stock market. The Egyptian stock market is one of the leading

[2] Fama (1998) defend the efficient market hypothesis and claims that the long-term return anomalies are fragile. In addition, he claims that the computation errors of the cumulative average abnormal returns using different methodologies (CARs, Buy and Hold, Rebalancing methods) are the main cause of the overreaction and underreaction anomalies in stock markets.

emerging markets in the Middle East and North Africa region (MENA) based on the statistics of the World Federation of Exchanges (WFE, 2010). In addition, the thesis links between the long- term overreaction phenomenon and the regulatory policies (price limits and circuit breakers). Finally, the study examines the effect of regime switch – from strict price limits to circuit breakers – on the volatility spillover, delayed price discovery and trading interference hypotheses[3].

The existing body of literature has investigated the overreaction phenomenon using traditional methodologies; either cross-sectional or time series analyses. However, none of the existing studies has combined the two dimensions using panel data models involving cross section-time series analysis (CSTS). Ignoring time dimension may lay the estimation open to bias (Cressy and Farag, 2011). Moreover, none of the existing studies has investigated the overreaction phenomenon dynamics using a dynamic panel data model and system GMM in

[3] Price limits are regulatory tools in both equity and futures markets in which further trading is prevented for a period of time with the intention of cooling market traders' emotions and reducing price volatility. Within circuit breakers regime, trading may be stopped - for a pre-specified duration – across the whole market or for a particular stock if stock prices or market index hit a pre-determined level (Kim and Yang (2008)).
Volatility spillover hypothesis states that price limits cause stock price volatility to spread out over a few days subsequent to the event (limit hit) (Kim and Rhee (1997)). Delayed price discovery hypothesis states that the price discovery mechanism is delayed due to the suspension of trading for a period of time (Kim and Rhee (1997)). Therefore, it is argued, price limits prevent security prices from reaching their intrinsic values and equilibrium levels. According to the trading interference hypothesis, Fama (1989), Telser (1989), Lauterbach and Ben-Zion (1993) and Kim and Rhee (1997) claim that if trading is prevented by price limits, then shares become less liquid and this leads to intensive trading activity during the following trading days. Detailed discussions of the above mentioned hypothesis are provided in chapter 5.

particular. In addition, none of the existing literature has identified the main unobservable factors that may be used to construct the so-called Unobservable portfolios[4].

Finally, regulatory policies (price limits and circuit breakers) play an important role in cooling down stock market volatility in both developed (trading halts) and emerging markets. However, none of the existing body of the overreaction literature has investigated the link between regulatory policies and overreaction hypothesis. The above-mentioned gaps in the literature are the main motivation for this thesis.

1.3 Research contributions

One of the most important contributions of this thesis is the novel methodology. A panel data model is used for the first time in the finance literature to examine the overreaction hypothesis. There are many benefits of using panel data models (Hsiao 2004:p3). Firstly, panel data models take individual stock heterogeneity into consideration; ignoring individual heterogeneity may lay the estimation open to bias and inconsistent estimates (Baltagi, 2010). Secondly, panel data models are less vulnerable to collinearity among variables, are more informative, offer more degrees of freedom and less variation (Baltagi, 2010: p7). Thus panel data models are more efficient and provide reliable parameter estimation compared with either cross section or time series models ((Baltagi, 2010: p7). Thirdly, more complicated models can be estimated i.e. dynamic models. Fourthly and most importantly, panel data models are

[4] I use companies fixed effects as a new portfolio formation approach. Fixed effects are defined as the unobservable factors that cause the regression line to shift up or down across companies. Further discussion is provided in chapter 4.

better at identifying the so called unobservable effects (either fixed or random), which cannot be detected through both pure time series and cross section analyses

The main contribution of chapter three is the use of the dynamic panel data model in investigating the overreaction phenomenon. Unobservable factors (fixed effects) are then used as a new methodology to construct portfolios by contrast the traditional size-based portfolios. Finally, the chapter attempts to identify unobservable factors. It concludes that management quality, corporate governance and political connections of the board of directors are the main observable correlates to the unobservables, thus adding new insights to the existing panel data models. It is worth mentioning that this chapter is the first in the literature to investigate the relationship between firms' corporate governance compliance, the political connections of the board of directors and the overreaction phenomenon.

Chapter four is the first to link the long-term overreaction phenomenon with the change in regulatory policies, namely the switch from strict price limits to circuit breakers. In addition, this study is the first to augment the Fama and French three-factor and the Carhart (1997) four-factor models by including contrarian and unobservable factors based on the company heterogeneity.

The main contribution of chapter five is that it is the first to investigate the effect of regime switch (from strict price limits to circuit breakers) on overreaction, volatility spillover, delayed price discovery and trading interference hypotheses.

Finally, this study is the first to investigate empirically the short and long–term overreaction phenomenon, the relationship between regulatory policies and the volatility spillover, delayed price discovery and the trading interference hypotheses in the Egyptian stock market, one of the leading markets in the Middle East and North Africa region (MENA).

1.4 Background about the Egyptian economy

1.4.1 Introduction

The world economy witnessed in 2008 the worst global financial crisis since the great depression of the 1930s. This had substantial implications for the world financial system. Subsequent growth rates in leading developed economies were therefore expected to be zero or negative. The crises instantly spread out and were transmitted to the leading global economies with the result that investment and consumption have been frozen in the UK and Europe and economic growth has started to slow down in many countries since 2009, three years after the crisis erupted.

President Obama signed in February 2009 the biggest bailout plan in the history as the US Congress passed the Recovery and Reinvestment Act. Under this Act the US administration provided US $787 billion package to stimulate the economy and create 3.5 million jobs. Similarly, the external competitiveness of the second biggest world economy, namely Japan, deteriorated as the Yen rose dramatically against the Euro and the US$.

The impact of the global financial crisis has spread to the vast majority of emerging economies, particularly those having direct links with the leading economies. The liquidity position of countries has been remarkably affected as foreign direct investments, external demand and the exports of emerging markets have been dramatically diminished.

The effect of the global financial crisis on the Egyptian economy has been cushioned as the Egyptian economy, and particularly the Egyptian banks, are less integrated into the international financial system. Despite the remarkable growth in the value of the foreign direct investment (FDI) and the portfolio investment funds, they have been proportionately small compared with other emerging economies. However, the Egyptian economy has been exposed to indirect external shocks such as the decline in tourism, fluctuations in international natural gas prices, and a potential shift in foreign direct investment (FDI) flows.

1.4.2 Egypt's main economic indicators

The Egyptian economy for decades was highly centralised. However, the economic reform process was greatly accelerated during the era of the former President Hosni Mubarak (1981-2011). International institutions increasingly supported the Egyptian government to take actions towards the liberalisation of trade and stock market; as a result the GDP growth rate reached 7.2% in 2007 and 4.2% in 2008 during the global financial crisis, while the vast majority of the leading economies languished with negative or zero growth.

Because the Egyptian economy had made such effective steps towards economic reform and enhancement of the investment climate, the Economic Reform Forum of the World Bank in 2008 chose Egypt among the seven best-performing countries in the world. The growth rate since then has fallen and in 2011 is estimated at a lower 1.5% - 3.5% due primarily to the political tension in the Middle East region following the Arab Spring and the Egyptian revolution. However, in 2012, once the parliamentary and the presidential elections have been run, the economy is expected to recover once more and to grow at a modest 5% annual rate.

The Egyptian economic reform programme started in 1994 when the Egyptian government announced a major privatisation programme covering large swathe of publicly owned companies. 411 companies were sold since 1994 for Egyptian pounds (LE) 57 billion. The remarkable success in the programme has positively affected the development of Egyptian capital markets as the vast majority of the companies were sold to the public and anchor investors (ownership greater than 50%) via IPOs through the stock market.

Table 1.1 summarises the main results of the privatisation programme over the period 2000-2011. We can see that in numerical and value terms privatisations peaked in the period 2005-2007, and rose again in 2008-9 after a major dip during the financial crisis.

Table 1.1: Privatisation Programme 2000/2001-2009/2010

	Total Sales Companies/Assets (100% state-owned)		Other Public Sector Sales		Joint Venture Sales		Total Sales		GDP	%of Total Sales to GDP
	No.	Value in LE Millions	No.	Value in LE Millions	No.	Value in LE Millions	No.	Value in LE Millions	Value in LE Billions	
2000/2001	11	252	--	--	7	118	18	370	391	0.09
2001/2002	7	73	--	--	3	879	10	952	379	0.25
2002/2003	6	49	--	--	1	64	7	113	418	0.03
2003/2004	9	428	--	--	4	115	13	543	485	0.11
2004/2005	16	824	--	--	12	4,819	28	5,643	539	1.05
2005/2006	47	1,843	1	5,122	18	7,647	66	14,612	618	2.37
2006/2007	45	2,774	1	9,274	7	1,559	53	13,607	745	1.83
2007/2008	20	745	0	0	16	3,238	36	3,983	896	0.44
2008/2009	16	1,590	0	0	1	63	17	1,653	1,039	0.16
Dec-09	--	--	--	--	1	4	1	4	1,181	0.00
Grand Total	338	24,440	2	14,396	70	18,516	411	57,366		

Source: The Egyptian Ministry of Investment

Table 1.2 presents selected economic and financial indicators for the Egyptian economy over the period 2005 – 2010. The figures presented in table 1.2 show that foreign direct investment (FDI) amounted to US$ 4.3 billion in 2010 compared to US$ 5.2 in 2009. The net FDI investments of the oil sector represent over 50% of the total FDI during the last two years. The private sector in the Egyptian economy is now regarded as the engine of economic growth.

The private sector contributed around two-thirds of the total GDP over the period 2003/04-2007/08. The official statistics of the fiscal year 2008/09 also show that the growth rate in the private sector is 3.31% compared to 1.35% growth rate in the public sector. Foreign reserves increased from US$ 34.2 billion in 2008/09 to US$ 36 billion in 2009/10, meanwhile the inflation rate decreased from 13.2% in Dec 2009 to 10.3% in December 2010.

The inflation rate in Egypt has been remarkably high over the past few years; it reached 11% in 2010 and was expected to increase during 2011 to 15% due to the political tension. This caused a devaluation of the Egyptian pound against the US$ by 5% during the first quarter of 2011. The value of the external Egyptian debt was US$ 34.5 billion in 2010 of which 23% represented short-term debt.

The external debt balance represented 14.5% of the GDP in 2010. On the other hand, the foreign exchange currency exceeded this debt liability over the past few years. Finally, since 2008 Egypt has been regarded as one of the world's main exporters of natural gas (representing 50% of all merchandise exports). The trade deficit is moreover usually compensated by the revenue from service sector, in particular by Suez Canal transit fees and revenue from tourism.

Table 1.2: Selected Economic and Financial Indicators

	Jun-05	Jun-06	Jun-07	Jun-08	Jun-09	Mar-09	Mar-10
GDP at Market Prices (LE Billions)	538.5	617.7	744.8	895.5	1,038.6	771.6	893.5
GNP (LE Billions)	563.3	649.4	787.4	949.2	1,081.7	805.5	915.4
Real GDP (% Growth Rate)	4.5	6.8	7.1	7.2	4.6	4.7	5.1
Real Per Capita GDP (% Growth Rate)	2.5	4.9	4.9	5.1	2.5	NA	NA
Average Per Capita Income	7,693.2	8,657.6	10,211.1	12,030.0	13,654.8	13,526.0	15,332.1
Share of Private Sector in GDP (%)	61.7	60.3	62.4	61.6	62.8	62.5	63.6
Overall Fiscal Balance (% GDP)	(9.6)	(8.2)	(7.3)	(6.8)	(6.9)	(5.4)	(7.3)
Net FDI in Egypt (%GDP)	4.4	5.7	8.5	8.1	4.3	0.7	0.8
Public Domestic Debt (% GDP)							
Net Domestic Budget Sector Debt	72.5	72.0	64.2	53.5	54.1	53.3	55.7
Net Domestic General Government Debt	51.5	53.8	49.6	42.7	45.0	43.5	47.8
Net Domestic Public Debt	52.3	53.9	48.8	43.2	45.8	44.4	48.6
Inflation Rates							
CPI (% Growth Rate)	11.4	4.2	11.0	11.7	16.2	13.3	12.9
WPI (% Growth Rate)	9.9	4.1	11.8	--	--	--	--
PP (% Growth Rate)	--	4.1	11.8	17.7	2.5	(7.0)	13.2
Exchange Rates							
Official Exchange Rate (LE/ US$)	6.006	5.747	5.710	5.500	5.510	5.570	5.460
Interest Rates							
Interest Rate on T-Bills (91 days)	10.1	8.8	8.7	7.0	11.3	10.2	10.1
Broad Money (% Growth Rate)	13.6	13.5	18.3	15.7	8.4	6.9	9.8
External Debt							
External Debt (% GDP)	31.1	27.6	22.8	20.1	17.0	16.7	14.8
External Debt (% Exports of G&S)	100.3	82.4	70.4	59.9	64.4	293.6	295.5
Debt Service (% Current Receipts)	7.9	7.3	5.9	3.9	5.3	4.8	4.8
Debt Service (% Exports of G&S)	9.4	8.5	6.9	4.6	6.2	5.7	5.8
Population (% Growth Rate)	1.97	1.93	2.23	2.06	2.18	NA	NA
Domestic Savings (LE Billions)	84.6	105.7	121.2	150.4	129.1	101.4	130.4
National Savings (LE Billions)	109.4	137.4	163.8	204.1	172.2	135.3	152.3

Source: Ministry of Economic Development, Ministry of Finance, and Central Bank of Egypt.

1.5 Overview about the Egyptian Exchange (EGX)[5]

1.5.1 The history of the Egyptian Exchanges

The Egyptian exchange is the oldest stock market in the MENA (Middle East and North Africa) region. The Alexandria stock exchange was founded in 1883 followed by the Cairo stock exchange in 1903. It is worth mentioning that the Alexandria exchange is one of the oldest futures markets in the world, particularly in cotton forward contracts. The vast majority of trading volume in the Alexandria futures market was done with the Liverpool Cotton Exchange until 1950.

The Egyptian economy had grown significantly and before 1950 the Cairo and Alexandria stock exchanges were regarded as one of the top five stock exchanges in the world. The number of listed companies had reached 228 with a total market capitalisation of 91m Egyptian pounds. By the early 1960s, however, the vast majority of private firms had been nationalised by the socialist government. Therefore the role of the Cairo and Alexandria stock exchanges was dramatically diminished; the number of listed firms declined to a nine after thirty years.

By contrast, in the 1990s the former president Mubarak adopted a comprehensive economic reform strategy. The Cairo and Alexandria stock exchanges were re- activated with large scale flotations. 656 companies were listed by 1992. The two stock exchanges were linked with one automated trading system; this facilitated the implementation of the privatisation programme

[5] The main source of information in this section is the EGX annual reports (1996-2010)

starting from 1992, in which a number of IPOs of state-owned companies were executed through the Cairo and Alexandria stock exchanges.

1.5.2 Main Stock Market Indices[6]

The EGX 30 index is the main Egyptian stock market index and the most widely used as an market benchmark and barometer. EGX performance could be tracked through the S&P-IFC Global and Investable Indices from 1996 and 1997 respectively.

The EGX30 was initially launched in 2003 as a free-floated market capitalization weighted index and was retroactively computed as of 1 January 1998 with a base value of 1000 points. The major international financial institutions provide information and analysis of the performance of the Egyptian exchange based on the EGX30. The EGX30 is, like most world indices, weighted by the market capitalisation of its constituent stocks. It avoids cross holdings and industry concentration and excludes bankrupt companies and any companies ‘consumed’ in merger and acquisition deals. To reflect market activity, the index is rebalanced and updated every six months.

In 2006 the Egyptian exchange launched a new market index, namely the Dow Jones EGX Egypt Titans 20 Index (DJ20) jointly with the leading global index provider Dow Jones indexes. The DJ20 tracks the 20 blue chips of the Egyptian stock market in terms of free-float adjusted market capitalisation, sales and net income.

[6] EGX annual reports (1996-2010)

In March 2009 the EGX then introduced two new price index products, namely EGX70 and EGX100, to track the performance of the most active 70 and 100 companies excluding the constituents of the EGX30. More recently, in 2010, the EGX launched the EGX20 capped index (allowing only a 10% maximum weight to any of its constituent stocks) with the aim of capturing the performance of the most active 20 companies in terms of market capitalisation and liquidity.

1.5.3 Stock market regulations

1.5.3.1 Price Limits

Since 1996 EGX trading regulations imposed strict price limits (SPL) for all the listed shares, amounting to absolute changes of more than 5% of the current stock price. The limit is activated for a particular stock only when stock return hits the upper or lower limit; then the trading on the share is suspended for the rest of the trading session. The SPL is only removed in case of any corporate action. The SPL was first launched by the regulator with the intention of cooling down the market and avoiding excess volatility. In 2002 the regulator commenced a new price ceiling system, namely circuit breakers (CB) in which the price limits were widened to +-20% for the most actively traded shares in the EGX. Within the new CB regime, trading would be halted for 30 minutes should the stock price change for a particular stock hit +-10%.

During the 30 minute trading halt, brokers must inform their clients of the temporary suspension of the trading session. In addition brokers are allowed to cancel or adjust traders' orders to adjust their portfolio positions. When the trading session is resumed and if the stock return for a given share has hit the upper or lower limit (now +-20%), trading is suspended until the end of the trading session.

1.5.3.2 Intra-day trading mechanism:

The Intra-day trading mechanism was launched in 2004 by the regulator for the listed shares in the main and the OTC markets for the most actively traded companies on the market.

1.5.3.3 Settlement:

The settlement mechanism in the EGX is as follows:

- T (trading day) + 0 for securities traded by the Intra-day trading system.
- T (trading day) +1 for government bonds.
- T (trading day) +2 for all other securities.

1.5.3.4 Tax system

According to the capital market law No.95/1992 no taxes are imposed on both dividends and capital gain in addition to coupon payments for individuals.

1.5.3.5 Foreign investments

There are no regulatory restrictions on foreign investment or profit repatriation in the Egyptian stock market.

1.5.3.6 Trading hours

The trading hours of the market are shown in the table below.

Table 1.3: Trading hours at the EGX

Main Market	Trading hours
Trading session	10:30am – 2:30pm
Bonds Market (Primary Dealers)	10:30am – 2:30pm
NILEX (SMEs Market)	11am-12pm
Over-the-Counter Market	9:45am- 11:15am

Source:www.egyptse.com

1.5.3.7 Short selling

To support stock market liquidity the EGX has permitted margin trading and set up regulations for short selling of the most actively trading stocks.

1.5.4 The performance of the Egyptian stock market

The Egyptian stock market was classified by the Economist in 2010 as one of the best six emerging markets (CIVETS)[7] offering significant potential growth over the next decade. In addition, the World Federation of Exchanges' (WFE) statistics in 2010 reported that the Egyptian exchange achieved average gain of 15% during 2010, ahead of many leading world emerging stock exchanges i.e. China, Brazil, and Czech Republic, and ahead of all Arab stock markets excepting those of Qatar (25%) and Casablanca (21%) . The Morgan Stanley International index MSCI and S&P IFCI reported that the annual growth rates for the EGX during 2010 were 9% and 13% in US$ respectively. By comparison, the average growth rate for emerging markets was 12% in US$.

[7] Colombia, Indonesia, Vietnam, Egypt, Turkey and South Africa

The Egyptian stock market achieved reasonable performance indicators during 2008-2010 even though the negative impact of the global financial crisis affected the vast majority of the stock markets throughout the world. The main market indicators diminished only slightly in 2010 as compared to 2009. The total value traded during 2010 was LE 321 billion compared to LE 448 billion in 2009, meanwhile the total trading volume was 33 billion securities in 2010 compared to 37 billion securities in 2009. The market capitalisation of the main market was LE 488 billion (40% of the GDP) during 2010 compared to LE 500 billion in 2009. During 2010 the EGX achieved attractive P/E of 14.7 compared to 13 in 2009; however, based on the statistics of the S&P/IFC composite index for emerging markets the average P/E is 13.5. On the other hand, the dividend yield increased from 6.5% in 2009 to 7.1% in 2010 and the emerging market average dividend yield was 1.8%.

Trading volume, dominated by financial institutions, rose from 37% in 2009 to 52% in 2010, while individual investors share fell to 48% of trading volume in 2010 compared to 63% in 2009. Foreign investments accounted for 22% of the total trading volume in 2010 and total foreign capital inflow fell from LE8.4 billion in 2010 compared to LE5 billion in 2009. Foreign investments in EGX were dominated by Europe (43%), the US (27%) and Arab investments (24%).

The UK investors were the first in the Egyptian stock market and accounted for 37% of the total foreign investments in 2010. Finally, the OTC trading volume sharply declined from LE 115 billion in 2009 to LE billion in 2010. Table 1.4 presents the main market indicators for the Egyptian stock exchange (EGX) over the period 2001-2010.

Table 1.4: Main Market Indicators for the Egyptian stock exchange (EGX) 2001-2010

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Total Volume (bn shares)	1.3	0.9	1.4	2.4	5.3	9.1	15.5	25.5	36.6	33
Volume of Listed Securities	1.2	0.7	1.2	1.8	4.2	7.8	11.4	21.9	28.6	28
Volume of Unlisted Securities	0.1	0.2	0.2	0.6	1.1	1.3	3.7	3.6	8	5
Total Value Traded (LE bn)	31.8	34.2	27.8	42.3	160.6	287.0	363	529.6	448.2	321
Value Traded (Listed Sec)	24.7	25.8	23.0	36.1	150.9	271.1	321.5	475.9	333.5	273
Value Traded (Unlisted Sec)	7.1	8.4	4.8	6.2	9.7	15.9	41.5	53.7	114.7	48
Number of Transactions (m)	1.1	0.8	1.2	1.7	4.2	6.8	9	13.5	14.6	10
Number of Transactions (Listed Securities)	1.1	0.7	1.2	1.7	4.0	6.6	8.7	12.8	13.5	10
Number of Transactions (Unlisted Securities)	0.01	0.1	0.02	0.1	0.2	0.2	0.3	0.7	1.1	0.4
Average Monthly Value Traded (LE billion)	2.7	2.9	2.3	3.5	13.4	23.9	1488	1656	1822	1300
Average Monthly Value Traded (Listed Securities)	2.1	2.2	1.9	3.0	12.6	22.6	1318	1436	1356	1105
Average Monthly Value Traded (Unlisted Securities)	0.6	0.7	0.4	0.5	0.8	1.3	170	220	466	194
Turnover Ratio (%)	14.1	9.5	11.5	14.2	31.1	48.7	38.7	70.3	49.9	42.9
Foreign Participation as a % of Total Value Traded	13.3	17.3	12.7	20.5	16.4	16.6	19.2	20	12.7	16.5
Arab Participation as a % of Total Value of Traded	2.9	1.8	7.8	7.0	13.9	13.6	12.5	10	6.3	6.1
Number of Trading Days	246	249	244	249	249	244	244	244	249	247
Average Company Size (LE million)	101	106	176	294	613	897	1766	1259	1633	2302
Number of Traded Companies	251	261	260	233	241	227	237	222	229	211
Market Capitalisation (LE bn)	112	122	172	234	456	534	768	474	500	488
Market Capitalisation % GDP	30	29	35	43	74	80	86	45	41	40

Source: The Egyptian Exchange , annual reports 2001-2010

1.6 The structure of the thesis

The thesis comprises six main chapters; chapter one consists of six main sections; in section one I discuss the theoretical and conceptual background of the topic. Section two presents the main objectives and motivation of the study. Section three focuses on the main contribution of the thesis. Sections four and five present background about the Egyptian economy and an overview of the Egyptian stock exchange respectively. Finally, section six presents the structure of the thesis.

Chapter two introduces a comprehensive literature survey of the overreaction phenomenon. The chapter mainly is divided into seven main sections. Section 1 includes introduction and motivation. Section two presents summary of the short-term overreaction in developed and emerging markets. In section 3 I present the development of the long term overreaction in both developed and emerging markets. In section 4 I present the possible interpretation to the overreaction phenomenon, namely the variation of risk (beta), seasonality and size effects, bid-ask spread and the tax hypothesis. Section five analyses the overreaction to specific events such as the overreaction to corporate actions (merger, acquisition and earnings and dividends announcements), to rumours and to the international sport championships results. Section six refutes the main arguments of the opponents of the overreaction phenomenon. Finally, section seven summarises and concludes.

Chapter three investigates the short–term overreaction using a novel methodology, namely, dynamic panel data model using system GMM. Chapter three consists of five main sections. Section one includes the main objectives and motivation of the chapter. Section two presents the theoretical background about the traditional models and the proposed new model to explain the short-term overreaction. Section three describes the dataset used in the analysis. Section 4 presents the econometric modeling and the empirical results. Finally, section five summarises and concludes.

Chapter four, on the other hand, investigates the long–term overreaction phenomenon for all listed shares in the Egyptian stock exchange. Chapter four consists of six main sections. I present in section one the main objectives and motivations of the chapter. Section two discusses the theoretical arguments and the alternative measures of the long–term performance. Section three presents the alternative sources of the contrarian and momentum abnormal returns. Section four describes the dataset used in the analysis. Section 5 describes the econometric modeling and the empirical results. Finally, section six summarises and concludes.

Chapter five investigates the effects of regime switch on the overreaction phenomenon. Chapter five consists of six main sections. Section one includes the main motivation and objectives of the chapter in addition to the theoretical background about the evolution of the different types of regulatory policies. In section two I analyse the academic debate about the impact of the circuit breakers and price limits. Section three presents a comprehensive literature review of the different types of regulatory policies. Sections four describes the dataset used in the analysis. Section five presents the econometric modeling and the empirical results. Finally, section six summarises and concludes.

Chapter six presents a summary of the main findings of the thesis. Chapter six consists of six main sections. Sections one and two present the research objectives and main results of the thesis respectively. Sections three and four analyse the main contributions and research limitations respectively, while section five analyses the policy implication. Finally, section six provides suggestions for future research.

Chapter 2 : Literature Review

2.1 Introduction

The literature on the overreaction phenomenon is separated into long–term and short-term behaviour. The existing literature has extensively explored the overreaction phenomenon in developed markets. However, few studies have investigated the overreaction effect in emerging markets, generally recognised to be less informationally efficient and therefore more likely to be subject to market anomalies. Recent strands of research have concluded that - to the contrary of the efficient market hypothesis - using past prices, stock returns are predictable both over short and long horizons. See for example Shiller (1981) and De Bondt and Thaler (1985).

This constitutes a newly added market anomaly[8] in which changes in investor information result in an initial reaction (buying or selling), a price trend (down or up) and finally a partial reversal of the trend as investors revise their estimate of the impact of this new information. This phenomenon is called the *overreaction effect* and implies that stock returns are negatively serially correlated. Therefore stocks that performed poorly (Loser portfolios) during a portfolio formation period (the period over which the model is estimated) may outperform the market during the test period (the period over which the model is tested).

On the other hand, the good performers (Winner portfolios) on this theory are expected to underperform the average market return in the test period. Therefore, based on the market

[8] Others include the January and Monday effects in addition to small firm effect and low PE ratio.

shocks and whether they represent good or bad news, stock returns may be predictable and a 'contrarian' strategy may earn abnormal return by selling Winners short and buying Losers. De Bondt and Thaler (1985) thus devised a zero investment portfolio in which cash from short sales of Winners is used to finance investment in Losers. The overreaction hypothesis provides clear evidence of invalidity of Weak Form market efficiency (Fama, 1976) as investors can predict stock returns using past stock prices (Conrad, et al. (1997) and Baytas and Cakici (1999)).

The main objective of this chapter is to conduct a comprehensive literature survey of the overreaction phenomenon. The chapter mainly is divided into seven main sections. Section one includes introduction and motivation. Section two presents summary of the short-term overreaction in developed and emerging markets. In section three I present the development of the long term overreaction in both developed and emerging markets.

In section four I present the possible interpretation to the overreaction phenomenon, namely the variation of risk (beta), seasonality and size effects, bid-ask spread and the tax hypothesis. Section five analyses the overreaction to specific events such as the overreaction to corporate actions (merger, acquisition and earnings and dividends announcements), rumours and the international sport championships results. Section six refutes the main arguments of the opponents of the overreaction phenomenon. Finally, section seven summarises and concludes.

2.2 Short –term overreaction

In this section, I present the literature on the short-term overreaction hypothesis in both developed and emerging markets.

2.2.1 Developed Markets

Zarowin, (1989) investigates the short–term overreaction phenomenon and whether or not size and seasonality effects can explain this phenomenon. Monthly returns data are collected over the period 1927-1985 for the listed shares in the NYSE. Zarowin formed equally size portfolios based on past returns performance and calculated the risk-adjusted abnormal performance of the two extreme portfolios, namely Winners and Losers following De Bondt and Thaler (1987). Results support the short-term overreaction in the NYSE as Losers significantly outperformed Winners by 2%-2.5% per month regardless their size. In addition, Zarowin argues that short-term overreaction is considered a clear violation of the efficient market hypothesis and regarded as a new market anomaly.

Atkins and Dyl (1990) investigate the short–term overreaction in the US. They define the event as stock prices that experienced a large price change (based on the Wall Street Journal) in a single trading day. In addition, they examine the proposed relationship between the short-term reversals and the bid-ask spread. Daily return data are collected for all listed shares in the NYSE over the period 1975-1984. Using the mean-adjusted, market and risk-adjusted returns to calculate the abnormal returns, they find strong evidence of short –term overreaction in case of bad news and weak evidence in case of good news. When they control for the bid-ask spread, they found that price reversals are minimised and traders could not profit from the overreaction anomaly. This implies market efficiency. They conclude that the bid-ask spread is not the main source of the overreaction phenomenon in the NYSE.

Bremer and Sweeney (1991) examine the short-term price reversal phenomenon in the US. They define the event as stocks that experienced at least -10% price drops in a single trading day. Daily stock return data are collected for all listed shares in the Fortune 500 over the period 1962-1986. Using the mean adjusted returns, results show evidence of price reversal in the US; positive cumulative excess returns (2.2%) tend to be following the large negative price drop over two days following the event. The price reversal phenomenon is unrelated to weekend and turn-of-the-year effects.

Liang and Mullineaux (1994) investigate the short-term overreaction in NYSE and ASE over the period 1963-1988. They define the event based on the residuals of the market model, and then the three largest positive and negative events have been selected for each firm/year. Daily return data are collected over 401 days pre (200) and post (200) event. Using the event study methodology following Brown and Warner (1985), they find significant price reversal post negative and positive events. They also find that stock prices tend to decrease pre positive events (shocks) and increase pre negative shocks. Their results support the short-term overreaction hypothesis.

Park (1995) argues that the predicted stock returns following large one-day price dramatic changes are biased due to both sample selection bias and bid-ask spread. Therefore Park (1995) investigates the effect of the bid-ask spread on the estimated stock returns following one-day large price changes and the potential market microstructure explanation to this phenomenon.

Daily price data of all listed shares of NASDAQ/NMS are collected over the period 1984-1987. They calculate the stock returns based on the average bid-ask prices compared with the traditional returns based on closing prices and define the event if the absolute value of the market-adjusted abnormal returns exceeded 10% change in a particular day. Using the compounded cumulative abnormal returns (CARs), they find that bid-ask spread did not fully explain price reversals following the large one day price drop. In addition, they find evidence of the short–term market overreaction; however, the contrarian profits are not large enough to be exploited due to transaction costs.

Cooper (1999) investigates the short-term overreaction phenomenon and the impact of alternative filter rules on contrarian profits of large capitalisation in the NYSE and AMEX. Weekly return and trading volumes data are collected for the 300 large firms in the NYES and AMEX - to minimise the bid-ask spread bias - over the period 1962-1993. Cooper uses the filter rule methodology by specifying Losers and Winners based on minimum amount of lagged weekly returns and trading volume growth. Cooper finds evidence of the overreaction phenomenon in the NYSE. In addition, he finds that the lower the trading activity the higher the price reversals. Results show that the filter rule strategies outperformed the buy and hold counterparts.

Nam et al. (2001) find evidence of mean reversion in NYSE using the asymmetric non-linear transition generalized autoregressive conditional model ANSTGARCH. They also find that the reversal from negative to positive returns is quicker than the reversal from positive to negative returns; in addition their findings support the overreaction hypothesis.

Schnusenberg and Madura (2001) examine the short–term overreaction and underreaction of six main market indices in the US to avoid the potential bid-ask spread bias. They define the event based on the best (Winners) and worst (Losers) index historical performance. Daily price data are collected for major six stock indices in the US equity market since inception and until 1997, namely; DJIA, NYSE, NASDAQ, S&P500, Russel 3000, and Wilshire 5000. They use the mean–adjusted return and ARIMA models to estimate the expected returns.

They find evidence of market underreaction in the following day subsequent to the event for the six market indices. In addition, they find significant short-term overreaction for the Losers and underreactions for the Winners over the 60 days following the event, these results are consistent with Fama (1998). They find that the less constituents (i.e. NASDAQ) in the index the greater degree of underreaction for the Winners.

Larson and Madura (2003) investigate the relationship between overreaction/underreaction and the information disseminated to the market in the short-term based on the classification of the Wall Street Journal (informed/uninformed event). They define the event as stocks that experience at least +-10% daily price change over a three-day event window. Daily returns data are collected for the listed shares in the NYSE over the period 1988-1995. They estimate the market model using the methodology of Brown et al. (1988) with the estimation window is (-260,-41), the examination window (-3, +20) and the event window (+81-+300). They find evidence of the overreaction phenomenon in cases of uninformed events. Their results support the overconfidence and self-attribution bias by Daniel, Hirshleifer and Subrahmanyam (1998).

Ma et al. (2005) investigate the short-term overreaction in the US. They define the event as stocks that experienced the largest price change reported in the Wall Street Journal. Daily price data of a sample of (852) Winners and Losers listed in NYSE and NASDAQ are collected over the period 1996-1997. They find little evidence of price overreaction in the NYSE for both Winners and Losers; however, they find significant price reversal and evidence of the overreaction phenomenon in the NASDAQ market. They conclude that investors may interpret the new information differently in the NYSE and NASDAQ.

Michayluk and Neuhauser (2006) investigate the overreaction hypothesis in the NYSE in response to the Asian financial crises in 1997. Daily price data are collected for 6276 stocks over 60 days following the crash. They find significant evidence of market overreaction to the Asian financial crises over one week following the Asian market crash. In addition, they find that both size and CAPM-beta did not explain the initial price decline following the crash. Finally they present evidence of short-term return predictability during the Asian stock market crash.

Lo and Coggins (2006) investigate the daily and hourly overreaction phenomenon in the Australian stock market and whether or not trading volume and stock liquidity explain price reversals. Daily and hourly price data are collected for the top 200 companies listed in the

Australian stock exchange ASX from 2000 to 2002. Following the methodology of Lo and MacKinlay (1990), they find strong evidence of short–term contrarian profits; however these strategies are no longer profitable after controlling for transaction costs. They find a positive relationship between price reversals and order imbalance and that the overreaction phenomenon can be explained by temporary liquidity imbalance.

Spyrou et al. (2007) examine the short term overreaction and underreaction to market shocks in the UK. Daily closing price data are collected for four stock market indices, namely, the FT30, FTSE100, FTSE250 and FTSE Small Cap over the period 1988 to 2004. They define the event (positive or negative shocks) when return on the market index is above or below two standard deviations over (-60,-11) day estimation window. They find no evidence of overreaction to market shocks for big firms, as no significant abnormal returns are found on the following days subsequent to the shock. On the other hand, they find evidence of market underreaction for small and medium size firms. Price reversals occur during 12-20 days following the event. They find no effect of the seasonality, bid-ask spread, and time varying risk in their results.

Recently, Lobe and Rieks (2011) investigated the out of sample estimation of the short-term overreaction hypothesis in the German stock market. They define the event as stocks experienced price change at least 10% as a proxy of positive and negative shocks. Daily data are collected for four main German stock market indices since inception, namely, DAX30, MDAX, SDAX, technology. Using the market and size–adjusted abnormal returns over a five-day post-event, they find significant evidence of short-term overreaction in the German stock market and this overreaction is not due to size or bid-ask spread. In addition, they find asymmetric price reaction to positive and negative shocks. When they controlled for the transaction costs, the contrarian profits were negligible. Their results support the efficient market hypothesis in the German stock market.

2.2.2 Emerging Markets

Few studies have investigated the short-term overreaction phenomenon in emerging stock markets. Bowman and Iverson (1998) investigate the short-term overreaction hypothesis in the New Zealand stock exchange. Weekly return data for all listed shares are collected over the period 1967-1986. They define the event as stock that experienced at least 10% weekly price change. They find strong evidence of the overreaction phenomenon in the New Zealand stock market as abnormal returns for Losers one week post-event (2.4%) outperform Winners (-1.5%). The overreaction phenomenon was not due to bid ask bounce, non-synchronous trading or size effect.

Otchere and Chan (2003) investigate the short–term overreaction in the Hong Kong stock exchange (HKSE). They argue that the Hong Kong stock market is unique for international investors as neither capital gains nor dividends are taxed. Daily data are collected over two periods around the Asian financial crises pre (1996-1997) and post crisis (1997-1998). They use three different methods to calculate the abnormal returns, namely, mean-adjusted, market model and the CAPM. They find little but significant evidence of price overreaction in the HKSE pre the Asian financial crises. They also find that price reversals are more pronounced for Winner than for Losers. In addition, when they controlled for transaction costs, there was no evidence of contrarian profits. The overreaction phenomenon is diminished during the crises period and cannot be explained by either bid-ask spread or the day of the week effect.

Farag and Cressy (2010) investigate the short-term overreaction and the disposition effect in the Egyptian stock exchange (EGX) over the period 2005-2008. Daily data are collected for 20 companies listed in the EGX and experience one-day dramatic change in stock return (defined as a change greater in absolute value than 10% of the current intraday price). They argue that the existing body of the literature ignores the time dimension in the analysis and this may lay the estimation open to bias due to company heterogeneity. Using a panel data model, they find that the fixed effect model best suits the EGX data and the unobservable factors play an important role in explaining the overreaction phenomenon. Their results support the disposition effect as past Losers outperform past Winners. Table 2.2 presents a summary of the literature on the short-term overreaction.

2.3 Long–term overreaction

The existing body of research on the long-term overreaction is impressive, although we shall find that the interpretation of this phenomenon is controversial (Gunaratne and Yonesawa (1997), Shiller (1981), De Bondt and Thaler (1985) and Conrad, et al. (1997). In this section, I present the literature on the long-term overreaction hypothesis in both developed and emerging markets.

2.3.1 Developed markets

De Bondt and Thaler (1985) are considered the first to elaborate the overreaction hypothesis which, as we have seen, claims that, contrary to the EMH, stock prices are predictable. They argue that the overreaction phenomenon should attract the attention of finance researchers as it represents a behavioural principle that can be applied in many other contexts. Motivated by work in cognitive psychology on intuitive prediction, monthly returns data are collected from NYSE. They form a three-year non-overlapping portfolio ranking based on the top and bottom 50 cumulative excess returns in the formation period 1926-1982.

De Bondt and Thaler calculate the cumulative average abnormal residuals and find that Loser portfolios – on average – outperform the market by 19.6% during the three-year formation period. However, the Winners achieve 5% less than the market. This suggests that the cumulative average abnormal residual of the arbitrage portfolio (Losers-Winners) equals 24.6%. This implies that the overreaction effect is asymmetric as it is much larger for the Losers. In addition they find evidence of the seasonality effect as most of the abnormal returns occur in January, consistent with the turn-of-the-year effect anomaly. Finally, they find results consistent with Graham's arguments that the overreaction hypothesis becomes very clear within the first 24-36 months of the test period.

Howe (1986) investigates the long–term overreaction in the NYSE. Weekly data are collected over the period 1963-1981. The event is defined as stocks that experienced arbitrary large (+-50%) weekly return and the estimation and events windows are defined as 52 weeks pre and post large price change. Using the OLS and Scholes-Williams (S-W) technique to measure the systematic risk in case of good (+50%) and bad news (-50%), results reveal that Losers have greater systematic risk than those of Winners. Howe (1986) finds evidence to support the overreaction hypothesis; Winners perform poorly during the event window (30% less than the market). However, Losers achieve positive and significant cumulative abnormal returns of 14% during the first five weeks of the event window. Finally, Howe (1986) concludes that the overreaction phenomenon in the NYSE cannot be attributed to January effect.

De Bondt and Thaler (1987) in a follow-up paper, re-investigate the overreaction hypothesis with more focus on size and seasonality effects. In addition, they examine the relationship between time-varying risk premia and market efficiency and whether the variation in CAPM-beta can explain the Loser-Winner anomaly. Using the same dataset and methodology of De Bondt and Thaler (1985), they find that Losers' January returns are negatively related to the returns of the formation period. In addition, the excess returns of January of the Winners are negatively related to December excess returns due to the tax–loss hypothesis. They also find that the variation in CAPM-beta cannot explain the Winner–Loser anomaly. Finally, they claim that the Winner–Loser anomaly is not attributed to the size effect (small firms have greater growth opportunity and more volatile compared to big firms effect). On the other hand,

De Bondt and Thaler (1990) conclude that professional financial analysts overreact (the tendency to make extreme forecasts) in the same pattern as naive undergraduates. Therefore they argue that the behavioural interpretation should be taken into consideration when explaining stock market anomalies. Moreover, Amir and Ganzach (1998) conclude that there is a direct relationship between the forecast horizon and the prediction bias, as they find greater overreaction and underreaction to analysts' forecasts in the long term.

Brown and Harlow (1988) examine the overreaction hypothesis as well as the intensity effect in the NYSE over the period 1946-1983. They define the intensity effect as "the shorter the duration the initial price change the greater price reversal". Their results are consistent with De Bondt and Thaler (1985) who find evidence of the overreaction and intensity effects in the NYSE of America particularly for the Losers. Alonso and Rubio (1990) investigate the overreaction phenomenon in the Spanish stock market. Monthly return data are collected for all the listed shares over the period 1965-1984. They use the market model to calculate the cumulative excess returns for the three-year non-overlapping portfolios as well as two size portfolios, namely 'big' and 'small', following the methodology of De Bondt and Thaler (1985). Their results support the existence of the overreaction phenomenon in the Spanish stock market, as Losers outperform Winners by 24.5% over the 12 months following the formation period.

Chopra et al. (1992) investigate long-term performance using an innovative methodology to re-evaluate the overreaction phenomenon for all listed shares in the NYSE over the period 1936-1986. They use the the estimated market compensation per unit of beta risk instead of CAPM–beta, with adjustments for size and time variation in beta. They adopt the Buy-and Hold returns measure to rank portfolios during a five-year ranking period; in addition, the formation period is defined as a set of overlapping five-year intervals.

Their results support the overreaction phenomenon in the NYSE as Losers are found to outperform Winners by 9.5% per year; in addition the overreaction phenomenon cannot be attributed to size effect. However, the overreaction is found to be much stronger for small firms. Chopra et al. (1992) argue that past returns, beta and size are highly correlated; therefore ignoring any of them will lay the estimation open to the omitted variable bias. They also find strong evidence of the January effect.

Brailsford (1992) examines the mean reversion return behaviour and the Winner-Loser anomaly in the Australian stock market over the period 1958 to 1987. Following the methodology of De Bondt and Thaler (1985), cumulative abnormal returns (CARs) are calculated over three-year non-overlapping portfolios using the zero-one market model. Brailsford (1992) finds no evidence of a Winner-Loser anomaly in the Australian stock market: the difference in CARs for the Loser-Winner arbitrage portfolios is found insignificant.

Chen and Sauer (1997) investigate the stability of the overreaction hypothesis in the NYSE in the light of the results of Chopra et al. (1992). Monthly return data are collected over the period 1926-1992. Using the methodology of Chopra et al. (1992), they find that returns on the contrarian strategies are not stable over time, and that the overreaction hypothesis operates during the pre-World War II period. In addition, they find that extreme portfolios are less likely to remain extreme portfolios in subsequent periods as the standard deviation as a function of time in the rank period is U-shaped. Finally, they find a highly significant relationship between market risk premium and arbitrage portfolio returns.

Clare and Thomas (1995) investigate the long-run overreaction hypothesis in the UK. Monthly data are collected from the London Business School Share Price Database (LSPD) for 1000 companies over the period 1955-1990. Following the methodology of De Bondt and Thaler (1985), they find that past Losers outperform Winners by 1.7% per year. They argue that this limited overreaction effect is attributed to size effect. Similarly, Dissanaike (1997) investigates the overreaction hypothesis in the UK.

Monthly returns data are collected for 925 large companies from the LSE over the period 1975-1991. Using the buy and hold portfolios and rebalancing methods[9], he finds evidence of the overreaction hypothesis in the UK large firms. In addition, they find that Losers tend to be riskier than Winners and this causes Losers' superior returns. The variation in CAPM beta does not seem to explain the Loser-Winner anomaly in the UK. Campbell and Limmack (1997) provide additional support for the existence of the long-term overreaction phenomenon in the UK.

Dissanaike (2002) extends his previous work in this paper to investigate whether the size effect may explain the stock price reversal in the FT500. Using the same dataset and the methodology of Dissanaike (1997), his results show that there is no evidence that the Winner-Losers anomaly is explained by size. This result is consistent with the overreaction literature in the UK (see Levis 1989a). Dissanaike (2002) argues that, during the past few years, there is a positive relationship between firm size and stock return, (Dimson and Marsh, 1998). Finally,

[9] The Buy and Hold and the Rebalancing methods are explained in more detailed in chapter 4.

Dissanaike claimed that the sample of FT500 is biased towards big size firms and his results are not in favour the efficient market hypotheses.

Gunaratne and Yonesawa (1997) examine the mean reversion and overreaction phenomena in the Japanese stock market. Monthly return data are collected from the Japanese stock market over the period 1955-1990. Using the market-adjusted model, they form 20 non- overlapping four-year portfolios; they find evidence of overreaction phenomenon in the Japanese stock market as past Losers outperform Winners by 11% per annum. In addition, the variation of CAPM-beta partially explains the mean reversion phenomenon between rank and test periods. The overreaction hypothesis cannot be attributed to the seasonality effect anomalies.

Odean (1998) examines the disposition effect of Shefrin and Stattman (1985) – the tendency of selling Winners short and buying Losers – in the NYSE. To examine the disposition effect, Odean analyses 10000 accounts and the trading records of a large brokerage house over the period 1987-1993. Results show that on average investors realise their gains faster than their losses and the vast majority of them are involved in tax motivated selling pressure in December. In addition, investors show their preferences to hold Losers and to sell Winners.

Richards (1997) investigates the overreaction phenomenon for the country level using monthly data of 16 national market indices over the period 1969–1995. Using the methodology of De Bondt and Thaler (1985), results show evidence of price reversals in smaller markets, and this might be explained by the small country effect. Richards argues that the cross border equity flow is not sufficient to remove the mispricing in equity prices.

Baytas and Cakici (1999) investigate the performance of the arbitrage portfolios based on size and past performance in seven stock markets, namely the US, UK, Canada, Japan, Germany, France and Italy. In addition, they examine whether firm size can explain the holding period returns of Losers and Winners. Five-year annual return data are collected over the period 1982-1991. Following Conrad and Kaul's (1993) methodology, they find evidence of overreaction phenomenon in all countries except the US. Their results are consistent with the literature on price overreaction and particularly Conrad and Kaul's (1993). They also find that long term investment strategies based on size outperform those of based on long-term past performance. Finally, they find that long-term price reversals might be explained by firm size.

Mun et al. (2000) use non-parametric methodology to investigate the overreaction hypothesis in the US and Canada. They find significant risk–adjusted residual returns in the short and intermediate horizon in the US sample; however they find evidence of contrarian profits in the intermediate term in the Canadian stock market. In addition, the variation of CAPM-beta does not explain the contrarian profits in both markets.

Balvers et al. (2000) find significant evidence of mean reversion phenomenon in market indices across 16 developed countries. They suggest a new trading strategy, the "parametric contrarian strategy", based on exploiting the mean reversion (share prices revert to their fundamental values over time) to better predict stock returns. This follows the work of Richards (1997). They conclude that the parametric contrarian strategy outperforms the traditional Buy and Hold method.

Gaunt (2000) investigates long-term overreaction phenomenon and the role of size in the Australian market. Monthly returns and market capitalisation data are collected over the period 1974-1997. Following the methodologies of De Bondt and Thaler (1985) and Brailsford (1992), Gaunt constructs three-year non-overlapping portfolios using the zero-one market model to rank the portfolios into Losers and Winners. Using both cumulative rebalancing methods and buy and hold excess returns, Gaunt finds evidence of price reversal in both Winners and Losers. In addition, the Loser-Winner anomaly disappeared when the buy and hold method is used. Gaunt (2000) finds evidence of the small firm effect as Losers tend to be smaller and less liquid than Winners; therefore, the profitability of the Loser-Winner arbitrage portfolio is not exploitable in the Australian Market.

Benou and Richie (2003) investigate the long-term overreaction phenomenon for large firms that experienced dramatic monthly price drop (at least 20%) in the US over the period 1990-2000. Monthly return data are collected over one, two and three–year test periods. Following Fama (1998), they estimated the cumulative abnormal returns CARs and found positive and significant abnormal returns one year following the event. In addition, they found highly significant price reversals for technology stocks. However, results show evidence of underreaction for service stocks. Their results support the overreaction hypothesis in the US. They argue that buying large firms that experienced a large price drop is a profitable investment strategy. Similarly, Hirschey (2003) finds evidence of the overreaction hypothesis in both S&P500 and NASDAQ firms.

Chiao et al. (2005) examine the role of size and book-to-market ratios in explaining the overreaction hypothesis in the Japanese stock market. Monthly price data are collected for the listed shares in the Tokyo stock exchange (TSE) over the period 1975-1999. They construct size-BM portfolios based and prior returns and find strong evidence of persistent overreaction phenomenon in the Japanese market. In addition, they find that size and book-to-market ratios are correlated with the price reversals.

Mazouz and Li (2007) investigate the overreaction hypothesis and whether or not size and time varying risk factors may explain this phenomenon in the UK. Monthly price data of the constituent of the FTSE all shares market index are collected over the period 1972-2002. Using both cumulative abnormal returns and buy and hold methods, and following the methodology of De Bondt and Thaler (1985), they find strong evidence of price overreaction in the London stock exchange. In addition, they find that Losers outperform Winners by 16.4% and 18.3% using CARS and BAH methods respectively. They find no evidence of the January effect on the contrarian profits; however, size effect cannot fully explain the overreaction phenomenon.

Dissanaike and Lim (2010) investigate whether contrarian strategies based on advanced accounting valuation measures such as residual earnings and Ohlson models outperform the traditional measures such as book-to-market, earnings–to–price and cash flow-to-price ratios. Price and accounting data are collected from LSE for all the listed shares (excluding investment and unit trusts) over the period 1987-2001. They find that both the residual earnings and the Ohlson models outperform the traditional strategies based on B/M and E/P.

In addition, they find that traditional cash flow-to-price ratios outperform the advanced accounting measures. They recommend that investors' size and the technical knowledge of more advanced models are the main determinant of the optimal portfolio formation.

2.3.2. Emerging markets

Da Costa (1994) investigates the overreaction hypothesis in the Brazilian stock market. Monthly data are collected from the Sao Paulo stock exchange (BOVESPA) over the period 1970-1989. Da Costa constructs eight non-overlapping portfolios (the test and formation period are two years) following the methodology of De Bondt and Thaler (1985). Results support the overreaction hypothesis in the Brazilian stock market. In addition, the variation in CAPM-beta cannot explain Winner-Loser anomaly.

Fung (1999) investigates the overreaction hypothesis in the Hong Kong stock market. Monthly return data of the constituents (33 companies) of the HSI market index are collected over the period 1980-1993. Fung adopts the buy and hold method following Conrad and Kaul (1993) to reduce the bid-ask spread bias. Results supported the overreaction phenomenon in the Hong Kong stock market as Losers outperform Winners by 10% one year after portfolio formation.

Ahmad and Hussain (2001) investigate the long-term overreaction and seasonality in returns in the Kuala Lumpur Stock exchange (KLSE). Daily price data are collected for 166 listed shares in KLSE over the period 1986-1996. They use the daily market-adjusted excess returns to rank and construct three-year non-overlapping portfolios. Using the traditional arithmetic (cumulative) excess return and the buy and hold methods, they find evidence of price overreaction in the KLSE as both Losers and Winners experienced significant reversals over the three-year test period. In addition, results show that the overreaction phenomenon is not dominated by size effect. They find evidence of the seasonality effect (Chinese New Year) in the KLSE.

Chin et al. (2002) find evidence of overreaction in the New Zealand stock exchange. They also find that all contrarian strategies based on the accounting valuation ratios earned superior cumulative abnormal returns over the period 1988-1995. Wang et al. (2004) investigate the overreaction phenomenon in the Shanghai and Shenzhen stock market over the period 1994-2000. Weekly return data are collected for 244 A shares 57 B shares (A-share market is opened for local Chinese investors while B- share market is for foreign investors). They use the market-adjusted model to calculate the abnormal returns and to construct Winner and Losers portfolios. They find that “A” shares have the tendency to overreact more than “B” shares.

Saleh (2007) finds evidence of the overreaction hypothesis in the Amman stock exchange on the long-term (i.e. 48 month test periods). However, during the short- run, he finds evidence of momentum as Losers tend to be Losers during 3, 12, 16 and 36 month test periods. In addition, no evidence of size or January effect is found to explain the overreaction phenomenon. Table 2.1 presents a summary of the literature on the long-term overreaction.

2.4 Possible explanations to the overreaction hypothesis

In this section I discuss possible underlying explanations for what has been attributed to the overreaction of investors to new information. These include uncontrolled-for variations in beta, seasonality effects, size effect, bid-ask spread and tax loss hypothesis.

2.4.1 Variation in beta

Chan (1988) introduces an alternative interpretation to the traditional psychological one for the overreaction phenomenon. He argues that the risk of the Winners and Losers is not constant over time. Therefore the estimation of the abnormal returns is likely to be sensitive to CAPM-beta and the variation in risk between estimation and test periods. Using the same data and the methodology of De Bondt and Thaler (1985), Chan finds that Losers tend to be bigger in size at the beginning of the rank period and betas for the Losers are smaller and safer than those of Winners within the rank period. Chan also finds large shift in the value of betas from formation to test periods. Loser stocks changed from being safer – as compared with Winners – at the beginning of the formation period to riskier within the test period. He concludes that the overreaction phenomenon and the Loser - Winner anomaly can be attributable to the variation in risk; controlling for the variation in CAPM-betas, the contrarian strategy achieves only a small abnormal return.

2.4.2 Seasonality effect

The seasonality effect is defined as repetitive stock price movements around trend line.Davidson and Dutia (1989) investigate the overreaction hypothesis for all the listed shares in the NYSE and AMEX over the period 1963-1985 to determine if a seasonality effect is the underlying explanation of effects attributable to overreaction. They calculate the predicted and cumulative predicted errors based on the market model. They construct two portfolios, namely, highest and lowest cumulative predictive errors. Their results contradict the overreaction hypothesis as Winners (Losers) continued to be Winners (Losers) as abnormal returns earned in year (t-1) are positively related to the abnormal returns earned in year (t). They also find evidence of a January anomaly as 25% of the Winners occur in January, whereas Losers are no longer Losers in January.

2.4.3 Size effect

Zarowin (1990) replicates the methodology of De Bondt and Thaler (1985) and reexamines the overreaction hypothesis in the NYSE over the period 1926-1982. Contrary to De Bondt and Thaler (1985), Winners and Losers are defined as the highest and lowest quintiles of the cumulative excess returns over the formation period. Zarowin (1990) finds that the variation in size is the main cause of the superior performance of Loser portfolios over those of Winners. Zarowin (1990) also finds that the excess abnormal returns disappeared – except for those on January - when controlling for size and this supports the role of tax loss selling hypothesis in explaining the January effect. He also finds evidence of short–term overreaction over one month and this anomaly cannot be explained by size effect.

Lo and MacKinlay (1990) investigate the proposed association between the overreaction phenomenon and the profitability of contrarian strategies. Using weekly autocorrelation data of the equal and value-weighted indices over the period 1962-1987, they find evidence of positive auto-correlation in the stock market index. However, individual stock returns are found to be negatively serially correlated. They argue that this suggests that overreaction is not necessarily the only interpretation of the contrarian profits as less than 50% of the contrarian's expected profits may be attributed to the overreaction phenomenon.

2.4.4 Bid-ask spread

The bid-ask spread originating in the work of Roll (1983) may potentially explain the overreaction phenomenon. The bid-ask spread consists of the difference between the buying and selling price of a stock. The idea behind it is that at the end of the day (when prices are measured) one may randomly end on a buy or a sell order. Since these two prices differ by the bid-ask spread a negative autocorrelation of stock prices is obtained. Atkins and Dyl (1990) find that the shift between bid and ask prices may cause a temporal patterns in stock returns and this shift may explain the overreaction hypothesis.

Kaul and Nimalendran, (1990) investigate whether bid-ask spread or overreaction phenomenon determines the short-term properties of stock returns on the NASAQ. Two series of returns are collected, namely, stock returns both including and excluding the bid-ask spread over the period 1983-1987. Using the variance ratio (variance ratio is used to measure the relative magnitudes of daily stock returns errors as the result of overreaction or bid-ask spread, Kaul and Nimalendran, (1990)), they find that bid-ask spread is the main source of stock price reversals. Kaul and Nimalendran (1990) show that over 23% and 50% of stock return variances for big and small firms respectively can be explained by bid-ask errors. As a result they find little evidence of the overreaction phenomenon in NASDAQ firms.

Cox and Peterson (1994) investigate the role of the bid-ask spread and stock liquidity in explaining stock price reversals following a large one-day return drop (at least 10% following Bremer and Sweeney (1991)). Daily price data are collected for all listed shares in NYSE, AMEX, and NMS over the period 1963–1991. They calculate the stock abnormal returns as mean-adjusted, market model and the market-adjusted returns respectively. The estimation window is from 105 through six days pre-event and the post-event window is from 21 to 120 days post-event. However, the event window is from 1-20 days post-event. They find strong evidence of price post-event reversals post-event, but the degree of reversal diminishes over time. In addition, they find evidence of small firm effect as small firms reverse more than large. Finally, they find that the price reversal phenomenon can be attributed to the bid-ask spread. Therefore their findings do not support the short-term overreaction.

Akhigbe et al. (1998) investigate the short-term overreaction in the NYSE during 1992. The dataset consists of stocks that experienced a large percentage change over one day during 1992 as published in the Wall Street Journal. The estimation window is from (-220, -20) days pre-event and the event window is (-5, +4) days post-event. Using the market model to calculate the abnormal returns, they compare the expected abnormal return with the average percentage of bid-ask spread. Results show evidence of the overreaction hypothesis as Losers experienced greater reversals than the average percentage bid-ask spread during the next two days subsequent to the event. They conclude that the bid-ask spread (after controlling for the day of the week and the initial price change in event day) has significant explanatory power of the price reversal phenomenon during 1992.

Conrad, et al. (1997) investigate the main characteristics of the short-term overreaction in the US and whether or not the bid-ask spread is the main source of the profits for a contrarian strategies. They use weekly data from both NASDAQ from 1985-1989 and NYSE/AMEX from 1990-1991. Using the bid returns data, their results show that the measurement errors and the bid-ask spreads (negative serial co-variances) are the main source of the contrarian profits. Therefore there is no evidence of the overreaction hypothesis in both NASDAQ and NYSE/AMEX in the short-term. In addition, the inclusion of the transaction costs eliminates the contrarian profits. The authors highlight that the measurement errors may lead to misinterpretation to the weak-form market efficiency.

2.4.5 Tax loss hypothesis

The tax hypothesis attempts to explain the overreaction phenomenon by reference to the role of tax in determining investor behaviour. George and Hwang (2007) investigate whether or not long-term price reversal for the Winners can be explained by this hypothesis. They argue that investors are reluctant to sell high locked- in capital gain securities (Winners) to postpone tax payments. This suggests that high locked- in capital gain stocks are expected to have higher prices and lower expected returns compared to non-locked-in capital gain stocks[10].

Monthly data are collected for NYSE, AMEX, and NASDAQ over the period 1963-2001 in addition to Hong Kong monthly data from 1980-2000. They use three alternative measures of returns to test the overreaction hypothesis, namely, the traditional return, five-year high and

[10] Capital gain stocks are said to be locked in if investors are unable or unwilling to sell their shares due to high capital gain taxes.

five-year low measures, as well as two additional measures to test the lock-in hypothesis, namely, equal-weighted gain and loss and equal-weighted gain only measures. They find strong evidence of the tax hypothesis as Winners reversal diminished because the traditional reversal measures are subsumed in the locked-in measures. In addition, no price reversals are found for non January Loser portfolios. They also find no evidence of price reversals for both Winners and Losers in the Hong Kong stock exchange where no capital gain or dividends taxes are imposed. Their results are inconsistent with the overreaction hypothesis.

Hoitash and Krishnan (2008) find evidence that high speculative intensity[11] or herding behaviour may explain long-term investor overreaction in the US over the period 1985–2004. This may occur because of the expected serial autocorrelation caused by noise traders. Yalcin (2008) by contrast investigates the gradual information diffusion model of Hong and Stein (1999) which argues that as long as different traders hold different sets of information, investors only respond to the information they know and thus the expected stock prices might be biased. Yalcin (2008) finds that the contrarian profits diminish gradually by the increase of the rate of information dissemination in the NYSE from July 1980 to December 2004.

2.5 Overreaction to specific events

In this section I discuss studies that relate stock market overreaction to a number of different events including the so-called earnings phenomenon, the trading behaviour of insiders,

[11] defined as the adjusted autocorrelation in daily trading volumes based on the amount of information arrived in the market)

takeover rumours, and adjustments in foreign exchange markets and going concern audit opinion announcements.

Zarowin, (1989) investigates the overreaction to the *earnings phenomenon* in the US. He creates a trading rule based on firms that experience good earnings (Winners) and bad earnings (Losers). All listed firms with seven consecutive years of earnings (six years pre the event and the current earning year) are included in a sample from NYSE over the period 1971-1981. Zarowin forms two portfolios, namely, the worst performer and best performer based on the earning performance measure. He calculated average excess return over the 36 months subsequent to the extreme earnings year following De Bondt and Thaler (1985). Results show that the poorest earning portfolio outperforms the best earning portfolio by 16.6% over the test period due to the differences in firm size. Therefore the overreaction to earning hypothesis is not supported.

Seyhun (1990) investigates *the trading behaviour of insiders* in NYSE, ASE and NASDAQ around the October 1987 stock market crash. Daily stock data are collected over the period from January 1975 to November 1988. Seyhun finds evidence of the overreaction hypothesis during the crash as insiders became heavy buyers after the crash so that extreme Losers became Winners over the three years subsequent to the crash.

Abarbanell and Bernard (1992) examine the overreaction/underreaction of *financial analysts to earnings announcements*. EPS and price forecasts quarterly data are collected for 178 firms over the period 1976-1986. They find evidence of analysts' underreaction to earnings announcements rather than overreaction. In addition, and contrary to the results of De Bondt and Thaler (1990), they conclude that extreme earnings forecasts by analysts cannot be explained by the overreaction hypothesis.

Jegadeesh and Titman (1995) investigate the reaction of stock prices to *common factors and firm-specific information* in the US. Weekly data are collected from the ASE and the NYSE over the period 1963-1990. They find evidence of underreaction to the stock market common factors and significant evidence of market overreaction to firm-specific information. In addition, they find that the main source of the contrarian profits in the short horizon is the overreaction to firm specific information. They argue that price pressure of liquidity motivated traders is the main cause of price reversal.

Michaely et al. (1995) examine the immediate and long-term reaction to *two main dividend policies*, namely, cash dividends initiation and omission. The sample includes all listed companies in both the NYSE and AMEX that initiated or omitted cash dividends over the period 1964-1988. Stocks abnormal returns are calculated based on the Buy and Hold strategy for three days pre and post-events. They find that the short-run price effect of dividends omission is negative; however the price impact on dividends initiation is positive. In addition, the market reaction for both dividends initiation and omission are equal. They also find highly significant long-term drift subsequent to dividend omissions. Their results are not consistent with De Bondt and Thaler (1985).

Zivney et al. (1996) investigate the market *overreaction to takeover rumours* in the US. They examine over 2000 takeover rumours articles published in the "Heard on the Street" (HOTS) and "Abreast of the Market" (AOTM) columns in the Wall Street Journal. The sample represents all listed shares subject to takeover in the NYSE and AMEX over the period 1985-1988. Using the market-adjusted residual return following the methodology of Brown and Warner (1985), they find negative abnormal returns one year post takeover rumours. Therefore they conclude that the buy on rumours strategy is not profitable. However, the authors recommend that selling short subsequent to rumours (published on AOTM) 100 days after the rumour day, earns 20% cumulative annual abnormal returns.

Larson and Madura (2001) investigate the short-term overreaction *to adjustments in the foreign exchange market.* They analyse the effect of extreme one-day exchange rate adjustments on a sample of developed and emerging markets. Daily data of 15 (five emerging and 10 industrial currencies) exchange rates are collected over the period 1988-1995. Using the event study methodology following Brown et al. (1988), results fail to support the efficient market hypothesis. Interestingly, they find evidence of investor underreaction in the industrial economies, and overreaction in the emerging economies.

Chelley-Steeley (2001) uses the Kalman filter methodology to estimate *price adjustments for the daily opening and closing prices of the Dow Jones market index*. They find that overreaction at the opening prices involves both higher volatility and negative autocorrelation.

In addition, they find greater tendency of overreactive behaviour of the stock market index at the opening prices than those of closing prices.

Kadiyala and Rau (2004) investigate the overreaction/underreaction towards *four main corporate events in the US,* namely, cash and equity financed acquisition, share buyback and equity offerings. They find that the announcements of corporate events after good news (i.e. positive earnings surprise) outperforms those events after bad news announcements (negative earnings surprise) apart from the information convoyed in the corporate event. They also find no evidence of market overreaction to the corporate events.

Schaub (2006) finds evidence of overreaction to the *going concern audit opinion announcements* in the US. They analyse 79 announcements published in the Wall Street Journal over the period 1984-1996. Using the risk adjusted model to calculate the abnormal returns, they find significant negative abnormal returns (-15.31%) subsequent to the announcements followed by positive and significant cumulative abnormal returns (10.33%) 10 days post the announcement day.

Edmans et al. (2007) investigate the relationship between *investor's mode* and stock returns. They find significant negative abnormal returns (-7% monthly) as the result of market reaction to losses by national football teams especially in the western European countries. In addition, they find weak evidence of market reaction to international cricket, rugby, and basketball international competitions. They argue that investors may earn abnormal returns by selling short the futures on market indices before major sports events in the western European countries. On the other hand, Vergin (2001) finds evidence of price overreaction to the outstanding performance in the National Football League (NFL) games compared to the previous 2-5 games in the US between 1981 and 1995.

2.6 Opponents of the contrarian strategy

A large strand of the literature argues that the overreaction phenomenon can be attributed simply to the computation errors in abnormal returns. Another large body of the literature however believes that momentum is the most profitable trading strategy. In this section I present the alternative views of the opponents of the contrarian trading strategy.

Jegadeesh and Titman (1993) examine the relative strength strategies over 3-12 month periods. Daily stock returns data are collected around earnings announcement dates from NYES and AMEX over the period 1965-1989. They consider 16 different relative strength strategies (selecting stocks based on past 1-4 quarters returns and hold them for the same period). They find that the strategy based on buying past Winners (six months) and holding them for another six months earns 12.01% compounded excess returns on average. In addition, they find that Winner portfolios earn higher excess returns during seven months and 36 months of the formation period. They conclude that the profitability of the relative strength strategies cannot be attributed to size or systematic risk.

Jegadeesh and Titman (2001) re-examined the alternative interpretations of momentum profits documented in their earlier paper in 1993. They provide evidence that the momentum profits during the 1990s is genuine and is not due to data mining or data snooping biases. In addition, they find evidence that the positive momentum profit in the test periods is sometimes associated with price reversals. Therefore they argue that the behavioural models such as the representative heuristic of Tversky and Kahneman (1974) and self-attribution of Daniel et al. (1998) and Hong and Stein (1999) provide a partial interpretation of the momentum anomaly.

2.6.1 Computation errors

Conrad and Kaul (1993) claim that the long-term cumulative average abnormal return is upwardly biased. They argue that (CARs) accumulate monthly measurement errors (bid-ask spread and non-synchronous trading[12]) as well as the true abnormal return over a long period and this leads to spurious returns. Conrad and Kaul (1993) claim that the Buy and Hold method is the most relevant technique to measure the long-term performance[13].Monthly data are collected from the NYSE over the period 1926-1988 and using the methodology of De Bondt and Thaler (1985), they find no evidence of market overreaction as CARs are found to be upwardly biased. For instance the non-January cumulative abnormal returns are 12.2% under the CARs, however it is actually -1.7% under the BAH technique. They show that Losers outperform Winners only in January and this is not due to the overreaction phenomenon.

[12] Non- synchronous trading is defined as infrequent trading.
[13] Chapter 4 includes detailed discussion of the alternative measures of the abnormal returns.

On the other hand, Loughran and Ritter (1996) show (using monthly data form NYSE over the period 1929-1988) that the results of Conrad and Kaul (1993) are driven by survivorship bias and long-term mean reversion. They find that the strong explanatory power of price in the pooled regression of Conrad and Kaul (1993) is due to the tendency for low (high) stock prices to be followed by high (low) returns. They claim that the discrepancies in results between De Bondt and Thaler (1985) and Conrad and Kaul (1993) are due to the inclusion of AMEX firms in the sample. Loughran and Ritter (1996) argue that the results of De Bondt and Thaler (1985) are not driven by the bias in CARs, but by the bid-ask spread bias. They further argue that bid-ask spreads affect monthly CARs of low–priced stocks. They conclude that the bid-ask spread bias is found to be the main cause of the long-term overreaction when forming portfolios based on CARs.

Dissanaike (1994) compares the alternative techniques of measuring long-term cumulative abnormal returns, namely, arithmetic method CARs, rebalancing method RB and buy and hold method BAH. Dissanaike argues that the rank period returns using the arithmetic method is biased and leads to inaccurate ranks for both Winners and Loser portfolios. Monthly returns data are collected for the FT500 over the period 1981-1991. The results show the sensitivity of the rank and test period returns to the different approaches of computing the cumulative abnormal returns and hence it may alter the conclusion of the overreaction hypothesis. Dissanaike finds that the rebalancing method RB is more accurate than the arithmetic method.

Ball et al. (1995) investigate the measurement error in raw abnormal returns of contrarian portfolios. Monthly returns data are collected from NYSE and AMEX. Using the buy and hold method to calculate the abnormal returns over non-overlapping five years, they find that the profitability of contrarian strategy is substantially driven by low-priced Losers in the portfolios. They find little evidence of the January anomaly, however negative abnormal returns are found in the June-end portfolios. Kim (2009) used the Morgan Stanley Capital Index (MSCI) data for 16 developed countries from 1969 to 2007 to examine the profitability of the contrarian strategies. Results provide evidence against the contrarian strategy as the mean reversion rate of stock prices is very slow across the sample. This suggests that the contrarian strategies might be profitable but only in the very long term.

2.6.2 Contrarian or momentum

Conrad and Kaul (1998) investigate 120 different trading strategies over the period 1923-1989 in the NYSE. They find that less than 50% of the trading strategies earn significant abnormal returns. The contrarian strategies are found to be profitable in the long term during 1926-1947; however the authors find that the momentum strategies are profitable in the short term (3-12 months).

Rouwenhorst (1998) investigated the Winner–Loser anomaly in 12 European stock markets, namely, Austria, Belgium, Denmark, France, Germany, Italy, The Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom. Monthly return data are collected over the period 1978-1995. Portfolios are constructed following the methodology of Jegadeesh and Titman (1993). They find evidence of momentum profits in the internationally diversified portfolios as past Winners outperform past Losers by 1.5% per month. In addition, the return continuations are detected for small and big firms in all the 12 countries, however small firms exhibit more return continuation. Their results support the findings of Jegadeesh and Titman (1993).

Schiereck et al. (1999) investigate the contrarian and momentum strategies in the German stock market. They find consistent results with behavioural finance literature as momentum strategies are found to be profitable in the short term, however contrarian strategies are found to be profitable in the long term.

Kang et al. (2002) investigate the short-term overreaction and the intermediate–term momentum strategies and the main source of the contrarian/momentum profits in the Chinese stock market 1994-2000. Weekly stock price data are collected for 163 companies in 1994 and 286 companies over the period 1995-2000. Using the methodologies of Lo and MacKinlay (1990) and Jegadeesh and Titman (1995), they find evidence of the short-term overreaction and intermediate–term momentum profits. They also find that the overreaction profits are dominating in case of equal-weighted portfolio strategies, however momentum profits are prevailing when they use the value-weighted portfolio strategies. They conclude that the high proportion of individual investors and the unreliable information (rumors) are the main source of the contrarian profits.

Demir et al. (2004) examine the short and intermediate momentum strategies in the Australian market. Daily volume weighted average price data are collected for all the approved stocks (462 stocks) over the period 1990-2001 and all shares (772 stocks) included in the All

Ordinaries Index of the Australian Stock Exchange (ASX) over the period 1996-2001. They construct momentum portfolios based on 30, 60, 90, 180 day estimation and test periods. Using the buy and hold excess returns method, they find that taking long positions on Winners for 30, 60, 90 and 180 days and selling short Losers yields significant abnormal returns ranging from 5.34% to 0.46% per month. In addition, they find that momentum profits are prevailing for both big and small companies. The momentum profits are significantly higher than those of the US and European markets.

Xiang et al. (2002) find that cross-sectional returns are predictable by insider trading activities in US over the period 1985 to 1996. In addition, book-to-market and size cannot explain momentum profits. They conclude that the overreaction phenomenon can be seen as the main reason for the intermediate momentum profits. On the other hand, Hon and Tonks (2003) find evidence of momentum profits in the UK. However, they conclude that this momentum is not prevailing over the whole period 1955-1996; therefore it is not considered as a main feature of the UK stock market.

Forner and Marhuenda (2003) extend the study of Alonso and Rubio (1990) and reexamine the overreaction hypothesis in the Spanish stock markets. They use different methodology and test periods (6, 12, 60 month windows in addition to the 36 month window previously analysed by Alonso and Rubio (1990)). Using the CAPM model they construct two portfolios, namely, Losers and Winners based on the extreme residual returns using CARs following De Bondt and Thaler (1985) and BAH following Conrad and Kaul (1993). Monthly return data are collected over the period 1963-1997.

They find that one-year and five-year momentum and contrarian strategies earn significant abnormal returns. Contrary to Alonso and Rubio (1990), no significant abnormal returns are detected within the 36 month test period. Their results support the existence of the momentum profits in the short term and the contrarian profits in the longer term, even after accounting for time varying risk. They argue that their results cannot be attributed to data snooping bias.

George and Hwang (2004), using the methodology of Jegadeesh and Titman (1993), find that the profitability of momentum strategies can be explained by the previously published 52-week high price data rather than the traditional past return rank period. They also find no evidence of long-term price reversal based on the 52-week high price rule over the period 1963–2001. They conclude that there is no relationship between short-term momentum and long-term reversals; they are likely to be two separate phenomena.

Antoniou et al. (2005) argue that studying the contrarian strategies in emerging markets is more profitable due to market inefficiency and the possibility of returns predictability. They examine the out-of-sample evidence of the overreaction profitability and the main sources of the contrarian profits in the Athens stock market. Weekly price data are collected for all listed shares and the ASE General Price Index over the period 1990-2000. The portfolio investment strategy is based on short sell previous Winners and take long position on the Losers following the methodology of Lo and MacKinlay (1990) and Jegadeesh and Titman (1995).

They find that negative serial correlations leads to statistically significant short-term contrarian profits in the ASE. They find that this profit is not fully attributed to market frictions or risk. The Fama French three-factor model explains the contrarian profit considerably better than the CAPM. Siganos (2007) finds evidence of the momentum profits in the UK over the period 1975-2001 and concludes that – contrary to the literature – investors can maximise their momentum profits by including small firms of both Losers and Winners in their portfolios.

Gutierrez and Pirinsky (2007) define two different types of momentum strategies, namely, firm-specific abnormal returns and relative returns momentum. The former shows continuing long-term return performance consistent with the underreaction hypothesis. However, the latter shows a reversal in one year consistent with the overreaction hypothesis. In addition, they find that institutional investors tend to buy securities based on past high returns and avoid past poor securities.

McInish et al. (2008) examine the profitability of both contrarian and momentum strategies in seven Pacific-Basin stock markets. Weekly returns data are collected from Japan, Taiwan, Korea, Hong Kong, Malaysia, Thailand and Singapore over the period 1990-2000. Using the methodology of Lo and Mackinlay's (1990) and Jegadeesh and Titman (1995), they find evidence of contrarian profits in five out of seven countries. Contrarian profits are reported in Japan while momentum profits are found in both Japan and Hong Kong. In addition, they find that Losers display momentum and Winners display reversals. Combining Winners and Losers in a trading strategy earns abnormal returns for one week.

Wu (2011) investigates the dynamic relationship between mean reversion and momentum strategies in the Chinese stock market using the methodology of Balvers and Wu (2006). Daily returns data are collected for the "A" shares listed in the Shanghai Stock Exchange (SHSE) over the period 1990-2001. Wu finds no significant abnormal returns for the pure short-term (3-12months) momentum strategy of Jegadeesh and Titman (1993). However he finds highly significant abnormal returns for the pure contrarian strategy for all holding periods. Wu also finds that the combined strategy (momentum + contrarian, 12 month formation and test periods) results in a significant excess return of 22.2%. His results support the overreaction hypothesis in the Chinese market.

2.7 Summary

The main objective of this chapter has been to conduct a comprehensive literature survey of the overreaction phenomenon and to address issues raised by its critics. I have presented the literature on both short and long-term overreaction and in both developed and emerging markets. Moreover, I have analysed the competing explanations for events attributed to overreaction, namely, the variation of risk (beta), seasonality and size effects, bid-ask spread and the tax hypothesis. In addition, I have analysed the overreaction to specific events, such as the overreaction to corporate actions (merger, acquisition and earnings and dividends announcements), to rumours and to international sport championship results. Finally, I have critically discussed the main arguments of the opponents of the overreaction phenomenon.

The main findings of this chapter are that both short and long-term overreaction phenomenon have been extensively investigated in developed markets in the 1980s and 1990s using both the cumulative average abnormal return (arithmetic and rebalancing method) and the buy and hold methods. However, a new strand of literature has recently begun to investigate the overreaction phenomenon in emerging markets. The literature survey illustrated the ongoing debate about the existence of the overreaction phenomenon itself and whether or not other factors (the change in risk (beta), firm size, seasonality, and bid-ask spread) are really the main source of contrarian profits.

I showed that one deficiency of the existing body of the literature is that it has investigated the overreaction phenomenon using either cross section or time series data alone. None of the existing studies has combined these two dimensions by using a panel data model. Ignoring the time- or the cross-sectional dimensions may however lay the estimation open to questions of bias (Cressy and Farag (2011)). Moreover, existing studies have largely ignored the dynamics of the process of overreaction. To do this requires the use of a dynamic panel data model and of system GMM in particular.

Finally, the existing body of the literature on overreaction has not investigated the link between regulatory policies and overreaction hypothesis. Regulatory policies (price limits and circuit breakers) adopted by policy makers to reduce volatility, may play an important role in explaining what we observe in these markets. This requires a particular kind of data that this study, unlike those in the literature, is able to provide. The above mentioned gaps in the literature are therefore main motivation for this thesis and we shall attempt to fill these gaps in the empirical chapters that follow.

Table 2.1: Summary of the literature on the Short-term overreaction

Authors, date and title	Market	Estimation and Event windows	Sample & study period	Methodology	Summary of empirical findings
Atkins, A. & Dyl, E. (1990) Price Reversals, Bid-Ask Spreads, and Market Efficiency.	NYSE US	Estimation window (-70 , -11 days) Event window (-10, +10 days)	Daily return data for all listed shares over the period 1975-1984. Three Losers and three Winners	Mean-adjusted, Market-adjusted returns Risk-adjusted returns	Strong evidence of short–term overreaction for bad news. Weak evidence of short –term overreaction in case of good news. Bid-ask spread is not the main source of the overreaction phenomenon. Consistent results with De Bondt and Thaler.
Bremer, M. & Sweeney, R. (1991). The Reversal of Large Stock-Price Decreases.	NYSE US	Event window (-20, +20 days)	Daily stock returns for all listed shares in the Fortune 500 over the period 1962-1986.	Mean adjusted returns	Evidence of price reversal phenomenon in the US. Price reversal phenomenon is unrelated to both the weekend and turn-of-the-year effects.
Cox, D. & Peterson, D. (1994) Stock Returns Following Large One-Day Declines: Evidence on Short-Term Reversals and Longer-Term Performance.	NYSE, AMEX, and NMS US	The estimation window is (-105 to +6) days pre-event and the post-event window is (+21 to +120) days post-event. The event window is (+1 +20) days post-event.	Daily price data for all listed shares in NYSE, AMEX, and NMS over the period 1963 – 1991.	Mean-adjusted returns. Market model. Market- adjusted returns.	Strong evidence of price reversals post-event. The degree of reversals is diminished over time. Evidence of small firm effect as small firms was found to reverse more than large firms. The price reversal phenomenon can be attributed to the bid -ask spread. Therefore their findings do not support the short term overreaction.
Liang, Y. & Mullineaux, D. (1994) Overreaction and Reverse Anticipation: Two Related Puzzles?	NYSE & ASE US	Event window (-200 , +200 days)	Daily stock returns for all listed shares 1963-1988	Event type methodology of Brown and Warner (1985). Form four base	Significant price reversal post negative and positive events. Stock prices tend to decrease pre positive events (shocks) and increase pre negative shocks.

				portfolios and 16 control portfolios.	Support the overreaction hypothesis.
Zivney, T., Bertin, W. & Torabzadeh, K. (1996) Overreaction to Takeover Speculation.	NYSE &AMEX US	Event window (-20 ,+252 days)	All listed shares subject to takeover in the NYSE and AMEX 1985-1988.	Market-adjusted residual return following the methodology of Brown and Warner (1985)	Negative abnormal returns one year post takeover rumours. The buy on rumours strategy is not profitable. Selling short the subsequent rumours 100 days after the rumours day, earns 20% cumulative annual abnormal returns.
Akhigbe, A., Gosnell, T. & Harikumar, T. (1998) Winners and Losers on NYSE: A Re-Examination Using Daily Closing Bid-Ask Spreads.	NYSE US	Estimation window (-220 ,+20 days Event window (-5,+4)	Stocks that experienced large percentage change over one day during 1992 as published in Wall Street Journal	The market model to calculate the abnormal returns. Compare the expected abnormal return with the average percentage of bid-ask spread.	Results showed evidence of the overreaction hypothesis. Losers experienced greater reversals than the average percentage bid-ask spread during the next two days subsequent to the event. The bid- ask spread has significant explanatory power of the price reversal phenomenon.
Bowman, R. & Iverson, D. (1998) Short-run overreaction in the New Zealand stock market.	New Zealand	Estimation window (+21 , +80 weeks Event window (-5,+10 weeks)	Weekly return data for all listed shares were collected over the period 1967 - 1986	Market model Risk adjusted model. Weekly CARs.	Bowman and Iverson (1998) investigated the short-term overreaction hypothesis in the New Zealand stock exchange. They found strong evidence of the overreaction in the New Zealand stock market as abnormal returns for Losers one week post-event (2.4%) outperform Winners (-1.5%). The overreaction phenomenon was not due to bid ask bounce, non-synchronous trading or size effect.

Cooper, M. (1999) Filter Rules Based on Price and Volume in Individual Security Overreaction.	NYSE & AMEX US	Alternative filter rules based on weekly returns and trading volumes.	300 large firms to minimise the bid-ask spread bias over the period 1962-1993.	Filter rule methods by specifying Losers and Winners based on minimum amount of lagged weekly returns and growth in trading volume Compare filter rules to Buy and hold abnormal returns.	Supporting evidence of the overreaction phenomenon in the NYSE. The lower the trading activity the higher the price reversals. The filter rules strategies outperformed the buy and hold counterparts.
Schnusenberg, O. & Madura, J. (2001) Does U.S. Stock Market Indexes Over– or Underreact?	US DJIA, NYSE, Nasdaq, S&P500, Russel 3000, and Wilshire 5000	Estimation window (-1,-60) and the event windows (+1, +2, +5, +10, +30, +60)	Daily price data were collected for major six stock indices in the US equity market since inception and until1997	They defined the event based on the best (Winners) and worst (Losers) index historical performance. They used the mean –adjusted return and ARIMA models to estimate the expected returns.	Evidence of the market underreaction in the following day subsequent to the event for the six market indices. Significant short-term overreaction for the Losers and underreactions for the Winners over the 60 days following the event, the fewer constituents (i.e. Nasdaq) in the index the greater degree of underreaction for the Winners.
Otchere, I. & Chan, J. (2003) Short-Term Overreaction in the Hong Kong Stock Market: Can a Contrarian Trading Strategy Beat the Market?	HKSE Hong Kong	Estimation window (-70,-10) and the event windows (-7, +7).	Daily data over two periods pre (1996-1997) and post (1997-1998) Asian financial crises 1996-1998.	Three different methods to calculate the abnormal returns, mean-adjusted, market model and the CAPM. Buy–and-Hold abnormal returns.	Little but significant evidence of price overreaction pre the Asian financial crises. Price reversals were more pronounced for Winner. The overreaction phenomenon is diminished during the crises period and cannot be explained by either bid –ask spread or the day of the week effect.
Larson, S. & Madura, J. (2003) What drives stock price behaviour following	NYSE US	Estimation, examination and windows are (-	Listed shares 1988-1995	They defined the event as at least +-10% daily price	They found significant evidence of the overreaction phenomenon in case of uninformed events.

extreme one-day returns.		260, -41), the examination window (-3, +20) and the event window (+81-+300)).		change over three-day event window. They estimated the market model using the methodology of Brown et al. (1988)	No evidence of overreaction in case of informed events. Their results supported the overconfidence and self-attribution bias by Hirshleifer and Subrahmanyam (1998).
Demir, I., Muthuswamy, J. & Walter, T. (2004) Momentum returns in Australian equities: The influences of size, risk, liquidity and return computation.	ASX Australia	30, 60, 90, 180 day estimation and test periods	Daily volume weighted average price data for all the approved stocks 1990-2001 and all shares included in the in the All Ordinaries Index 1996-2001.	They constructed momentum portfolios based on the buy and hold excess returns method.	They found that taking long positions on Winners and selling short Losers yields significant abnormal returns range from 5.34% to 0.46% per month. Momentum profits were prevailing for both big and small companies. Momentum profits are significantly higher than those of the US and European markets
Ma, Y. Beach, L. & Hasan, T. (2005) The Stock Price Overreaction Effect: Evidence on Nasdaq Stocks	Nasdaq NYSE US	Estimation Window (-120, -21) and event windows (-5, +5, (+1, +2) (+3, +10) (+11, +20) (+21, +50).	Daily price data of a sample (852) of Winners and Losers listed in NYSE and NASDAQ over the period 1996-1997.	The market model to calculate the abnormal returns, CARs.	Little evidence of price overreaction in the NYSE for both Winners and Losers. Significant price reversal as evidence of the overreaction phenomenon in Nasdaq market. Investors may interpret and analyse the new information differently in the NYSE and NASDAQ.
Antoniou, A. & Galariotis, E. (2005) Contrarian Profits and the Overreaction Hypothesis: the Case of the Athens Stock Exchange.	ASE Athens	Buy and Hold for 1-4 quarters returns period.	Weekly price data for all listed shares over the period 1990-2000.	The investment strategy based on short sell previous Winners and go long on the Losers following the methodology of Lo and MacKinlay	Negative serial correlations leads to statistically significant short-term contrarian profits in the ASE. These profits are not fully attributed to market frictions or risk. Fama French three- factor model explained the contrarian proffers

				(1990) and Jegadeesh and Titman (1995).	well better than the CAPM.
Schaub, M. (2006) Investor overreaction to going concern audit opinion announcements.	US	Estimation window (-299,-50) and the event windows (+1, +10)	Analysed 79 announcements published in the Wall Street Journal Daily price data over the period 1984-1996	Using the risk adjusted model to calculate the abnormal returns. Event study methodology.	Significant negative abnormal returns (-15.31%) subsequent to all the 79 announcements followed by positive and significant cumulative abnormal returns (10.33%) 10 days post the announcement day. Evidence of overreaction to the going concern audit report.
Michayluk, D. & Neuhauser, K. (2006) Investor Overreaction During Market Declines: Evidence from the 1997 Asian Financial Crisis.	NYSE, AMEX, Nasdaq US	Event windows +1, +5, +30, +60 days	Daily price data for 6276 stocks over 60 days around the crash	Cumulative abnormal returns and return correlations.	Significant evidence of market overreaction to the Asian financial crises over one week following the market crash. Both size effect and CAPM beta did not explain the initial return decline following the crash. Evidence of short-term return predictability during Asian stock market crash.
Lo, K. & Coggins, R. (2006) Effects of order flow imbalance on short horizon contrarian strategies in the Australian equity market.	ASX Australia	Five lags of autocorrelation for hourly and daily returns on individual securities.	Daily and hourly price for the top 200 companies from 2000 to 2002.	Following the methodology of Lo and MacKinlay (1990)	Strong evidence of short –term contrarian profits. Contrarian strategies were no longer profitable after controlling or transaction costs. Positive relationship between price reversals and order imbalance. The overreaction phenomenon can be explained by temporary liquidity imbalance.
Spyrou, S. Kassimatis, K. & Galariotis, E. (2007) Short-term overreaction,	LSE UK	Positive or negative shocks when the market	Daily closing price FT30, FTSE100, FTSE250 and	Calculate AR and CARs using a mean-adjusted.	No evidence of overreaction to market shocks for big firms. No significant abnormal returns

underreaction and efficient reaction: evidence from the London Stock Exchange.		return is above or below two SD over -60,-11 day estimation window	FTSE Small Cap over the period 1988 to 2004.		were found on the following days subsequent to the shock. Evidence of market underreaction for small and medium size firms. Price reversals occurred during 12-20 days following the event. No effect of the seasonality bid-ask spread, and time varying risk on their results.
McInish, T., Ding, D. & Pyun, C. (2008) Short horizon contrarian and momentum strategies in Asian markets: An integrated analysis.	Japan, Taiwan, Korea, Hong Kong, Malaysia, Thailand, and Singapore	Rank period one, two and four weeks.	Weekly returns data were collected over the period 1990-2000	Using the methodology of Lo and MacKinlay's (1990) and Jegadeesh and Titman (1995). Weighted relative strength portfolios. long/short position in Positive/negative excess return stocks.	Evidence of contrarian profits in five out of seven countries. Contrarian profits were reported in Japan while, momentum profies were found in both Japan and Hong Kong. Losers on display momentum and Winners display reversals. Combining Winners and Losers in a trading strategy earn abnormal return that last for one week.
Farag, H & Cressy, R. (2010) Do unobservable factors explain the disposition effect in emerging stock markets?	EGX30 Egypt	Estimation period (-6 to -106) and event window (+1 to +120)	Daily data are collected over the period 2005-2008	Panel data methods and the event study following the methodology of Cox and Peterson (1994)	Fixed effect model best suits the EGX data. The unobservable factors play an important role in explaining the overreaction phenomenon. Their results support the disposition effect as past Losers outperform past Winners.
Lobe, S. & Rieks, J. (2011) Short-term market overreaction the Frankfurt stock exchange.	DAX30, MDAX, SDAX, technology Germany	1-5 day window post-event	Daily data were collected for four main market indices since inception namely, DAX30, MDAX,	Calculate AR using the market and size – adjusted abnormal returns over five-day post-event,	Significant evidence of short-term overreaction in the German stock market. Price overreaction is not due to size or bid-ask-spread. They found asymmetric price

			SDAX, technology		reaction to positive and negative shocks. When they controlled for the transaction costs, the contrarian profits were negligible. Their results supported the efficient market hypothesis in the German stock market.

Table 2.2: Summary of the literature on the Long-term overreaction

Authors, date and title	Market	Rank and test periods	Sample & study period	Methodology	Summary of empirical findings
De Bondt, W. & Thaler, R. (1985) Does the Stock Market Overreact?	NYSE US	three-year non overlapping portfolios	Listed shares 1926-1982	Cumulative average abnormal residuals (CAAR)	Results support the overreaction hypothesis as Losers outperforms Winners by 24.6%. Evidence of seasonality effects (turn of the year effect).
Howe, J. (1986) Evidence on Stock Market Overreaction	NYSE US	52 weeks pre and post-event (50% weekly price change.	Listed shares 1961-1983	OLS and Scholes-Williams. Cumulative average abnormal returns (CAAR)	Evidence of the overreaction hypothesis. Overreaction phenomenon cannot be attributed to January effect.
De Bondt, W. & Thaler, R. (1987) Further Evidence on Investor Overreaction and Stock Market Seasonality.	NYSE US	Three-year non overlapping portfolios	Listed shares 1926-1982	Cumulative average abnormal residuals (CAAR)	The excess returns of January for the Winners are negatively related to December excess returns The variation in CAPM-beta cannot explain the Winner –Loser anomaly. The Winner –Loser anomaly is not attributed to the size effect.
Chan, K. (1988) On the Contrarian Investment Strategy.	NYSE US	Three-year non overlapping portfolios	Listed shares 1926-1982	Cumulative average abnormal residuals (CAAR)	There is a large change of betas from the formation to the test period. The overreaction phenomenon and the Winner –Losers anomaly are due to the variation of risk. When controlling for the variation of CAPM-betas, the contrarian strategy achieved small abnormal return,
Zarowin, P. (1989) Does the Stock Market Overreaction to Corporate Earnings Information?	NYSE US	Three-year non overlapping portfolios	listed shares 1971-1981	Compare the excess returns of two extreme earnings portfolios	Poorest earning portfolio outperform best earning portfolio by 16.6% over the test period. The abnormal return achieved due to

					differences in size. The overreaction to earning hypothesis is not supported
Davidson, W. & Dutia, D. (1989) A Note on the Behaviour of Security Returns: A Test of Stock Market Overreaction and Efficiency.	NYSE and AMEX US	One year non overlapping portfolios	listed shares 1963-1985	Calculated the cumulative predicted errors based on the market model for two extreme portfolios.	contradicted to the overreaction hypothesis Winners (Losers) continued to be Winners (Losers) Evidence of January anomaly as 25% of the Winners occur in January, and Losers were no longer Losers in subsequent January.
Alonso, A. & Rubio, G. (1990) Overreaction in the Spanish Equity Market.	Spain	Three-year non overlapping portfolios	listed shares 1967-1984	Following the methodology of De Bondt and Thaler (1985)	Results supported the overreaction phenomenon in the Spanish stock market. Losers outperform Winners by 24.5% 12 months after formation period.
Zarowin, P. (1990) Size, Seasonality, and Stock Market Overreaction.	NYSE US	Three year non overlapping portfolios	Listed shares 1926-1982	Following the methodology of De Bondt and Thaler (1985).	The variation in size is the main cause of the superior performance of Loser portfolios over those of Winners. The excess abnormal returns disappeared – except for those on January- when controlling for size. Evidence of the January effect.
Chopra, N., Lakonishok, J. & Ritter, J. (1992) Measuring abnormal performance: Do stocks overreact?	NYSE US	Five-year ranking period. Five-year overlapping formation period.	Listed shares 1936-1986	Calculated the abnormal returns with adjustments for size and time variation in beta. Used the Buy-and Hold returns to rank portfolios.	Results supported the overreaction phenomenon Consistent results with De Bondt and Thaler (1985) Losers were found to outperform Winners by 9.5% per year. The overreaction phenomenon cannot be attributed to size effect. Strong evidence of January effect.

Brailsford, T. (1992) A Test for the Winner-Loser Anomaly in the Australian Equity Market: 1958-87	Australia	Three-year non overlapping portfolios	Listed shares 1958-1987	Cumulative average abnormal residuals using zero-one market model following De Bondt and Thaler	No evidence of the Winner-Loser anomaly in the Australian stock market The difference in CARs for the Losers-Winner portfolios is insignificant.
Jegadeesh, N. & Titman, S. (1993) Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency.	NYES and AMEX	Buy and Hold for 1-4 quarters returns period.	Listed shares 1965-1989	16 different relative strength strategies over 3-12 month horizons.	Buying past Winners (6 months) and holding them for another 6 months earns 12.01% compounded excess returns on average. the profitability of the relative strength strategies cannot be attributed to size or systematic risk
Conrad, J. & Kaul, G. (1993) Long-Term Market Overreaction or Biases in Computed Returns?	NYSE US	Three-year non overlapping portfolios	Listed shares 1926-1982	Cumulative average abnormal residuals (CAAR) and BAH. Zero-one market model following De Bondt and Thaler	No evidence of market overreaction. Long-term abnormal returns of the contrarian strategies are upwardly biased due to measurement errors. Buy and Hold method is the most relevant techniques to measure the long-term performance January CARs were 12.2% under the CARs and - 1.7% under the BAH
Da Costa, N. (1994) Overreaction in the Brazilian stock market.	BOVESPA Brazil	Two-year non overlapping portfolios	Listed shares 1970-1989	Cumulative average abnormal residuals (CAAR) and BAH. Zero-one market model following De Bondt and Thaler	Results supported the overreaction hypothesis. The variation in CAPM-beta could not explain Winner-Loser anomaly. The overreaction effect is asymmetric.
Clare, A. & Thomas, S. (1995) The Overreaction Hypothesis	FTA All Share Index	Three-year non overlapping	Listed shares 1955-1990	Cumulative average abnormal residuals (CAAR).	Past Losers outperform Winners by 1.7% per year. This limited overreaction effect is

and the UK Stock market.	UK	portfolios		Zero-one market model following De Bondt and Thaler.	attributed to the size effect Overreaction hypothesis is not supported by using annual data.
Ball, R., Kothan, S. & Shanken, J. (1995) Problems in measuring portfolio performance An application to contrarian investment strategies.	NYSE and AMEX. US	Three-year non overlapping portfolios	Listed shares 1925-1984 For NYES 1962-1984 For AMEX	Buy- and Hold abnormal returns Jensen alpha	The contrarian strategy profitability is much driven by low-priced Losers. Limited evidence of the January abnormal returns anomaly. Negative abnormal returns were found in the June-end portfolios.
Loughran, T. & Ritter, J. (1996) Long-Term Market Overreaction: The Effect of Low-Priced Stocks.	NYSE US	Three-year non overlapping portfolios	Listed shares 1929-1988	Cumulative average abnormal residuals (CAAR). Buy- and Hold	The results of Conrad and Kaul (1993) were driven by the survivor bias. The discrepancies in results between De Bondt and Thaler (1985) and Conrad and Kaul (1993) were due to the inclusion of AMEX firms. Bid –ask-spread bias was found to be the main cause of the long-term overreaction when forming portfolios based on CARs Losers outperform Winners more using buy and hold method compared to CARs.
Chen, C. & Sauer, D. (1997) Is Stock Market Overreaction Persistent Over Time?	NYSE US	Five-year ranking period. Five-year overlapping formation period.	Listed shares 1926-1992	Calculated the abnormal returns with adjustments for size and time variation in beta. Following the methodology of Chopra et al. (1992).	The returns on the contrarian strategies are not stable over time, The overreaction hypothesis is prevailing during the pre-war period. The extreme portfolios are less likely to remain extreme portfolios during the subsequent periods. Highly significant relationship between market risk premium and arbitrage portfolio returns.

Dissanaike, G. (1997) Do Stock Market Investors Overreact?	FT500 UK	Two-year ranking period. Two-year non overlapping formation period.	925 Large companies 1975-1991	Buy and hold and rebalancing methods.	Past Losers portfolios outperform Winners. Losers tend to be riskier than Winners. The variation in CAPM beta does not seem to explain the Loser- Winner anomaly in the UK. Results supported the overreaction hypothesis in the UK
Gunaratne, P. & Yonesawa, Y. (1997) Return reversals in the Tokyo Stock Exchange: A test of stock market overreaction.	TSE Japan	20 non overlapping portfolios. Four –year rank and test periods.	Listed shares 1955-1990	Risk adjusted model. CARs Following De Bondt and Thaler (1985). Time varying beta of Chan (1988)	Evidence of the overreaction phenomenon in the Japanese market. Past Losers outperformed Winners by 11% per annum. The variation of CAPM-beta partially explains the mean reversion between rank and test periods. The overreaction hypothesis cannot be attributed to the seasonality effect anomalies.
Rouwenhorst, K. (1998) International Momentum Strategies.	12 European stock markets	Buy and Hold for 1-4 quarters returns period.	Listed shares 1978-1995	16 different relative strength strategies over 3-12 month horizons. Following the methodology of Jegadeesh and Titman (1993).	They found evidence of momentum profits in the internationally diversified portfolios. Past Winners outperform past Losers by 1.5% per month. Return continuations found for Small-Medium-Big firms in all the 12 countries Results supported the findings of Jegadeesh and Titman (1993).
Fung, A. (1999) Overreaction in the Hong Kong stock market.	HIS Hong Kong	Two-year rank period. Two-year non overlapping formation	33 stocks constituents of the HSI market index 1980-1993	estimated the cumulative excess returns using the buy and hold method of Conrad and Kaul (1993) to	Results supported the overreaction phenomenon in the Hong Kong stock market. Losers outperform Winners by 10% in year one after portfolio formation.

		period.		reduce the bid-ask spread bias	
Schiereck, D., De Bondt, W. & Weber, M. (1999) Contrarian and Momentum in Strategies in Germany.	DAX FSE Frankfurt	Rank periods 1, 3, and 6 months and 12 month test period.	375 major listed shares 1961-1991	CARs and Buy and Hold to calculate the excess cumulative returns.	Consistent results with the behavioural finance literature. Momentum strategies were found to be profitable in the short run. Contrarian strategies were found to be profitable in the long horizon.
Baytas, A. & Cakici, N. (1999) Do markets overreact: International evidence.	Seven stock markets namely , US, UK, Canada, Japan, Germany, France and Italy	Five-year rank and test period based on the holding period returns (HPR)	Five-year annual return data over the period 1982-1991	Holding period returns are used to sort and classify stocks into Losers and Winners, following Conrad and Kaul's (1993)	Evidence of overreaction phenomenon in all countries but the US. Consistent results with the literature on price overreaction and particularly Conrad and Kaul's (1993). Long term investment strategies based on size and price outperforms those of based on long-term past performance. Long–term price reversals might be explained by firm size.
Gaunt, C. (2000) Overreaction in the Australian equity market: 1974–1997.	Australia	Three-year non overlapping portfolios	Listed shares 1974-1997	Following the methodologies of De Bondt and Thaler (1985) and Brailsford (1992) cumulative rebalancing methods and buy and hold excess returns	Evidence of price reversal phenomenon in both Winners and Losers. Loser-Winner anomaly disappeared when buy and hold method is used. Evidence of small firm effect as Losers tends to be smaller and less liquidity than Winners. The profitability of the Loser-Winner arbitrage portfolio is not exploitable in the Australian Market.
Ahmad, Z. & Hussain, S. (2001) KLSE Long Run Overreaction and the Chinese New Year Effect.	Malaysia, Kuala Lumpur Stock exchange	Three-year non overlapping portfolios	166 listed shares over the period 1986-1996.	Market-adjusted excess returns to rank and construct portfolios. Cumulative excess	Evidence of price overreaction in the KLSE. Both Losers and Winners experienced significant reversals over the test period. The overreaction phenomenon is not

	(KLSE			return and the buy and hold methods,	dominated by size effect. Evidence of the seasonality effect (Chinese New Year) in the KLSE.
Kang, J., Liu, M.-H. & Ni, S. (2002) Contrarian and momentum strategies in the China stock market: 1993–2000.	China	Eight different horizons (i.e., 1, 2, 4, 8, 12, 16, 20 and 26 weeks) for both formation and holding periods.	163 shares in 1994 and 286 companies over the period 1995-2000	Using the portfolio formation methodologies of Lo and MacKinlay (1990) and Jegadeesh and Titman (1995),	Evidence of the short- term overreaction and intermediate –term momentum profits. The overreaction profits were dominating in case of equal-weighted portfolio strategies. The high proportion of individual investors and the unreliable information (rumors) are the main source of the contrarian profits. Momentum profits were prevailing when they used the value-weighted portfolio strategies
Dissanaike, G. (2002) Does the Size Effect Explain the UK Winner-Loser Effect?	FT500 UK	Four-year ranking period. Four -year non overlapping formation period.	925 Large companies 1975-1991	Buy and hold and rebalancing methods. Same methodology of Dissanaike (1997)	Results showed that there is no evidence to suggest that the Winner-Losers anomaly might be explained by size. This result is consistent with the overreaction literature in the UK (see Levis 1989a). Dissanaike claimed that the sample of FT500 is biased towards big size firms. Results were not in favour the efficient market hypotheses.
Benou, G. & Richie, N. (2003) The reversal of large stock price declines: The case of large firms.	US	Three different test periods. One, two and three – year test periods.	Monthly return data for Large firms experienced dramatic price drop (at least 20%) 1990-2000.	The market-adjusted model. The risk-adjusted model using GARCH 11). CARs following Fama (1998)	Positive and significant abnormal returns over one year following the event. Highly significant price reversal for technology stocks. Evidence of underreaction for the service stocks. Their results support the overreaction hypothesis in the US. Buying large firms that experienced

					large price drop is a profitable investment strategy.
Forner, C. & Marhuenda, J. (2003) Contrarian and Momentum Strategies in the Spanish Stock Market.	Spain	6, 12, 36, 60 month-formation and test periods	Monthly return data 1963-1997.	Losers and Winners portfolios extreme based on the extreme residual returns using CARs following of De Bondt and Thaler (1985) and BAH following Conrad and Kaul (1993)	The one-year and five-year momentum and contrarian strategies earn significant abnormal return. Their results supported the existence of the momentum profits in the short run and the contrarian profits in the longer horizons even after controlling for time varying risk. Finally, they argued that their results were not due to the data snooping bias.
Chiao, C., Cheng, D. & Hung, W. (2005) Overreaction after Controlling for Size and Book-to-Market Effects and its Mimicking Portfolio in Japan.	TSE Japan	Five-year formation and test periods	Monthly return data for the listed shares 1975-1999.	Two main portfolios namely; size-BM based and prior returns based portfolios. FF3-factor model.	Strong evidence of persistent overreaction phenomenon in the Japanese market. Size and book-to-market ration were correlated with the overreaction. Fama French three-factor model explained portfolios excess returns.
Siganos, A. (2007) Momentum returns and size of Winner and Loser portfolios.	LSE UK	Winner and Loser portfolios, includes the best and the worst 10, 20, 30, and 300 shares.	Monthly return data for the listed shares 1975-2001	Calculate momentum profits by ranking all the company based past six months market performance months. Three size portfolios were constructed based on mcap.	Evidence of the momentum profits in the UK. Investors can maximise their momentum profits by including small firms of both Losers and Winners in their portfolios. It is not necessarily for the investors to sell-short Losers as the momentum returns for the large portfolios remain constant.
Mazouz, K. & Li, X. (2007) The overreaction hypothesis in	LSE UK	Three-year non	The constituent of	CARS and BAH, and following the	Strong evidence of price overreaction in the London stock exchange

the UK market: empirical analysis.		overlapping portfolios	the FTSE All shares market index over the period 1972-2002	methodology of De Bondt and Thaler (1985) in portfolio formation	Losers outperform Winners by 16.4% and 18.3% using CARS and BAH methods respectively. No evidence of January effect on the contrarian profits; however size effect cannot fully explain the overreaction phenomenon.
George, T. & Hwang, C.-Y. (2007) Long-Term Return Reversals: Overreaction or Taxes?	NYSE, AMEX, and Nasdaq US and Hong Kong	Five-year-formation and test periods	All listed shares 1963-2001 (US) 1980-2000 (HK)	three alternative measures to test the OH; traditional return, Five-year high and five-year low measures, Two additional measures to test the lock-in hypothesis equal-weighted gain and loss and equal-weighted gain only measures	They found strong evidence of the tax hypothesis. Winner reversal diminished as the traditional reversal measures were subsumed in the locked-in measures. No price reversals were found for non January Loser portfolios. No price reversals for both Winners and Losers in Hong Kong where no capital gain or dividends tax. Their results are inconsistent with the overreaction hypothesis.
Dissanaike, G. & Lim, K.-H. (2010) The Sophisticated and the Simple: the Profitability of Contrarian Strategies.	LSE UK	Three-year formation and test periods	All the listed shares (excluding investment and unit trusts) over the period 1987-2001	Portfolio formation methodologies: book value, earnings, cash flow or operating cash flow or residual income model and Ohlson model. Buy-and-hold returns	The residual earnings and the Ohlson models outperform the traditional strategies based on B/M and E/P. The traditional cash flow to price ratio outperforms the advanced accounting measures. They recommended that investors' size and the technical knowledge of more advanced models are the main determinants of the optimal portfolio formation.
Wu, Y. (2011) Momentum Trading, Mean Reversal and Overreaction in Chinese Stock	Shanghai Stock Exchange	Six and 12 months formation	Daily data for the "A" listed shares 1990-2001	methodology of Fama and French (1988) and Balvers and Wu (2006)	No significant abnormal returns for the pure short-term (3 - 12 months) momentum strategy of Jegadeesh and Titman (1993).

Market.	(SHSE)	and test periods			Highly significant abnormal returns for the pure contrarian strategy for all holding periods. The combined strategy (momentum + contrarian) results in a significant excess return 22.2%. their results supported the overreaction hypothesis in the Chinese market.

Chapter 3 : Short-term overreaction: Unobservable portfolios?

3.1 Introduction

The existing body of literature on the overreaction phenomenon has extensively used time series analysis. This can be found in the papers of De Bondt and Thaler, (1985), Conrad and Kaul (1993), Jegadeesh and Titman (1995), Da Costa, (1994), Loughran and Ritter (1996) and Dissanaike (1997). Another much smaller strand of the literature has used cross-sectional analysis to investigate the phenomenon. The work of Bremer and Sweeney (1991), Cox and Petersen (1994), Otchere and Chan (2003), Larson and Madura (2003), Ma, Beach, and Hasan (2005) is illustrative. If these two dimensions have not been combined, the analysis is subject to criticism. Hsiao (2004) and Baltagi (2010), for example, argue that ignoring the time dimension raises the question of bias due to group (company) heterogeneity. Ignoring the dynamics of the process also raises questions of bias in the estimation (Arellano and Bond (1991).

Therefore, in this chapter I present a new methodology to investigate the overreaction phenomenon, the two-way fixed effects panel data model (see Farag and Cressy (2010)[14]), and in addressing the dynamics of the process I employ the Blundell and Bond (1998) two-step Difference GMM estimator which adds dynamics into the process. Finally, I attempt to explain the measured unobservable effects by means of observable variables. These include

[14] This paper has been published based on my earlier work in this chapter and based on small sample of 20 companies.

corporate governance compliance, political connection of board members, and management quality.

The main contribution of this chapter then is, firstly, the use of static and dynamic panel data models to investigate the overreaction phenomenon; secondly, to use the results from this analysis to form 'unobservable' portfolios based on the fixed effects model. Interestingly, we shall see that the Unobservable portfolios outperform the traditional size portfolios. Thirdly, I investigate the relationship between firms' corporate governance compliance, the political connections of the board of directors and the overreaction phenomenon.

I use data from the Egyptian stock market. This adds an additional dimension since my study is the first to empirically investigate the overreaction phenomenon in this market, one of the leading markets in the Middle East and North Africa region (MENA).

This chapter is organised as follows: section 2 presents the theoretical background about the traditional models and the proposed new model to explain the short – term overreaction. Sections 3 describes the dataset used in the analysis. Section 4 presents the econometric modeling and the empirical results. Finally, section 5 summarises and concludes.

3.2 Theoretical background

3.2.1 Traditional theories

According to the overreaction hypothesis, the greater the initial shock proportional price change at time 0 the greater the subsequent price reversals (De Bondt and Thaler (1985)).

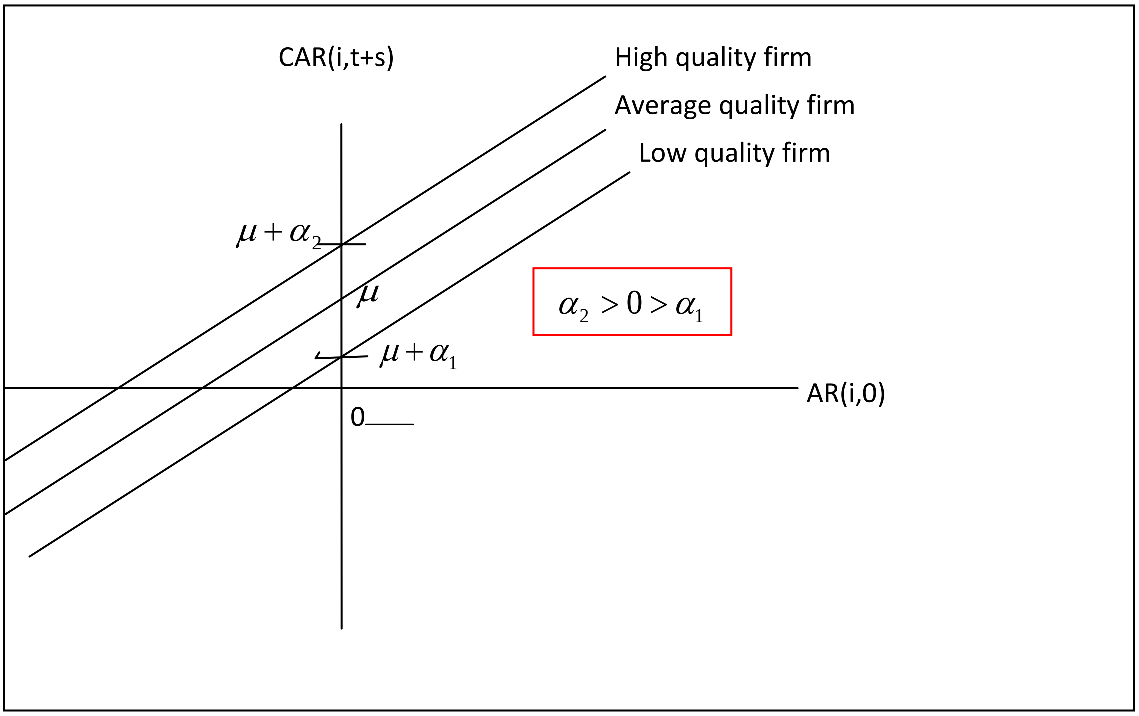
Cressy and Farag (2011) argue that small companies are riskier and more informationally opaque compared with large companies. Therefore, the inverse relationship between cumulative abnormal returns $\mathbf{CARs_t}$ and the initial abnormal return $\mathbf{ARs_0}$ is expected to be stronger for small firms. This relationship is econometrically represented by a negative slope of the regression line with respect to a measure of firm size (Cox and Peterson (1994)).

3.2.2 A new model: Unobservable effects

Fixed, unobservable effects in two dimensions, I argue, can potentially provide a better explanation of the behavior of cumulative abnormal returns compared with the traditional one-dimensional models. The panel data model, in particular the fixed effects model, allows that in addition to observable factors i.e. typically size and trading volume, can explain the overreaction to dramatic price changes between companies, there are also unobservable effects (group and period) that may play a potentially important role (Farag and Cressy (2010)). Cressy and Farag (2011) argue that company effects can be described as 'permanent' (independent of time in the reversal window) or 'temporary' (one period duration). They suggest that these effects might be explained as a proxy of firm quality; however they were not able to empirically identify observable correlates for these effects.

Figure 3.1 presents a graphical illustration of the relationship between initial price reaction (AR(i,0)) and subsequent cumulative abnormal returns (CARs). In the traditional model the CARs are the same (μ) for high and low quality firms. However, and in the light of the unobservable effects model, these CARs shift up or down based on company heterogeneity (quality) ($\mu+\alpha_2$ for higher quality firms, μ for average quality firms and $\mu+\alpha_1$ for low quality firms) where $\alpha_2 > 0 > \alpha_1$. If alpha is positive, the effect of (permanent) firm quality on a price fall (e.g.) is to counteract the fall; if negative, to reinforce it (Cressy and Farag (2011). Thus for high quality firms, dramatic price fall is subsequently corrected (reversed) to some degree. For low quality firms, it is subsequently accentuated.

Figure 3-1: Post-event CARs determined by market cap and unobservable effects



On the other hand, temporary factors (period effects) common to all companies may shift the intercepts $\mu+\alpha_1$ and $\mu+\alpha_2$ up (positive effects) or down (negative effects) in any given period (Cressy and Farag (2011)).

3.3 Data

To examine the short-term overreaction hypothesis in the Egyptian stock market, daily data for stock prices, free float market capitalisation and the EGX 30 market index are utilised for 100 listed stocks with no price limits on the exchange (EGX) over the period 2003-2009. I define the event for a given stock as the experience of a one-day price rise (Winners) or price fall (Losers) of at least 10% as the result of one of the following events:

Event (A): Sharm El Sheikh Terrorist Attacks (24 July 2005).

Event (B): The Lebanon War, (12 Jul 2006) as a proxy for the tension in the Middle East region.

Event (C): The Announcement of the Constitutional Change, (25-Dec 2006) as a proxy for a political reform.

Event (D): The formation of the new government, (27-Dec 2005).

I initially defined the events in the line of the literature (shares that experienced at least 10% one day price change). I then clarified the main causes of these events. Therefore these events are the most influential events in the Egyptian stock exchange during the period of study.

I use the EGX 30 index, a free-floated market capitalisation weighted index to represent the Egyptian stock market benchmark Farag and Cressy (2010). Data were collected from the, Egyptian stock exchange in addition to Egypt for Information Dissemination Company (EGID).

It is worth mentioning that the 100 companies included in the sample are the most actively traded companies in the Egyptian stock exchange (EGX). Therefore, the sample seems to be homogeneous and highly unlikely to be affected by the less frequently traded shares or outlier bias.

Following Cox and Peterson (1994), Cressy and Farag (2011) and Farag and Cressy (2010) methodologies, the estimation period for betas is (-105, -6) and test period is (+1, +120) days. I use the market model as a benchmark to measure the abnormal returns with betas estimated for each security over the 100 days prior to the event. Other measures are also tried, namely, the CAPM model and market-adjusted abnormal return, but qualitatively the results remain the same. This is also in line with the literature (Cox and Peterson, 1994).

3.4 Econometric modeling and empirical results

I use the Event Study methodology to estimate the abnormal returns during the test period. Following the methodology of Bremer and Sweeney (1991) and Cox and Peterson (1994), I begin by defining daily returns.

3.4.1 Daily Returns

The return variable R_t is defined as the first difference in the natural logarithm of the closing price over two consecutive trading days:

$$R_t = Log\ P_t - Log\ P_{t-1} \qquad (1)$$

Where p_t is the closing price of the stock in day (t) adjusted for dividends, rights issue, stock dividends, and stock split.

3.4.2 Stock abnormal returns (ARs)

Stocks' abnormal returns in the test period are defined as the residuals of the market model following Cox and Peterson, (1994) and Farag and Cressy (2010).

$$AR_{it} = R_{it} - \alpha_i - \beta_i R_{mt}, \quad t = 0,1,2.....,T \tag{2}$$

where

$$R_{it} = \alpha_j + \beta_j R_{mt} + \varepsilon_{it} \tag{3}$$

where, α_i and β_i are the results of the market model, R_{it} is the stock return on day (t), R_{mt} is the daily market returns of the EGX market index and T = 120 days. The parameters of the market model are estimated over the estimation window (-105—6). I used both symmetric GARCH and asymmetric TARCH models to estimate the abnormal returns and to control for any potential serial correlation in the return time series. I obtained similar results for the two methods (Benou and Richie (2003).

3.4.3 Cumulative abnormal returns (CARs)

Cumulative abnormal returns (*CARs*) and cumulative average abnormal returns (*CAARs*) are calculated as follows following Cox and Peterson, (1994) and Farag and Cressy (2010):

$$CAR_{it} = \sum_{\tau=1}^{t} AR_{i\tau} \tag{4}$$

$$CAAR_t = \sum_{i=1}^{I} CAR_{it} / I \tag{5}$$

where I = 100 is the number of stocks in the sample

I use t-test statistic to examine whether or not there is a significant difference in CARs between Winners and Losers for a given day within the event window. The statistic is defined as follows:

$$t-stat = AR_t / S(AR_t)$$
$$S(AR_t) = \sqrt{\sum_{t=a}^{n} (AR - AAR)^2 / n-1} \qquad (6)$$

Where S is the standard deviation of securities' abnormal returns.

3.4.4 Descriptive statistics

The descriptive statistics for the four events (A-D) are presented in Table 3.1. The sample size is 100 companies over 120 days as test periods. The initial one-day abnormal return on event day (AR_{i0}) for the Loser events (A and B) are -5.60% and -3.17% respectively. However, the initial abnormal return on event day for the Winner events (C and D) is 7.11% and 6.52% respectively. Cumulative abnormal returns (Car_{it}) over event window (120 days) for the Losers are 14.59% and 7.46 % for events A and B respectively and for the Winners are -20.52% and -35.19% for events C and D respectively.

This suggests that buying Losers on average not only earn positive abnormal returns over the period following the event but also (as in DeBondt and Thaler, 1985) these portfolios outperform the Winner portfolios. Specifically, cumulative average abnormal returns three days before the event - as a proxy for the leakage of information (Leak) - for the Losers are 1.07% and -0.12 % respectively and for the Winners are 0.66% and -0.56% respectively.

Table 3.1: Descriptive Statistics

	Mean	S.D	Skewness	Kurtosis
		Panel A: Loser Event A		
Car_{it}	0.1459	0.5331	0.8378	3.5184
AR_{i0}	-0.0560	0.0305	-0.9938	5.4384
Lnmcap	19.557	2.1201	-0.2359	3.4275
Leak	0.0107	0.0364	0.3326	3.9305
Private	0.5000	0.5051	0.0000	1.0000
		Panel B: Loser Event B		
Car_{it}	0.0746	0.4560	0.8879	4.2309
AR_{i0}	-0.0317	0.0515	2.4385	5.3944
Lnmcap	19.684	1.6846	0.1821	2.4302
Leak	-0.0012	0.0619	-3.9771	2.3192
Private	0.5000	0.5051	0.0000	1.0000
		Panel C: Winner Event C		
Car_{it}	-0.2052	0.6675	0.2085	6.1621
AR_{i0}	0.0711	0.0389	1.3019	4.4327
Lnmcap	19.731	1.8593	-0.3922	3.6710
Leak	0.0066	0.0422	0.9448	4.0901
Private	0.5000	0.5051	0.0000	1.0000
		Panel D: Winner Event D		
Car_{it}	-0.3519	0.5917	-0.3775	2.7186
AR_{i0}	0.0652	0.0312	1.86134	6.0601
Lnmcap	19.604	1.3670	0.1102	2.3783
Leak	-0.0056	0.0417	-2.1486	3.1620
Private	0.5000	0.5051	0.0000	1.0000
Number of observations is 12000 observations (100 companies * 120 days).				

Average firm size proxied by market capitalisation of the Losers are 312 million and 354 million Egyptian pounds respectively, whereas the average firm size for the Winners are 370 million and 326 million Egyptian pounds. Finally, 50% of the sample was formerly state-owned companies.

3.4.5 Correlation matrix

Table 3.2 presents the correlation matrix for the Winners and Losers covariates.

Table 3.2: Correlation Matrix

	Lnmcap	ARio	Leak	Private
Panel A: Loser Event A				
Lnmcap	1.0000			
ARio	-0.0388	1.0000		
Leak	0.0040	-0.1455	1.0000	
Private	0.1262	-0.2257	-0.2555	1.0000
Panel B: Loser Event B				
Lnmcap	1.0000			
ARio	0.0146	1.0000		
Leak	0.1174	-0.0589	1.0000	
Private	0.4507	0.2362	-0.0816	1.0000
Panel C: Winner Event C				
Lnmcap	1.0000			
ARio	-0.1087	1.0000		
Leak	0.2641	0.3422	1.0000	
Private	0.2989	-0.0848	-0.0007	1.0000
Panel D: Winner Event D				
Lnmcap	1.0000			
ARio	0.0014	1.0000		
Leak	0.0562	-0.1267	1.0000	
Private	-0.1532	-0.0597	0.1030	1.0000

***, **,* indicate significance at the 1%, 5% and 10% levels.
Number of observations is 12000 observations (100 companies * 120 days).

The reported correlations show that there is no potential multicollinearity as none of these correlations is above 0.50 or statistically significant, even at 10%.

3.4.6 The overreaction hypothesis

I investigate the overreaction phenomenon firstly by examining the significance of the abnormal returns pre- and post- each of the four events. Table 3.3 presents the average abnormal returns and t- statistics for the Losers and Winners over event window (–5 to +5). It is clear that both Losers and Winners - as expected - have highly significant abnormal returns on event day (p value < 0.001).

For event A (***Terrorist Attacks***), we notice positive abnormal returns pre-event (-4 to -1 days) which may indicate investors' optimism and herding behaviour. The average abnormal return on event day is negative -5.61% and highly significant at 0.001. We also notice that the effect of event (A) continues (the so-called price continuation phenomenon, (Kim and Rhree (1997)) for the subsequent three days post-event, as the average abnormal return is negative and highly significant (at 5%). Price reversal occurs on the fourth day, as positive abnormal returns are found on day 4 as well as a positive and significant (at 10%) abnormal return on day 5.

Table 3.3: Average abnormal returns (AARs) for Losers and Winners

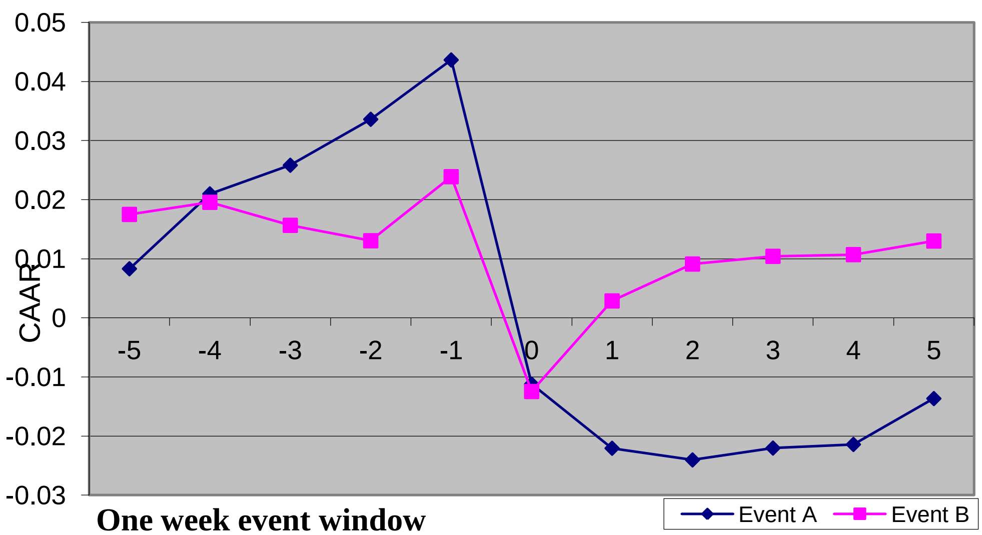
	Losers				**Winners**			
	Event A		**Event B**		**Event C**		**Event D**	
	AR	t. value	AR	t. value	AR	t. value	AR	t. value
-5	0.0076	1.5545	0.0164	3.6968***	-0.0082	-1.6781*	-0.0139	-3.8321***
-4	0.0132	3.2188***	0.0036	0.9181	-0.0076	-1.6032	-0.0021	-0.5180
-3	0.0057	1.6057**	-0.0021	-0.4622	-0.0015	-0.2217	-0.0065	-1.8253*
-2	0.0071	1.8626*	0.0013	0.2268	0.0016	0.3584	-0.0038	-0.6696
-1	**0.0107**	**2.0852****	-0.0012	-0.1316	0.0165	**2.0974****	-0.0155	-0.9416
0	**-0.0561**	**-12.9808*****	**-0.0317**	**-4.351*****	**0.0711**	**12.9446*****	**0.0652**	**14.7585*****
1	**-0.0102**	**-2.0736****	**0.0135**	**2.3198****	-0.0019	-0.2682	-0.0045	-0.7875
2	**-0.0027**	**-2.0399****	0.0071	1.4715	-0.0042	-0.6728	-0.0141	-2.4994**
3	**-0.0029**	**-2.0098****	0.0027	0.6223	-0.0023	-0.4373	-0.0027	-0.6476
4	0.0009	0.2347	0.0004	0.1173	0.0015	0.2596	0.0029	0.6588
5	0.0076	1.8693*	0.0019	0.4245	0.0044	0.7254	0.0024	0.4093

***, **,* indicate significance at the 1%, 5% and 10% levels.
Number of observations is 12000 observations (100 companies * 120 days).

With regard to event B (the Lebanon War), the average abnormal return on event day is negative -3.17% and highly significant at 0.001. However, price reversal occurs on day one post-event as we notice positive (1.35%) and highly significant (at 5%) abnormal returns on day one post-event. There is no leakage of information, as insignificant abnormal returns are found over the five days pre-event B.

Figure 3-2 shows the results of plotting cumulative average abnormal returns (*CAARs*) over time, for the Losers over one week pre and post-events. The asymmetric overreaction is clear from figure 3-2 as stock price reversal of event (B) occurs on day one while the price reversal of event (A) occurs in the fourth day post-event.

Figure 3-2: Cumulative average abnormal returns for Losers

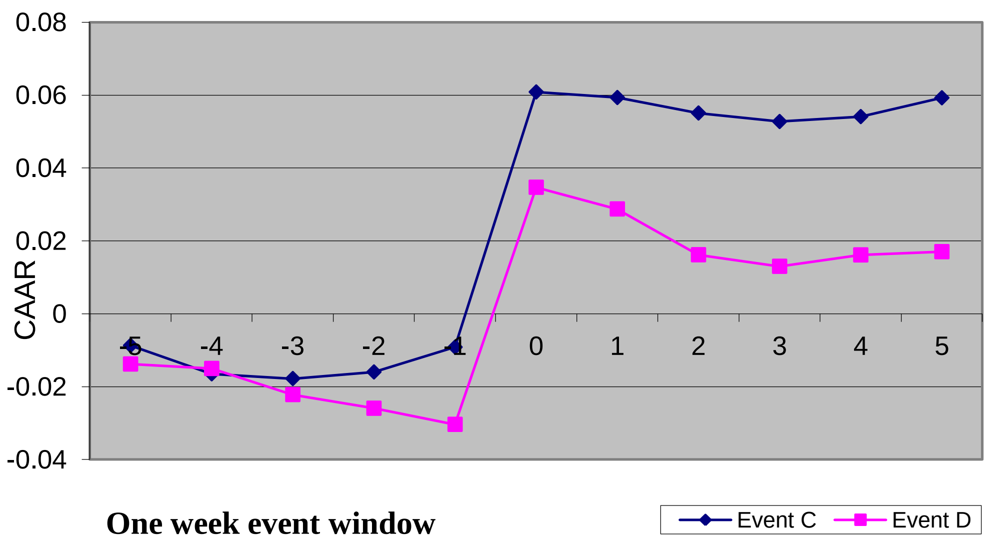


Winners have highly significant (p value < 0.001) abnormal returns (7.11% and 6.52%) on event day for events C (the announcement of the constitutional change) and D (the formation of the new government) respectively. In addition, price reversal occurs on day one post-event for both events. We also notice positive and significant (at 5%) abnormal returns for event C on day one pre-event; this implies the leakage of information effect.

It is worth mentioning that the overreaction phenomenon and the subsequent price reversals are clear for the Losers rather than those of the Winners. Chan (1988) argues that Losers are more risky during the estimation window compared with Winners. This suggests that Losers are on average bigger in size, therefore they are expected to react to the new information more efficiently that those of Winners (Chan (1988)). These results are consistent with the literature on overreaction hypothesis as Losers on the short- term are expected to outperform Winners (Cox and Peterson (1994) and Bremer and Sweeney (1991)).

Figure 3-3 shows the results of plotting Cumulative *Average* Abnormal Returns (*CAARs*) over time, for the Winners over one week pre and post-events.

Figure 3-3: Cumulative average abnormal returns for Winners

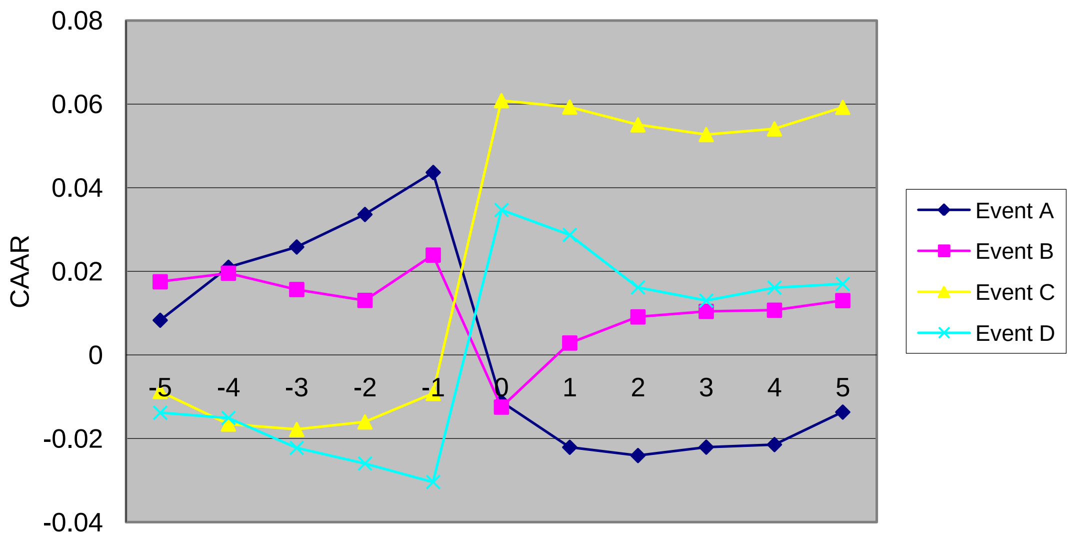


I conclude that the terrorist attacks have significant effects on stock price movements for three days post event. However, the Lebanon war as a proxy for the tension in the Middle East region had no effect on the average abnormal returns in the Egyptian stock exchange.

Furthermore, there was no significant average abnormal return as the result of the announcement of constitutional change and the formation of a new government.

Figure 3-4 shows the results of plotting Cumulative *Average* Abnormal Returns (*CAARs*) over time, for the Winners and Losers over one week pre- and post-events.

Figure 3-4: Cumulative average abnormal returns for Winners and Losers



To summarise, findings are consistent with the literature on overreaction. Past Losers outperform past Winners so that investors may achieve abnormal returns by selling Winners and buying Losers.

3.4.7 The optimal holding period

I now discuss the optimal holding period for Winners and Losers. Table 3.4 reports the cumulative average abnormal returns for Losers and Winners over the following periods CAAR(-5, -1), CAAR (+1, +3), CAAR (+4, +10), CAAR (+21, +50), CAAR (+51, +120), and CAAR (+1, +120).

With regard to event (A), the cumulative average abnormal return pre-event window (-5, -1) is negative and highly significant; this suggests – as discussed above – both herding behaviour and investor optimism. Highly significant negative abnormal returns are reported on the following day due to the terrorist attacks. CAAR (+21, +50), and (+51, +120) windows have positive and abnormal return at a level of 5%. The optimal holding periods are (+21, +30), (+51, +60), and (+41, +50) as the cumulative average abnormal returns are 4.40%, 3.89% and 3.72% respectively. However, the optimal holding period for event (B) is (+31, +40), as the cumulative average abnormal returns is 5.36%. The optimal selling period for the Winners events (C) and (D) are (+41, +50), and (+71, +80) respectively as we notice positive cumulative average abnormal returns over these periods (1.75% and 0.01% respectively). These findings support the argument that past Losers outperform past Winners.

The results presented in table 3.4 suggest that stock prices in the short term for both Losers and Winners are not predictable as the cumulative average abnormal returns five days pre event (as a proxy for the leakage of information) are positive and highly significant for event A and negative and highly significant for event D. This may imply the effect of investor optimism and herding behavior in the Egyptian stock market.

On the other hand, Losers may achieve cumulative average abnormal returns quicker than those of Winners as the optimal holding periods for the Losers are (+21, +30) and (+31, +40) days for events A and B respectively. However, the optimal holding period returns for the Winners are (+41, +50) and (+71, +80) days for events C and D respectively. This suggests that Losers on average outperform Winners and investors may achieve abnormal return by adopting the contrarian strategy by selling Winners and Buying Losers.

Table 3.4: Cumulative average abnormal returns for Losers and Winners over event window

	Loser				Winner			
	Event A		Event B		Event C		Event D	
	CAAR	t. value	CAAR	t. value	CAAR	t. value	CAAR	t. value
CAAR(-5, -1)	0.0442	4.3367***	0.0182	1.0320	-0.0091	-0.6260	-0.0318	-2.2355**
CAAR (+1,+3)	-0.0103	-1.3035	**0.0232**	**2.4000****	-0.0084	-0.8859	-0.0213	-2.5359**
CAAR (+4, +10)	-0.0202	-1.5722	0.0096	0.6974	-0.0207	-1.2872	-0.0130	-0.8731
CAAR (+11,+20)	-0.0258	-1.5302	0.0286	1.7410*	-0.0364	-1.8625*	-0.0744	-4.8753***
CAAR (+21,+30)	**0.0440**	**2.6806****	-0.0214	-1.7046*	-0.0284	-1.6095	-0.0297	-2.8938***
CAAR (+31,+40)	0.0129	0.8168	**0.0536**	**3.3828*****	-0.0044	-0.2696	-0.0119	-0.8013
CAAR (+41,+50)	**0.0372**	**2.1367****	-0.0003	-0.0159	**0.0175**	**1.0686**	-0.0105	-0.7185
CAAR (+51,+60)	**0.0389**	**2.2478****	0.0037	0.3419	-0.0277	-2.7228**	-0.0282	-2.0974**
CAAR (+61,+70)	0.0181	1.1175	-0.0015	-0.1280	-0.0138	-0.7880	-0.0333	-2.5463**
CAAR (+71,+80)	0.0258	1.5835	-0.0121	-0.9497	-0.0222	-1.5291	**0.0001**	0.0027
CAAR (+81,+90)	0.0191	1.1156	0.0156	0.8437	-0.0168	-0.9501	-0.0173	-1.0317
CAAR (+91,+100)	0.0085	0.5045	-0.0073	-0.5856	-0.0216	-1.8115**	-0.0242	-1.2570
CAAR (+101,+110)	-0.0140	-0.6897	-0.0072	-0.5663	-0.0336	-3.0108***	-0.0348	-2.3560**
CAAR (+111,+120)	0.0089	0.4647	-0.0090	-0.7796	0.0116	1.2655	-0.0567	-4.9903***
CAAR (+21,+50)	0.0941	3.1020***	0.0319	1.0002	-0.0153	-0.4314	-0.0521	-1.9923*
CAAR (+51,+120)	0.1053	2.1986**	-0.0178	-0.4985	-0.1240	-2.6274**	-0.1945	-3.2825***
CAAR (+1,+120)	0.1455	1.9336*	0.0737	1.1440	-0.2022	-2.1365**	-0.3736	-4.2565***

***, **,* indicate significance at the 1%, 5% and 10% levels.
Number of observations is 12000 observations (100 companies * 120 days).

Figures 3-5, 3-6 and 3-7 show the results of plotting Cumulative *Average* Abnormal Returns (*CAARs*), for Winners and Losers over 120 days post-event. It is clear from the figures that past losers outperform past winners, so that investors can achieve abnormal returns by selling winners and buying losers (the disposition effect). These results are consistent with the literature on price reversal (De Bondt and Thaler1985). Similar results were found by Cox and Petersen, (1994); Larson & Madura, (2003); Ma, Tang and Hasan, (2005) and Farag and Cressy (2011).

Figure 3-5: Cumulative average abnormal returns for Losers over event window

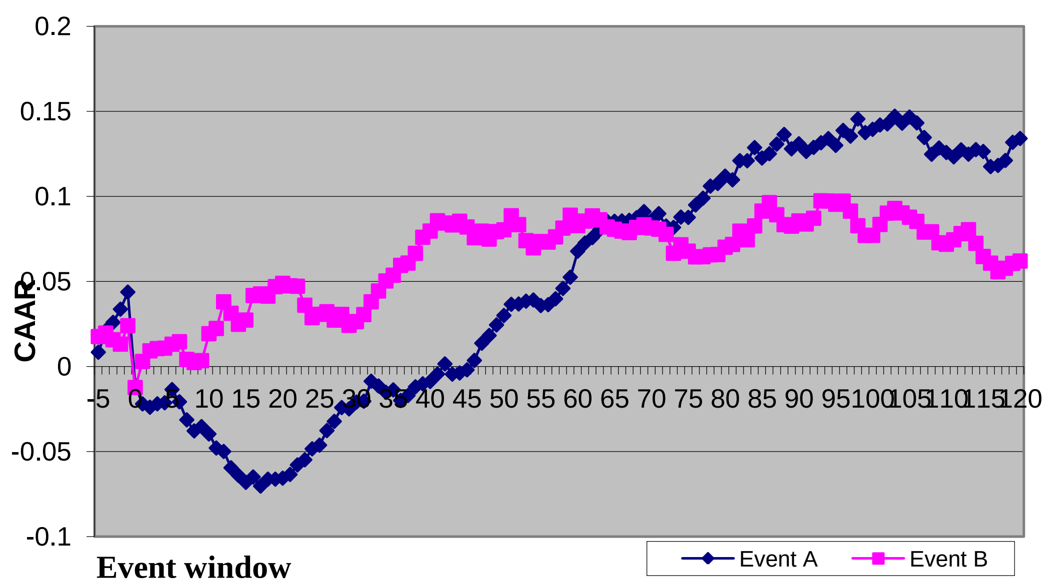


Figure 3-6: Cumulative average abnormal returns for Winners over event window

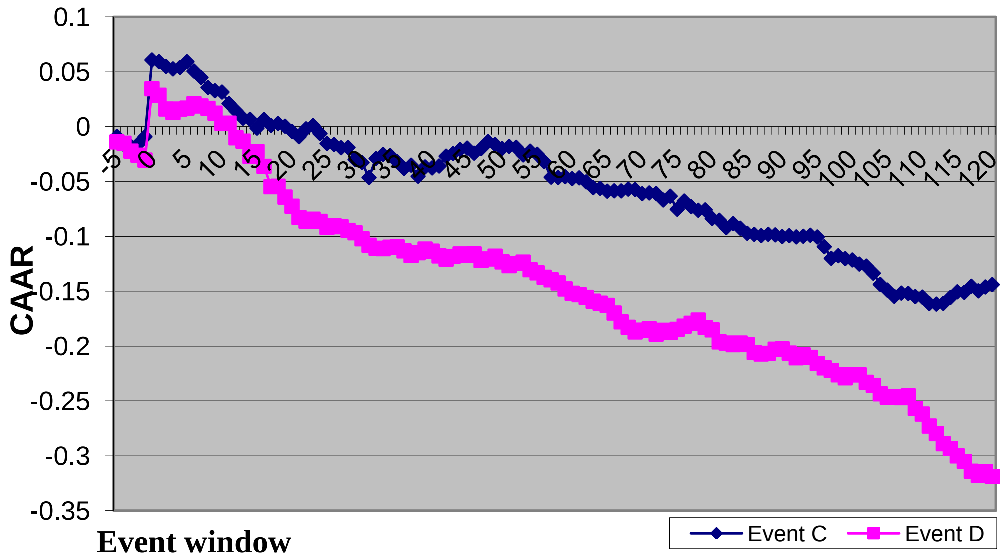
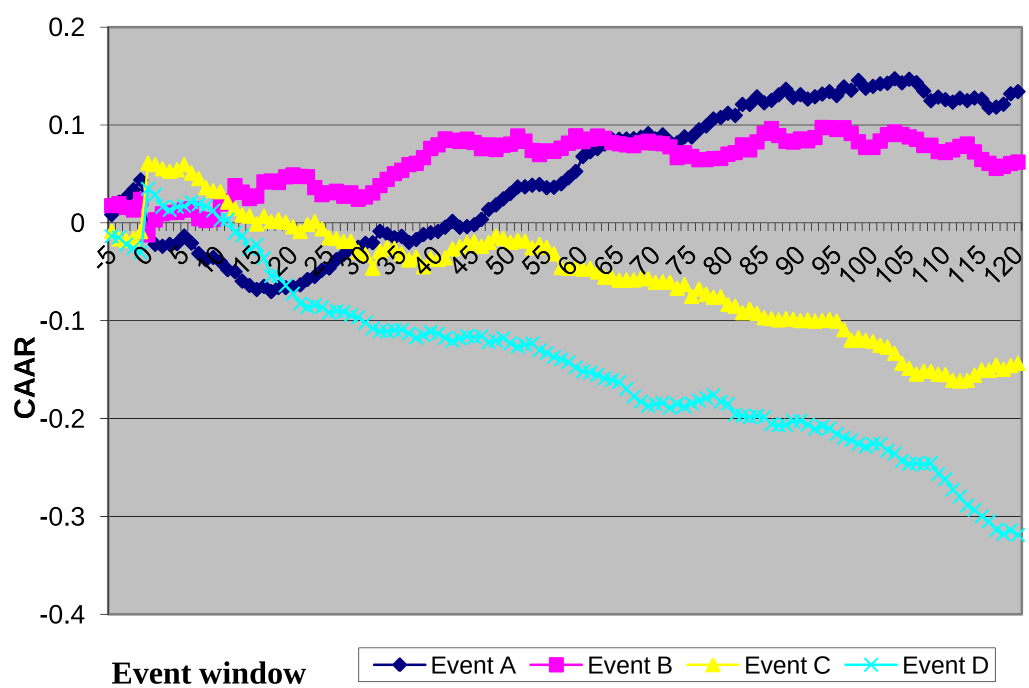


Figure 3-7: Cumulative average abnormal returns for Winners and Losers



3.4.8 Cross-sectional regression

Following Cox and Petersen, (1994), Farag and Cressy (2010), Cressy and Farag (2011), Larson and Madura, (2003); Ma, Tang and Hasan, (2005), I obtain average returns on each firm's stock over the whole time period. I then estimate the following cross-sectional regression by regressing cumulative average abnormal returns CAR_i against initial abnormal returns in event day AR_{i0}, along with firm size (natural log of the free float mcap one day before the event to avoid the endogeniety problem), and a dummy variable representing the company ownership which will be defined below.

In addition, I include a Leak_i variable representing the cumulative average abnormal returns for three days before the event date to capture the leakage of information into the market and the effects of insider information. These can be considered proxies for market inefficiency (see Larson and Madura 2003).

The dummy variable (Private) is a proxy of firm ownership and is equal to one if the company was privately held before IPO. This is consistent with the Egyptian economic reform programme started in 1997; as we have seen in chapter (1) a number of -state-owned companies were floated on the Egyptian stock exchange in the period. I model CAR(i), then, as follows:

$$CAR_i = \mu + \beta_1 \mathrm{AR}_{i0} + \beta_2 \mathrm{lnmcap}_i + \beta_3 \mathrm{Leak}_i + \beta_4 \mathrm{private}_i + \varepsilon_i, \quad i = 1,...100 \qquad (7)$$

where

$CAR_i = \sum_{t=1}^{120} CAAR_{it} /100$

AR_{i0} = Initial abnormal return in event day t = 0.

$private_i$ is a dummy variable = 1 if the company was privately held before IPO; = 0 otherwise

$\ln mcap_i$ is the natural log of the free floated market cap of company (i) one day before the event.

$Leak_i$ is cumulative average abnormal returns for three days before event date as a proxy for the leakage of information.

ε_i = a white noise error term for stock (i)

Cox and Peterson (1994) argue that there is a negative relationship between firm size and the cumulative average abnormal returns (small firm effect). If so small firms have higher price reversals compared to large firms; this is due to higher degree of risk. If size effect holds in the Egyptian stock market we are expecting negative sign for lnmcap variable.

Moreover, Cox and Peterson (1994) and Larson and Madura (2003) argue that there is a positive relationship between abnormal returns on event day (AR_{i0}) and the cumulative average abnormal returns. This suggests the magnitude effects of the overreaction hypothesis (the higher the initial price changes the higher the subsequent price reversals). Therefore we expect positive sign for AR_{i0}. Larson and Madura (2003) on the other hand argue that the leakage of information may play an important role in explaining the overreaction hypothesis due to the role of noise trading and information inefficiency in emerging markets. Therefore $Leak_i$ is expected to have positive and significant coefficient. Finally, I incorporate $private_i$ variable into the analysis to investigate the performance of private and state owned companies; this is due to the recent economic reform programme adopted by the Egyptian government.

Table 3.5 presents the results of the cross-sectional OLS regression of equation 7. It is clear that the models are reasonably well specified (F statistics are highly significant for Winners and Losers). The average adjusted R-squared is 23.29% and 22.63% for the Losers and Winners respectively.

The negative sign of *lnmcap* as a proxy for firm size suggests the presence of a small firm effect, as small firms tend to have greater reversals compared with large firms in the post-event period. This result is consistent with the literature on the overreaction phenomenon (e.g., Cox and Peterson (1994) and Farag and Cressy (2010).

Interestingly, the leakage of information variable (*Leak*(i)) is positive and highly significant for events A and D respectively. This suggests the role of insider trading and information inefficiency in the Egyptian stock market for particular types of events namely terrorist attacks (some international agencies issue warning about potential terrorist acts in some regions) and the formation of the new government.

Table 3.5: Cross Sectional Regressions

	Losers		Winners	
	Event A	**Event B**	**Event C**	**Event D**
C	1.2342**	1.7719**	1.9500*	1.1827
	(0.5963)	(0.7581)	(1.0102)	(1.1555)
Lnmcap	-0.0665**	-0.1042***	-0.0988*	-0.0174
	(0.0319)	(0.0410)	(0.0501)	(0.0575)
Leak	0.4020***	-0.9480	-2.9608	4.5557**
	(0.0721)	(1.1972)	(2.2338)	(1.8844)
ARio	2.6280	-2.9834**	-5.2833**	0.7006
	(2.3067)	(1.4622)	(2.3474)	(2.5030)
Private	0.4371***	0.3391**	0.3517*	-0.4660***
	(0.1438)	(0.1453)	(0.1747)	(0.1568)
R^2	0.2896	0.2704	0.2942	0.2596
Adj R^2	0.2265	0.2394	0.2315	0.2211
F.stat	4.5868***	3.8202***	4.6895***	3.3522**
	(0.0034)	(0.0059)	(0.0030)	(0.0174)
White test for heteroskedasticity	0.9545	0.1837	0.4293	0.6241

*, **,*** indicates significance at the 1%, 5% and 10% levels.
Number of observations is 100 observations.

The initial abnormal returns on event day (ARi_0) on the other hand are insignificant for both events A and D. This result is consistent with Cox and Peterson (1994) as incorporating size effect in the regression does remove the effect of the initial abnormal returns. However, initial abnormal returns on event day (ARi0) are highly significant for events B and C.

Furthermore, private firms have greater CARs than state-owned firms for both Losers and Winners (except in the case of Event D). The management quality of private firms usually outperforms the management quality of state owned firms in the Egyptian context. This may explain the positive and significant relationship of private variable in table 3.5. However event D has the least significant results in table 3.5 (i.e. firm size and initial abnormal returns on event day). This may explain the weak investor reaction to this event. In addition, Private variable will be dropped from the analysis due to the assumptions of panel data model.

As mentioned above, it is necessary to drop the dummy variable (Private) from the fixed effects regression due to collinearity problems it introduces. Therefore I re-estimated the cross section regression of equation 7, dropping the dummy variable (Private). The results were virtually unchanged.

3.4.9 Panel data econometrics

In this section I explain the structure of the two-way panel data econometrics I use subsequently.

There are two main competing models of panel data econometrics, namely, fixed and random effect as in equations 8 and 9.

$$y_{it} = X'_{it}\beta + \alpha_i + \lambda_t + \varepsilon_{it} \qquad \text{(Two way fixed effect model)} \qquad (8)$$

$$y_{it} = X'_{it}(\beta + h_i) + (\alpha + u_i) + \lambda_t + \varepsilon_{it} \qquad \text{(Two way random effect model)} \qquad (9)$$

where: α_i is unobserved firm-specific (time-constant) effect for company i, λ_t is time-specific effect for period t, u_i is group-specific random effect, h_i is a random vector that induces the variability of the parameters across individuals, ε_{it} is a white noise error term.

Unobservable factors in stock price reversal may thus be either random or fixed (Farag and Cressy 2010). The fundamental distinction between the FE and RE model is whether the unobservable effects embodies elements that are correlated with the regressors. A fixed effects model allows that the effects may be correlated with the regressors (covariates) whilst a random effects model does not: random effects are part of the error term and hence any correlation with the covariates implies an endogeneity problem. (Greene 2012).

Farag and Cressy (2010) and Cressy and Farag (2011) argue that observable factors (variables) e.g. size, trading volume and the leakage of information are not the only variables that explain the price reversal phenomenon[15].In equation 8, unlike equation 7, the relationship may shift up or down based on the sign of the firm fixed effect coefficient α_P (positive) or α_N (negative). It may also shift up or down as a results of factors common to firms in a given time period, via the time-specific effect λ_t . I argue that these effects may explain the company heterogeneity in response the dramatic change in stock prices.

I estimate the two-way first order autoregressive fixed/random effect (*FE/RE) models* to obviate the serial correlation in CAR_{it}, as in the following equation:

$$
\begin{aligned}
&CAR_{it} = \beta_0 + \alpha_i + \lambda_t + \beta' x_{it} + \varepsilon_{it},\ i = 1,...100;\ t = 1,....120 \qquad && fe \\
&CAR_{it} = \beta_0 + \beta' x_{it} + (\alpha \ + u_i) + \lambda_t + \varepsilon_{it},\ i = 1,...100;\ t = 1,....120 && re \qquad (10) \\
&\varepsilon_{it} = \rho \varepsilon_{i,t-1} + \eta_{it}
\end{aligned}
$$

Where β_0 =common intercept for all i,t

x_{it} = independent variables

α_i = company-specific effect for company i

λ_t = time-specific effect for period t

ε_{it} = white noise error term.

Note that for the random effects model I use the GLS-estimator, a weighted average of between-firm and within-firm effects. $|\rho| < 1$and η_{it} is independent and identically distributed

[15] This paper has been published based on my earlier work in this chapter and based on small sample of 20 companies.

(i.i.d.) with zero mean and variance $=\sigma_\eta^2$. Baltagi and Wu (1999) derive a transformation of the data that removes the AR (1) component. Their $C_i(\rho)$ can be written as:

$$y^*_{it_{ij}} = \begin{cases} (1-\rho^2)^{1/2} y_{it_{ij}} & \text{if} \quad t_{ij} = 1 \\ (1-\rho^2)^{1/2}\left[y_{i,t_{ij}} \left\{ \dfrac{1}{1-\rho^{2(tij-ti,_{j-1}}} \right\}^{1/2} - y_{i,t_{i,j-1}} \left\{ \dfrac{\rho^{2(tij-ti,_{j-1}}}{1-\rho^{2(ti,j-ti,_{j-1}}} \right\}^{1/2} \right] & \text{if} \quad t_{ij} > 1 \end{cases} \tag{11}$$

Using the analogous transform on the independent variables generates transformed data without the AR (1) component.

3.4.10 Fixed effects (FE) or Random effects (RE)?

An advantage of the RE model is that we can include time-invariant variables (e.g. Private and AR(i,0), to obviate the problem of errors being correlated with independent variables. This allows time-invariant variables to play a role as explanatory variables. However, in the fixed effect model these variables are absorbed in the intercept.

To decide whether a fixed or random effect model should be used in the estimation, I use the Hausman test with the Null "individual effects are uncorrelated with the other regressors". The Hausman test statistic is distributed as $\chi^2(K)$. Rejecting the Null is in favour of the fixed effect model.

There are two methodological problems in using the Hausman test: Firstly, the test requires strict exogeneity of the error term. Hence correlation between regressors and the error term causes both the FE and RE estimators to be inconsistent. Secondly, the test is usually implemented assuming that both the idiosyncratic error term and the unobserved effect have constant variances. If this assumption fails to hold, the Hausman test has a non-standard limiting distribution implying that the resulting test could have an asymptotic size smaller or larger than the nominal size of the test. Therefore I estimate the Wooldridge (2002) robust version of Hausman test. Finally, the Hausman test is an asymptotic one, implying that the sample size should be large for it to be valid.

In addition to Hausman, I use the Lagrange Multiplier statistic of Breusch and Pagan (1980) to investigate the existence of the random effect. Following Farag and Cressy (2010) this is defined as.

$$LM = \frac{nT}{2(T-1)}\left[\frac{\sum_i\left(\sum_t e_{it}\right)^2}{\sum_i\sum_t e_{it}^2} - 1\right]^2 \sim \chi^2(1) \tag{12}$$

Where e_{it} is the OLS pooled regression residual, LM statistic is distributed as $\chi^2(1)$ for company and period effects (Baltagi (2008)).

As a robustness check, I also generate the RE estimator by applying pooled OLS after the following transformation (Wooldridge 2002):

$$\begin{aligned} &CAR_{it} = \beta' \chi_{it} + \alpha + \mu_i + \varepsilon_{it} \\ &(CAR_{it} - \theta\overline{CAR}_i) = \beta'(x_{it} - \theta\overline{\chi}_i) + \alpha(1-\theta) + \{(1-\theta)\mu_i + (\varepsilon_{it} - \theta\overline{\varepsilon}_i)\},\ i = 1,...100;\ t = 1,....120 \end{aligned} \tag{13}$$

where $\theta = 1 - \sqrt{\frac{\sigma_{\varepsilon}{}^{2}}{T\sigma_{\mu}^{2} + \sigma_{\varepsilon}{}^{2}}}$

Note that μ_i are assumed to be random variables (i.i.d. random effect) and that $Cov(\chi_{it}, \mu_i) = 0$. Then we are able to obtain consistent estimates using pooled OLS. θ ranges from 0 and1and if $\theta = 1$ then the estimation of both FE and RE is identical; if $\theta = 0$ then the RE estimators is identical with the pooled OLS. The degree of biasness of the RE estimator depends on the magnitude of θ. If $\sigma_{\mu}^{2} >> \sigma_{\varepsilon}^{2}$ then θ will be close to 1and the RE estimator will be least biased.

In addition to these tests, I run the main panel data diagnostic tests to examine autocorrelation, heteroskedasticity as well as the stationarity of residuals specifically I use the Wooldridge and Modified Wald test for group-wise heteroskedasticity, LM test and Baltagi-Wu LBI tests for serial correlation. However, to test the stationarity of residuals I use the Levin–Lin–Chu (LLC) stationarity test.

Table 3.6 presents the results of the two-way random and fixed effect models of equation 10. All time-invariant variables, namely, Private and ARio are removed from the fixed effect estimation for reasons of collinearity.

Table 3.6 reports similar coefficients and signs for both random and fixed effect models. Interestingly, and in contrast with the cross-sectional regressions, the sign of lnmcap (our proxy for firm size) is positive for both Losers and Winners. This suggests underlying company heterogeneity in the data and the biased estimation of the OLS regressions.

In addition, size coefficients in the two-way model are highly significant for both Losers and Winners. The leakage of information variable is positive in sign and highly significant for all the events except C. This reflects the increasing role of insider information in the Egyptian stock market and thus market inefficiency.

Table 3.6: Static Panel Data Models

	Loser				**Winner**			
	Event A		**Event B**		**Event C**		**Event D**	
	RE	**FE**	**RE**	**FE**	**RE**	**FE**	**RE**	**FE**
C	-2.6871***	-2.6741***	-3.633***	-3.7991***	-4.5833***	-4.7388***	-9.1548***	-9.7601***
	(0.1517)	(0.0012)	(0.1312)	(0.0016)	(0.1896)	(0.0011)	(0.2268)	(0.0009)
Lnmcap	0.1487***	0.1494***	0.1947***	0.3830***	0.2298***	0.2262***	0.4538***	0.4613***
	(0.0046)	(0.0047)	(0.0052)	(0.0213)	(0.0051)	(0.0051)	(0.0065)	(0.0063)
Leak	0.0396***	0.0388***	0.0357***	0.0351***	-0.0017	-0.0034	0.0355***	0.0328***
	(0.0092)	(0.0091)	(0.0085)	(0.0083)	(0.0080)	(0.0078)	(0.0072)	(0.0068)
ARio	0.1443 (0.7930)	---	0.6973 (0.9868)	---	-.0.3260 (0.9072)	---	-0.5599 (0.6307)	---
Private	-0.0203 (0.1083)	---	-0.2149** (0.1015)	---	0.0434 (0.1415)	---	0.1075 (0.1626)	---
Adj R^2	0.2849	0.2707	0.3673	0.4199	0.3979	0.3156	0.2704	0.5736
Wald test chi^2	130.46***	---	118.61***	---	223.20***	---	248.51***	---
F.stat	---	12.77***	---	18.28***	---	16.55***	---	334.97***

***, **,* indicate significance at the 1%, 5% and 10% levels.
Number of observations is 12000 observations (100 companies * 120 days).

The initial abnormal return in event day variable (ARio) is insignificant for all events, however its sign changes from positive (Losers) to negative (Winners). This result is consistent with Cox and Peterson (1994) as size does remove the effect of initial returns on subsequent price behavior. The time-invariant variable Private is insignificant except for B, however its sign changes from negative (Losers) to positive (Winners).

Results reported in table 3.6 show that we can reject the null that all independent variables are zero (at well below 1 percent for both Winners and Losers). Finally, the average adjusted R-squared is 34% and 39% for the Losers and Winners respectively[16].

Table 3.7 presents the diagnostic tests for the static panel data models. To establish the existence of fixed effects, I run the redundant fixed effect tests (company and time effects) of equation 10. This rejects the null hypothesis that all fixed effects are zero. In addition, we also reject the nulls that specifically company and periods fixed effects are zero for both Winners and Losers.

To determine which of the random or fixed effects model a better description of the data is I perform the Breusch & Pagan LM random effect test using the residuals of the OLS regression. The Chi-squared values for company and period effects for events B and D are marginally significant. However for events A and C they are insignificant, so that we cannot confidently reject the null of no random effects.

However, we can reject the null hypothesis of the Hausman test that "individual effects are uncorrelated with the regressors". This suggests that the random effect estimators are biased and that therefore the fixed effects model is preferred. I also estimate the Wooldridge (2002) robust version of Hausman test and got the same conclusion.

[16] I deal with time-invariant variables, the potential endogeniety between market capitalisation and CARs and the problem of slope instability by using the system GMM model of equation 19.

Testing for the presence of heteroscedasticity, I run the modified Wald test for group-wise heteroskedasticity in the fixed effects model. The test rejects the null of homosksdasicity implying that the estimated standard errors of the coefficients of the model are biased. I shall shortly deal more effectively with this problem using the system GMM estimator.

Table 3.7: Panel Data Diagnostic tests

	Losers		Winners	
	Event A	**Event B**	**Event C**	**Event D**
Redundant fixed effects				
By group	3.1641***	3.3458***	5.0966***	3.5145***
By time	1.5459***	1.6517***	1.3238**	1.1990*
By group & time	1.9898***	2.1962***	2.4661***	1.8869***
Breusch & Pagan LM random effect test	2.1421	2.076*	2.012	2.1119*
Hausman test	12.359***	10.958***	14.646***	9.278***
Modified Wald test for group-wise heteroskedasticity in fixed effects models.	42.781***	39.854***	49.511***	32.874***
Modified Bhargave et al DW test	1.9981	1.9778	1.9697	1.9785
Baltagi-Wu LBI serial correlation	2.0057	2.0001	1.9921	1.9822
Theta	0.8781	0.8685	0.8268	0.8297
Levin–Lin–Chu (LLC)	-33.057***	-31.758***	-41.257***	-15.861***

***, **,* indicate significance at the 1%, 5% and 10% levels.
Number of observations is 12000 observations (100 companies * 120 days).

We note, however, that the random effect model is estimated using GLS which relaxes the assumption of heteroskedasticity, so that bias in this model from this source at least is obviated. Modified Bhargave et al DW and Baltagi-Wu LBI serial correlation tests are also applied and indicate that the estimated residuals are serially uncorrelated.

Regarding the choice between random and fixed effects models, theta-estimates range from 82% to 86%, suggesting no significant difference between fixed and random effect approaches in our dataset[17]. Finally, examining stationarity of the time series, the Levin–Lin–Chu (LLC) test for the existence of a unit root rejects the null that the panels contain unit root and hence the underlying time series can be assumed to be stationary.

3.4.11 Unobservable or size portfolios?

In this section I introduce Unobservable portfolios and examine their performance compared with the traditional portfolios. Unobservable portfolios are formed on the basis of fixed effects estimated on the pre-event data. If the FEs are important predictors of post-event returns such portfolios should outperform those constructed according to traditional criteria.

To further develop the analysis I therefore test the hypothesis that Unobservable portfolios outperform traditional size portfolios. Therefore I form two main portfolios, namely, size and Unobservable portfolios. Company size quintiles are ranked into an ascending order based on the company's market capitalisation within the estimation window. I use both market capitalisation and free float market capitalisation as a proxy of size.

However, to form the Unobservable portfolios I re-estimate equation 10 within the estimation window, and then sort the companies' fixed effects into an ascending order. All sample firms are grouped into five quintiles based on company fixed effects and market capitalisation. I then estimate the cumulative average abnormal returns CARs for two size portfolios, namely, Big and Small portfolios as well as High and Low Fixed effects based on the first and the fifth quintile of each portfolio.

[17] Theta - by definition - ranges from 0 and 1 and if theta =1 then the estimation of both FE and RE is identical (equation 13).

It is worth mentioning that these portfolios are expected to satisfy the poolability conditions of the panel data model. Poolability tests are designed to examine group (company) and time slopes stability (Farag and Cressy (2010). The Null hypothesis of poolability by company $H_0 : \beta_{ik} = \beta_k$ the test F statistic is:

$$F_{Obs} = \frac{(e'e - \sum e_i'e_i /[(n-1)K]}{\sum e_i'e_i /[n(T-K)]} \sim F((n-1)K, n(T-K)) \quad (14)$$

And the F test of the poolability test by time is:

$$F_{Obs} = \frac{(e'e - \sum e_t'e_t /[(T-1)K]}{\sum e_t'e_t /[T(n-K)]} \sim F((T-1)K, T(n-K)) \quad (15)$$

Where $e'e$ is the sum squared errors of the pooled OLS, $e_i'e_i$ and $e_t'e_t$ are the sum squared errors of the OLS regression for company (i) and period (t) respectively. Rejection of the Null means that the panel data are not poolable (Cressy and Farag 2011).

Figures 3-8, 3-9, 3-10, and 3-11 present the cumulative average abnormal returns CARs for both size and unobservable (fixed effects) portfolios for the Losers (events A and B). It is clear that in case of bad news (Losers) low fixed effects portfolios not only outperform high fixed effects ones, but they also outperform small and big size portfolios. In addition, the arbitrage portfolios LMH outperform SMB portfolios on average.

Figure 3-8: Unobservable portfolios for event A

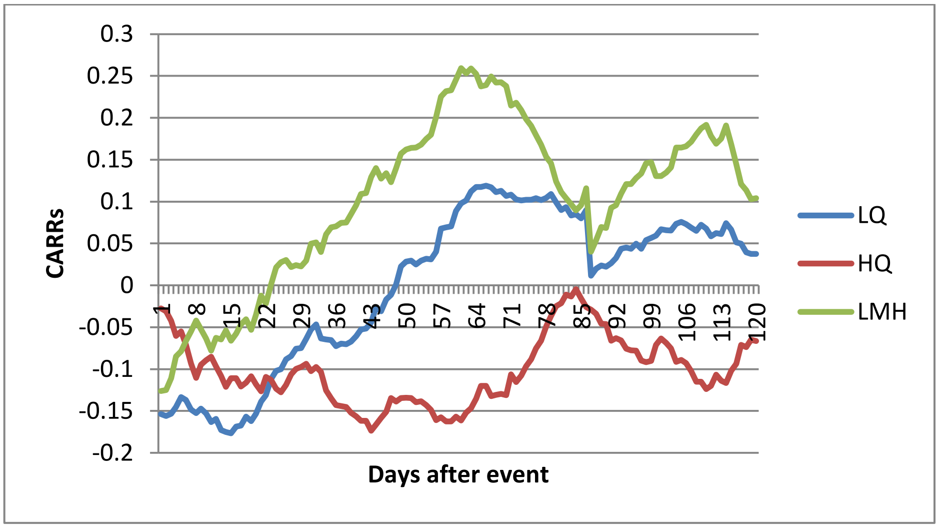
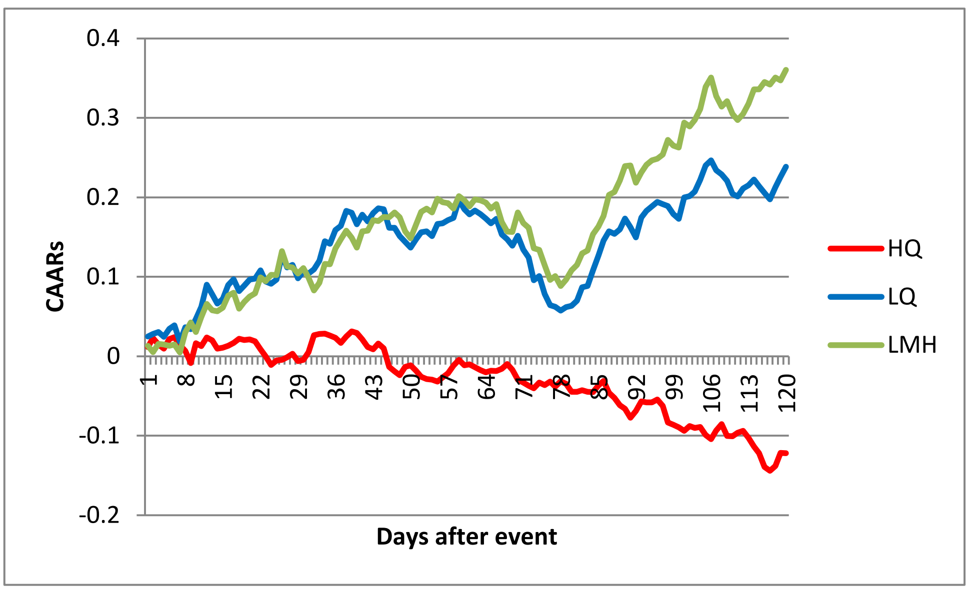


Figure 3-9: Unobservable portfolios for event B[18]



[18] HQ and LQ stand for high and low fixed effects respectively, however LMH stands for the arbitrage portfolio low – high fixed effects.

Figure 3-10: Size portfolios for event A

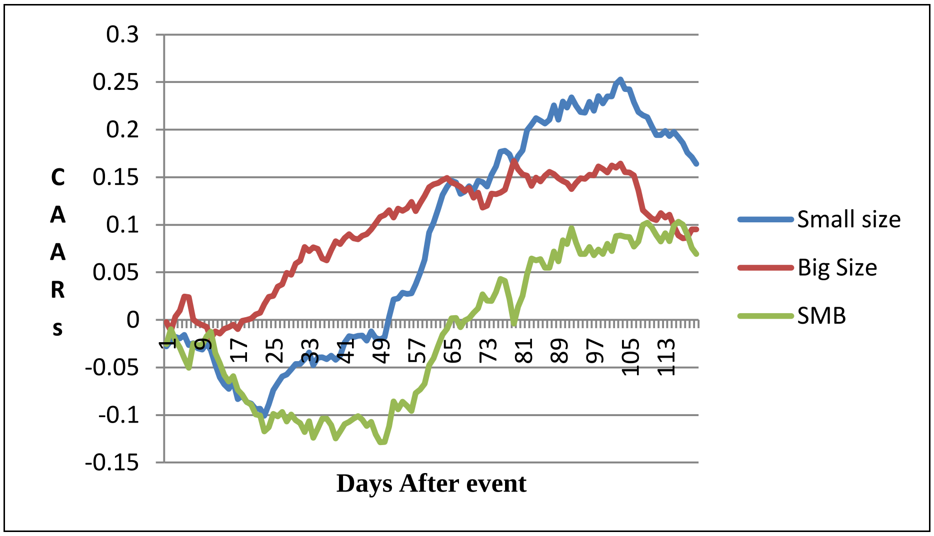
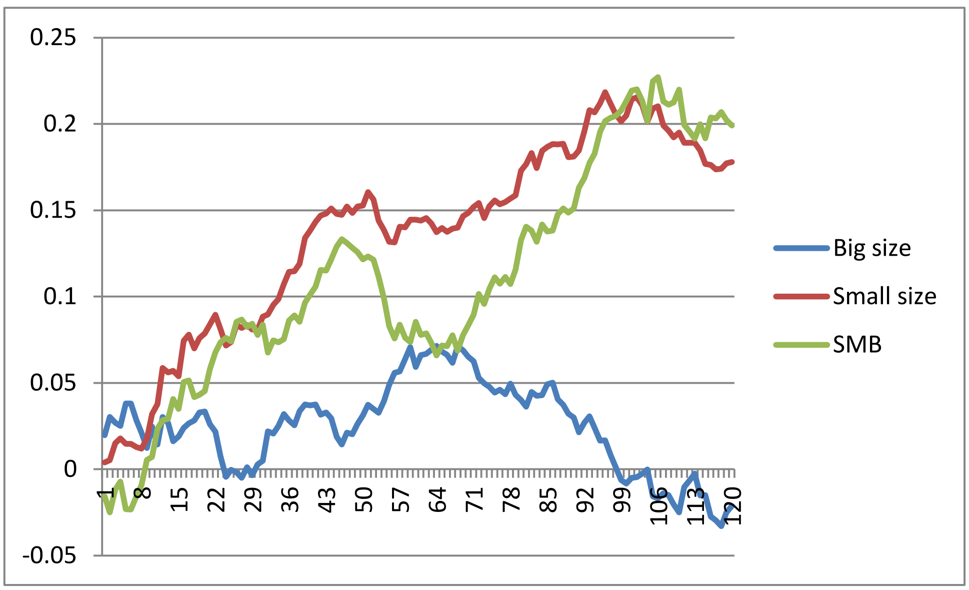


Figure 3-11 Size portfolios for event B



On the other hand, figures 3-12, 3-13, 3-14, and 3-15 present the cumulative average abnormal returns CARs for both size and unobservable (fixed effects) portfolios for the

Winners (events C and D). In cases of good news (Winners), high fixed effects portfolios outperform those of low fixed effects. However, small portfolios outperform big. .Finally, the arbitrage portfolio HML outperforms SMB portfolios.

Figure 3-11: Unobservable portfolios for event C

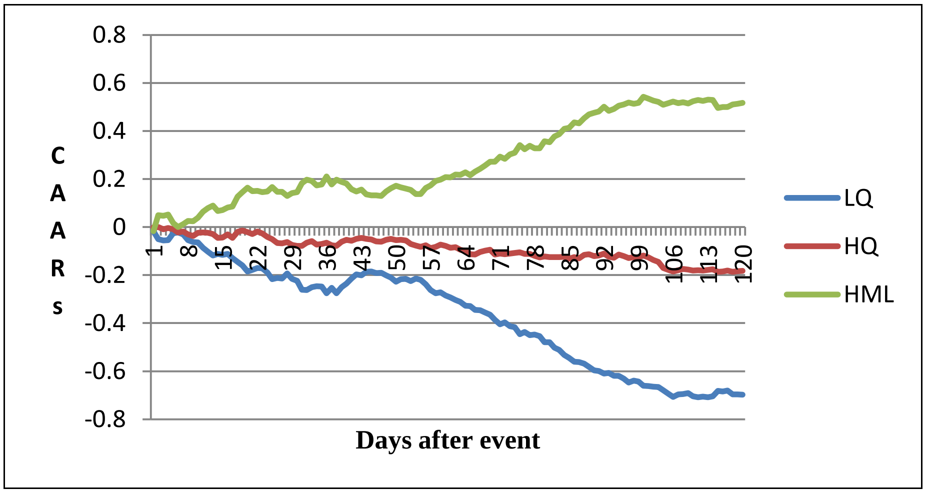


Figure 3-12: Unobservable portfolios for event D

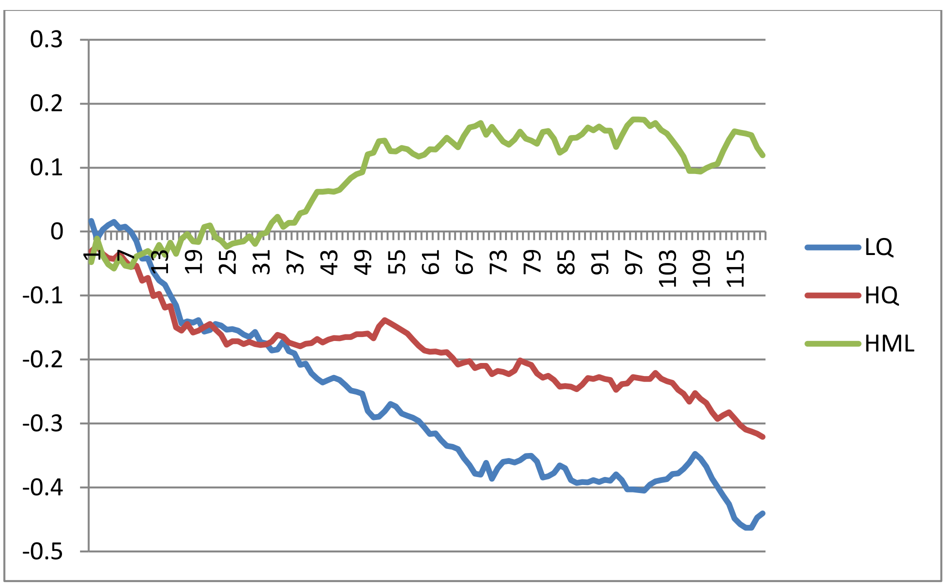


Figure 3-13: Size portfolios for event C

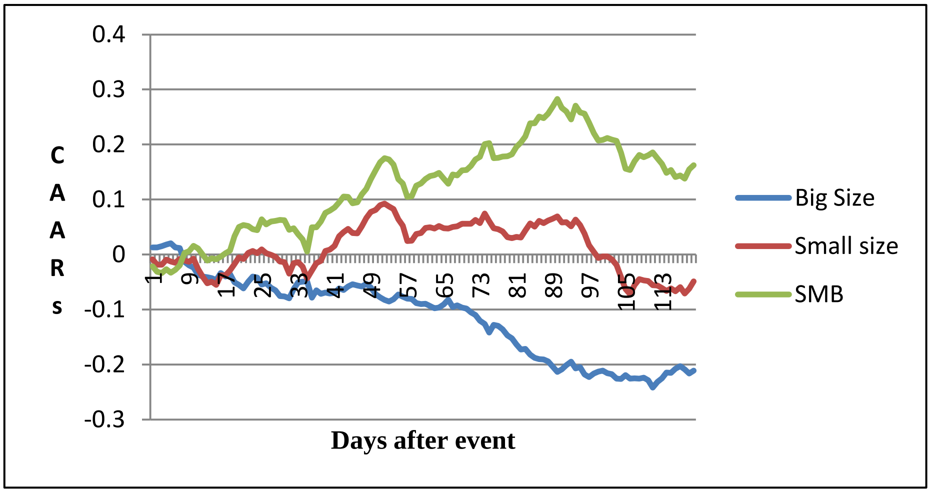
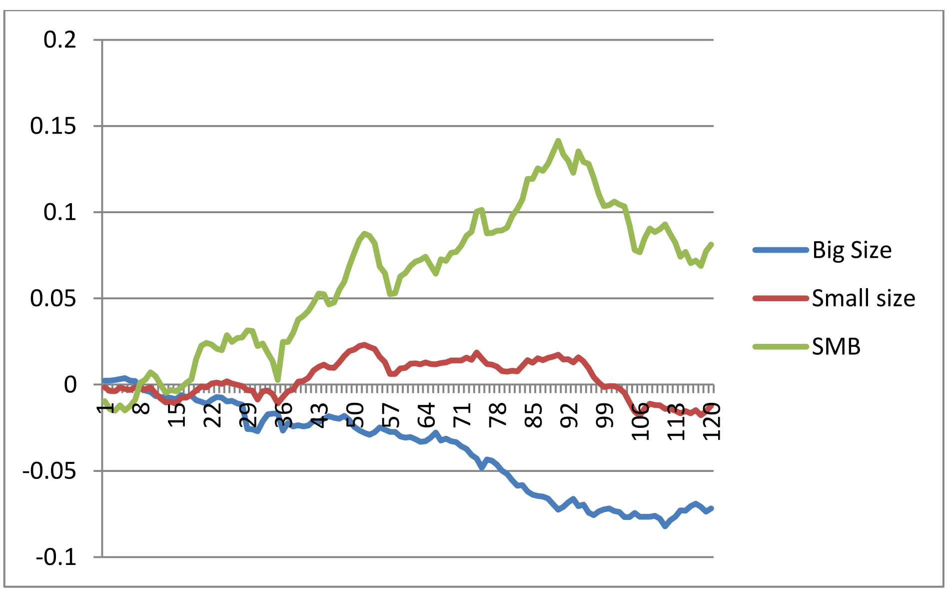


Figure 3-14: Size portfolios for event D



3.4.12 System GMM dynamic panel data model

Many econometrics problems may arise in the estimation of equation 10. Firstly, firm size may be endogenous and correlated with residuals. Secondly, the fixed effect model assumes that errors are correlated with company fixed effects. Thirdly, due to the assumptions of these models, in order to get estimates of the fixed effects we need to remove all covariates that do not vary with time or company (Farag and Cressy 2010). Therefore, by definition, time-invariant variables cannot be included in FE models (i.e. in our case, AR(i0), Private). Finally, serial correlation and heteroskedasicity may bias the estimation.

In this chapter I initially estimate the Arellano and Bond (1991), Arrellano and Bover (1995) and Blundell and Bond (1998) two-step Difference GMM estimator to obviate the above problems. The main assumption of the first step in the estimation is that the errors are independent and homoskedastic across companies and over time (Beck and Levine 2004). In the second step, we construct a consistent variance- covariance matrix using the residuals derived from the first step (Beck and Levine2004).

As linear GMM estimators, the Arellano-Bond and Blundell-Bond estimators have one- and two-step variants, though the two-step method is asymptotically more efficient, and the standard errors are less biased (Arellano and Bond 1991; Blundell and Bond 1998).

The general form of the Difference-GMM is (Roodman 2009):

$$\begin{aligned} CAR_{it} &= \mu_0 + \alpha\, CAR_{it-1} + \beta' x_{it} + \varepsilon_{it} \\ \varepsilon_{it} &= \mu_i + v_{it} \\ E(\mu_i) &= E(v_{it}) = E(\mu_i v_{it}) = 0 \end{aligned} \qquad (16)$$

The disturbance term thus has two orthogonal components, namely, the fixed effects μ_i and the idiosyncratic shocks v_{it} (Roodman (2009). The GMM estimator uses the first differences to transform equation 16 into:

$$\begin{aligned} \Delta CAR_{it} &= (\alpha - 1)CAR_{it-1} + \Delta\beta' x_{it} + \Delta\varepsilon_{it} \\ \Delta\varepsilon_{it} &= \Delta\mu_i + \Delta v_{it} \end{aligned} \tag{17}$$

Lagged levels are used as instruments for the regression in differences. By transforming the regressors by first differencing, the fixed company-specific effects are removed as they are – by definition – time-invariant. However, the new error term $\varepsilon_{it} - \varepsilon_{it-1}$ which is correlated with the lagged dependent variable $CAR_{it-1} - CAR_{it-2}$, now represents a source of potential bias (Beck and Levine2004).

Arellano and Bond (1991) introduce the following moment conditions to deal with this problem, assuming that the error term ε is not serially correlated and the independent variables are uncorrelated with error term.:

$$\begin{aligned} &E\left[y_{i,t-s}.(\varepsilon_{i,t} - \varepsilon_{i,t-1})\right] = 0 \quad \textit{for } s \geq 2; t = 3,........., T \\ &E\left[X_{i,t-s}.(\varepsilon_{i,t} - \varepsilon_{i,t-1})\right] = 0 \quad \textit{for } s \geq 2; t = 3,........., T \end{aligned} \tag{18}$$

On the other hand, Blundell and Bond (1998) claim that there are major conceptual and statistical shortcomings of the first difference GMM i.e. when the explanatory variables are persistent over time, lagged levels of these variables are weak instruments. This may lead to biased coefficients especially in case of small samples.

To overcome these conceptual and statistical drawbacks, Blundell and Bond (1998) introduce the system GMM estimator. The new estimator of GMM combines in a system the first differenced equation with the same equation expressed in levels.

Lagged levels are used as instruments for the regression in differences; however I used the lagged (three lags) differences of Mcap as instruments in the equation in level. Arellano and Bover (1995 argue that using additional lagged differences would result in redundant moment conditions. Therefore Blundell and Bond (1998) propose additional moment conditions for the regression in levels (the second equation in the system) as in equation 19.

$$\begin{aligned} &E\left[y_{i,t-s} - y_{i,t-s-1}).(v_i + \varepsilon_{i,t})\right] = 0 \qquad for\ s = 1,\ t = 3,........,T \\ &E\left[X_{i,t-s} - X_{i,t-s-1}).(v_i + \varepsilon_{i,t})\right] = 0 \qquad for\ s = 1;\ t = 3,........,T \end{aligned} \qquad (19)$$

Thus, I use the moment conditions presented in equations 18 and 19 to overcome the drawbacks of the first difference GMM and to obtain consistent and efficient parameter estimates.

The system GMM has main assumptions i.e. fixed individual effects, endogenous regressors, the idiosyncratic error terms (not fixed effects) are of hetroskedastic and serially correlated, the idiosyncratic error terms are uncorrelated across companies (groups) and, finally, a smaller number of time periods (T) compared with the number of groups (N) (small T and large N) Roodman (2009).

To satisfy the assumptions of the system GMM and in order to alleviate the severe serial correlation identified in CARs for the Egyptian stock price data (Cressy and Farag (2010)), I chose five-day (weekly) rather than daily returns. This results in 20 pre-event and 24 post-event observations per firm.

I also include in this analysis a new dummy variable "DumQ" as a proxy for the direction of firm reaction to the events or companies' unobservable effects. It is based on the rankings of fixed effects within the estimation window and takes the value of 1 in the case of positive unobservable effects and 0 for negative effects.

$$\begin{aligned} &CAR_{it} = \beta_1 CAR_{it-1} + \beta' x_{it} + \varepsilon_{it}, \quad i = 1,...100;\ t = 1,...24 \\ &\varepsilon_{it} = \mu_i + v_{it} \end{aligned} \tag{20}$$

Where $\beta' = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)$ and $x_{it}' = (AR_{i0}, \mathrm{Lnmcap}_{it}, \mathrm{Leak}_{it}, \mathrm{Private}_{\mathrm{i}}, \mathrm{DumQ}_{\mathrm{i}})$

To examine the residuals of the system GMM, I report the Arellano-Bond test, AR (1) and AR (2), for serial correlation with null hypothesis of "No serial correlation". We are particularly interested in AR (2) as the test of AR (1) usually rejects the null hypothesis) (see Roodman, 2009). I also report the Hanson and Sargan tests of exogeniety of instruments and the over-identifying restrictions in the two-step GMM criterion function. The Null hypothesis of Sargan and Hanson tests is that "the instruments are exogenious" Therefore the insignificant value of both tests indicates that the estimation is well specified.

I also examine the residuals of the system GMM for a unit root using Levin, Lin–Chu (2002), as in equation 20. The null hypothesis is then $H_0 : \phi_i = 0$ for all i versus the alternative $H_a : \phi_i < 0$

$$\Delta y_{it} = \phi y_{i,t-1} + Z'_{it}\gamma_i + \sum_{j=1}^{p} \theta_{ij} y_{i,t-1} + \mu_{it} \tag{21}$$

where y_{it} is the variable being tested; and μ_{it} is a stationary error term. The Z'_{it} term can represent panel-specific means and a time trend, finally, p is the number of lags. I also use Harris–Tzavalis (1999), Breitung (2000; Breitung and Das 2005), unit root tests under the null hypothesis that all the panels contain a unit root.

Table 3.8 presents the outputs for the system GMM model defined of equation 20. The system GMM results reject the hypothesis that the lagged CAR coefficient is zero. I interpret this as a rejection of a static model in favour of a dynamic model. Interestingly, and consistent with the estimation of the two-way fixed effects model, and in contrast with the cross-sectional regressions, the sign of lnmcap (our proxy for firm size) is positive for both Losers and Winners.

This suggests concealed company heterogeneity and clearly indicates the bias introduced by simple OLS estimation involving only one dimension and no fixed effects (Baltagi (2008)). The size coefficients are highly significant for Losers but insignificant for the Winners. This may reflect the greater effect of size on the cumulative average abnormal return in cases of negative shocks (the so-called 'leverage' effect). However, the leakage of information variable is positive in sign and highly significant for all the events. This, we believe, reflects the important role of insider information and thus the existence of significant market inefficiency in the Egyptian stock exchange.

Table 3.8: System GMM estimates

	Losers		Winners	
	Event A	**Event B**	**Event C**	**Event D**
L.Carit	0.0398***	0.0338***	0.0375***	0.0500***
	(0.0083)	(0.0064)	(0.0063)	(0.0038)
Lnmcap	0.0060***	0.0075**	0.0036	0.0051
	(0.0016)	(0.0029)	(0.0024)	(0.0042)
Leak	0.9110**	0.9518***	1.9778***	1.4372***
	(0.3825)	(0.1129)	(0.3992)	(0.0800)
ARio	0.0180	0.1152***	-0.1795	-0.0506
	(0.0179)	(0.0362)	(0.0981)	(0.0429)
Private	-0.0162**	-0.0153***	-0.0085	-0.0080***
	(0.0074)	(0.0038)	(0.0092)	(0.0032)
DumQ	-0.0194***	-0.0133***	-0.0050*	-0.0046*
	(0.0065)	(0.0044)	(0.0079)	(0.0026)
Wald test chi^2	111.92***	403.33***	167.24***	213.6***
Arellano Bond test for AR (1)	-3.91***	-2.60***	-4.03***	-4.77***
Arellano Bond test for AR (2)	-0.93	0.51	1.20	-1.33
Sargan test	2.884	2.012	2.164	5.156*
P value	(0.196)	(0.146)	(0.179)	(0.107)
Hansen test	20.14	32.58	12.93	35.36
P value	(0.267)	(0.341)	(0.298)	(0.592)
Difference in Hansen Tests for Exogeniety:				
GMM instruments for levels:				
Hansen test excluding group	8.69	23.49	8.46	30.24
Difference	11.45	9.09	4.47	5.12
Instrumental variables				
Hansen test excluding group	17.14	29.46	10.35	28.58
Difference	3.00	3.12	2.58	6.79
Levin-Lin- Chu unit root test	-9.2090***	-10.699***	-13.432***	-9.4198***

***, **,* indicate significance at the 1%, 5% and 10% levels.
Number of observations is 2400 observations (100 companies * 24 weeks).

The coefficients for initial returns on event day are insignificant for Losers and Winners except for event B. This result is consistent with Cox and Peterson (1994) as including size removes the effect of initial returns on subsequent price behavior. ARio coefficients are positive in sign for Losers, however, and interestingly, they are negative for Winners. This suggests the existence of a leverage effect in the Egyptian stock market.

More importantly, the DumQ variable (our proxy for companies' unobservable factors) is negative and highly significant for Winners and Losers. This suggests that low unobservable effects portfolios outperform high unobservable effects portfolios. It is worth mentioning that both Losers and Winners Unobservable portfolios significantly outperform the traditional size portfolios.

This result is new to the literature on price overreaction. Finally, and in contrast with the OLS regression results, amongst the Losers and Winners formerly private firms have lower CAARs than formerly state-owned firms. This again may suggest potential bias in the estimation arising from the absence of the time dimension in the cross-sectional regression.

We also notice that the economic significance of the variables is less than those of the fixed and random effects estimation presented in table 3.6. However we are interested in the consistency of the signs across different panel data models rather than the economic significance to investigate the effect of company heterogeneity on the overreaction hypothesis.

We note that the specification tests are satisfactory. The tests regarding serial correlation reject the absence of first order, but not second order serial correlation, and the Hansen tests do not reject the over-identifying restrictions. The models are well specified as Wald test statistics are highly significant.

3.4.13 What are these unobservable factors?

Cressy and Farag (2011) pointed out that the unobservable firm factors might be interpretable as measures of firm quality. However, they were not able to show evidence to support this interpretation. To remedy this deficiency in this chapter I shall investigate possible empirical correlates for these unobserved factors.

To this end I choose Market Value Added (MVA) as a proxy for management quality and performance. MVA is defined as the management value added and is measured by the difference between the market value of the company and the value of its capital (equity) supplied by ordinary shareholders. Based on the model presented in Cressy and Farag (2011), the sign of the management quality variable is expected to be negative as the higher the firm quality the lower the company heterogeneity.

The existing body of the literature emphasises the increasing role of corporate governance (CG) as a means of improving company performance. See for example Millstein and MacAvoy (1998), Core et al. (1999), Mallin (2001), Brown and Caylor (2004), Core et al. (2006), Bhagat and Bolton (2008) and Mallin (2010). CG characteristics such as the separation of the roles of the CEO and Chairman, board independence and various types of committees (e.g. remuneration and audit) are identified in the literature as keys to 'good' governance. But the main practical question is, does better CG improve company performance? Therefore, the sign of the corporate governance compliance variable is expected to be negative; this suggests that the better corporate governance characteristic the lower the firm heterogeneity and lower overreaction to market shocks.

The Egyptian Corporate Governance code (2003-2006) recommended firms to disclose in their annual reports whether or not they comply (fully or partially) with the code. There were few provisions for the Egyptian Corporate Governance code; however they were not obligatory. During the period of study, some companies have partially complied (none has fully complied) with the code while the others have not[19]. I define the corporate governance compliance variable as a dummy variable takes the value of 1 for company i if it (fully or partially) complies with the Egyptian Corporate Governance Code, and is 0 otherwise.

Despite this, there is a debate in the literature about the relationship between corporate governance and agency cost with some authors arguing that CG improvement increases agency costs in the company. For example, McKnight and Weir (2009) found that the number of non-executive directors and duality had little effect on agency cost and Vafeas and Theodorou (1998), and Weir, Laing, and McKnight (2002) found that the duality (the separation of the roles of CEO and Chairman) has no effect of company performance. Finally, McKnight and Weir (2009) using UK data found that the existence of a nomination committee

[19] I collected this information from the companies' annual reports.

did in fact increase agency costs (measured by sales to assets ratio). However, greater board ownership was associated with lower agency costs in the company.

Regarding proxies for agency costs, Ang et al. (2000) and Singh and Davidson (2003) use the Sales Assets Ratio (SAR) to measure this variable. SAR can be regarded as a measure of management's efficiency in using assets to generate sales revenue. Ang et al. (2000) thus argue that a higher SAR ratio implies lower agency costs as it reflects greater management efficiency in doing this. Therefore the sign of the agency cost variable is expected to be positive as the higher the agency cost the higher the company heterogeneity and the higher overreaction to market shocks.

Finally, I include as an empirical proxy for unobservables the role of political connections of the company. In Egypt, political connections have an important direct impact on company performance. I argue that the greater the political connections on the board the better a company's performance and the more it is subject to insider information. This suggests a higher degree of market inefficiency for stocks of companies with political connections, and greater permanent company-specific effects accordingly. Therefore the sign of this variable is expected to be positive. I measure political connections by the presence of a Minister, a Member of Parliament, and by ruling party members on the board of directors.

It is worth mentioning that the existing body of the literature has not investigated the nature of the fixed effects (unobservable factors). These unobservable may lay the estimation open to the omitted variable and misspecification biases. One of the contributions of this chapter is to try to explain what these factors are. Although the political connection of the board members might be observable factor (it may minimise the omitted variable bias), however for some companies this is unobservable factors to the existing shareholders due to the information inefficiency and the weak corporate governance practices in the Egyptian stock market. In addition, none of the existing studies has investigated the effect of the political connection of the board members on the overreaction phenomenon.

To empirically examine the effect of the above variables on company fixed effects, I carry out a cross-sectional regression using ordinary least squares (OLS) with the company-specific effects (fixed effects) as dependent variable and the lagged value of market value added (MVA), the corporate governance dummy and the political connections (dummy) as in the following equation. The company fixed effects (company heterogeneity) have been estimated based on the residuals of equation 10 (the first order autoregressive fixed effects).

$$Fe_i = \alpha_i + \beta_1 MVA_i + \beta_2 CG_i + \beta_3 Polcon_i + \beta_4 SAR_i + \varepsilon_i \qquad (22)$$

where: Fe_i is company fixed (specific) effects,

MVA_i is the lagged company market value added measured by the difference between the market and book value of equity/book value of equity.

CG_i is dummy variable takes the value of 1 for company i if it (fully or partially) complies with the Egyptian Corporate Governance Code, and is 0 otherwise.

$Polcon_i$ is dummy variable takes the value of 1 if there is a Minister, Member of Parliament member, or Ruling Party member on the board of directors, and is 0 otherwise.

SAR_i is the lagged sales to assets ratio as a proxy for agency costs.

To empirically identify the unobservable factors, table 3.9 presents the outputs of equation 22. The corporate governance dummy (CG) is negative in sign and highly significant for the Losers but only marginally significant for Winners. This suggests an inverse relationship between corporate governance characteristics and the company heterogeneity (fixed effects).

The negative sign may be interpreted as meaning that better corporate governance characteristic indicates lower firm heterogeneity and lower overreaction to market shocks. The sustainability in the management policies and company's strategic objectives are possible interpretations for this inverse relationship. This in turn reduces the conflict between shareholders and management.

Management value added (MVA, our proxy of the management quality) is also negatively and significantly related to permanent differences in the market's overreaction to news, for all events (except for event D). This might be explained as meaning that better management quality is associated with smaller permanent differences in investor reaction to news that affects its performance. Higher management quality suggests higher efficiency in the firm and this in turn is reflected in stock price reactions. Therefore, the better the quality of management the more efficiently is the stock priced and the less permanent investors' overreaction accordingly. This result is consistent with Cressy and Farag (2011). Sales to assets ratio SAR (our proxy for agency cost) is positive and insignificant for both Winners and Losers. This suggests that agency cost has a null effect on company heterogeneity.

Table 3.9: Cross Sectional Regressions explaining unobservable factors

	Losers		Winners	
	Event A	**Event B**	**Event C**	**Event D**
C	0.0002	-0.0063	0.0413***	0.0912***
	(0.0121)	(0.0052)	(0.0069)	(0.0121)
Pol	0.0034**	0.0048**	0.0066**	0.0051
	(0.0014)	(0.0021)	(0.0031)	(0.0041)
CG	-0.0034**	-0.0261***	-0.0191*	-0.0322*
	(0.0015)	(0.0062)	(0.0099)	(0.0181)
MVA	-0.0004**	-0.0008***	-0.0004*	-0.0014**
	(0.0002)	(0.0002)	(0.0002)	(0.0007)
SAR	0.0036	0.0003	0.0002	0.0001
	(0.0032)	(0.0003)	(0.0004)	(0.0006)
R2	0.2112	0.3734	0.2162	0.2144
Adj R2	0.2897	0.3177	0.2465	0.2145
F.stat	3.0112***	6.7054***	3.1036***	3.0706***
White test for heteroskedasticity	0.7414	0.3518	0.5392	0.5148

*, **,*** indicates significance at the 1%, 5% and 10% levels.
Number of observations is 100 observations.
The descriptive statistics for the company heterogeneity (fixed effects) are 0.052%, 7.056%, -0.015 %, and 0.054% for the mean, maximum, minimum and standard deviation respectively.

The political connection variable is found positive and highly significant for both Winners and Losers (except for event D). This suggests that the higher degree of political connections the firm has, the higher the company's heterogeneity and the less efficiency of its price.

The models are well specified as F statistics are highly significant. The adjusted R squared range from 21% and 32%. In addition, the residuals seem homoskedastic as the results of White tests are insignificant. It is worth mentioning that the correlation matrix reports that there is no potential correlation between the independent variables. I examine the potential endogeniety between a company's fixed effect (company heterogeneity) and the independent variables. The Hausman test cannot reject the null that the regressor is exogenous; therefore there is no potential endogeniety problem in the estimation, in particular between firm size and the company's heterogeneity

3.5 Summary and conclusions

Existing empirical studies of stock price reversal have used either cross section or time series regressions. I argued that this wastes information and may lead to potential biases in the results. Combining group and time dimensions may therefore result in better estimates of the coefficients. Such studies also ignore the dynamic aspects of overreaction; namely the tendency for past abnormal returns to influence future returns. In this chapter I have used Egyptian stock market data and both traditional and dynamic panel data methods to deal with these problems. Unobservable factors reflecting heterogeneity in the data emerge automatically from this estimation process and I have investigated their potential role as criteria for portfolio formation.

Using daily price data from the Egyptian stock market on a sample of 100 companies which experienced dramatic one-day price change as the result of four main events over the period 2003 to 2009, I found negative and significant abnormal returns for one of these, namely the terrorist attacks. These lasted for three days after the event. However, the Lebanon war as a proxy for the tension in the Middle East region had no effect on the average abnormal returns in the Egyptian stock exchange. Furthermore, there was no significant average abnormal return from either the announcement of the constitutional change or the formation of the new Egyptian government.

The traditional fixed and random effects models showed that – in contrast with the cross-sectional regressions – the sign of our proxy for firm size (lnmcap)) was positive for both

Losers and Winners. This suggested the presence of underlying company heterogeneity in the data and confirmed our suspicions regarding biases introduced by simple OLS estimation. The dynamic model estimated using system GMM produced estimates consistent with those of the two-way fixed effects model and contrasted with those of the cross-sectional regressions. In particular the sign of the firm size variable) was again positive for both Losers and Winners. This once more suggests concealed company heterogeneity and indicates biases produced by estimation using simple OLS. The size coefficients were highly significant for Losers but insignificant for Winners. This may reflect, in case of negative shocks, the greater effect of size on the cumulative average abnormal return (the so-called 'leverage' effect).

I found also that the leakage of information variable (Leak) was positive in sign and highly significant for all the events. This, I believe, reflects the important role of insider information and thus market inefficiency in the Egyptian stock exchange. The coefficients for initial returns on event day are insignificant for Losers and Winners except for event C. This result is consistent with Cox and Peterson (1994) as size removes the effect of initial returns on subsequent price behavior.

More importantly, including the DumQ variable (the proxy for company unobservables) in the system GMM suggests that low unobservable effects portfolios outperform high unobservable effects portfolios. Both Losers and Winners Unobservable portfolios significantly outperformed the traditional size portfolios. This result is new to the literature on price overreaction.

Interestingly, I found that low fixed effects portfolios for Losers not only outperformed those of high fixed effects, but also outperformed small and big size portfolios. In addition, the arbitrage portfolio LMH (fixed effects) outperforms SMB portfolios on average. High fixed effects Winners outperform low fixed effects portfolios on average, however small size portfolios outperform those of big size on average. This result is new to the literature as I argue that the portfolio formation based on fixed effects may be used as a new profitable construction strategy to achieve higher abnormal return than the traditional size portfolios.

To identify the potential unobservable factors, I regressed the company's fixed effects against potential unobservable variables i.e. corporate governance compliance, political connections, agency costs and the management quality. I found a positive and significant relationship between the political connections of the board members and the company heterogeneity in addition and interestingly, I found an inverse relationship between both management quality and corporate governance compliance the company heterogeneity. This suggests that the better the management quality the lower the company heterogeneity and the more efficiency the share price.

I conclude that investors can exploit the Egyptian market imperfection and achieve abnormal returns as the results of major events. Past Losers significantly outperform past Winners post-events over the event window. In addition, the panel data approach adds a new dimension to the existing models and offers interesting insights and reveals the importance role of unobservable firm-specific factors in addition to the observable size in the analysis of the overreaction phenomenon. Finally, constructing portfolios based on some unobserved factors i.e. management quality, corporate governance and political connections of board members significantly outperform traditional portfolios based on size.

Chapter 4 : Long-term performance: momentum or overreaction?

4.1 Introduction

The main objective of this chapter is to investigate the long-term overreaction phenomenon for all listed shares in the Egyptian stock exchange over the period 1998-2009. The chapter also investigates the role of size, the stability of beta and the seasonality effect on the overreaction hypothesis in the Egyptian stock market. Finally, I investigate whether the contrarian and the unobservable (fixed effect) factors are already incorporated in pricesby using the Fama and French three-factor model and the Carhart (1997) four-factor model.

The main contribution of this chapter is that it is– to the best of my knowledge – the first work to link the overreaction hypothesis with a change in regulatory policies, namely, the switch from strict price limits to circuit breakers. In addition, I augment the traditional Fama and French three-factor model and the Carhart (1997) four-factor model by including a contrarian factor and an unobservable factor based on company heterogeneity. Finally, this is the first empirical study of the long-term overreaction phenomenon in the Egyptian stock market – one of the leading stock exchanges in the Middle East and Mena reign (MENA).

De Bondt and Thaler (1985) using monthly return data investigated the so called long-term overreaction and found that past Losers significantly outperform past Winners by 24.6% of positive risk-adjusted abnormal returns in the subsequent period on average. De Bondt and Thaler (1985) argue that the main cause of this market anomaly is due to the overreaction to the new information. Huang (1998) argues that in the event of good news stock prices initially overstate the equilibrium prices then price reversals occur in the subsequent periods to move them back nearer to equilibrium levels. However, in cases of bad news, stock prices initially understate their equilibrium levels followed by reversals in the later period.

The overreaction hypothesis posits that an extreme movement in stock prices will be followed by subsequent price reversal (movement in the opposite direction), noting that the bigger the initial price movement the greater subsequent price reversal that is expected. This is considered a violation of the Weak Form market efficiency (De Bondt and Thaler 1985).

The existing body of literature argues that the claimed overreaction phenomenon of De Bondt and Thaler (1985) is mainly due to computation errors in beta between the estimation and the event window (Chan, 1988), or to the small firm and seasonality effects (January effect) (Zarowin, 1990).

This chapter is organised as follows: section 2 presents the academic debate about the measurements of the long-term performance using two competing methods, namely, cumulative abnormal returns and buy and hold. In section 3, I discuss the alternative sources of the contrarian and momentum abnormal returns. Section 4 describes the dataset used in the analysis. Section 5 presents the methodology and the empirical results. Finally, section 6 summarises and concludes.

4.2 Empirical literature debate: Long-term performance CARs or BH?

There is a remarkable debate in the existing body of the finance literature regarding the use of different measures of returns in empirical work. The two main rival candidates are Cumulative Average Residual returns (CARs) and the Buy and Hold abnormal return (BH). Dissanaike (1994) argues that the rebalancing method (RB) provides a more accurate measure for excess returns over CARs. He found that the CAR method underestimated the actual excess returns 36 months after portfolio formation by 28.3%. Dissanaike (1994) also found that the portfolio performance is sensitive to the method of test and rank period calculations. In this section I present the pros and cons for each methodology. In addition I highlight the different types of biases and measurement errors for contrarian and momentum strategies in the empirical literature.

4.2.1 Cumulative average residual returns CARs

The cumulative average residual return is the most and widely used method in the existing body of the finance literature. Many researchers used the cumulative average residuals, e.g. De Bondt and Thaler, (1985), (1987), Chen, (1988), and Alonso and Rubio, (1990). However, Dissanaike (1994) argues that the arithmetic cumulative average residuals as in equation 1 may result in spurious abnormal returns as the calculated returns are not the same as the actual returns that investors experience.

$$\overline{R}_{CAR} = \sum_{i=0}^{T}\left(\sum_{i}^{N}\frac{R_{it}}{N}\right) - \sum_{i=0}^{T} R_{mt} \qquad (1)$$

Where CAR is the cumulative average residuals, N is the number of shares, T is the number of time periods. R_{it} and R_{mt} are the monthly (t) stock and market returns respectively for share i.

The more realistic technique for measuring long-term abnormal returns is the rebalancing method (RB) - which provides more convincing return metric. Within the RB methods dividends are assumed to be reinvested in a given portfolio using equal weights as in equation 2.

$$\overline{R}_{RB} = \prod_{i=0}^{T}\left(\sum_{i}^{N}\frac{R_{it}}{N}\right) - \prod_{i=0}^{N} R_{mt} \qquad (2)$$

where N is the total number of securities in the portfolio, T is the total number of months (t) in the test period. The RB approach assumes that each portfolio is rebalanced on a monthly basis. This implies equal amounts are assumed to be invested in the individual stocks each month during the test period. This suggests significant transaction costs may be associated with the rebalancing method. Blume and Stambaugh (1983) argue that the results from the RB approach are subject to the bid-ask spread bias due to the existing divergence between the closing prices observed and the actual prices. This leads returns to be upwardly biased as a result. However, the bias may be reduced when the BH approach is adopted. In addition, the RB method could negatively affect the contrarian strategy if only a few stocks were to reverse and the others do not. In that case the allocation of funds between Losers and Winners may be diverted away Dissanaike (1994 and 1997).

4.2.2 Buy and Hold Abnormal Returns (BHARs)

The BH method assumes that equal investments are invested. There is no monthly rebalancing process in the BH method as opposed to the RB and CAR methods. In addition, it assumes that all dividends are reinvested for each stock as in the following equation

$$\overline{R}_{BH} = \frac{1}{N}\sum_{i}^{N}\left(\prod_{t=0}^{T} R_{it} - \prod_{t=0}^{T} R_{mt}\right) \qquad (3)$$

Conrad and Kaul (1993) argue that in comparison with CARs, the abnormal return of the contrarian strategy is spuriously exaggerated when calculating long-term performance. Furthermore, Conrad and Kaul (1993) and Ball et al. (1995) find that underpriced stocks have greater upward bias. Consequently, if Losers have lower returns than the Winners, there will be an obvious upward bias to the results and this will generate spurious contrarian profits (see also Forner and Marhuenda, 2003).

In contrast with the CARs, the BH method involves lower transaction costs and is less tending to the infrequent trading problems, Dissanaike (1994). Dissanaike (1994) argues that the BH method is preferred over the RB method when testing the overreaction hypothesis. He claims that the rebalancing process may affect the contrarian strategy (negatively or positively).

The overreaction hypothesis states that by buying Losers and selling Winners, investors can achieve abnormal returns as Winners are assumed to be overpriced and Losers are assumed to be underpriced at the portfolio formation date. The contrarian profits for Loser portfolios are likely to be much more significant if price reversals do not occur at the same time for individual shares. Therefore investors would sell shares whose prices have increased and buy shares whose prices have not yet reversed, Dissanaike (1994). This suggests that it would be more realistic to follow the contrarian strategy without adding the monthly rebalancing effect.

One of the drawbacks of the BH method is that Winners over time carry more weight in the portfolio than Losers when a particular stock is delisted or dropped out during the test period; this may lead to a reduction in diversification. According to the assumptions of the BH, all stocks bought at the beginning of the test period should be held until the end of test period (e.g. 24 or 36 months) (Gaunt 2000). This is in fact unrealistic assumption of the BHARs and may bias the estimates of abnormal returns. Gaunt (2000) presents three different alternatives to overcome this complication. Firstly, to reinvest the proceeds of the delisted stock equally amongst the remaining stocks. Secondly, to reinvest the proceeds according to the market capitalisation of the remaining stocks. Thirdly, to invest the proceeds in the market index (Gaunt 2000).

To conclude, Fama (1998) claims that the RB CARs approach outperforms the Buy and Hold BH approach as the later implies fewer theoretical and statistical problems than long-term BH. In addition, Roll (1983) argues that using monthly returns is less likely to be affected by the choice of CARs or BH. Dissanake (1994) argues that the BH approach may lead to less benefit from diversification in the longer run. Finally, Loughran and Ritter (1996) claim that there is a little difference between BH and CARs in test period returns calculations, and they argue that the results of Conrad and Kaul (1993) are affected by the survivorship bias.

4.3 Alternative sources of the contrarian and momentum abnormal returns.

Chan (1988), Lehman (1990), Park (1995), Dissanaike (1997), and Conrad et al. (1997) concluded that the contrarian or momentum abnormal returns have four main sources, namely, measurement errors and biases, portfolio construction and evaluation methodology, time-varying market risk between rank and test windows and, finally, the overreaction to the firm specific information (Kang et al. 2002). In this section I shed the light on these four alternative sources of overreaction and momentum abnormal returns.

4.3.1 Biases and measurement errors in contrarian strategies.

Contrarian profits may be spurious due to the bid-ask spread. Stocks may be wrongly classified as Winners or Losers when bid-ask prices are used in portfolios' returns calculation. This leads to magnifying the short-term contrarian profits, Lehmann (1990), Park (1995), Conrad et al (1997) and Kang et al (2002). The bid-ask spread bias arises when the initial transaction of selling Winners and/or buying Losers is done at the bid and ask prices respectively. However, the corresponding transaction is done based on ask and bid prices respectively Lehmann (1990), Conrad et al (1997) and Kang et al (2002).

A survivorship bias arises when the data base excludes the companies that have ceased to exist due to liquidation, delisting, and fail to comply with the stock exchange regulations. As the survivor companies look better and have higher performance (returns) than those that no longer exist, this leads to overestimation of portfolios' average return.

A data-snooping bias arises when the empirical results of a particular research are driven and highly influenced by the results of other empirical researches especially if large number of empirical studies is carried on based on same datasets Conrad et al (1997) and Kang et al (2002). A data-snooping bias may lead to a data mining bias which is defined as when a researcher is drilling into the same dataset to reach to a particular result.

A look-ahead bias occurs especially in testing market efficiency when a researcher assumes that all the relevant information is reflected in the share prices while it is not. For example, forming portfolios based on June (fiscal year) accounting data, whilst the data will not be available for investors due to the information lag in financial reports in addition to the lagged response of the market, Conrad et al (1997) and Kang et al (2002).

Roll (1983), Conrad and Kaul (1993) and Lyon et al. (1999) defined the rebalancing bias as fixed weights that are commonly used in portfolios' monthly returns calculations. These results in both high and low returns as stocks are sold by the end of the formation period and then the proceeds are reinvested at the original (fixed) weights. However, in the rank period, high return stocks for instance have increased their weight in the portfolio and the opposite is correct for low return stocks. The rebalancing bias results in underweighting the previously high return stocks and overweighting the previously low return stocks in the rank period.

Finally, non-synchronous trading may result in cross correlation between returns on traded (liquid) and non-traded (illiquid) stocks. This leads to spurious contrarian profits as liquid shares tend to react contemporaneously to the new information, however, illiquid shares respond to the new information with lag once the next trading occurs. Therefore, portfolio returns are likely to suffer from lead-lag reaction in addition to serial correlation, Lo and MacKinlay (1990), Cohen (1979) and Miller et al. (1994).

4.3.2 Portfolio construction and evaluation methodology.

There is a debate about the use of the non-overlapping test periods (three to five years) and then estimate one overall statistical test on the aggregate data Dissanaike (1997). In fact, using non-overlapping test periods (3-5) results in unavoidable loss of information. In addition, there is always the likelihood that the outcome of the contrarian strategy is influenced by economy-wide cyclical factors, Dissanaike (1997).

Bali and Kothari (1989), Dissanaike (1997) introduce an alternative methodology which allows overlapping within the formation and test periods. However, the main drawback to this methodology is the inevitable inter-temporal structure in return distribution as well as in the betas, Forner and Marhuenda (2003).

4.3.3 Long-term performance with risk and size adjustments.

Chan (1988) argued that there are many critics to the contrarian strategy in the academic literature. He introduced an alternative interpretation to the contrarian profits. Chan (1988) argued that the risk of Winners and Losers varies over time between formation and test periods. Therefore the achieved abnormal return may be due to the approach used in measuring risk and/or measurement errors in beta estimations during the formation and test periods of Winners and Losers. Thus the estimation of beta in the formation period will be biased if we used it as a risk factor in the test period. For instance, betas will be underestimated in the test periods for Loser portfolios as Losers tend to be riskier in the formation period. Conversely, the betas will be overestimated in the test periods for Winner portfolios as Winners tend to be less risky in the formation period (Chan, 1988).

On the other hand, the market values of both Winners and Losers vary during the rank period (small firm effect). De Bondt and Thaler (1985) found significant large variances between the market capitalisation of Losers (-45%) and Winners (365%), however, they found that the median of Losers were greater than of those of Winners at the beginning of the rank periods. Surprisingly, the median of market capitalisation of the Losers became smaller than those of Winners in the subsequent test periods. This suggests that – if market value is a good proxy for risk – Losers are safer at the beginning of the rank periods and switch into higher risk class by the end of the formation period (Chan 1988).

4.3.4 Overreaction to firm-specific information and lead-lag structure.

Lo and MacKinlay (1990) claim that not only the overreaction to firm-specific information is the main source of contrarian profits but also the lead-lag structure in stock returns. The lead-lag structure is considered as one of the main sources of contrarian profits, which is related to the market efficiency as some stocks may react more quickly to the information than others (Kang et. al 2002). Lo and MacKinlay (1990) found significant and large positive cross-serial covariance between small stocks and lagged large stocks returns. However, they found weak cross-serial covariance between large stocks and lagged small stocks returns. They claim that the main source of short-term contrarian profits is the positive cross-serial covariance (the size-related lead-lag structure) rather than the overreaction to firm-specific information (Kang et. al 2002).

Contrastingly, Jegadeesh and Titman (1995) claim that the lead-lag structure is not a fundamental source of momentum profits in the US. However, (Kang et. al 2002) found that the lead-lag structure is the main source of momentum but not the contrarian profits in the Chinese stock market.

4.4 Data

I used the EGX30 index, a free floated market capitalisation weighted index (Galariotis (2004) shows that the selection of a value weighted or an equally weighted index does not alter the main findings. However, I used the EFG equally weighted index and obtained similar results.
Daily stock returns were adjusted for stock dividends, stock split and dividend yields over the period January 1998-December 2009 (144 months). The number of stock in the sample ranges from 180-251 companies according to the number of listed and traded shares in the Egyptian stock exchange. The main source of data is the Egyptian stock exchange. For each stock to be included in the sample, I made sure that each stock has continuous trading behaviour during the formation period and traded at least once during the test period) Forner and Marhuenda (2003).

The vast majority (84%) of the Egyptian companies have June as the end of their fiscal year. Therefore all portfolios are formed starting from January to allow all financial information and financial statements to be disseminated and to be reflected on stock prices in addition, to be available for all investors. This will overcome the look-ahead bias.

I excluded all financial sectors and property investment companies from the sample as the recorded values of assets in financial sectors' companies for instance are actually market rather than book values. In addition, property investment companies usually reevaluate their book value of assets. Therefore the book to market equity ratio may not have same interpretation as those of other types. Fama and French (1992) argue that financial sector companies have higher leverage than those of other sectors; this may lead to higher degree of financial distress. Twelve financial and property investments firms were excluded from the initial sample (3% of the total number of firms). The mean values of returns excluding financial and investment property firms do not change significantly.

I investigate the effect of delisting following De Bondt and Thaler (1985 and 1987) and Brailsford (1992), so that companies that are delisted or dropped out before the formation date are not included in the analysis. However, if a firm is delisted or dropped out during the test period, it is excluded from the analysis and set its last return to minus one in order to minimise the difference between Losers and Winners portfolios, De Bondt and Thaler (1985 and 1987) and Brailsford (1992). In the Egyptian stock exchange the number of delisted firms is 11 during the period of study due to failing to comply with the Egyptian stock exchange regulations or upon the company's request. Therefore the survivorship bias is highly unlikely to arise.

The portfolio formation process starts from December each year to avoid the so called look-ahead bias. Therefore there is enough time for the financial statements and reports to be available to all participants and to be reflected in stock prices. It worth mentioning that all listed shares in the Egyptian stock exchange are required to publish their annual reports within 90 days of the end of the financial year.

As no other studies in the literature investigated the long-term overreaction phenomenon in the Egyptian stock market, there is no potential data-snooping or data mining bias (Sullivan et al. 1999, 2001). Finally, and following Lehmann (1990) and Kang et al (2002), I skipped one trading day between portfolio formation and portfolio holding periods to overcome the bid-ask spread bias.

4.5 Methodology and empirical results

In this section I present the methodology and the main findings of the empirical models. The methodology adopted in this chapter is based on identifying non-overlapping 24-month periods during 1998-2009.

4.5.1 Daily Returns

The monthly return variable R_t is defined as the first difference in the natural logarithm of the closing price over one month. The monthly returns are adjusted for dividends, rights issue, stock dividends, and stock split.

$$R_t = Log\ p_t - Log\ p_{t-1} \qquad (4)$$

where p_t is the closing price of the stock in month (t).

4.5.2 Security abnormal returns (ARs)

There are three widely used methods to calculate the residual returns in the existing financial literature, namely, market model, CAPM, and market-adjusted excess returns. The later is a special case of CAPM with zero α and $\beta = 1$.

Da Costa (1994) found that both CAPM and market-adjusted excess returns have similar results. Following De Bondt and Thaler (1985, 1987), Brailsford (1992), Da Costa (1994), Gaunt (2000) and Forner and Marhuenda (2003) I will adopt the market-adjusted excess returns method.

$$\mu_{it} = R_{it} - R_{mt} \tag{5}$$

where μ_{it} : is the market-adjusted abnormal return for stock i in month t.

R_{it} : is the monthly return on company i over the period t

R_{mt} : is the return on an value weighted EGX30 index in month t

4.5.3 Cumulative residual return over the rank period (CARs)

All companies are ranked into ascending order based on the cumulative abnormal (CAR) returns over the rank period. Then top (best performing) and bottom (worst performing) deciles are identified and selected to form the Winner and the Loser portfolios (Brailsford, 1992) and (Gaunt, 2000).

$$CU_i = \sum_{t=-24}^{0} \mu_{i\tau} \quad (6)$$

where CU_i : is the cumulative market-adjusted abnormal return for stock i over the period from 24 months prior to the start of the test period.

4.5.4 Cumulative abnormal residual returns over the test period (CARs)

I then compute the cumulative average residual returns for all securities in the Losers and Winners portfolios for the next 24 months (the test period), they are denoted $CAR_{L,z,t}$ and $CAR_{W,z,t}$ respectively.

$$CAR_{p,n,t} = \sum_{t=1}^{T} \left[(1/N) \sum_{i=1}^{N} \mu_{i,t} \right] \quad (7)$$

where $CAR_{p,n,t}$ is cumulative average market-adjusted abnormal residual returns for month t of test period n for Winners and Losers portfolios p and N are the number of stocks in each portfolio. If a security's return is missing in a particular month following portfolio formation then this stock will be dropped permanently from the portfolio and the CAR is calculated as a mean of remaining residual returns, De Bondt and Thaler (1985). This involves an implicit rebalancing process (Fama 1998).

The above estimated $CAR_{p,n,t}$ based on equation (7) assumes implicit monthly rebalancing and is not actually consistent with the explicit rebalancing strategy RB (Brailsford (1992).

Roll (1983) describes equation (7) as the arithmetic method in which returns are aggregated across all stocks and over time. This involves implicit monthly rebalancing using monthly equal weights. Although Roll (1983) argues that the empirical research using monthly returns is less affected by the choice of the returns calculation methodology, Dissanaike (1994) argues that the arithmetic approach yields unrealistic results as the monthly returns are aggregated not multiplied.

To clarify the above debate, if the monthly prices for a particular stock were 50, 25 and 40 for a particular three months respectively, the arithmetic returns yields +10% if the relevant returns are aggregated while the rebalancing approach (compounding) yields -20% (Dissanaike 1994). The heterogeneity in these two results may be greater in case of higher volatility in the return time series (Dissanaike, 1994).

For the above reasons, and following Roll (1983), Dissanaike (1994), Loughran and Ritter (1996), Fama (1998), I adopt in this chapter the more realistic approach in return calculations, namely, the rebalancing approach (RB) in which dividends are assumed to be reinvested in the portfolio using equal weights, as in equation 8:

$$CAR_{P,N.T} = \prod_{i=0}^{T}\left(\sum_{i}^{N}\frac{R_{it}}{N}\right) - \prod_{i=0}^{N} R_{mt} \tag{8}$$

In this equation N is the total number of securities in the portfolio, T is the total number of months in the test period. The cumulative abnormal return (CAR) during the rank period for each firm i is then

$$CAR_i = \prod_{i=-24}^{0} R_{it} - \prod_{i=-24}^{0} R_{mt} \qquad (9)$$

This methodology is repeated for each non-overlapping two-year period so that the rank periods are 1998-1999, 2000-2001, 2002-2003, 2004-2005, and 2006-2007 and the matching test periods are 2000-2001, 2002-2003, 2004-2005, 2006-2007, and 2008-2009.

Average CARs are calculated for both portfolios and each month between t=1 and t=24 for all 5 test periods. They are denoted $ACAR_{W,t}$ and $ACAR_{L,t}$

$$ACAR_{p,t} = \frac{\sum_{z=1}^{N} CAR_{p,n,t}}{N} \qquad (10)$$

where $ACAR_{p,t}$ is the average CAR across the test periods (N=5) for each Winner and Loser portfolios p for each month between t=1 and t=24 for all the 5 test periods. It is worth mentioning that the choice of the formation and test periods is made arbitrarily in the existing literature. In addition, due to data limitation I use two-year non-overlapping tests and formation periods. Moreover, and to measure the sensitivity to the formation period length, I repeated the above methodology using four-year (48 months) non-overlapping formation and test periods.

4.5.5 Long-term overreaction Hypotheses

The overreaction hypothesis suggests that $ACAR_{W,t} < 0$ and $ACAR_{L,t} > 0$ for $(t > 0)$, this implies that $(ACAR_{L,t} - ACAR_{W,t}) > 0$. The contrarian strategy is tested via the following null hypotheses:

$H_1 : ACAR_{L,t} = 0$, $H_2 : ACAR_{W,t} = 0$, $H_3 : (ACAR_{L,t} - ACAR_{W,t}) = 0$, where $t = 1.......24$

To test whether or not the average residual returns is significantly different from zero for Winners and Losers, I estimate the standard t- test on the means of $ACAR_{W,t}$ and $ACAR_{L,t}$ as follows:

$$t_{p,t} = \frac{ACAR_{p,t}}{S_p \big/ \sqrt{N}} \tag{11}$$

$$S^2{}_p = \frac{\sum_{n=1}^{N} (AR_{p,n,t} - AR_{p,t})^2}{N-1} \tag{12}$$

where S_p is the sample standard deviation for Losers and Winners portfolio p . S_p is mainly estimated to test H1 and H2 respectively.

Then I pooled the estimate of the population variance in CAR_i to assess whether or not there is a significant difference in investment performance at any time t

$$S_t^2 = \frac{\sum_{n=1}^{N} (CAR_{W,n,t} - ACAR_{W,t})^2 + \sum_{n=1}^{N} (CAR_{:L,n,t} - ACAR_{L,t})^2}{2(N-1)} \tag{13}$$

where S_t^2 is the population standard deviation, and the t-statistic for H3 as in equation 14:

$$t_{L-W,t} = \frac{ACAR_{L,t} - ACAR_{W,t}}{\sqrt{2S_t^2 / N}} \tag{14}$$

Table 4.1 presents the results of the cumulative average abnormal returns for the five test periods over the period 2000-2009. The results presented in table 4.1 show that in two out of five test periods we can reject the null that the average residual returns are significantly different from zero.

In addition, Losers outperform Winners as we notice positive and highly significant market-adjusted abnormal returns for the arbitrage portfolios (Losers – Winners) in 2006-2007 and 2009-2009 respectively. This suggests significant contrarian profit in the Egyptian stock market starting from 2006. This result is inconsistent with the efficient market hypothesis and indicates a clear violation of the Weak Form of the Efficient Market Hypothesis. De Long et.al (1991) argues that the noise trading is the main source of the contrarian profits as irrational expectations destabilise the stock market.

A closer look at the analysis and the results presented in table 4.1 reveals highly significant market-adjusted abnormal returns in the test periods 2006-2007 and 2008-2009. This may be due to the change in regulations from strict symmetric (+ / - 5%) price limit to the circuit breaker regime. The regulator switched the price limit regime from strict price limits (+/-5) to wider limits (+/-20%) associated with trading halts for 30 minutes to cool down the market (Circuit Breakers) in the period 2006 to 2009.

Table 4.1: Cumulative average market-adjusted abnormal returns for the five two–year test periods 2000-2009

Rank Period	Test Period	Mean CAR			
		Loser	Winner	Loser - Winner	t- value
1998-99	2000-01	0.2121	0.1439	0.0682	1.5042
2000-01	2002-03	-0.1561	0.0780	-0.2341	-1.7221*
2002-03	2004-05	-0.1211	0.1029	-0.2241	-1.7913*
2004-05	**2006-07**	**0.1637**	**-0.2459**	**0.4097**	**4.2470*****
2006-07	**2008-09**	**0.2312**	**-0.1906**	**0.4218**	**4.9838*****

The overreaction hypothesis suggests that $ACAR_{W,t} < 0$ and $ACAR_{L,t} > 0$ for ($t > 0$). This implies that $(ACAR_{L,t} - ACAR_{W,t}) > 0$. The contrarian strategy is tested via the following null hypotheses: $H_1 : ACAR_{L,t} = 0$, $H_2 : ACAR_{W,t} = 0$, $H_3 : (ACAR_{L,t} - ACAR_{W,t}) = 0$, where $t = 1.......24$. To test whether or not the average residual returns are significantly different from zero for both Winners and Losers, I use a standard t- test on the means of $ACAR_{W,t}$ and $ACAR_{L,t}$.

***, **,* indicate significance at the 1%, 5% and 10% levels.

The number of observations varies across time. It ranges from 180-251 companies.

The results presented in table 4.1 suggest that the abnormal return subsequent to 2006 might be due to the effect of regulatory policies or price limits regime change[20]. However, it is clear from table 4.1 that the overreaction phenomenon is prevailed in the post price-limit period of the Egyptian stock market.

Table 4.2 presents the average monthly cumulative average abnormal return ACAR over 24 months into the test period. The results presented in table 4.2 show that both Losers and Winners have significantly reversed after the formation period. We notice that Losers have reversed starting from the third month of the test period.

[20] I investigate this claim in more detail in chapter 5

Table 4.2 reports positive and highly significant cumulative average abnormal returns for the losers over the remaining 22 months of the test period. The longer the test period is, the greater the average cumulative average market-adjusted abnormal return, and by the 24^{th} month Losers have achieved a 20% market-adjusted abnormal return.

The Winner portfolios, on the other hand, have also significantly reversed immediately after the formation period. Nonetheless, table 4.2 shows that by forming the arbitrage portfolio (selling Winners and buying Losers) we can achieve significant and positive abnormal return during 3-6 months and 12-24 months after the formation period.

The above results are consistent with the literature on the overreaction phenomenon e.g. De Bondt and Thaler (1985), Brailsford (1992), Da Costa (1994), Gaunt (2000) and Forner and Marhuenda (2003).

I thus argue that investors can achieve significant and positive abnormal return by adopting a contrarian strategy (zero-investment portfolio) in the Egyptian stock market taken over a two-year investment horizon.

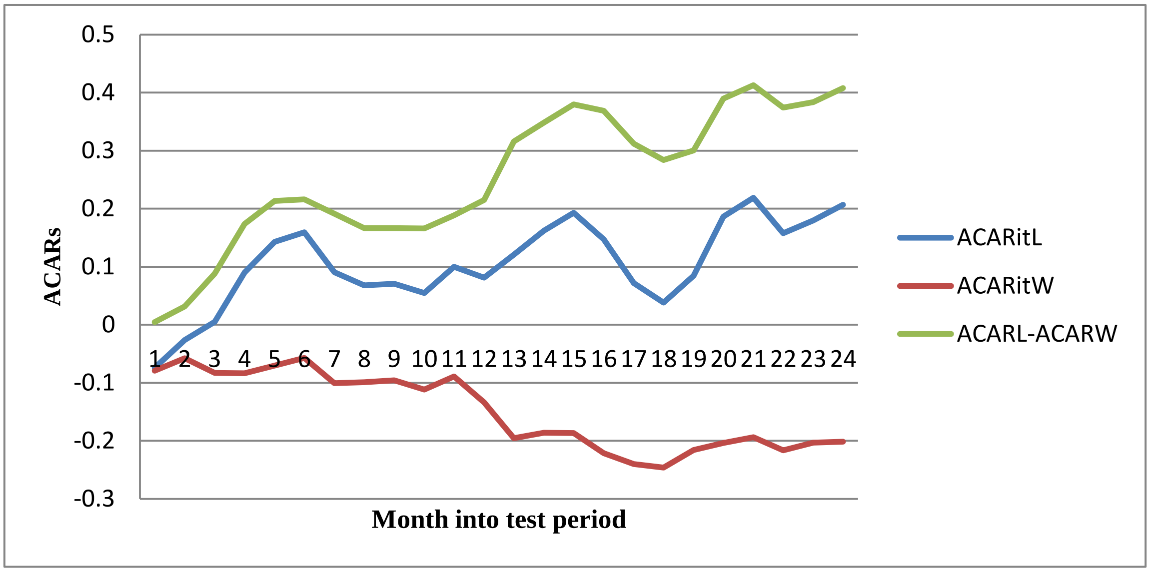
Table 4.2: Average monthly cumulative average abnormal return (CAR) over the 24 months of the test period

Month into Test period	Loser		Winner		Loser-Winner	
	ACAR	t-stat	ACAR	t-stat	ACAR	t-stat
1	-0.0743	-1.9984**	-0.0790	-2.4351**	0.0047	0.0379
2	-0.0262	-0.7046	-0.0577	-1.5789	0.0315	0.2523
3	0.0050	0.1349	-0.0830	-2.5570**	0.0880	0.7038
4	0.0899	2.4178**	-0.0838	-2.5818***	0.1737	1.9189**
5	0.1430	3.8458***	-0.0705	-2.1722**	0.2135	2.7071***
6	0.1591	4.2789***	-0.0572	-1.5610	0.2162	2.7291***
7	0.0906	2.4364**	-0.1009	-3.1085***	0.1915	1.9311*
8	0.0676	1.8173*	-0.0489	-1.1765	0.1164	1.3310
9	0.0705	1.8969*	-0.0459	-1.1551	0.1664	1.3309
10	0.0545	1.4649	-0.1117	-3.4412***	0.1662	1.3286
11	0.0697	1.5807	-0.0889	-2.7400***	0.1586	1.5081
12	0.0809	2.1747**	-0.1339	-4.1254***	0.2148	2.7173***
13	0.1207	3.2467***	-0.0553	-1.5158	0.1760	2.2266**
14	0.1622	4.3637***	-0.1859	-5.7287***	0.3482	3.7842***
15	0.1929	5.1898***	-0.1868	-5.7548***	0.3797	3.0365***
16	0.1471	3.9564***	-0.2213	-6.8191***	0.3684	3.4461***
17	0.0717	1.9298**	-0.2402	-7.4013***	0.3120	3.1947***
18	0.0379	1.0201	-0.2460	-7.5802***	0.2840	2.2707**
19	0.0546	1.2745	-0.2160	-6.6537***	0.2705	2.4031**
20	0.1860	5.0033***	-0.2036	-6.2738***	0.3896	3.1158***
21	0.2188	5.8853***	-0.1941	-5.9789***	0.4129	3.7014***
22	0.1578	4.2440***	-0.2162	-6.6596***	0.3739	3.0302***
23	0.1798	4.8358***	-0.2035	-5.9684***	0.3832	3.0646***
24	0.2065	5.5547***	-0.2014	-6.2049***	0.4079	4.2618***

***, **,* indicate significance at the 1%, 5% and 10% levels.
The number of observations varies across time. It ranges from 180-251 companies.

Figure 4.1 presents the graphics of these findings. The average cumulative average market-adjusted abnormal returns, or ACARs, for the Losers, Winners and the arbitrage (Loser–Winner) portfolio are charted. It is clear from figure 4.1 that the Losers' portfolio outperforms the Winners' and that cumulative average market-adjusted abnormal returns can be achieved by constructing the zero-investment or arbitrage portfolio of De Bondt and Thaler (1985).

Figure 4-1 Average cumulative average abnormal return over 24 months



4.5.6 Long-term overreaction: the sensitivity to formation period length.

To measure the sensitivity of our results to the formation (rank) period length, I repeated the same methodology using different formation and test periods, namely, four-year (48 months) non-overlapping formation and test periods. I calculated the monthly average cumulative average abnormal returns (ACARs) for two individual test periods, namely, 2002-2005 and 2006-2009.

Table 4.3 presents the average cumulative average market-adjusted abnormal returns for the two four-year test periods in 2002-2009. The results show positive and highly significant abnormal returns for the arbitrage portfolio (Losers–Winners) in the post-Limit period (2006-2009). These results are consistent with results of the ACAR over 24 months of the test period presented in table 4.1. It suggests also that the overreaction phenomenon is only significant during the period 2006-2009. Therefore, I conclude that there is no effect of the change in the formation period length on the results.

Table 4.3: Average cumulative average market-adjusted abnormal returns for two four–year test periods 2002-2009

Rank Period	Test Period	Mean CAR			
		Loser	Winner	Loser – Winner	t- value
1998-01	2002-05	- 0.7579	- 0.8967	0.3387	1.1603
2002-05	**2006-09**	**0.4346**	**- 0.2403**	**0.6750**	**2.8990*****

The overreaction hypothesis suggests that $ACAR_{W,t} < 0$ and $ACAR_{L,t} > 0$ for ($t > 0$), this implies that $(ACAR_{L,t} - ACAR_{W,t}) > 0$. The contrarian strategy is tested via the following null hypotheses: $H_1 : ACAR_{L,t} = 0$, $H_2 : ACAR_{W,t} = 0$, $H_3 : (ACAR_{L,t} - ACAR_{W,t}) = 0$, where $t = 1.......48$. To test whether or not the average residual returns are significantly different from zero for both Winners and Losers, I use the standard t- teat on the means of $ACAR_{W,t}$ and $ACAR_{L,t}$.

***, **,* indicate significance at the 1%, 5% and 10% levels.
The number of observations varies across time. It ranges from 180-251 companies.

Figure 4.2 presents the average cumulative average abnormal returns for the Losers, Winners and the arbitrage (Loser–Winner) portfolio over the 48 months of the test period 2002-2005. The results are shown graphically in Figure 4.2 where I have defined ACARL, ACARW as the ACARs for Losers and Winners respectively, and ACARL-W as the ACAR for the arbitrage portfolio.

It is clear from figure that initially both Losers and Winners continue to be Losers and Winners continue to be Winners (the momentum effect); however, Winners, and more dramatically, Losers, reverse near the end of the test period[21]. In addition, the arbitrage portfolio achieves positive abnormal returns after 37 months following the formation period though never reaching above 20%.

[21] It might be argued that this final reversal may reflect other factors uncontrolled for in our model. This criticism is potentially correct, and is dealt with in Chapter 3 of the thesis where we allow for unobservable firm- and time-specific fixed effects (in addition to observable variables). We find that these factors do indeed possess explanatory power for the overreaction phenomenon. However, they do not in any way dispose of it.

Figure 4.2 Average cumulative average abnormal returnACARs for the 48 month period 2002-2005.

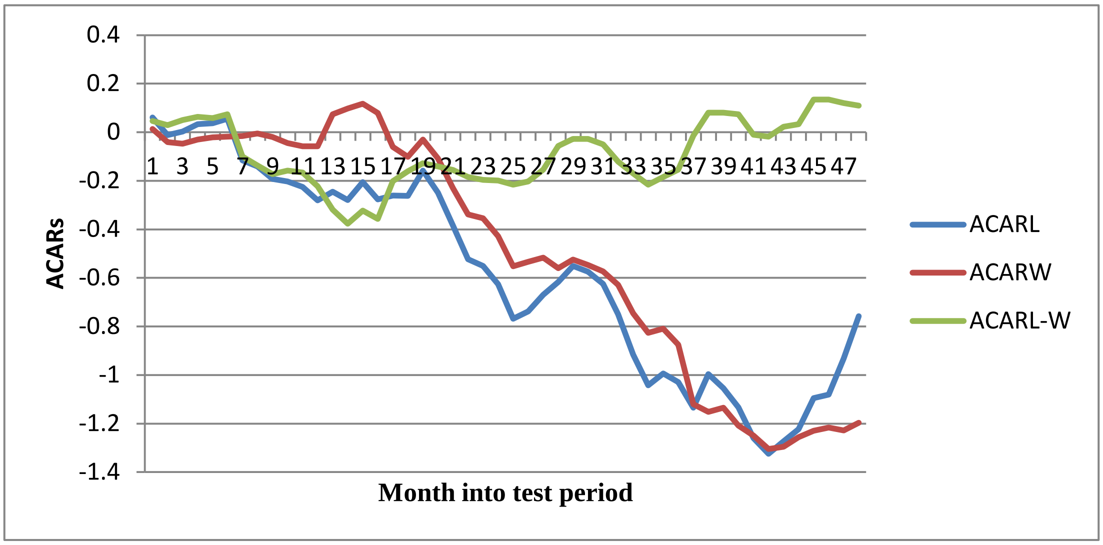


Table 4.4 presents the average cumulative average abnormal returns ACAR for the Losers, Winners and the arbitrage (Loser–Winner) portfolio over 48 months into the test period 2002-2005. It is clear from table 4.4 that Losers reversed immediately after the formation period for six months following the formation period. However, losers reversed again and continue to be losers (momentum behaviour) until the end of the test period (7-48 months).

Winners, on the other hand, reversed starting from the second month following the formation period up till the end of the test period (except for the period 13-16 months following the formation period). In addition, the arbitrage portfolio achieves positive (but not significant) market-adjusted abnormal returns after 37 months following the formation period. I argue that the overreaction behavior is not detected in the Egyptian stock market during the test period 2002-2006.

Table 4.4: Average monthly cumulative average abnormal return over the 48 months of the test period 2002-2005

Month into	**Loser**		**Winner**		**Loser-Winner**	
Test period	ACAR	t-stat	ACAR	t-stat	ACAR	t-stat
1	0.0303	0.2016	0.0069	0.0393	0.0234	0.0441
2	0.0060	0.0402	-0.0203	-0.1160	0.0143	0.0268
3	0.0017	0.0112	-0.0233	-0.1332	0.0250	0.0470
4	0.0166	0.1102	-0.0153	-0.0871	0.0318	0.0598
5	0.0186	0.1238	-0.0104	-0.0594	0.0290	0.0546
6	0.0277	0.1844	-0.0092	-0.0525	0.0369	0.0694
7	-0.0579	-0.3852	-0.0078	-0.0446	-0.0501	-0.0942
8	-0.0708	-0.4704	-0.0023	-0.0132	-0.0685	-0.1287
9	-0.0960	-0.6382	-0.0096	-0.0546	-0.0864	-0.1625
10	-0.1017	-0.6762	-0.0225	-0.1283	-0.0792	-0.1490
11	-0.1124	-0.7470	-0.0292	-0.1667	-0.0832	-0.1563
12	-0.1400	-0.9307	-0.0286	-0.1634	-0.1113	-0.2093
13	-0.1223	-0.8132	0.0371	0.2118	-0.1594	-0.2997
14	-0.1397	-0.9289	0.0485	0.2769	-0.1882	-0.3539
15	-0.1026	-0.6819	0.0586	0.3344	-0.1612	-0.3029
16	-0.1386	-0.9216	0.0396	0.2261	-0.1782	-0.3350
17	-0.1305	-0.8678	-0.0300	-0.1715	-0.1005	-0.1889
18	-0.1313	-0.8730	-0.0508	-0.2902	-0.0805	-0.1513
19	-0.0793	-0.5273	-0.0154	-0.0879	-0.0639	-0.1201
20	-0.1243	-0.8266	-0.0537	-0.3063	-0.0707	-0.1329
21	-0.1926	-1.2805	-0.1149	-0.6560	-0.0777	-0.1460
22	-0.2614	-1.7376*	-0.1694	-0.9666	-0.0920	-0.1729
23	-0.2753	-1.8304*	-0.1769	-1.0096	-0.0984	-0.1850
24	-0.3132	-2.0824*	-0.2140	-1.2215	-0.0992	-0.1865
25	-0.3838	-2.5513**	-0.2757	-1.5737	-0.1080	-0.2030
26	-0.3686	-2.4509**	-0.2669	-1.5234	-0.1017	-0.1912
27	-0.3350	-2.2271**	-0.2579	-1.4721	-0.0770	-0.1448
28	-0.3083	-2.0496**	-0.2797	-1.5963	-0.0286	-0.0537
29	-0.2755	-1.8320*	-0.2620	-1.4954	-0.0135	-0.0254
30	-0.2870	-1.9078**	-0.2734	-1.5603	-0.0136	-0.0255
31	-0.3121	-2.0747**	-0.2867	-1.6365*	-0.0253	-0.0476
32	-0.3747	-2.4910**	-0.3143	-1.7939*	-0.0603	-0.1134
33	-0.4578	-3.0433***	-0.3730	-2.1287**	-0.0848	-0.1593
34	-0.5209	-3.4632***	-0.4128	-2.3557**	-0.1081	-0.2033
35	-0.4970	-3.3045***	-0.4047	-2.3098**	-0.0923	-0.1735
36	-0.5146	-3.4210***	-0.4373	-2.4956**	-0.0773	-0.1453
37	-0.5672	-3.7712***	-0.5598	-3.1949***	-0.0074	-0.0140
38	-0.4979	-3.3105***	-0.5757	-3.2857***	0.0778	0.1462
39	-0.5269	-3.5029***	-0.5672	-3.2370***	0.0403	0.0758
40	-0.5669	-3.7687***	-0.6040	-3.4470***	0.0371	0.0698
41	-0.6296	-4.1860***	-0.6246	-3.5647***	-0.0050	-0.0095
42	-0.6618	-4.4002***	-0.6524	-3.7233***	-0.0094	-0.0178
43	-0.6362	-4.2300***	-0.6476	-3.6957***	0.0113	0.0213
44	-0.6111	-4.0627***	-0.6277	-3.5821***	0.0166	0.0312
45	-0.5475	-3.6400***	-0.6148	-3.5086***	0.0673	0.1265
46	-0.5405	-3.5932***	-0.6078	-3.4688***	0.0673	0.1266
47	-0.4659	-3.0974***	-0.6138	-3.5032***	0.1479	0.2781
48	-0.3790	-2.5196**	-0.5984	-3.4149***	0.2194	0.4124

***, **,* indicate significance at the 1%, 5% and 10% levels.
The number of observations varies across time. It ranges from 180-251 companies.

Figure 4.3 presents the average cumulative average abnormal returns ACAR for the Losers, Winners and the arbitrage portfolio over 48 months into the test period 2006-2009. It is clear from figure 4.3 that Losers outperform Winners' portfolio and cumulative average market-adjusted abnormal returns can be achieved by constructing the arbitrage portfolio.

Figure 4.3 Average cumulative average abnormal return for 48 months over 2006-2009.

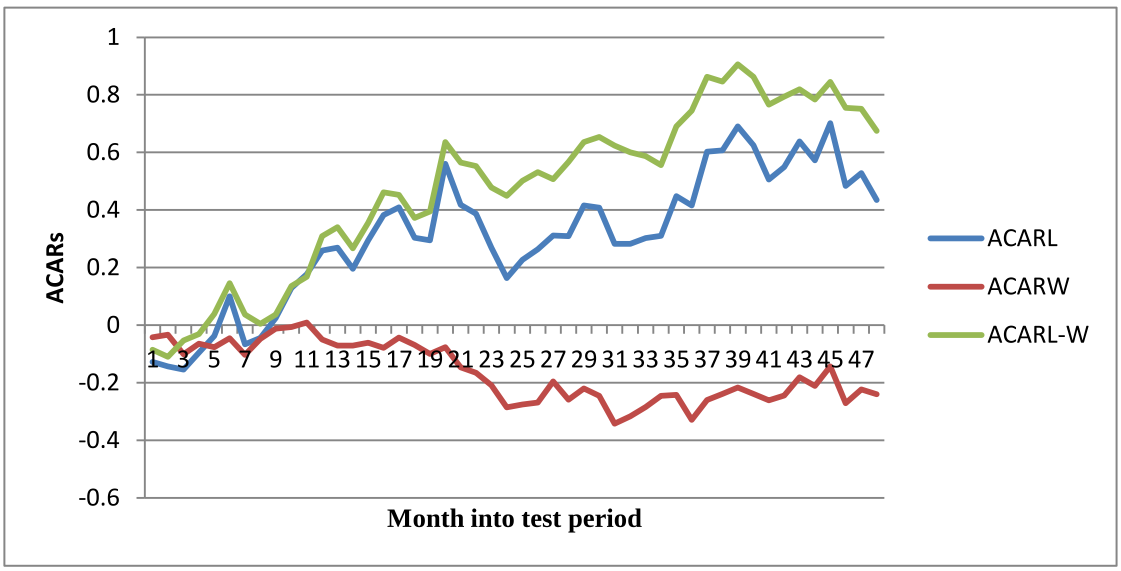


Table 4.5 presents the monthly cumulative average market-adjusted abnormal return ACAR over 48 months into the test period 2006-2009. It is clear from table 4.5 that Winners have significantly reversed immediately after the formation period. However, Losers have reversed starting from the ninth month as we notice positive market–adjusted abnormal returns during the remaining 40 months of the test period (9-48). This suggests that the overreaction phenomenon has been detected in the Egyptian stock market over the test period 2006-2009.

The arbitrage portfolio earns positive abnormal returns starting from the fifth month after the formation period, however, highly significant and positive market-adjusted abnormal returns can be detected starting from month 36 (3 years) as the average cumulative abnormal return on the arbitrage portfolio is 74%. It is worth mentioning also that by time the arbitrage portfolio achieves greater market-adjusted abnormal returns. The maximum abnormal returns of 90% can be achieved 39 months into the test period. This suggests that the long-term investors have the opportunity to achieve significant and positive abnormal returns by adopting the contrarian strategy of selling Winners and buying Losers.

To summarise, the above analysis and findings suggest that the overreaction phenomenon in the Egyptian stock market is not sensitive to the length of the formation period. In addition and within the two and four non-overlapping formation periods, overreaction phenomenon has not been detected for the period governed by the strict price limit regime. Results show that there is no significant market-adjusted abnormal return from the contrarian strategy. Losers continue to be Losers and Winners are reversed and thus there are no positive and significant abnormal returns for the arbitrage portfolio during the strict price limit period.

On the other hand, the overreaction phenomenon is clear during the circuit breaker regime (2006-2009) for both the short (two years) and longer (four years) formation periods. Results show positive and highly significant market-adjusted abnormal returns for the arbitrage portfolio. The main interpretation to this is the delayed price discovery hypothesis (Kim and Rhee, 1997).

Table 4.5: Average monthly cumulative average abnormal return over 48 months into the test period 2006-2009

Month into	**Loser**		**Winner**		**Loser-Winner**	
Test period	ACAR	t-stat	ACAR	t-stat	ACAR	t-stat
1	-0.1272	-0.7841	-0.0418	-0.5862	-0.0854	-0.2182
2	-0.1430	-0.8810	-0.0331	-0.4639	-0.1099	-0.2807
3	-0.1548	-0.9537	-0.1012	-1.4173	-0.0536	-0.1370
4	-0.0959	-0.5912	-0.0649	-0.9100	-0.0310	-0.0792
5	-0.0381	-0.2349	-0.0771	-1.0805	0.0390	0.0997
6	0.1000	0.6163	-0.0458	-0.6423	0.1459	0.3727
7	-0.0665	-0.4097	-0.1028	-1.4405	0.0363	0.0928
8	-0.0440	-0.2710	-0.0480	-0.6731	0.0041	0.0104
9	0.0243	0.1500	-0.0126	-0.1768	0.0370	0.0944
10	0.1292	0.7963	-0.0063	-0.0888	0.1356	0.3464
11	0.1766	1.0885	0.0086	0.1211	0.1680	0.4292
12	0.2593	1.5981	-0.0497	-0.6968	0.3091	0.7897
13	0.2686	1.6552	-0.0711	-0.9965	0.3397	0.8680
14	0.1962	1.2088	-0.0709	-0.9941	0.2671	0.6825
15	0.2945	1.8150*	-0.0614	-0.8604	0.3559	0.9094
16	0.3826	2.3579**	-0.0793	-1.1117	0.4620	1.1803
17	0.4089	2.5200**	-0.0432	-0.6059	0.4522	1.1553
18	0.3037	1.8717*	-0.0686	-0.9612	0.3723	0.9513
19	0.2948	1.8164*	-0.1002	-1.4038	0.3949	1.0091
20	0.5601	3.4517***	-0.0762	-1.0680	0.6363	1.6258
21	0.4180	2.5757***	-0.1467	-2.0556**	0.5647	1.4427
22	0.3870	2.3846**	-0.1661	-2.3277**	0.5531	1.4132
23	0.2690	1.6579*	-0.2094	-2.9342***	0.4784	1.2224
24	0.1637	1.0091	-0.2860	-4.0067***	0.4497	1.1490
25	0.2263	1.3947	-0.2754	-3.8581***	0.5017	1.2818
26	0.2630	1.6206*	-0.2689	-3.7681***	0.5319	1.3590
27	0.3109	1.9158**	-0.1959	-2.7454***	0.5068	1.2949
28	0.3090	1.9039**	-0.2586	-3.6227***	0.5675	1.4500
29	0.4158	2.5625**	-0.2202	-3.0846***	0.6360	1.6249*
30	0.4080	2.5145***	-0.2460	-3.4465***	0.6540	1.6710*
31	0.2823	1.7399*	-0.3419	-4.7904***	0.6242	1.5949
32	0.2825	1.7411*	-0.3173	-4.4460***	0.5998	1.5326
33	0.3020	1.8609*	-0.2851	-3.9942***	0.5870	1.4999
34	0.3097	1.9086*	-0.2457	-3.4424***	0.5554	1.4190
35	0.4481	2.7617***	-0.2421	-3.3919***	0.6902	1.7635*
36	0.4160	2.5635***	-0.3291	-4.6116***	0.7451	1.9938**
37	0.6029	3.7150***	-0.2604	-3.6486***	0.8633	2.2056**
38	0.6070	3.7407***	-0.2390	-3.3492***	0.8460	2.1616**
39	0.6899	4.2515***	-0.2163	-3.0302***	0.9062	2.3153**
40	0.6246	3.8491***	-0.2385	-3.3416***	0.8631	2.2052**
41	0.5057	3.1163***	-0.2608	-3.6549***	0.7665	1.9585**
42	0.5495	3.3865***	-0.2448	-3.4298***	0.7943	2.0295**
43	0.6377	3.9299***	-0.1812	-2.5395**	0.8190	2.0925**
44	0.5727	3.5291***	-0.2106	-2.9512***	0.7833	2.0013**
45	0.7013	4.3215***	-0.1435	-2.0111**	0.8448	2.1585**
46	0.4833	2.9785***	-0.2716	-3.8055***	0.7549	1.9889**
47	0.5286	3.2575***	-0.2232	-3.1279***	0.7518	1.9710**
48	0.4346	2.6784***	-0.2404	-3.3682***	0.6750	1.9947**

***, **,* indicate significance at the 1%, 5% and 10% levels.

The number of observations varies across time. It ranges from 180-251 companies.

Fama (1989), Lehmann (1989), and Lee, Ready, and Seguin (1994) argued that price limits interfere with the price discovery mechanism as trading usually ceased (when prices hit the limit) until the limits were revised. Therefore, at the limit hit day these constraints (limits) prevent stock prices from reaching their equilibrium levels until the following trading day (session) (Kim and Rhee, 1997). On the other hand, within the circuit breaker regime (wider price limits) investors have more time (during the trading halts) to adjust their portfolios. This may lead to overreactive behavior by some speculative traders due to the lack of informational efficiency and the noise trading in emerging markets.

The existing body of the literature argues that the reported overreaction phenomenon by De Bondt and Thaler (1985) is mainly due to computation errors in beta between the estimation and the event window (Chan, 1988), or due to small firm effect (size effect) and seasonality effects (January effect) (Zarowin, 1990). In this section of the chapter, I investigate firstly the role of the size effect and whether or not the overreaction phenomenon is mainly due to small firm effects. I also investigate the stability of beta within the formation and test periods. Finally, I present the results of the effects of the seasonality effect on the overreaction phenomenon.

4.5.7 Long-term overreaction: the sensitivity to size effect.

The above methodology is repeated using Small and Big size portfolios based on the companies' market capitalisation to investigate whether or not the overreaction phenomenon can be explained by the size effect. In December of each year all listed shares (excluding financial sector and property investment companies) are ranked - based on market capitalisation (firm size) - in an ascending order. This is done over the period 1998-2009 and for each of the formation and test periods. The median value of firm size is then used to split the stocks into two main categories, namely, Small and Big (S and B) [22].

To investigate the size effect on the long-term overreaction, I estimate the average monthly cumulative average market-adjusted abnormal return over 24 months into the test period for small and big firms based on market capitalisation.

Table 4.6 presents the results of the monthly cumulative average market-adjusted abnormal return over 24 months for small firms.

The results presented in table 4.6 shows that price reversal for the Losers occurs starting from the fourth month until the sixth month and then reverse again and continue to be Losers (momentum effect) until month 12. However, starting from month 15 until the end of the test period, Losers earn positive and significant market-adjusted abnormal returns.

The price reversals of the small Winners, on the other hand, occur immediately after the formation period as we notice highly significant and negative abnormal returns on the first month of the test period and then starting from the eighth month.

[22] Following the literature on price limits, I use market capitalisation as a proxy for firm size as all the firms included in the sample are listed in the EGX. None of the literature used other measures i.e. total assets due to the drawback of accounting measures.

The results of the arbitrage portfolio report highly significant and positive abnormal returns starting from month 13; this suggests that the overreaction behavior is prevailing in small firms' portfolios.

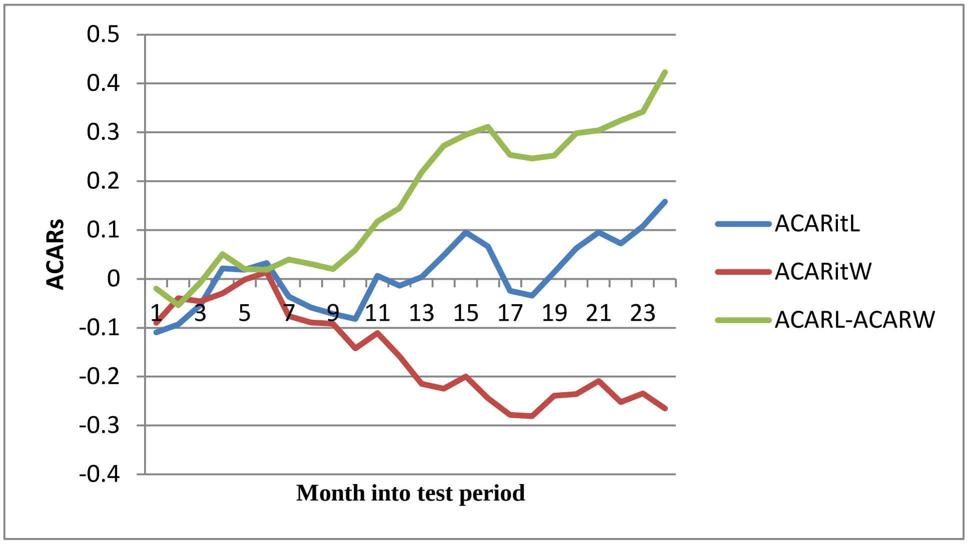
Table 4.6: Average monthly cumulative average abnormal return over 24 months into the test period for small firms

Month into Test period	Loser		Winner		Loser-Winner	
	ACAR	t-stat	ACAR	t-stat	ACAR	t-stat
1	-0.1096	-3.5021***	-0.0897	-2.1113***	-0.0199	-0.1977
2	-0.0931	-2.9727***	-0.0392	-0.9231	-0.0538	-0.5351
3	-0.0535	-1.7080*	-0.0460	-1.0821	-0.0075	-0.0743
4	0.0215	0.6872	-0.0294	-0.6912	0.0509	0.5059
5	0.0186	0.5943	-0.0015	-0.0355	0.0201	0.2000
6	0.0322	1.0296	0.0134	0.3151	0.0188	0.1873
7	-0.0360	-1.1494	-0.0758	-1.7834*	0.0398	0.3959
8	-0.0584	-1.8655**	-0.0892	-2.0991***	0.0308	0.3064
9	-0.0714	-2.2821***	-0.0915	-2.1524***	0.0200	0.1993
10	-0.0823	-2.6279***	-0.1419	-3.3392***	0.0597	0.5932
11	-0.0063	-0.2026	-0.1110	-2.6105***	0.1173	1.1661
12	-0.0138	-0.4396	-0.1588	-3.7367***	0.1451	1.4421
13	0.0039	0.1252	-0.2147	-5.0515***	0.2186	2.1734***
14	0.0480	1.5331	-0.2245	-5.2822***	0.2725	2.7091***
15	0.0953	3.0455***	-0.1994	-4.6926***	0.2948	2.9306***
16	0.0668	2.1352***	-0.2442	-5.7451***	0.3110	3.0920***
17	0.0247	0.7881	-0.2785	-6.5532***	0.2539	2.5237***
18	0.0342	1.0917	-0.2805	-6.6009***	0.3147	2.4494***
19	0.0133	0.4241	-0.2388	-5.6187***	0.2521	2.5061***
20	0.0625	1.9970***	-0.2358	-5.5488***	0.2983	2.9660***
21	0.0951	3.0369***	-0.2091	-4.9193***	0.3041	3.0237***
22	0.0721	2.3049***	-0.2524	-5.9376***	0.3245	3.2262***
23	0.1078	3.4428***	-0.2343	-5.5134***	0.3421	3.4011***
24	0.1582	5.0524***	-0.2652	-6.2406***	0.4234	4.2092***

***, **,* indicate significance at the 1%, 5% and 10% levels.
The number of observations varies across time. It ranges from 180-251 companies.

Figure 4.4 presents the average cumulative average abnormal returns ACARs for the Losers, Winners and the arbitrage (Loser–Winner) portfolio over 24 months into the test period 2006-2009 for small firms.

Figure 4.4 Average cumulative average abnormal return over 24 months into the test period 2000-2009 for small firms



It is clear from figure 4.4 that small Losers outperform small Winners' portfolio and cumulative average market-adjusted abnormal returns can be achieved by constructing the arbitrage portfolio. Table 4.7 presents the results of the average monthly cumulative average abnormal return over 24 months for big firms.

The results presented in table 4.7 show that price reversal for the big Losers occurs immediately after the second month following the formation period. In addition, highly significant and negative abnormal returns for the Losers are found in months five and six and from month 10-16 and finally from month 20-24.

The price reversal for the big Winners occurs immediately after the formation period as we notice highly significant and negative abnormal returns over the 24 months following the formation period. In addition, the arbitrage portfolio earns highly significant and positive abnormal returns over the period 11-24 month. It is clear from the table that big Losers outperform big Winners and investors can achieve abnormal returns by forming the arbitrage portfolio (Losers–Winners).

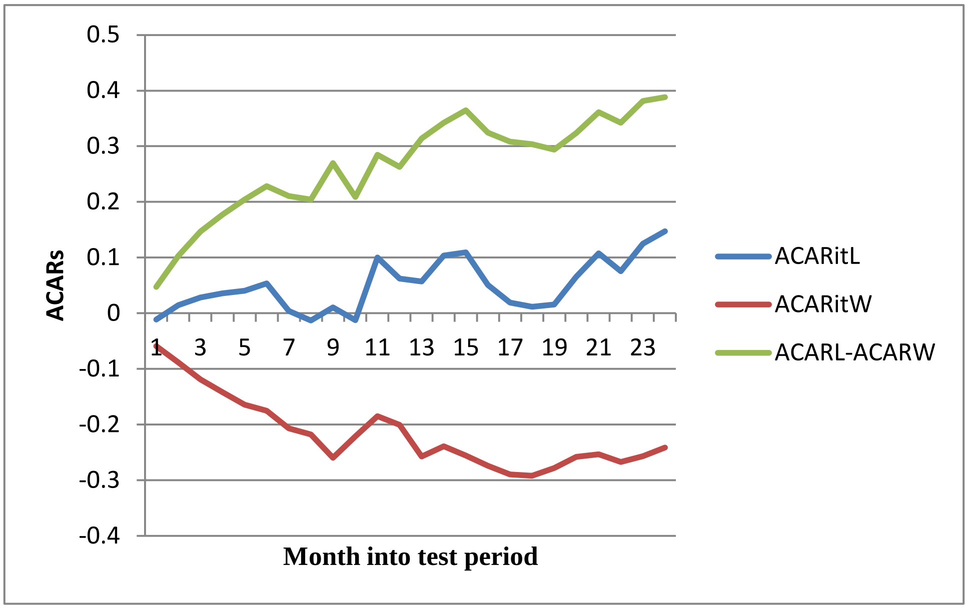
Table 4.7: Average monthly cumulative average abnormal return over 24 months into the test period for big firms

Month into Test period	Loser		Winner		Loser-Winner	
	ACAR	t-stat	ACAR	t-stat	ACAR	t-stat
1	-0.0115	-0.5541	-0.0591	-2.0687**	0.0476	0.3810
2	0.0148	0.7134	-0.0881	-3.0863***	0.1029	0.8238
3	0.0282	1.3630	-0.1185	-4.1505***	0.1467	1.1747
4	0.0358	1.7283*	-0.1414	-4.9529***	0.1772	1.4187
5	0.0403	1.9463**	-0.1641	-5.7466***	0.2044	1.6363
6	0.0535	2.5829***	-0.1749	-2.1248**	0.2283	1.8282*
7	0.0040	0.1940	-0.2065	-2.2337***	0.2105	1.6857*
8	-0.0131	-0.6345	-0.2175	-2.6183***	0.2044	1.6363
9	0.0105	0.5049	-0.2593	-3.0822***	0.2698	2.1598**
10	-0.0122	-0.5898	-0.2209	-2.7385***	0.2087	1.6712*
11	0.1004	4.8503***	-0.1846	-2.4645**	0.2850	2.2818**
12	0.0624	3.0131***	-0.2003	-2.0148**	0.2627	2.1030**
13	0.0569	2.7503***	-0.2571	-3.0037***	0.3140	2.5141**
14	0.1035	4.9986***	-0.2390	-3.3696***	0.3425	2.7419***
15	0.1092	5.2747***	-0.2556	-3.9531***	0.3648	2.9210***
16	0.0506	2.4438**	-0.2736	-4.5832***	0.3242	2.5958***
17	0.0192	0.9277	-0.2893	-5.1321***	0.3085	2.4699**
18	0.0117	0.5660	-0.2920	-5.2267***	0.3037	2.4316**
19	0.0159	0.7681	-0.2780	-4.7363***	0.2939	2.3530**
20	0.0660	3.1881***	-0.2579	-4.0345***	0.3240	2.5937***
21	0.1077	5.2021***	-0.2533	-3.8714***	0.3610	2.8903***
22	0.0755	3.6455***	-0.2668	-4.3457***	0.3423	2.7407***
23	0.1247	6.0241***	-0.2564	-3.9822***	0.3812	3.0519***
24	0.1472	7.1108***	-0.2410	-3.4397***	0.3882	3.1080***

***, **,* indicate significance at the 1%, 5% and 10% levels.
The number of observations varies across time. It ranges from 180-251 companies.

Figure 4.5 presents the average cumulative average abnormal returns ACARs for the Losers, Winners and the arbitrage (Loser–Winner) portfolio over 24 months into the test period 2006-2009 for big firms. It is clear from figure 4.5 that big Losers outperform big Winners' portfolio and cumulative average market-adjusted abnormal returns can be achieved by constructing the arbitrage portfolio.

Figure 4.5 Average cumulative average abnormal return over 24 months into the test period 2000-2009 for big firms.



To conclude, the findings presented in the above tables and figures show evidence of a genuine investors' overreactive behavior in the Egyptian stock market and it is not due to small firm effect. Losers are found to outperform Winners for big and small firms and abnormal returns can be achieved by forming the arbitrage portfolios. Therefore contrarian strategy by buying Losers and selling Winners is likely to be a profitable strategy by the investors in the Egyptian stock market.

4.5.8 Long-term performance with risk adjustment (robustness to time-varying market risk)

In order to investigate the overreaction/momentum hypothesis, Claire and Thomas (1995) run the following regression:

$$R_{PLMW} = R_{PL} - R_{PW} = \alpha_i + \eta_{ii} \qquad t = 1.........n \qquad \text{Overreaction hypothesis} \qquad (15)$$

where R_{PLMW} is the difference between the returns on the Loser and Winner portfolios α_i is the constant term and η_{it} is the white noise error term. The simple *t*- statistic of α_i suggests whether or not there is a significant positive or negative difference in means for the Losers and Winners. Significant and positive α_i supports the overreaction hypothesis; however significant and negative α_i supports the momentum hypothesis.

In addition, Zarowin (1990) controls for time-varying risk. Therefore to take this into account I run two additional regressions (after controlling for autocorrelation) as follows:

$$r_{Pt} - r_{ft} = \alpha_i + \beta_i \, (r_{mt} - r_{ft}) + \eta_{it} \qquad P \in (W, L) \qquad (16)$$

$$R_{PLMW} = \alpha_i + \beta_i \, (r_{mt} - r_{ft}) + \eta_{it} \qquad t = 1.........n \qquad (17)$$

where α_i is the Jensen performance index, β are the CAPM betas as a difference between the respective market risk of the two portfolios (Winner and Losers) and r_{ft} is the risk free rate (one month Treasury Bill at the beginning of each month (Zarowin,(1990)) .

Significant and positive α_i implies the overreaction hypothesis while significant and negative α_i suggests the momentum hypothesis.

Significant and positive β suggests that Losers may embody higher systematic risk than Winners. In addition, Winners may imply higher degree of systematic risk in case of significant and negative β is found.

To investigate the overreaction hypothesis, and following Zarowin (1990), Claire and Thomas (1995) and Kang et.al (2002), table 4.8 shows the long-term performance with risk adjustment (robustness to time-varying market risks) as in equations 16 and 17 (estimated using Ordinary Least Squares). The results presented in table 4.8 show that the coefficients of systematic risk β are positive in all periods and highly significant in the *aggregate period* of the *arbitrage portfolio*. In addition, the coefficients of beta for the Losers are greater than those of Winners; this suggests that Losers tend to be riskier than Winners and the difference in returns can be explained by the differences in the systematic risk.

The positive and significant α_i of the arbitrage portfolio supports the overreaction hypothesis in the test periods during the circuit breakers regime (2006-2007 and 2008-2009). However, the negative α_i supports the momentum hypothesis during the strict price limit regime (2001-2002 and 2002-2003).

Table 4.8: Long- term performance with risk adjustment (Robustness to time – varying risk)

Test	Loser				Winner				Loser - Winner			
Period	α	β	F-test	ADJ R^2	α	β	F-test	ADJ R^2	α	β	F-test	ADJ R^2
2000-01	0.0049 (0.0092)	0.3626*** (0.1131)	10.277***	0.0190	-0.0210*** (0.0079)	0.3461*** (0.0979)	12.509***	0.0235	**-0.0259 (0.0218)**	0.0165 (0.1459)	0.0128	0.0021
2002–03	0.0115 (0.0106)	0.3807** (0.1584)	5.781**	0.0099	-0.0012 (0.0072)	0.2799*** (0.1069)	6.8557***	0.0121	**-0.0128 (0.0125)**	0.1009 (0.1866)	0.2922	0.0015
2004–05	0.0190* (0.0109)	0.6062*** (0.0967)	39.278***	0.0740	-0.0135* (0.0072)	0.4141*** (0.0643)	41.423***	0.0778	0.0325 (0.0224)	0.1921* (0.1106)	3.0171*	0.0042
2006-07	0.0210** (0.0088)	0.4826*** (0.0916)	17.460***	0.0332	-0.0086 (0.0058)	0.2572*** (0.0604)	21.64***	0.2952	0.0296*** (0.0102)	0.2254*** (0.0964)	19.911***	0.0380
2008-09	0.0079 (0.0087)	0.8156*** (0.0626)	19.68***	0.2604	-0.0036 (0.0064)	0.5169*** (0.0462)	23.79***	0.4506	0.0115*** (0.0006)	0.2987*** (0.0764)	1.7550	0.0016
Aggregate	0.0055 (0.0039)	0.6197*** (0.0379)	26.70***	0.0997	-0.0068** (0.0028)	0.5004*** (0.0274)	25.16***	0.2143	**0.0123*** (0.0048)**	**0.1193*** (0.0471)**	**28.24*** **	**0.0830**

To control for risk I run these additional regression models (after controlling for auto correlation) following Zarowin (1990), Claire and Thomas (1995) and Kang et.al (2002),

$$r_{Pt} - r_{ft} = \alpha_i + \beta_i (r_{mt} - r_{ft}) + \eta_{it} \qquad P \in (W.L)$$

$$R_{PLMW} = \alpha_i + \beta_i (r_{mt} - r_{ft}) + \eta_{it} \qquad t = 1.........n$$

where R_{PLMW} is the difference between the returns on the Loser and Winner portfolios α_i (the constant term) is the Jensen performance index, β are the CAPM betas as a difference between the respective market risk of the two portfolios (Winner and Losers), r_{ft} is the risk free rate (one month Treasury Bill at the beginning of each month and η_{it} is the white noise error term. Significant positive α_i confirms the overreaction hypothesis while significant negative α_i confirms the momentum hypothesis. ***, **,* indicate significance at the 1%, 5% and 10% levels.

The number of observations varies across time. It ranges from 180-251 companies.

4.5.9 The variation of risk performance between rank and test periods

Brailsford (1992) argues that risk adjusted returns are biased due to the bias in the market-adjusted model parameters estimated in the rank period. Following Chan (1988), and Gaunt, (2000), abnormal returns can be tested by examining the value of α in the following Sharp – Linter CAPM equation:

$$r_{it} - r_{ft} = \alpha_i + \beta_i (r_{mt} - r_{ft}) + \varepsilon_{it} \tag{18}$$

Where the value weighed EGX30 market index is the market portfolio r_{mt}. I initially estimate equation 18 over the test period in which beta is assumed to be constant. The null hypothesis is $\alpha_i = 0$ this suggests that asset (i) has no abnormal return. This implies that size effect is ignored in the above equation. However, at the beginning of the test period Loser stocks are usually smaller in size than Winners – if the size effect if significant – this suggests that our null hypothesis is biased by the size effect (Chan 1988). I then estimate the betas and the abnormal returns simultaneously in the test period.

To examine risk performance and whether or not betas are stable over the rank period and test periods, I modify equation 18 following Chan (1988) for the Losers, Winners and the arbitrage portfolio (Losers –Winners) as follows:

$$r_{it} - r_{ft} = \alpha_{1i}(1 - D_t) + \alpha_{2i} D_t + \beta_i (r_{mt} - r_{ft}) + \beta_{iD} (r_{mt} - r_{ft}) D_t + \varepsilon_{it} \tag{19}$$

where t= 1 to 48 months, r_{it} is continuously compounded return on portfolio i at time t, r_{mt} is the return on an value weighted EGX30 index in month t, r_{ft} is the risk-free rate. Importantly, D_t is a dummy variable equal to zero in the rank period (t< 25) and is equal to one in the test period (t > 24). ε_{it} is assumed to be normally distributed with two variances σ_{i1}^2 and σ_{i2}^2 for the rank and test periods respectively. Chan (1988) argues that there should not be significant difference in α 's between equation 18 and 19 in the rank and test periods separately.

The outcomes of the above regression allow us to estimate different α_i and β_i for the rank and test periods. $\hat{\alpha}_{1i}$ and $\hat{\alpha}_{2i}$ are the average abnormal returns for the rank and test periods respectively, however, $\hat{\beta}_i$ and $(\hat{\beta}_i + \hat{\beta}_{iD})$ are the estimated betas for the rank and test periods respectively. If $\hat{\beta}_{iD}$ is not significantly different from zero, then betas are assumed to be constant throughout the rank and test periods.

Finally, I run the aggregate *t* test statistics for the entire period (1998-2009) under the null hypothesis and using the Central Limit theorem (Chan 1988). The test statistics is given as follows:

$$U = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} t_i \sqrt{(T_i - 3)/(T_i - 1)} \approx N(0,1) \qquad (20)$$

Table 4.9 presents the findings of testing the existence of the abnormal returns and the Stability of risk factor (beta) throughout rank and test periods. The results presented in table 4.9 show that the abnormal return during the rank periods α_{1i} is negative for Losers for all rank periods and highly significant for the aggregate period. However, the average abnormal return for the Winners is positive for all the rank periods and highly significant in the aggregate period. The abnormal return for the arbitrage portfolio (Losers-Winners (LMW)) is negative and highly significant in all rank periods in addition to the aggregate rank period.

Price reversal behaviour can be detected as the abnormal return coefficient α_{2i} is positive for the Losers and negative for the Winners in all test periods. In addition, the arbitrage portfolio (LMW) supports the overreaction behaviour as we notice a change in the sign of α_{2i} from negative in the rank period to positive in the test period. Moreover, highly significant abnormal return is detected in the aggregate test period.

Table 4.9 also shows that test period betas $\beta_i + \beta_{iD}$ for the Losers are greater than those of rank periods β_i except for the following test periods: 2000–2001 and 2002-2003. In addition, the aggregate beta for the test period for Loser portfolios is highly significant and outperforms beta in the rank period. This suggests that Losers are more risky during the test period. This result is consistent with Chan (1988). Chan argues that the risk of Loser portfolios is higher during the test period and moreover, Losers are on average bigger in size than those of Winners.

Betas of the Winner portfolios in the rank periods significantly exceed those of test periods (except for the 2008- 2009 test period). The coefficient of β_{iD} (the change in beta from rank to test period) is negative and highly significant in the aggregate test period for the winners. We also notice that betas of the Losers are greater than those of Winners in the aggregate test period; β_{iD} is positive and highly significant. This suggests that beta is not constant over time throughout the rank and the test periods. These results are consistent with Chan (1988) and Gaunt (2000).

Table 4.9: Abnormal returns and the Stability of risk throughout rank and test periods

Rank Period	Test Period	Loser				Winner				Loser - Winner			
		α_{1i}	α_{2i}	β_i	β_{iD}	α_{1i}	α_{2i}	β_i	β_{iD}	α_{1i}	α_{2i}	β_i	β_{iD}
1998-	2000-	-0.0823***	0.0049	0.4445***	-0.1901	0.0031	-0.0210***	0.4110***	-0.0649	-0.0854***	0.0259	0.0335	-0.1252
1999	2001	(0.0122)	(0.0146)	(0.1202)	(0.2168)	(0.0057)	(0.0068)	(0.0591)	(0.1029)	(0.0133)	(0.0160)	(0.1383)	(0.2409)
2000-	2002-	-0.0148	0.0115	0.5948***	-0.2140	0.0168*	-0.0012	0.4594***	-0.1795	-0.0316**	0.0128	0.1345	-0.0345
2001	2003	(0.0120)	(0.0092)	(0.1493)	(0.2033)	(0.0089)	(0.0070)	(0.1128)	(0.1535)	(0.0143)	(0.0112)	(0.1815)	(0.2470)
2002–	2004-	-0.0292**	0.0190	0.1818	0.4244*	0.0205***	-0.0135*	0.6182***	-0.2041*	-0.0498***	0.0325***	-0.4363**	0.6285**
2003	2005	(0.0119)	(0.0140)	(0.1817)	(0.2202)	(0.0061)	(0.0071)	(0.0932)	(0.1129)	(0.0133)	(0.0155)	(0.2023)	(0.2451)
2004–	2006-	- 0.0029	0.0210***	0.4113***	0.0287	0.0322***	-0.0086	0.5673***	-0.2899***	-0.0351**	0.0296***	-0.1560	-0.3186**
2005	2007	(0.0103)	(0.0080)	(0.0935)	(0.1249)	(0.0087)	(0.0068)	(0.0808)	(0.1075)	(0.0129)	(0.0100)	(0.1174)	(0.1569)
2006-	2008-	-0.0084	0.0086	0.5988***	0.2405***	0.0087	-0.0036	0.8078***	0.1091	-0.0171*	0.0123	-0.2090**	0.1314
2007	2009	(0.0076)	(0.0074)	(0.0690)	(0.0807)	(0.0067)	(0.0065)	(0.0771)	(0.0904)	(0.0099)	(0.0097)	(0.1150)	(0.1347)
Aggregate		-0.0302***	0.0054	0.4911***	0.1324**	0.0176***	-0.0068**	0.4103***	-0.1013**	-0.0478***	0.0123**	-0.0808***	0.2337***
		(0.0044)	(0.0042)	(0.0458)	(0.0603)	(0.0029)	(0.0027)	(0.0328)	(0.0426)	(0.0051)	(0.0049)	(0.0585)	(0.0460)

Table 8 presents the results of Chan's (1988) model estimated using ordinary least squares. $r_{it} - r_{ft} = \alpha_{1i}(1 - D_t) + \alpha_{2i} D_t + \beta_i (r_{mt} - r_{ft}) + \beta_{iD}(r_{mt} - r_{ft}) D_t + \varepsilon_{it}$

where t= 1 to 48 months, r_{it} is continuously compounded return on portfolio I at time t, r_{mt} is the return on an value weighted EGX30 index in month t, r_{ft} is the risk- free rate , D_t is a dummy variable equal to zero in the rank period (t<25) and is equal to one in the test period (t >24). ε_{it} is assumed to be normally distributed with two variances σ_{i1}^2 and σ_{i2}^2 for the rank and test periods respectively. ***, **,* indicate significance at the 1%, 5% and 10% levels.

The number of observations varies across time. It ranges from 180-251 companies.

4.5.10 Long-term overreaction with adjustment for the seasonality effect.

The existing body of the literature documented that the overreaction phenomenon is highly likely to occur in January (the January Effect). See for example, De Bondt and Thaler (1985, 1987), Zarowin (1990), and Clare and Thomas (1995).

In this section I investigate the seasonality effect in the Egyptian stock exchange by regressing the average monthly abnormal returns for the Losers, Winners and the arbitrage portfolio (Losers–Winners) on a set of dummy variables which take the value of one in the respective month and zero otherwise. I exclude the intercept to avoid the dummy variable trap., ε_t is a stochastic IID error term as in the following regression.

$$AR_{LMW\,it} = \alpha_1 M_{Jant} + \alpha_2 M_{Febt} + \alpha_3 M_{Mart} + ... + \alpha_{12} M_{Dect} + \varepsilon_{it} \qquad (21)$$

In addition I use the Cochrane-Orcutt two-step iterative technique to overcome the potential autocorrelation in equation 21. In the first step I estimate the following regression based on the residuals of the equation 21, i.e. $\hat{\varepsilon} = \rho\hat{\varepsilon}_{t-1} + \nu_t$. Then in the second step I run the Cochrane-Orcutt method using the following generalized least squares (GLS) equation. This equation is repeated in cases of higher order of autocorrelation.

$$y_t - \hat{\rho}\, y_{t-1} = \beta_0(1-\hat{\rho}) + \beta_1(X_t - \hat{\rho}\, X_{t-1}) + (\varepsilon_t - \hat{\rho}\, \varepsilon_{t-1}) \qquad (22)$$

Table 4.10 presents the findings of long-term overreaction with adjustment to seasonality effect. The findings presented in table 4.10 show evidence of the January effect in the arbitrage portfolio, as we notice positive and highly significant abnormal returns in January, whereas December reports negative and highly significant abnormal returns for the contrarian portfolio.

This result is consistent with the literature on the calendar effect and the tax–loss hypothesis as investors tend to sell Losers by the end of December to increase the capital losses and to reduce the tax burden at the end of the financial year followed by buying Winners in January. We also notice significant and positive abnormal returns in July as the vast majority of the listed companies in the Egyptian stock exchange have June as end of their financial year.

We notice positive and marginal significant abnormal returns in June (the end of financial year). This suggests that the significant abnormal return resulting from the overreaction phenomenon in the Egyptian stock market is not primarily due to the seasonality effect.

Table 4.10: Long–term overreaction with adjustment to seasonality effect

Test Period	Jan	Feb	March	April	May	June	July	Aug	Sept	Oct	Nov	Dec	ADJ R^2	DW
Aggregate														
Loser	0.0038	0.0600***	0.0014	0.0138	-0.0219*	0.0171	-0.0163	0.0253**	0.0024	-0.0469***	0.0125	-0.0027	0.014	2.14
	(0.0132)	(0.0132)	(0.0132)	(0.0132)	(0.0132)	(0.0132)	(0.0132)	(0.0132)	(0.0132)	(0.0132)	(0.0132)	(0.0132)		
Winner	-0.0120	-0.0290*	0.0691***	-0.0063	0.0138	-0.0159	0.0310**	0.0161	0.0142	0.0096	-0.0211	0.0192	0.024	2.14
	(0.0105)	(0.0148)	(0.0148)	(0.0148)	(0.0148)	(0.0148)	(0.0148)	(0.0148)	(0.0148)	(0.0148)	(0.0148)	(0.0148)		
Loser-Winner	0.0394***	0.0231	0.0665***	0.0726***	0.0184	0.0435*	0.0629**	0.0083	0.0292	0.0142	0.0284	-0.0730***	0.005	1.92
	(0.0177)	(0.0250)	(0.0250)	(0.0250)	(0.0250)	(0.0250)	(0.0250)	(0.0250)	(0.0250)	(0.0250)	(0.0250)	(0.0250)		

The table included the outputs of the equation 21 estimated using ordinary least squares. $M_{Jan}....M_{Dec}$ are set of dummy variables which take the value of one in the respective month and zero otherwise. I excluded the intercept to avoid the dummy variable trap, ε_t is a stochastic IID error term as in the following regression.

$$AR_{LMW\,it} = \alpha_1 M_{Jant} + \alpha_2 M_{Febt} + \alpha_3 M_{Mart} + ... + \alpha_{12} M_{Dect} + \varepsilon_{it}$$

***, **,* indicate significance at the 1%, 5% and 10% levels.

The number of observations varies across time. It ranges from 180-251 companies.

4.5.11 Is the contrarian factor priced? The Fama and French three-factor model.

In this section I investigate whether or not the overreaction factor is priced in the Egyptian stock market. Initially I estimate the traditional Fama and French three-factor model. I expect that Fama French three-factor model provides better explanation in risk-return relationship in the Egyptian stock market. Fama and French's three-factor model not only overcomes the major drawbacks of CAPM (a one –factor model) but it also does well in explaining the risk-return relationship in emerging markets. Cheung et al. (1993) found a weak risk-return relationship in both Korean and Taiwanese stock exchanges using the CAPM whilst, Huang (1998) found a negative risk–return relationship in the Taiwanese stock exchange.

$$r_{it} - r_{ft} = \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t + \varepsilon_{it} \qquad (23)$$

Following Fama and French (1993) the dependent variable in equations 23 is the excess returns (monthly returns minus the one month Treasury bill rate of return). r_i is the return on asset (i), r_f is the risk- free return, α_i is the abnormal returns that cannot be explained by the factors in the models, MKT is the value-weighted average market return ($r_{mt} - r_{ft}$) as in CAPM; r_m is the return on the market portfolio, β_i is the systematic risk of asset (i) relative to the market portfolio beta $\beta_i = Cov(r_i, r_m)/\sigma_M^2$ and σ_M^2 is the variance of market portfolio.

SMB is the difference between the return on a portfolio of small stocks and the return on a portfolio of big stocks. HML is the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks. β_i is the sensitivity of the asset returns to market portfolio, s_i is the sensitivity of the asset returns to return of SMB, h_i is the sensitivity of the asset returns to return of HML.

Considering now the mechanics of the estimation, in December of each year all listed shares (excluding financial sector and property investment companies) are ranked - based on market capitalisation (firm size) - in an ascending order over the period 1998-2009. The median value of firm size is then used to split the stocks into two main categories, namely, Small and Big size (S and B). All the listed firms are grouped into three main categories - based on book to market equity BE/ME - namely, Low BE/ME (bottom 30%), Medium BE/ME (middle 40%) and High BE/ME (high 30%).

Following Fama and French (1993), the book value of common equity = book value of shareholders' equity + deferred tax (balance sheet) + investment tax credit – book value of preferred stock.

Fama and French (1992b) arbitrarily grouped firm size and BE/ME into two and three categories as they found that BE/ME plays a much more important role in explaining the variation in stock returns. In addition they argued that there is no reason for the test results to vary according to these grouping choices.

Based on the intersection of the above two classifications (two size portfolios and three BE/ME portfolios), I construct six different portfolios namely, (S/L, S/M, S/H, B/L, B/M and B/H).

I match the BE/ME ratio for firms with fiscal year ending in June t-1 with monthly stock returns from January of year t to December of year t+1 (Fama and French 1993). I exclude all negative equity book values. BE/ME is then book common equity for the fiscal year ending in June t-1 divided by market equity at the end of December of t-1 (Fama and French 1993). (For example, the B/H portfolio contains the stocks in the Big size group and the High -BE/ME group as well.)

I calculate the monthly-weighted average returns on the six portfolios from January of year t to December of year t and the portfolios are reformed in January of the year t+1.
SMB portfolio returns are the monthly differences between the simple average of the returns on the three small size portfolios, namely, (S/L, S/M and S/H), and the big size portfolios, namely, (B/S, B/M and B/H).

$$SMB = 1/3\,[(S/L + S/M + S/H) - (B/L + B/M + B/H)] \qquad (24)$$

While the HML portfolios are the monthly difference between the simple average of the returns on the two high- BE/ME portfolios, namely, S/H and B/H and the two low- BE/ME portfolios, namely, S/L and B/L.

$$HML = 1/2\,[(S/H + B/H) - (S/L + B/L)] \qquad (25)$$

4.5.12 Augmented Fama and French and Carhart models.

Carhart (1997) augmented Fama and French three-factor model by adding a momentum factor. The main intuition of Carhart's model is to investigate whether the momentum factor is priced or not. Carhart's model is known in the financial literature as the Carhart four-factor model. In this section I augment further the Carhart (1997) four-factor model by including two additional variables, namely, LMW and HMLFE representing loser minus winner and high minus low fixed effects respectively. I include both LMW and HMLFE to examine whether or not the overreaction factor as well as the unobservable factors have been priced into returns. The model is then written:

$$r_{it} - r_{ft} = \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t + \lambda_i LMW_t + \gamma_i HMLFE + \varepsilon_{it} \tag{26}$$

In a well specified asset pricing model α_i should not be statistically different from zero. Therefore α_i is considered a simple excess-return measure. In the Fama and French three-factor model, the market factor, in addition to size and book-to-market equity factors, seems to explain better variations in stock returns. Equation on 26 then, provides an augmented Fama and French three-factor model by including an overreaction/momentum factor as well as the difference between low and high fixed effects portfolios. The main objective of including theses two additional factors is to examine whether or not the overreaction/momentum and/or other unobservable factors are already priced in to returns.

In terms of the mechanics of estimation, LMW is constructed as the difference between the returns on the Losers portfolio and the returns on the Winners portfolio for a given time period. To construct contrarian (overreaction) portfolios, six value-weighted portfolios are formed as follows; in December of each year all listed shares (excluding financial sector and property investment companies) are ranked - based on market capitalisation (firm size) - in an ascending order over the period 1998-2009. The median value of firm size is then used to split the stocks into two main categories, namely, Small(S) and Big (B).

All listed firms are grouped into three main categories based on cumulative abnormal return in year t-1, namely, Low CARs (bottom 30%), Medium CARs (middle 40%) and High CARs (high 30%). Based on the intersection of the above two classifications (two size portfolios and three CARs portfolios), I construct six different portfolios, namely, (S/LCARs, S/MCARs, S/HCARs, B/LCARs, B/MCARS and B/HCARs).

LMW portfolios are the monthly difference between the simple average of the returns on the two low CARs portfolios (Losers), namely, (LCARs/S, LCARs/B) and the two high CARs portfolios (Winners) namely; (HCARs/S, HCARs/B).

$$LMW = 1/2(LCARs/S + LCARs/B) - (HCARs/S + HCARs/B) \tag{27}$$

To construct the unobservable (fixed effects) portfolios I estimated equation 23 for all formation and the aggregate windows using panel data model. To construct the six unobservable value-weighted portfolios, in December of each year all listed shares (excluding financial sector and property investment companies) are ranked - based on market capitalisation (firm size) - in an ascending order over the period 1998-2009. The median value of firm size is then used to split the stocks into two main categories, namely, Small and Big size (S and B).

All the listed firms are then grouped into three main categories based on company fixed effects in year t-1, namely, Low FEs (bottom 30%), Medium FEs (middle 40%) and High FEs (high 30%). Based on the intersection of the above two classifications (two size portfolios and three FEs portfolios), I construct six different portfolios, namely, (S/LFEs, S/MFEs, S/HFEs, B/LFEs, B/MFEs and B/HFEs).

HMLFE portfolios are the monthly difference between the simple average of the returns on the two high FEs (unobservable) portfolios namely (HFEs/S, HFEs/B) and the low FEs portfolios (Winners), namely, (LFEs/S, LFEs/B).

$$HMLFE = 1/2(HFEs/S + HFEs/B) - (LFEs/S + LFEs/B) \tag{28}$$

Table 4.11 reports the Fama and French three-factor model and the augmented versions four and five-factor models over the period 2000-2009. The results show that the model is well specified as we cannot reject the null that all α_i's are insignificantly different from zero for all the models and for both Losers and Winners. Therefore the Fama and French three-factor model and the augmented models do well in explaining the returns on Losers, Winners and aggregate portfolios. MKT, HML LMW, and HMLFE are highly significant at 1% and 5% for the Winners and Losers. The MKT factor dominates all the other factors in the model and explains much of the variation in the portfolio returns.

HML loadings are positive in sign for the Losers and negative for the Winners; this implies that HML is positively correlated with the return on Loser portfolios and negatively correlated with the return on Winners. This suggests that value stocks (high book-to-market ratio) outperform growth stocks (low book-to-market ratio) for the Losers and the opposite is correct for the Winners.

The contrarian factor LMW on the other hand is positive for the Losers and negative for the Winners. This supports the previous results as Losers outperform Winners. Interestingly, HMLFE (High minus Low fixed effects) is negative in sign for both Winners and Losers; this suggests that lower fixed effects portfolios are not only positively correlated with the portfolios return but also outperform higher fixed effects portfolios. This result is consistent with main findings of the system GMM of chapter 3. The loadings of SMB are insignificant and quite small compared with other loadings; this suggests that size effect has a minor role in explaining portfolio returns in the Egyptian stock exchange.

Table 4.11: The Fama and French three-factor model and the augmented model for returns over the period 2000-2009

	Loser			**Winner**			**Aggregate**		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
C	-0.0002	-0.0041	-0.0050	-0.0070	-0.0053	-0.0066	-0.0003	-0.0021	-0.0028
	(0.0071)	(0.0046)	(0.0050)	(0.0048)	(0.0044)	(0.0050)	(0.0041)	(0.0037)	(0.0050)
HML	0.2661**	0.2922***	0.1907**	-0.1282**	-0.1577***	-0.1866**	0.1751**	0.2188**	0.1907**
	(0.1325)	(0.1089)	(0.0992)	(0.0673)	(0.0540)	(0.0742)	(0.0844)	(0.1098)	(0.0911)
SMB	0.0415	-0.0080	-0.0179	0.0598	0.0705	0.0796	0.0229	0.0009	0.0011
	(0.1222)	(0.0728)	(0.0750)	(0.0597)	(0.0550)	(0.0575)	(0.0736)	(0.0674)	(0.0677)
MKT	0.6829***	0.7842***	0.7800***	0.8157***	0.7898***	0.7994***	0.6439***	0.6676***	0.6668***
	(0.0694)	(0.0435)	(0.0443)	(0.0482)	(0.0447)	(0.0481)	(0.0397)	(0.0366)	(0.0370)
LMW	---	0.7825***	0.7795***	---	-0.2553***	-0.2588***	---	0.2261***	0.2236***
		(0.0541)	(0.0544)		(0.0548)	(0.0553)		(0.0465)	(0.0486)
HMLFE	---	---	-0.2146***	---	---	-0.1744***	---	---	-0.2506***
			(0.0284)			-(0.0258)			(0.0547)
ADJ R^2	0.4672	0.8053	0.8040	0.7217	0.7639	0.7625	0.6953	0.7451	0.7429
F.TEST	33.092***	98.597***	81.671***	103.86***	97.265***	77.410***	91.510***	87.940***	69.770***

The table presents the outputs of augmented Fama and French three- factor and the Carhart four- factor models as in equation 26

$$r_{it} - r_{ft} = \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t + \lambda_i LMW_t + \gamma_i HMLFE + \varepsilon_{it}$$

SMB is the difference between the return on a portfolio of small stocks and the return on a portfolio of big stocks. HML is the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks. β_i is the sensitivity of the asset returns to market portfolio, s_i is the sensitivity of the asset returns to return of SMB, h_i is the sensitivity of the asset returns to return of HML. LMW is constructed as the difference between the returns on the Losers portfolio and the returns on the Winners portfolio for a given time period. HMLFE portfolios are the monthly difference between the simple average of the returns on the two high FEs (unobservable) portfolios and the low FEs portfolios (Winners). ***, **,* indicate significance at the 1%, 5% and 10% levels.
The number of observations varies across time. It ranges from 180-251 companies.

Finally, all the models are well specified as F statistics are highly significant and the adjusted R squared range from 46%-80% for the Losers and from 69% to 76% for the Winners. I concluded that both the contrarian factor (LMW) and the fixed effects factor (HMLFE) are priced in the augmented 4 and 5 - factor models. This result is new to the literature on overreaction phenomenon.

4.6 Summary and conclusion

The main objective of this chapter has been to examine the long-term overreaction for all listed shares in the Egyptian Stock exchange over the period 1998-2009. In addition, I have investigated the validity of competing hypotheses to explain the phenomenon observed. These include the so-called size effect, the effects of time-varying risk, the stability of beta over the rank and test periods and the seasonality (calendar effect), Huang (1998). Finally, I investigate whether the contrarian and the unobservable (fixed effect) factors are priced in to returns by augmenting the Fama and French three-factor model and the Carhart (1997) four-factor model to include the contrarian and fixed effects factors.

The chapter has also helped to resolve the academic debate over alternative measures of long-term stock performance. The debate concerns the relative merits of cumulative abnormal returns (CARs) over the rebalancing method (RB) and buy and hold returns (BAHARs). Following Roll (1983), Dissanaike (1994), Loughran and Ritter (1996), and Fama (1998), in this chapter I adopted the more realistic approach in return calculations, namely, the rebalancing approach (RB).

I have argued that – following Fama (1998) – the RB CARs approach outperforms the buy and hold BH approach as the latter implies fewer theoretical and statistical problems than long-term BH. Roll (1983) argues that using monthly returns is less likely to be affected by the choice of CARs or BH. Dissanake (1994) argues that the BH approach may lead to less benefit from diversification in the longer term. Moreover, Loughran and Ritter (1996) claim that there is a little difference between BH and CARs in test period returns calculations, and they argue that the results of Conrad and Kaul (1993) are affected by the survivorship bias.

The chapter has also investigated the different types of biases and measurement errors that may explain the overreaction phenomenon i.e. bid-ask spread, survivorship bias, data-snooping bias, data mining bias, look-ahead bias, rebalancing bias and the non-synchronous trading bias. I adopted in the econometrics analysis methods to avoid and minimise the effect of the above mentioned biases.

The main contribution of this chapter is that it is – the first attempt to link the overreaction hypothesis with a change in regulatory policies, namely, the switch from strict price limits to circuit breakers. I augmented the traditional Fama and French three-factor model and the Carhart (1997) four-factor model by including the contrarian and the unobservable factors based on the company heterogeneity.

This is the first empirical study of the long-term overreaction phenomenon in the Egyptian stock market – one of the leading stock exchanges in the Middle East and Mena region (MENA).

The main findings presented in the chapter are evidence of a genuine overreaction phenomenon in the Egyptian stock market. The overreactive behaviour is not due to the small firm effect. Losers are found to outperform Winners for big and small firms and abnormal returns can be achieved by forming the arbitrage portfolio. Therefore a contrarian strategy of buying Losers and selling Winners is likely to be a profitable for investors in the Egyptian stock market. Combining with the short run results, the findings suggest that the overreaction phenomenon in the Egyptian stock market is not sensitive to the length of the formation period.

Interestingly, I found a link between changes in regulatory policies and the overreaction phenomenon in the Egyptian stock market. Results show that within the two and four non-overlapping formation periods, overreaction was not detected within the strict price limit regime. There is no significant market-adjusted abnormal return to adopting the contrarian strategy within the strict price limits regime as Losers continue to be Losers and Winners continue to be Winners; and thus there are no positive and significant abnormal returns for the arbitrage portfolio during the strict price limit period.

On the other hand, the overreaction phenomenon is present in the circuit breaker regime for both short (two years) and longer (four years) formation periods. Results here show positive and highly significant market-adjusted abnormal returns for the arbitrage portfolio. The main explanation of this seems to be the delayed price discovery hypothesis (Kim and Rhee, 1997).

The tests of the stability of beta coefficients show that beta for Loser portfolios in the aggregate test period is highly significant and outperforms beta in the rank period. This suggests that Losers are more risky during the test period. This result is consistent with Chan (1988) who argues that the risk of Loser portfolios is higher during the test period, with Losers are on average being bigger in size than those of Winners.

Conversely, betas of the Winner portfolios in the rank periods significantly exceeded those of the test periods (except for the 2008-2009 test period). In addition, the change in beta from rank to test period was negative and highly significant in the aggregate test period for the Winners. We also noticed that betas of the Losers are greater than those of Winners in the aggregate test period. This suggests that beta is *not* constant over time throughout the rank and the test periods. These results are consistent with Chan (1988) and Gaunt (2000).

The findings presented in the chapter also show evidence of the January effect in the arbitrage portfolio, as we notice positive and highly significant abnormal returns in January, whereas December reports negative and highly significant abnormal returns for the contrarian portfolio. This result is consistent with the literature on the calendar effect and the tax–loss hypothesis. Investors tend to sell Losers by the end of December to increase the capital losses and to reduce the tax burden at the end of the financial year followed by buying Winners in January.

We also noticed significant and positive abnormal returns in June and July of the year as the vast majority (84%) of the listed companies in the Egyptian stock exchange have June as the end of their financial year. This suggests that the significant abnormal returns resulting from the overreaction phenomenon in the Egyptian stock market is not mainly due to the seasonality effect.

The results of the augmented Fama and French and the Carhart (1997) models showed that the HML loadings were positive in sign for the Losers and negative for the Winners; this implies that HML is positively correlated with the return on Loser portfolios and negatively correlated with the return on Winners. This suggests that value stocks (high book-to-market ratio) outperformed growth stocks (low book-to-market ratio) for the Losers and the opposite is true for the Winners.

The contrarian factor LMW was found to be positive for the Losers and negative for the Winners. This suggests that Losers outperform Winners. Interestingly, HMLFE (High minus Low fixed effects) is negative in sign for both Winners and Losers; this suggests that lower fixed effects portfolios are positively correlated with the portfolios return and is consistent with main findings of the system GMM of chapter 3. Finally, the size effect has a minor role in explaining portfolio returns in the Egyptian stock exchange.

Chapter 5 Price limits and the overreaction phenomenon

5.1 Introduction

The term 'circuit breaker' originates in electrical engineering. In electrical engineering, circuit breakers are automated electrical shut downs of electrical activity designed to protect an electrical circuit from damage when the system's capacity is exceeded. The circuit breakers – in the context of Finance – were first launched in the NYSE in 1988 (Brady, 1988) following the stock market crash in 1987. During the market crash the Dow Jones Industrial Average (DJIA) decreased by 7.2% (554) points on 27th October 1987 (see Ackert et al., 2001). The main reason for launching this regulatory policy was to protect investors from the excessive stock price volatility by cooling down the market.

Circuit breakers became very popular and widely used by different stock exchanges over the world; however, the rules of the circuit breakers vary amongst the world's stock exchanges. Despite the popularity of the circuit breakers, there is a remarkable debate in the academic literature regarding the effectiveness of such regulatory tools, and whether or not circuit breakers actually reduce price volatility as intended.

According to the efficient market hypotheses (EMH), stock prices should reflect all information disseminated in the market, so that circuit breakers or any other regulatory policies may have a negative impact on stock markets (trading interference and volatility spillover hypotheses). In addition, imposing these regulatory polices itself implies a degree of market inefficiency and a clear violation of the semi-strong efficient market hypothesis, as circuit breakers prevent stock prices from reaching their equilibrium levels (Kim and

Rhee, 1997). According to Kim and Yang (2004), there are three main categories of circuit breakers, namely, price limits, firm-specific trading halts and market-wide circuit breakers.

5.1.1 Price limits

Price limits are regulatory tools in both equity and futures markets in which further trading is prevented for a period of time with the intention of cooling market traders' emotions and reducing price volatility. The trigger for such limits is when prices hit particular pre-specified price boundaries[23]. Table 5.1 presents price limits rules for a sample of international stock exchanges.

The proponents of price limits argue that they are efficient in reducing price volatility and providing time for both brokers and investors to adjust their portfolio positions. However, the opponents claim that these regulatory tools are useless as they lead to spreading out price volatility over a longer time, delaying price discovery, and interfering with trading activity.

5.1.2 Firm –specific trading halts

With firm-specific trading halts, trading is ceased for a given period of time within the session, or until the end of the trading session, for a particular stock(s) if prices hit the predetermined limit. The history of the firm-specific trading halts started in 1934 when Securities and Exchange Commission (SEC) was granted the power to suspend trading on

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[23] Price limits have a long history and were first implemented in the Japanese rice futures market (the Dojima exchange) in the eighteenth century (see Chung and Gan, 2005). In 1917, price limits on cotton futures contracts were used in the US. The Chicago Board of Trade (CBOT) adopted this regulatory tool in 1925 (Kim and Yang, 2004).

particular shares in the organised market (Kim and Yang (2004). The SEC extended this to the over-the-counter market in 1964 (Kim and Yang (2004).

The most popular example of firm-specific trading halts is that operated in the NYSE where there are two main types of trading halts, namely, news and order imbalance trading halts (Kim and Yang (2004). The former comes into operation when the regulator expects that disseminated news will have an impact on prices, whereas the latter comes into operation when there are large discrepancies between buy and sell orders (Kim and Yang (2004).

Table 5.1: Price limit rules for a sample of world stock exchanges.

Country	Stock exchange	Price limit
Austria	Wiener Borse AG	5%
Bangladesh	Dhaka SE	7.5–20%
Belgium	Brussels SE	5–10%
China	**	10%
Czech Republic	Prague SE	5%
Ecuador	Guayaquil SE	10–20%
Egypt	Egyptian SE	5–20%
Finland	Helsinki Exchange	15%
France	Paris SE	10–20%
Israel	Tel Aviv SE	15% (during opening)
Italy	Italian SE	10–20%
Japan	Tokyo SE	10–60%
Korea	Korea SE	15%
Latvia	Riga SE	15%
Lithuania	NSE of Lithuania	5–10%
Luxembourg	Luxembourg SE	5%
Malaysia	Kuala Lumpur SE	30%
Mauritius	SE of Mauritius	6%
Mexico	Mexican SE	10%
Peru	Lima SE	15%
Philippines	PSE	50% up, 40% down
Portugal	Lisbon and Oporto E	15%
Romania	Bucharest SE	15%
Spain	**	10%
Taiwan	Taiwan SE	7%
Thailand	Thailand SE	30%
Turkey	Istanbul SE	5%
Thailand	Thailand SE	30%

Source: Chung, J and Li Gan (2005), Estimating the Effect of Price Limit Hitting Days. Econometric Journal, Vol. 8, 81-82. **These countries have multiple exchanges where the same price limit rules apply.

Kyle (1988) argues that trading halts reduce price volatility and cool the markets down as they allow investors to adjust their portfolios or to cancel their orders. Therefore – from the perspective of regulators – trading halts may protect investors from incurring heavy losses. However, Kim and Rhee (1997) argue that trading halts also may delay price discovery mechanism. Trading halts, it is suggested, imply welfare loss for traders as they are unable to trade during the halts (Kim and Yang (2004).

Greenwald and Stein (1988) and Greenwald and Stein (1991) are regarded the main proponents of trading halts as they argue that trading halts provide a suitable time for the dissemination of information between brokers and traders, so that large price movements are expected post trading halts. Greenwald and Stein (1988) claim that these large price movements are not a cause for concern as long as there are no asymmetries of information between the traders and specialists. The appropriate objective of trading halts is to re-provide the timely information to *all* market participants.

Fama (1989) argues that trading halts historically failed to cool markets down and to decrease price volatility. In contrast, volatility is found to be higher under such halts (Lee, Ready, and Seguin (1994). Fama believes that all investors implement their *own* trading halts if they wish to analyse the disseminated information; these are called “homemade’’ trading halts, Fama (1989).

5.1.3 Market-wide circuit-breakers

Finally, with market-wide circuit breakers, trading may be stopped - for a pre-specified duration – across the whole market if the market index hits a pre-determined level. The

NYSE experience demonstrates that this is the most popular market-wide circuit breaker. Table 5.2 reports the regulations of market-wide circuit breakers in the NYSE since the market crash in 1987.

Table 5.2: The history of market-wide circuit breaker regulations

October 1988: the first implementation for circuit breaker	
250 point drop in DJIA	60 minutes trading halt
400 point drop in DJIA	120 minutes trading halt if additional 150 point drop in DJIA after trading resumes
January 1997: Circuit breakers have widener limits	
350 points drop in DJIA	30 minutes trading halt
550 points drop in DJIA	60 minutes trading halt if additional 200 point drop in DJIA after trading resumes
February 1998- present	
10% drop	60 minutes trading halt if before 2:00 p.m. 30 minutes trading halt if between 2:00 and 2:30 p.m. No trading halt if after 2:30 p.m.
20% drop	120 minutes trading halt if before 1:00 p.m. 60 minutes trading halt if between 1:00 and 2:00 p.m. Stop trading until the following trading day if after 2:00 p.m.
30% drop	Close the market for the day

Source: Ackert, L., Church, B. & Jayaraman, N. (2001) An experimental study of circuit breakers: The effects of mandated market closures and temporary halts on market behaviour. *Journal of Future Markets* 4, 182-208.
NYSE website

The theoretical and empirical models of trading halts can be extended and applied to market-wide circuit breakers (Kim and Yang, 2004). However, there are few papers analysing market-wide circuit breakers due to data availability. The NYSE, for instance, has applied market-wide circuit breakers only once since 1988 (see for example, Subrahmanyam (1994 &1997), Gerety and Mulherin (1992), Lauterbach and Ben-Zion (1993), and Goldstein and Kavajecz (2000)).

The existing body of literature on price limits studies narrow price limits in many stock exchanges i.e. Taiwan, Tokyo and Athens Stock Exchanges, Chen (1997), Kim and Rhee (1997), Phylaktis et al. (1999). The empirical findings of these papers are mixed, therefore we cannot really decide whether strict and narrow price limits decrease stock returns volatility and cool down the market.

The main objective of this chapter is to investigate, in the context of the Egyptian stock market, the effect of regulatory policies (price limits, circuit breakers) on four main hypotheses, namely, (i) the overreaction hypothesis, (ii) volatility spillover hypothesis, (iii) the delayed price discovery hypothesis and (iv) the trading interference hypothesis. In addition, the chapter investigates the impact of regulatory policies on the dynamic relationship between volume volatility relationships. Finally, it examines the effect of the regime switch (from strict price limits to circuit breakers) on the long-term volatility. In achieving these objectives the chapter provides a comprehensive literature review of price limits and the theoretical motivation for the evolution of regulatory policies.

One of the compelling reasons for studying price limits in the context of the Egyptian stock exchange is that it uniquely provides an example of the switch from strict price limits to circuit breakers The switch is accompanied by a move to much wider price limits (+/-20%) (see table 5.1).

The main contribution of this chapter is that it is the first study to investigate the overreaction hypothesis, volatility spillover hypothesis, the delayed price discovery hypothesis and the trading interference hypothesis simultaneously in the Egyptian stock market. Most importantly, it examines theses hypotheses across two different regimes, namely, strict price limits and circuit breakers. The existing body of the literature has investigated the effect of price limits or circuit breakers by examining the above mentioned hypothesis. However, due to the unique regulatory policies in the Egyptian stock market we can investigate and compare the effect of regime switch on the overreaction, volatility spillover, the delayed price discovery and the trading interference hypotheses.

There are a few stock exchanges throughout the world that have switched to a wider price limits, i.e. Thailand from 10% to 30%, and the Korean Stock Exchange from 6% to 15%. Therefore, there is an obvious policy implication in this chapter as we can identify the right band of price limits.

This chapter is organised as follows: section 2 presents the academic debate about the impact of the circuit breakers and price limits. In section 3 I present a detailed literature survey of price limits and circuit breakers in both emerging and developed markets. Section 4 describes the dataset used in the analysis. Section 5 presents the econometric modeling and the empirical results. Finally, section 6 summarises and concludes.

5.2 The impact of circuit breakers and price limits

In this section I present the theory of main effects of circuit breakers and price limits on volatility derived from the literature.

5.2.1 Information Hypothesis (Delayed price discovery)

The *information hypothesis* and the *delayed price discovery hypothesis* are used interchangeably in the Finance literature. According to this hypothesis, the price discovery mechanism is delayed due to the suspension of trading for a period of time. Therefore, it is argued, price limits prevent security prices from immediately reaching their intrinsic values and equilibrium levels (Phylaktis et al.(1999) and Kim and Rhee(1997)). Fama (1989), Lehmann (1989), and Lee, Ready, and Seguin (1994) argue that price limits interfere with the price discovery mechanism as trading usually ceases (when prices hit the limit) until the limits are revised. Therefore, at the limit-hit day these constraints (limits) prevent stock prices from reaching their equilibrium levels until the following trading day (session) (Kim and Rhee, 1997).

5.2.2 Overreaction Hypothesis

According to the overreaction hypothesis, price limits play an important role in cooling down stock price volatility. In efficient markets, investors usually react to new information arriving in the market, as a result of which, stock prices reach their equilibrium levels instantly. However, in less efficient markets i.e. emerging markets, information does not get disseminated to all investors at the same time. Therefore when new information arrives to the market, investors tend to overreact or underreact; share prices then move (up or down) towards their equilibrium levels.

Imposing price limits, on this theory, prevents speculative traders from overreacting to the information and allows more time for investors to analyse this new information and to adjust their portfolios, particularly during the trading halt period until the next trading session. Therefore price limits– in theory –should cool down market sentiment and reduce stock price volatility (Phylaktis et al. (1999), Chen (1997), Kim and Rhee (1997) and Chan et al. (2005).

5.2.3 Information asymmetry

The literature on price limits suggests that price limits provide time for information dissemination. Price limits are designed to minimise uncertainty and information asymmetry. Thus the improvement in information asymmetry depends on the effectiveness of the price limits (Chan et al. (2005), Madhavan and Smidt (1991) and Choi and Subrahmanyam (1994).

5.2.4 Order imbalance

The proponents of price limits argue that price limits provide enough time for the stock markets to correct order imbalance and to absorb large one-sided volume (supply or demand) (Chen et al., 2005). Contrary to that, Chan et al (2005) argued that price limits may be the main reason of order imbalance. They claim that as informed traders know in advance that trading will be ceased once prices hit the Upper or Lower limits, they will then buy or sell massively before trading is halted. Therefore the volume will be one-sided creating the problem of order imbalance, which in turn leads to speeding up the prices towards limits hits (magnet effect of price limits) (Cho et al. (2003) and Chen et al., (2005).

During the post limit period investors can adjust their orders based on their fundamental prices. This suggests that the trading will no longer be a one-sided volume and thus no order imbalance phenomenon will be observed during post limits period (Cho et al. (2003) and Chen et al., (2005).

5.2.5 Volatility spillover

Kyle (1988) and Kuhn et al. (1991) among others find that price limits are an inefficient tool in reducing volatility in the US. In addition, they find that price limits cause stock price volatility to spread out over a few days subsequent to the event (limit hit). Kuhn et al. (1991) argue that price limits prevent price changes above the target limit, therefore preventing immediate corrections in order imbalance. Lee et al. (1994) argue that when trading halts are announced, the news is disseminated by the media coverage, leading to dispersion of investors' belief about the equilibrium prices and thus some irrational traders are drawn to the market under the effect of excessive media coverage. This leads to an increase in both trading volume and volatility (Farag and Cressy (2011)).

5.2.6 Trading (liquidity) interference hypothesis

Fama (1989), Telser (1989), Lauterbach and Ben-Zion (1993) and Kim and Rhee (1997) claim that if trading is prevented by price limits, then shares become less liquid and this leads to intensive trading activity during the following trading days. Lehmann (1989) argued that order imbalances are corrected in the following days as informed traders will wait until the prices reach their equilibrium levels.

5.2.7 Magnet effect

Price limits may have a magnet effect in which stock prices are pulled closer to the upper or lower band. This leads to higher levels of volatility and trading volumes, see for example Subrahmanyam (1994) and Cho et al. (2003). The main reason for this phenomenon is the aggressive trading strategy by some investors (high trading volumes), who try to avoid position lock and illiquidity caused by imminent price limits hit.

In such cases traders may rush to submit orders that sometimes do not match with their trading objectives, which may lead to destabilising of the stock price behaviour (Goldstein and Kavajecz, 2004; Chanet al. 2005; Fernandes and Rocha, 2007; Wong, Chang & Tu, 2009, Hsieh et al. 2009).

5.2.8 Closing price manipulation

McDonald and Michayluk (2003) define the so called ‘suspicious’ trading halts when stock price movement during the trading session is in an opposite direction of a trading halt. Some noise traders (opportunistic) submit orders outside the limits and they know that these orders are unexecutable, so that they can terminate the trading session and preserve the most recent trade as the day’s closing price. Therefore closing prices may be subject to manipulation by noise trading investors or by fund managers, McDonald and Michayluk (2003), Felixson and Pelli (1999) and Carhart et al. (2002).

5.2.9 Information arrival modes

Farag and Cressy (2011)[24] show that there is a link between regulatory policies and the information arrival modes in emerging markets. They examine the effect of the switch from a strict price limit regime to a wider band limit regime with trading halts (circuit breakers) on the dissemination of information in the Egyptian stock exchange over the period 1998-2008. Farag and Cressy used the Mixture of Distributions Hypothesis (MDH)

[24] This paper has been published based on my earlier work in this chapter.

and the Sequential of Information Arrival Hypothesis (SIAH) as a proxy of the information arrival modes to the market. The former hypothesis assumes that information is reflected into the share price instantly; however the latter assumes that information arrives to the market in a sequential order and hence not all investors are informed and able to react upon this information. Therefore there is a delayed price reaction based on this hypothesis.

Farag and Cressy (2011) find that the mixture of distributions hypothesis (MDH) is prevailing within the Strict Price Limits. However, the sequential of information arrival hypothesis is prevailing within the circuit breakers regime. They claim that price volatility is higher within the circuit breakers regime due to the role of insider information and noise trading in emerging markets. They argue that during the trading halts period, investors have the chance to adjust their portfolios based on the new information arriving in the market. However, not all investors are informed; therefore price volatility might be greater within the circuit breakers regime.

5.3 Literature Review

In this section I summarise the literature on circuit breakers in both developed and emerging markets. Primarily I summarise the effect of imposing different types of circuit breakers on five main areas, namely, volatility and overreaction, price discovery and trading (liquidity) interference, magnet effect, market efficiency and equilibrium prices. Finally, I present the summary of the literature on the price limits in futures markets.

The effect of price limits on stock markets has been investigated in emerging markets rather than developed markets (except for futures markets). Firm-specific trading halts and market-wide circuit breakers are widely used in the developed markets.

5.3.1 Developed markets.

5.3.1.1 Volatility and overreaction

Gerety and Mulherin (1992) investigate the performance of daily trading volume when trading is halted in a particular trading session. They use hourly trading volume data of three market indices - the New York Stock Exchange (NYSE) from 1933-1988, the Dow Jones (DJ) 30 industrial index from 1933-1940 and the Dow Jones 65 Composite Index over the period 1941-1988. They estimate the expected and unexpected volatility following Brock and Kleidon (1992), and Davidian and Carroll (1987). Gerety and Mulherin (1992) find that the circuit breaker regime leads to an overreactive behaviour rather than cooling the market down as was intended. In addition they find that trading volume at the closing hour is highly related to the previous day's trading volume at the opening hour.

Lee et al. (1994) investigate the effect of trading halts on stock price volatility and trading volume. They adopt the price-matched case control methodology to isolate the volume - volatility effects on the share prices. Lee et al. (1994) control for firm-specific effects, the amount of information released and the relationship between media coverage and post trading halt activity. Using a sample of 852 trading halts of 449 firms on the NYSE during 1988, they find that trading halts increase both trading volume and stock price volatility by 230% higher than the following non halt control. In addition they find little evidence that the flow of information is not facilitated by the trading halts.

They argue that the media coverage plays an important role in explaining the post halt price behaviour due to the increase in heterogeneity of investors' beliefs.

Subrahmanyam (1994) examines the effect of circuit breakers on stock price volatility. Using the daily date of the New York Stock Exchange (NYSE) and Dow Jones Industrial Average (DJIA), the main finding of this paper is that imposing circuit breakers increases stock price volatility rather than cooling the volatility down as was intended. Furthermore, Subrahmanyam (1994) argues that circuit breakers regime has negative impact on stock market liquidity.

Santoni and Liu (1994) look at the volatility of the NYSE under circuit breakers and whether or not price limits reduce stock price volatility. Daily data are collected for the S&P 500 over the period July 1962 to May 1991. Using the ARCH model they find that imposing circuit breakers do not reduce the stock price volatility in the US. Edelen and Gervais (2003) investigate the effect of trading halts in the NYSE and find significant increases in volatility and information asymmetry following trading halts.

George and Hwang (1995) investigate stock price volatility over 24 hours for the most actively traded against the least traded shares listed in Tokyo stock exchange (TSE) over the period from January 1975 to December 1989. Using the Generalized Method of Moments (GMM), they find that price limits prevent share prices from reaching their equilibrium level when changes in share price are associated with order imbalance. Therefore, the most actively traded shares exhibit price continuation with high trading volumes.

Kim et al. (2008) look at the trading activity, liquidity, stock price volatility in addition to price discovery mechanism in the Spanish stock exchange around trading halts and price limit (Upper or Lower) hits. The Spanish stock market has a unique price limit regime which combines Strict Price Limits (+/- 15%) with discretionary trading halts based on news announcements for individual firms.

The data set consists of daily stock returns, trading volume for the listed shares in the Spanish Stock Exchange over the period January 1, 1998, to April 30, 2001. Kim et al. (2008) find that both trading volume and volatility increase immediately after trading halts. However, liquidity tends to be higher within trading halts regime compared to Strict Price Limits. They argue that investors are willing to provide liquidity as the degree of information asymmetry is reduced by the release of the new information during the trading halts.

5.3.1.2 Price discovery and trading (liquidity) interference

Greenwald and Stein (1991) investigate the relationship between the imperfection transactional mechanisms and the stock market crash in the NYSE. They find that circuit breakers play an important role in absorbing stock markets' large volume shocks and enhance the information inefficiency problems.

Kim and Rhee (1997) use daily stock price date from Tokyo Stock Exchange (TSE) over the period 1989-1992 to examine the price limits mechanism. Kim and Rhee (1997) investigate three main hypotheses, namely, volatility spillover, delayed price discovery, and trading Interference hypotheses. In TSE there are no Strict Price Limits as individual shares have different limit sizes based on the closing price in the previous day. They use the squared stock returns as a measure of stock returns volatility for all the listed shares in the TSE over a 21-day window for three different events, namely, stock hitting the limit, stocks hitting 0.90 and 0.80 of the limits.

The main finding of this paper is that imposing price limits leads to volatility spillover effects, as price limits prevent larger price changes. Therefore price limits do not cool down volatility but just spread the volatility over the subsequent days following hitting the Upper or the Lower limit. In addition they find evidence of price continuation and trading inference hypotheses as trading activity was found to increase following the limit-hit day(s).

Booth and Broussard (1998) investigate the probability that the predetermined circuit breakers will lead to trading halts in the US. Using daily data from the Dow Jones Industrial Average (DJIA) over the period 1928-1995, they find that fixed point circuit breakers in the DJIA are inefficient and inflexible, and would be more flexible by setting the trigger in relative measures.

Kryzanowski and Nemiroff (1998) examine whether the relationship between price discovery and the regulatory polices (trading halts) are stable over time. They analyse 823 trading halts from the Montreal stock exchange over three six-month sub periods arbitrarily chosen during the period 1988-1989. Kryzanowski and Nemiroff (1998) use the mean-adjusted model to measure the abnormal returns for stocks that experienced trading halts. They find that both volatility and trading volume tend to increase significantly around trading halts over two days subsequent to trading halts.

Corwin and Lipson (2000) investigate daily trading behaviour and shares liquidity around trading halts in the NYSE. The data set consists of 469 intraday trading halts for all listed shares over the period 1995-1996. They compare the normal trading activity (non halts sessions) with those of trading halts for 10 days before and after the halt. The NYSE individual shares may be subject to trading halts when a large order imbalance exists or when significant news is released and expected to affect the market value of shares. They find consistent results with Lee et al. (1994) as volatility tends to be higher following trading halts due to the decrease in liquidity around trading halts. In addition, they find higher volume of order submission and cancellation around trading halts; this suggests that investors are trying to adjust their portfolios during the halt period.

Christie et al. (2002) investigate the relationship between trading halts and the dissemination of information during the halts. In the NASDAQ there are two types of price discovery mechanisms associated with trading halts. One is the five-minute quotation period pre the resumption of trading. The second type is if a trading halt occurs after 4pm. In this case, trading will reopen the following day (trading session) with 90 minutes trading quotation. Christie et al. (2002) examine the effect of these two different reopening mechanisms on stock price movements, transaction costs, and trading activity. Data consist of 714 news-related trading halts in the NASDAQ over the period 1997- 1998.

They find that liquidity can be enhanced during the market closure as trading halts allow the dissemination of information and enable investors to adjust their portfolios. They also find highly significant increases in trading volume and stock price volatility during the 90 minutes quotation period in the following day (trading session).

McDonald and Michayluk (2003), on the other hand, examine such a type of trading halts that stimulate investors to take advantage due to the imperfection of the Paris Bourse. They do not argue about the effectiveness of the trading halts mechanism; however they define the suspicious trading halts as when stock price movement during the trading session is in an opposite direction of a trading halt.

Some noise traders submit orders outside the limits and they know that these orders are unexecutable, so that they can terminate the trading session and preserve the most recent trade as the day's closing price. Therefore closing prices may be manipulated by noise trading investors or by fund managers. The data set consists of daily transactions, quotes and orders of all continuously traded shares listed in the Paris Bourse during 1997-1998. Using the Wilcoxon rank sums test and ANOVA F-test they find that the closing price in the Paris Bourse can be manipulated by some noise traders using trading halt mechanism and this leads to a dramatic decrease in market liquidity for the rest of the trading session. Madura et al. (2006) investigate the consequences of trading halts for 656 trading halts in the NASDAQ in 1998. They compare the price behaviour pre, and post trading halts in order to examine investors' reaction to the halts. They find significant abnormal returns pre trading halts period in the NASDAQ however, they find no significant abnormal returns post trading halts.

Jiang et al. (2009) investigate the effect of trading halts on the informationally related shares in the NYSE. They define the informationally related shares based on the correlation between stock returns, trading volume and volatility within the same four digits of the SIC (industry classification). The data set consists of daily stock returns for the halted shares in the NYSE over the period 2003-2005. Using the methodology of Spiegel and Subrahmanyam (2000), they find a direct impact of liquidity on the correlation between halted and reference (non-halted) stocks. They also find that the effect of the liquidity is more significant for small firms.

5.3.1.3 Magnet effect

Abad and Pascual (2007) investigate the so called magnet effect of price limits (the acceleration of stock price movements towards their Upper/Lower limits) in the Spanish stock exchange (SSE) over the period from 2001-2003 for 114 listed shares. The Spanish stock exchange has a unique price limits mechanism in which trading session is temporarily ceased and switched to a volatility auction regime for five minutes when stock prices hit the limit. Following Madhavan (1992), they compare trading sessions with the limit hits with other normal trading sessions (no limit hits). Using FGLS they find that switching the limit regime does not create a magnet effect in the Spanish stock exchange.

5.3.2 Emerging markets

5.3.2.1 Volatility and overreaction

Huang (1998) investigates the overreaction hypothesis following up and down limit moves for all the listed shares in the Taiwan stock exchange during the period 1971-1993. Using the market model in the context of the event study methodology, he finds highly significant price reversals following up and down limit moves; these reversals are not due to size effects. Therefore the overreaction hypothesis is dominated in the Taiwanese stock market under a price limit regime. Diacogiannis et al. (2005) using the same methodology find similar results in the Athens Stock Exchange (ASE).

Phylaktis et al. (1999) investigate the effect of price limits on stock price volatility in the Athens Stock Exchange (ASE). They also examine the information and overreaction hypotheses. The dataset consists of daily and monthly closing prices for the most active 10 stocks in the ASE over the period from January 1990 to June 1996. Using the serial correlations of the daily returns and the time varying model (Generalized Autoregressive Conditional Heteroscedasticity - GARCH), they find that price limits have no effects on stock price volatility. Their results support the information and the overreaction hypotheses in the ASE.

Shen and Wang (1998) examine the effect of price limits on stock return autocorrelation and trading volume. Using daily date from the Taiwan stock exchange over the period from November 1988 to December 1995, and using the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and the Generalized Method of Moment (GMM), they find evidence of the impact of price limits on stock returns autocorrelation. They also find that the Upper limits have a positive and stronger impact than the Lower limits.

Kim and Limpaphayom (2000) look at the characteristics of shares that frequently hit the limit in Taiwan and Thailand stock exchanges. The dataset consists of daily and monthly returns over four years 1990-1993. They find that it is highly likely for the share to hit the limits if it has small market capitalisation (small firm effect), high volatility, and high trading volume.

Huang et al. (2001) investigate the information and overreaction hypothesis in the Taiwan stock market. The dataset consists of all Upper and Lower limit hits for three consecutive days for all listed shares in the Taiwan stock exchange over the period 1990-1996. The study extends the analysis to further investigate the intraday limit moves and near-limit cases. They use the market model in the context of the event study methodology to examine the overnight and trading time abnormal returns. The main findings of the paper support both the information and the overreaction hypotheses as a continuation pattern is found in the overnight period following limit moves and price reversal behaviour is reported in the subsequent trading days due to noise trading.

Lee and Chou (2004) investigate the characteristics of stock returns around intra-day price limits in Taiwan stock exchange and conclude that there is no significant relationship between intra-day price limits and stock return dynamics. The sign of the pre-event (limit) price movement and the market capitalisation play an important role in explaining the intraday return dynamics.

Nath (2005) investigates the effect of price limits on different groups of stocks listed in the National Stock Exchange (NSE) in India over the period 1999-2000. Nath concludes that price limits are found to be a useful tool in captivating volatility for some individual shares but not for the entire Indian stock market.

Kim and Yang (2008) examine the relationship between price limits and both information asymmetry and intra-day price volatility by investigating the information and the overreaction hypotheses in the Taiwanese Stock Exchange (TWSE). They identify three main types of limit hits, namely, closing, single, and consecutive. They use transaction data for all listed shares in the TWSE during 2000. They compare stock returns and variances during five-minutes in either 30 or 15 minutes before and after limits hit. Results show that there is a dramatic decrease in price volatility following consecutive limit hits; in addition, price limits are found unable to reduce information asymmetry in the TWSE.

5.3.2.2 Price discovery and trading (liquidity) interference

Lauterbach and Ben-Zion (1993) analyse stock price movements of small firms after imposing circuit breakers during the stock market crash of 1987 in the Tel Aviv Stock Exchange (TASE). They use a short window (form 13th to 28th October) of daily stock prices, firm characteristic and order imbalances data around the stock market crash (1987). Regressing order imbalances on firm specific characteristics, they find no evidence that circuit breakers affect the magnitude of the market decline. In addition, they find that during the crash (1987) the selling pressure were concentrated on both higher beta and bigger companies. They conclude that circuit breakers might have smoothed the fluctuations in share prices, i.e. reduced volatility.

Chen et al. (2004) following the methodology of Bossaerts and Hillion (2001), investigate the learning behaviour of rational investors and the role of past information within the strict (7%) price limits regime in Taiwan. Using daily data of 362 IPOs over the period 1991-1998, they find significant and positive abnormal returns in the four months post IPO. This suggests underreaction behaviour due to the delayed information hypothesis under price limits regime.

Chen et al. (2005) use daily data of 83 firms over the period from July 1999 to December 2002 form the Chinese stock exchange to investigate whether illiquid stocks are highly affected by price limits and are more vulnerable to hitting the limit more frequently than liquid shares. The regulator in the Chinese stock exchange set Strict Price Limits +-10% on the daily prices. Chen et al. (2005) analyse a sample of both A-shares (shares that are owned and traded by the Chinese investors) and B-shares (shares that are owned and traded by the non-Chinese investors).

Their main argument is that B-shares are less liquid than those of A-shares due to the discrepancies in ownership structure. If this is the case then there should be wider price limits for B-shares compared to A-shares. They find that B-shares are less liquid and have a wider bid-ask spread than those of A-shares. This suggests that B-shares hit the limits more frequently than those of A-shares. They also find a positive and systematic relationship between the bids - ask spread and the tendency to hit the limits.

Chan et al. (2005) investigate the effect of imposing wider price limits (+/- 30%) on price discovery mechanism, information asymmetry and order imbalance in the Kuala Lumpur Stock Exchange (KLSE) of Malaysia. They use order flow data and real-time transaction data over the period from January 1995 to December 1996. They identify two main groups, namely, the limit-hit and non limit-hit groups. Using the methodology of Madhavan and Smidt (1991) and Choi and Subrahmanyam (1994) and by comparing pre- and post-hit periods, they find no evidence that price limit enhances information asymmetry. They also find that price limits delay the information flow and lead to order imbalance. Kim (2001) finds similar results on the Taiwanese Stock Exchange and argues that the more restricted bands of price limits the higher the volatility of stock returns.

Bildik and Gulay (2006) investigate the effects of price limits on the volatility spillover, delayed price discovery, and trading interference hypotheses using the methodology of Kim and Rhee (1997). The data are collected from Istanbul stock market over the period 1998–2002. They find that volume weighted average prices (VWAP) provide stronger evidence for the volatility spillover, delayed price discovery, and trading interference hypotheses.

Chou et al. (2006) estimate the Value at Risk (VaR) using the two-limit type Tobit models. Following the methodology of Scholes and Williams (1977), they investigate the potential bias at VaR estimation due to the infrequent trading and price limits. Using daily stock returns of all listed shares in the Taiwan Stock Exchange (TWSE) together with the over the counter market data over the period 1998-2003, they find that the simulation models are reasonably well specified in the TWSE except for the OLS even in cases of higher volatility when prices hit the limits.

Chen et al. (2005) used the methodology of Kim and Rhee (1997) to investigate the volatility spillover and the trading interference hypotheses in the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE). Their results support the two hypotheses; in addition they find that the higher the book-to-market ratio the greater tendency to hit the limit.

5.3.2.3 Magnet effect

Cho et al. (2003), investigate the so-called 'magnet' effect of price limits. This effect implies the acceleration of stock price movements towards their Upper/Lower limits when limits are imposed. They use high-frequency data, namely, intra-day data from Taiwan stock exchange TWSE (5-minute return series on all the listed shares from January 3, 1998 to March 20, 1999). Cho et al. (2003) tackle the deterministic volatility pattern by standardising the 5-minute returns by its standard deviations. They find evidence of the so called ceiling magnet effect (price acceleration towards *upper* limits); however they find only weak evidence of floor magnet effect (price acceleration towards *lower* limits). They argue that the magnet effect is considered strong evidence against the overreaction hypothesis so that price limits fail as a tool to control price overreaction.

Hsieh et al. (2009) use transactional data from the TWSE to investigate the magnet effect. Using the Logit model their findings support the magnet effect in the Taiwanese stock exchange; they also find significant increase in the conditional probability when prices reach their upper limits and the opposite is correct when prices approach the lower limits.

Wong et al. (2009) investigate the intra-day dynamics of magnet effect (ceiling and floor) of the price limits in the Shanghai Stock Exchange (SHSE) using intra-day data (5-minute price returns half an hour prior to the limit hits) over the period January 2002 to December 2002. They use the methodology of Du et al. (2005) and find evidence of an acceleration of both trading activity and stock price volatility when prices approach limits hit. In addition they find an asymmetric price limit effect between ceiling and floor limits as trading volume tends to be lower when stock prices approach the lower limits.

5.3.2.4 Market efficiency

Lee and Chung (1996) investigate the effect of price limits on market efficiency in the Korean Stock Exchange KSE. The dataset consists of thirty active individual stocks over the period from January 1990 to December 1993. They use the conditional heteroscedasticity to test for efficient market hypotheses in the Korean Stock Exchange (KSE). They find evidence that the KSE seems to be inefficient due to price limit regime. They argue that opening prices reflect all the information that is not fully reflected during the previous trading session (day) due to price limits.

Lee and Kim (1995) investigate the effect of price limits on the parameters of the market model particularly on beta in the Korean stock exchange. They use the methodology of restricted regression analysis together with the two-pass regression to investigate whether or not the estimation of beta is biased. The dataset consists of all listed shares in the Korean Stock Exchange over the period 1990-1993. They find that the stochastic process of the returns and the parameters of market models are significantly affected by the price limits regime. They also find that the estimation of beta is biased and unstable over the time.

Rayoo and Smith (2002) investigate the random walk hypothesis in the Korean stock exchange (KSE) under different regimes of price limits during the period 1988-1998. They conclude that stock prices in the Korean stock exchange under wider bands of price limits (+-15%) follow the random walk hypothesis; however within thinner bands of limits the random walk process is not detected. Berkman and Lee (2002) conclude that the wider the price limits band the greater the long-term volatility and the lower the trading activities in the Korean stock exchange.

Naughton and Veeraraghavan (2004) investigate whether or not price limits are priced. The dataset consists of monthly stock returns over the period 1975-1996 in the Taiwanese stock exchange (TWSE). They augment the Fama and French three-factor model by adding the price limit factor. Naughton and Veeraraghavan (2004) find that size and price limits factors significantly explain the cross section of stock returns in Taiwan. They find that shares that hit the limit less frequently have significant returns and risk premium.

Kim and Park (2010) interestingly find a high direct relationship between the level of corruption together with low-quality public enforcement and the likelihood of adopting price limit regimes using a sample of international stock exchanges. They find no significant relationship between the information asymmetry and price limits regimes.

Recently, Farag and Cressy (2011) investigate the relationship between regulatory policies and the information arrival modes in the Egyptian stock market. They examine the effect of the switch from strict price limit regime to a wider band limit regime with trading halts (circuit breakers) on the dissemination of information in the Egyptian stock exchange over the period 1998-2008. Farag and Cressy (2011) use the Mixture of Distributions Hypothesis (MDH) and the Sequential of Information Arrival Hypothesis (SIAH) as a proxy of the information arrival modes. The former hypothesis assumes that information arriving in the market is reflected into the share price instantly; however the latter assumes that information arrives in a sequential order and hence not all investors are informed and able to react upon this information. Therefore there is a delayed price reaction based on this hypothesis.

Farag and Cressy (2011) find that the mixture of distributions hypothesis (MDH) is prevailing within the Strict Price Limits. However, the sequential of information arrival hypothesis is prevailing within the circuit breakers regime. They claim that price volatility is higher within the circuit breakers regime due to the role of insider information and noise trading in emerging markets. They argue that during the trading halts period, investors have the chance to adjust their portfolios based on the new information arriving in the market, however not all investors are informed; therefore, price volatility might be greater within circuit breakers regime.

5.3.2.5 Equilibrium prices

Chung and Gan (2005) investigate the relationship between price limits and the underlying equilibrium prices on limit-hitting days. In addition they examine the ceiling and cooling effects. The sample consists of 69 continuously traded stocks over the period 1987-1997. They use a mixture normal density and the Mixture of Distributions Hypothesis (MDH) - introduced by Clark (1973) and then developed by Epps and Epps (1976) and Tauchen and Pitts (1983) - as a proxy of the latent information content of the price limits. Using the maximum likelihood estimation of the effect of price limits on all listed shares in the Taiwanese stock exchange, they find evidence of the cooling effect as imposing price limits leads to cooling down the average stock returns. In addition, they find a significant effect of price limits on stock return volatility assuming that stock returns follow a simple normal density function. However, these effects disappear if the mixture normal density function is used.

Hsieh and Yang (2009) argue that equilibrium prices are unobservable when share prices hit the limit. Therefore they use the censored stochastic volatility model (SCV) to examine shares return process under price limits. The dataset consists of a sample of two actively traded shares in the Taiwanese stock exchange (TWSE) in addition to two futures contracts in the Chicago Board of Trade CBOT. They find that the SCV model offers better interpretation to risk–return relationships under price limits. In addition, they suggest that portfolio managers may use the censored stochastic volatility model (SCV) in order to obtain better estimates for risk under price limits.

Wei (2002) uses the censored generalised autoregressive conditional heteroskedasticity – GARCH – to model returns process under price limits. Wei (2002) concludes that price limits should be taken in consideration when modelling securities returns. He argues that price limits distort the behaviour of the return distribution causing negative kurtosis.

Hauser et al. (2006) investigate the effect of trading halts on the price discovery mechanism and the speed of adjustments to the new information. The dataset consists of all company announcements during 2001 in the Tel Aviv Stock Exchange (TASE). They find that during trading halts information dissemination of the announcements is faster. In addition they find that investors use trading halts periods to adjust their portfolios and that both volatility and trading volume increased subsequent to trading halts.

The literature on price limits is much diversified including many policy implications topics, i.e. leverage and stock market stability under price limits (Chowdahry and Nanda, 1998), market quotes and spread components between cross listed shares, (Kryzanowski and Nemiroff, (2001), describing the behaviour of asset pricing under price limits (Chou, 1999), the impact on the lead-lag portfolio returns (Chiao et al. (2004), trading strategies during circuit breakers Goldstein and Kavajecz (2004).

5.3.3 Price limits in Futures Markets

Due to the unique characteristics of futures markets the empirical results of the literature on price limits in equity markets cannot be generalised to futures markets. I present in this section the main findings of the effect of imposing price limits in futures market.

Ma et al. (1989) find that price limits decrease stock price volatility immediately after limit moves in the Treasury Bond futures market. They use Treasury Bond futures prices to test both the overreaction and the information hypotheses over the period 1980-1983 in the Chicago Board of Trade (CBOT). Ma et al. (1989) also examine the effect of imposing price limits on the behaviour of the commodities futures market. They find evidence of price reversal one day following limits hit associated with high trading volume. In addition they find that price limits lower volatility and do not disrupt the price discovery mechanism.

Arak and Cook (1997) investigate the effect of imposing daily price limits on the Treasury Bonds in the US stock market. The main objective is to investigate whether or not price limits destabilise price behaviour or act as a magnet in the U.S. Treasury Bond futures market. Daily price data are collected for the US Treasury Bonds over the period from 1980 to April 29 1987. In order to include a day into the dataset, the absolute value of the overnight price change should be twice as the standard deviation. Two empirical models are used to examine the effect of the price limits or news on the change in price. They find that price limits lead to little price reversal behaviour; this supports that the role of price limits as a stabiliser in the US futures market.

Ackert et al. (1997) investigate the impact of the changes in price limits regulations on investors' expectations. Using the of S&P 500 futures contracts, they find that circuit breakers fail to minimise both futures market volatility and investors expectations.

Chen (1998) investigates the overreaction hypothesis and the effect of price resolution in futures markets. The dataset consists of daily prices for 19 futures contracts. The main results of the paper relatively support the efficiency of futures market in the US with regard to information dissemination. In addition, he finds little evidence of the overreaction hypothesis in the US futures markets.

Chou et al. (2005) also investigate the relationship between price limits and default risk and whether or not price limits can reduce the effective margin requirements and to minimise default risk in the Taiwanese futures market. They find evidence that price limits can actually reduce the cost of contracts and the margin requirements only for low risk aversion investors. They also find that price limit is not an efficient tool to cool down the futures price volatility for risk averse investors.

Ackert et al. (2001) investigate the relationship between circuit breakers and both trading volume and price dynamics in the NYSE futures markets. They use experimental methods on nine different markets to analyse and compare the behaviour of prices under three regulatory policies, namely, temporary halt, no limit effects and market closure. They find that circuit breakers significantly affect trading volume as trading activities tend to be higher when prices are closer to limits hit. They also find no impact of temporary trading halts on trading behaviour.

Similarly, Holder et al. (2002) collect data of Treasury Bond futures prices from the Chicago Board of Trade (CBOT) over the period 1980-1988. They conclude that price limit moves can be predicted three hours prior to the first limit move as they argue that the true futures prices deviate from the actual prices. In addition they find evidence that the overreaction hypothesis may offer a better explanation to the behaviour of stock prices around limits than the information hypothesis in the US futures market.

There is a growing body of literature investigating the effect of price limits in futures markets, mainly the returns predictability under circuit breakers, price discovery mechanism and volatility of futures contracts, see for example, Kao and Ma (1992), Kuserk and Locke (1996), Berkman and Steenbeek (1998), Broussard (2001), Hall and Kofman (2001), Martens and Steenbeek (2001), Chen (2002), and Egelkraut et al. (2007),

To conclude, the effect of the different types of circuit breakers has been excessively investigated in both developed and emerging markets in addition to futures markets. The main finding of the empirical literature is that price limits increase volatility in the short run rather than cool the market down as was intended. However, there is no clear effect or evidence of price limits and/or circuit breakers in the longer-term due to the time-varying price volatility.

Kim and Yang (2004) argue that the time-varying price volatility makes it difficult to investigate the effect of regulatory policies on stock price movements. In this chapter I investigate the effect of both short and long-term effects of regulatory policies (price limits and/or circuit breakers) on stock price movements; this is one of the main contributions of this chapter[25].

On the other hand, the main findings of the empirical literature support the argument that imposing price limits results in delaying the price discovery mechanism and the so called magnet effect. The literature survey concludes also that the effects of price limits on price overreaction are mixed, Kim and Yang (2004). Moreover, the results of the empirical literature on trading halts are consistent for both developed and emerging markets as volatility and trading volume are found to be higher around trading halts. Trading halts support the process of information dissemination during the halt period as intended. Finally, the main conclusion of the empirical studies is that price limits have no value added to the stock markets; on the contrary these policies should have been reconsidered by the regulators, Kim and Yang (2004). Table 5.17 presents a summary of main findings of the literature on price limits and circuit breakers in equity markets.

[25] This result has been published in Farag and Cressy (2011) based on the earlier version of this chapter.

5.4 The data

The Egyptian Stock Exchange (EGX) has become one of the biggest and most promising emerging markets in Middle East and North Africa region, having grown substantially since the beginning of the Egyptian economic reform and privatisation program in mid-1990s.

The Egyptian stock exchange (EGX) has unique history of price limit regimes; this makes studying the EGX - amongst few other stock exchanges i.e. Korean stock exchange - interesting. Since 1996 EGX trading regulations have imposed strict (+-5%) price limits (SPL) for all the listed shares. The limit is activated for a particular stock only when stock returns hit the Upper or Lower limit, then the trading on these shares is suspended to the end of the trading session. The SPL is only removed in case of any corporate action. The SPL was first launched by the regulator to cool down the market and to avoid excess volatility.

In 2002 the regulator commenced a new price ceiling system, namely, circuit breakers (CB) in which the price limits have winded to (+-20%) for the most actively traded shares in the EGX. Within the new CB regime, trading is halted for 30 minutes when stock return for a particular stock hits (+-10%).

During the 30-minute trading halt, brokers should inform their clients about the temporary suspension of the trading session. In addition they are allowed to cancel or adjust traders' orders to adjust their portfolio positions. When the trading session is resumed and if stock return for a given share hits the Upper or Lower limit (20%), trading is suspended until the end of trading session.

The dataset consists of daily open, high, low and closing prices for all listed shares in the Egyptian stock exchange over the period 1999-2009, in addition to trading volumes as a proxy for trading activity and market capitalisation as a proxy for size. I use the EGX30 - a free-float market capitalisation-weighted index - as a benchmark.

5.5 Econometrics Modeling and empirical results

In this section, I present the econometric modeling used in this chapter to investigate the effect of the changes in regulatory policies on the overreaction hypothesis, volatility spillover hypothesis, delayed price discovery hypothesis, the trading interference hypotheses and the volume volatility relationship. In addition, I present the empirical results and the main findings.

The econometric modeling of this chapter depends on the methodologies of both Huang (1998), Kim and Rhee (1997) and Farag and Cressy (2011). The main difference between the methodology of this chapter compared to the papers of Huang (1998) and Kim and Rhee (1997) is that it is – to the best of my knowledge – the first to examine and compare the effect of regime switch (from Strict Price Limits to circuit breakers) on the overreaction, volatility spillover, the delayed price discovery and the trading interference hypotheses.

5.5.1 Overreaction hypothesis

To investigate the overreaction hypothesis under price limits and/or circuit breakers, I adopt the event study methodology of Brown and Warner (1980) and Huang (1998). I start in section 5.5.1.1 defining the returns measures I shall use.

5.5.1.1 Daily Returns

The return variable R_t is defined as the first difference in the natural logarithm of the closing price over two consecutive trading days:

$$R_t = Log\ p_t - Log\ p_{t-1} \qquad (1)$$

where p_t is the adjusted (dividends, stock split and stock dividends) closing price of the stock in day (t).

5.5.1.2 Stock Abnormal Returns (ARs)

I estimate the market model parameters α_i and β_i over estimation window 125 days (-140,-16) as in equation 2. Stocks' Abnormal Returns in the test period are defined as follows:

$$R_{it} = \alpha_i - \beta_i R_{mt}, \quad t = 0,1,2.....,T \qquad (2)$$

I define the event (t=0) as when stock prices hit the Upper or the Lower limit in both regimes (SPL +/-5%) and (CB +-10%). The Egyptian stock market is regarded as a thinly trading market so that and in order to avoid the infrequent trading bias, and following Huang (1998), I exclude those shares that are not traded at least 80% of trading days during the estimation window. Following Huang (1998), the event window is (-15, +15) and the security abnormal return in the post-event period has been estimated as in equation 3:

$$AR_{it} = R_{it} - \alpha_i - \beta_i R_{mt}, \quad t = 0,1,2.....,T \qquad (3)$$

where T = 31days around event (-15, +15), α_i and β_i are the parameters of the market model for each company over the estimation window using the OLS. In addition to the OLS, I use the GARCH and TARCH models to estimate security abnormal returns and obtained similar results as the OLS. R_{it} and R_{mt} are the returns on company (i) and the value weighted market index EGX30 respectively.

To further develop the analysis, I examine the effect of firm size on the overreaction hypothesis in the style of Huang (1998). Market capitalisation (as a proxy for size) is calculated for each share based on the average daily market capitalisation in the previous month (t-1). Firms included in the sample are ranked in an ascending order and grouped into five quintiles based on market capitalisation of the previous month. This process is updated according to the monthly market capitalisation rankings of the firms included in a sample. Therefore, daily average abnormal returns have been calculated for two groups, namely, Small-Big based on the first and fifth quintile.

5.5.1.3 Average and Cumulative Abnormal Returns (CARs)

The daily average abnormal return (*AAR*) for a given day for (*n*) events and the cumulative average abnormal returns for the event window (-15, +15) are calculated as in equations 4 and 5.

$$AAR_{it} = \frac{1}{n}\sum_{\tau=1}^{t} AR_{i\tau} \quad (4)$$

$$CAR_{it} = \sum_{\tau=1}^{t} AR_{i\tau} \quad (5)$$

The test statistic for a given day within event window is

$$t = AR_t / S(AR_t) \quad (6)$$

And the standard deviation of the Abnormal Returns is:

$$S(AR_t) = \sqrt{\sum_{t=a}^{n} (AR - AAR)^2 / n - 1} \quad (7)$$

5.5.1.4 Event definition

I define the Event in our analysis as when a stock hits its Upper or Lower limit within the two regimes (SPL and CB). The total number of events is 4221 over the period 1999-2009. 1655 and 771 events are associated with +5% and +10% Upper limit hits respectively; 1174 and 621 events are associated with -5% and -10% Lower limit hits respectively. Table 5.3 and figure 5.1 summarise the total number of events over the period 1999-2009.

Table 5.3: Summary statistics for the total number of events

year	Upper limit Hits		Lower limit Hits		Total no. of events
	+5%	+10%	-5%	-10%	
Total no. of events	1655	771	1174	621	4221
1999	163	0	81	0	244
2000	170	0	94	0	264
2001	174	0	115	0	290
2002	187	21	127	18	353
2003	194	34	139	21	388
2004	208	44	143	32	427
2005	283	52	223	43	601
2006	182	127	167	133	609
2007	38	146	35	106	325
2008	31	168	29	124	352
2009	24	179	21	144	368

Figure 5-1: Total number of events over the period 1999-2009

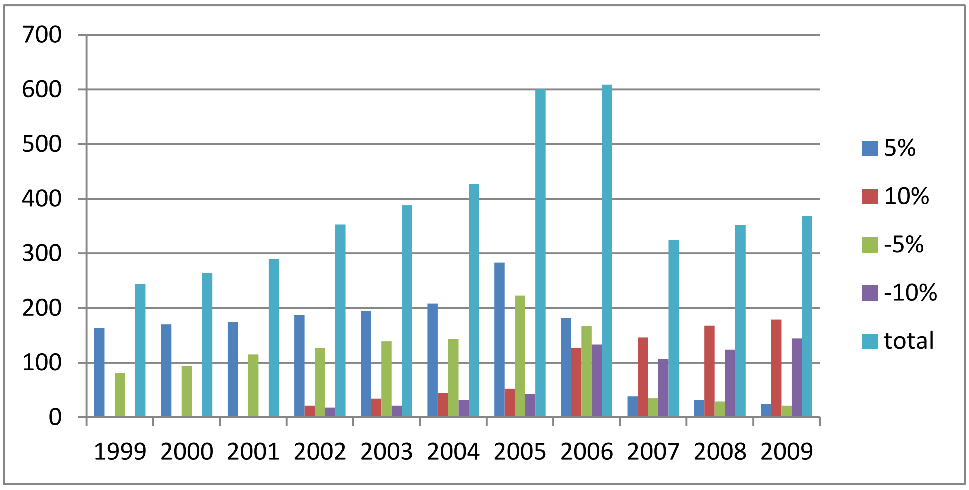

Table 5.3 shows that the total number of events associated with Upper limit hits (2426) is greater than those associated with Lower limits hits (1795) for the two regimes. The total number of the Upper limit hits is greater than those of the Lower limit hits by 41% and 24% for the (SPL) Strict Price Limits and CB regimes respectively. This suggests that either price limits or circuit breakers are more likely to prevent stock price increases rather than price decreases.

Table 5.4 presents the average abnormal returns and the cumulative average abnormal returns for the Strict Price Limits (SPL) Upper and Lower limit hits (+-5%). Table 5.4 shows that the average abnormal returns for the Upper limit hits on event day is positive (3.95%) and highly significant, meanwhile the average abnormal returns for the Lower limit hits on event day is negative (4.45%) and highly significant as well. Price reversals occur in the third day subsequent to Upper limit hits and on the second day for the Lower limit hits.

Table 5.4: Average abnormal returns for upper and lower limit hits within the Strict Price Limits regime

	Upper limit hits				Lower limit hits			
Days	+5%				-5%			
	AR(%)	CAR(%)	t(AR)	t(CAR)	AR(%)	CAR(%)	t(AR)	t(CAR)
-15	-0.1337	-0.1337	-0.7053	-0.7053	-0.1466	-0.1466	-0.7416	-0.7416
-14	0.4708	0.3371	2.3759**	1.1345	0.0436	-0.1030	0.2238	-0.3215
-13	-0.0091	0.3280	-0.0476	0.9721	0.0247	-0.0783	0.1620	-0.2275
-12	-0.0403	0.2877	-0.2522	0.6879	0.1019	0.0236	0.5391	0.0626
-11	-0.2779	0.0098	-1.5355	0.0199	0.1778	0.2014	1.0985	0.4825
-10	0.4274	0.4371	2.0443**	0.7266	0.2186	0.4200	1.1556	0.8003
-9	0.3331	0.7702	2.0270**	1.1084	0.1235	0.5435	0.6470	0.9827
-8	-0.1745	0.5957	-1.0198	0.7933	0.4712	1.0147	2.5957***	1.5929
-7	0.2254	0.8212	0.9448	1.0718	0.1224	1.1371	0.7364	1.6877*
-6	0.1820	1.0031	0.8574	1.1912	0.1869	1.3240	0.9184	1.7804
-5	0.1699	1.1730	0.6652	1.2834	0.3655	1.6895	1.6938*	2.0334**
-4	0.1105	1.2835	0.5700	1.3923	0.4626	2.1521	2.0669**	2.4037**
-3	0.1105	1.3941	0.5700	1.2337	0.4626	2.6147	2.0669**	2.4243**
-2	-0.1225	1.2716	-0.4642	0.9835	0.5427	3.1574	2.3646**	2.6531***
-1	0.2801	1.5517	1.8423*	1.7903*	0.1087	3.2661	2.4301**	2.4896**
0	**3.9534**	**5.5051**	**16.0287*****	**4.2220*****	**-4.4529**	**-1.1868**	**-26.737*****	**-2.7332*****
1	0.1362	5.6413	0.3454	4.052***	-0.3606	-1.5474	-0.5246	-0.7338
2	0.6337	6.275	1.7307*	3.3583***	0.1696	-1.3778	0.6839	-0.8564
3	-0.2785	5.9965	-0.9321	3.4481***	0.5106	-0.8672	0.7667	-0.5402
4	0.4493	6.4458	1.3325	3.6264***	0.8104	-0.0568	1.7195	-0.0612
5	0.4683	6.9141	1.7822*	3.718***	-0.4758	-0.5326	-2.0772	-0.2555
6	0.0938	7.0079	0.315	3.619***	-0.014	-0.5466	-0.0754	-0.2593
7	-0.2552	6.7527	-0.9973	3.326***	0.7228	0.1762	1.1274	0.1783
8	0.1858	6.9385	0.7209	3.3392***	-0.1532	0.023	-0.8588	0.0934
9	0.1855	7.124	0.7789	3.3875***	-0.2755	-0.2525	-1.252	-0.0574
10	0.1091	7.2331	0.318	3.2987***	-0.4219	-0.6744	-2.0937**	-0.2886
11	0.0062	7.2393	0.0217	3.2778***	0.1079	-0.5665	0.5671	-0.2285
12	0.4204	7.6597	1.7641*	3.4827***	-0.0441	-0.6106	-0.2445	-0.2573
13	0.2426	7.9023	0.8959	3.5581	-0.2921	-0.9027	-1.3307	-0.4106
14	0.3764	8.2787	1.4538	3.5337***	0.0475	-0.8552	0.2305	-0.3778
15	0.551	8.8297	2.5838***	3.6886***	-0.2898	-1.145	-1.3161	-0.5264

***, **,* indicate significance at the 1%, 5% and 10% levels. The number of observations varies across time. It ranges from 180-251 companies and the total number of events is 4221 events.

A possible explanation for this phenomenon is the Delayed Price Discovery hypothesis. According to this hypothesis Strict Price Limits delay or prevent stock prices from reaching their equilibrium levels for a few days after the event as trading is suspended until the end of trading session when prices hit the limits. Therefore the effect of limit hit continues in the following day(s) subsequent to up and down limit activation.

In addition, we notice the leakage of information effect one day pre the Upper event (AR= + 0.28% and marginally significant). This suggests that Upper limit hits might be predictable one day pre the event. As for the Lower limit hits, table 5.5 reports highly significant and positive abnormal returns five days pre the event. This suggests that the Lower limit hits may not be predictable under the strict (-+5%) price limit regime. The positive and significant abnormal returns five days pre vent may imply investor optimism towards stock prices and herding bahaviour[26].

Table 5.5 presents the average abnormal returns and the cumulative average abnormal returns for the +-10% Upper and Lower limit hits.

Table 5.5 shows that the average Abnormal Returns for the Upper and Lower limit hits on event day are (+11.32%) and (-8.63%) respectively and both are highly significant. Price reversal occurs on day one following the Upper and Lower limit hits; however, the latter is highly significant.

We notice the leakage of information effect for the Upper limit hits, as the abnormal returns on day one pre-event are highly significant, (although positive abnormal returns are found four days pre-event). This suggests that Upper limit hits might be predictable one day pre the event within the circuit breakers (CB) regime.

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[26] If there is a leakage of information effect we would expect negative and significant abnormal returns pre event.

As for the Lower limit hits, table 5.5 reports positive abnormal returns six days pre the event, which suggests that the Lower limit might not be predictable under the CB regime.

Table 5.5: ARs and CARS for Upper and Lower limit hits within the CB regime

Days	**Upper limit hits**				**Lower limit hits**			
	+10%				-10%			
	AR(%)	CAR(%)	t(AR)	t(CAR)	AR(%)	CAR(%)	t(AR)	t(CAR)
-15	-0.0352	-0.0352	-0.1146	-0.1146	0.7467	0.7467	1.9948**	1.9948**
-14	-0.1875	-0.2227	-0.7146	-0.8474	1.2343	1.9810	3.8296***	4.2844***
-13	-0.7487	-0.9714	-2.4672**	-1.3135	0.2616	2.2426	0.6871	3.3353***
-12	-0.0655	-1.0369	-0.2752	-1.2489	0.0250	2.2676	0.0923	3.2370***
-11	-0.5312	-1.5681	-1.7723*	-1.5640	0.6578	2.9254	1.5807	2.7832***
-10	-0.3646	-1.9327	-1.1692	-1.6915*	0.5777	3.5031	1.3842	2.3340***
-9	0.4298	-1.5029	1.5179	-1.0597	0.4586	3.9617	1.2985	2.6023***
-8	0.0697	-1.4332	0.3258	-1.1228	-0.0195	3.9422	-0.0672	2.4284**
-7	0.3477	-1.0855	1.0907	-0.6605	-0.4015	3.5407	-1.3467	2.0850**
-6	-0.1090	-1.1945	-0.4382	-0.4560	0.0780	3.6187	0.2473	2.0273**
-5	-0.1169	-1.3114	-0.3555	-0.3608	0.7022	4.3209	2.0623	1.9820**
-4	0.3177	-0.9937	0.9916	0.2769	0.4225	4.7434	1.1711	2.0687**
-3	0.3177	-0.676	0.9916	0.5384	0.4225	5.1659	1.1711	2.2486**
-2	0.0627	-0.6133	0.1490	0.9301	0.1050	5.2709	0.2430	2.5619**
-1	0.6043	-0.009	1.9668**	1.1639	0.3731	5.644	1.0595	2.6258***
0	**11.3280**	**11.319**	**30.6179***	**7.3844***	**-8.6362**	**-2.9922**	**-21.384***	**-2.9432***
1	-0.5768	10.7422	-0.9159	7.0178***	1.6122	-1.38	2.9928***	-1.9197*
2	-0.1945	10.5477	-0.3465	6.2229***	-0.6983	-2.0783	-1.9257*	-1.0556
3	0.6262	11.1739	1.4070	6.0432***	-0.0692	-2.1475	-0.1643	-1.1549
4	-0.0290	11.1449	-0.0701	5.7334***	-0.9047	-3.0522	-1.3984	-1.4125
5	0.0026	11.1475	0.0053	5.1626***	0.6204	-2.4318	1.0971	-0.6703
6	-0.1624	10.9851	-0.3823	5.0544***	0.0002	-2.4316	0.0007	-0.4215
7	0.2800	11.2651	0.5203	4.6873***	-0.5460	-2.9776	-1.7603*	-0.7332
8	0.2905	11.5556	0.6901	4.6616***	-1.3613	-4.3389	-1.7523*	-1.1866
9	1.0686	12.6242	1.9663**	4.5480***	-0.4132	-4.7521	-0.6104	-1.2211
10	-0.2191	12.4051	-0.5495	4.3324***	0.0724	-4.6797	0.1247	-1.3032
11	-0.1317	12.2734	-0.3226	4.1756***	-0.0407	-4.7204	-0.0837	-1.3312
12	0.1090	12.3824	0.2530	4.7106***	-0.2387	-4.9591	-0.5701	-1.1091
13	0.2646	12.647	0.6042	4.9524***	-0.2259	-5.685	-0.5191	-1.2902
14	-0.2947	12.3523	-0.7927	4.7403***	-0.4727	-6.1577	-1.3298	-1.3675
15	0.0048	12.3571	0.0135	4.7940***	-0.0682	-6.2259	-0.1595	-1.3481

***, **,* indicate significance at the 1%, 5% and 10% levels. The number of observations varies across time. It ranges from 180-251 companies and the total number of events is 4221 events.

Figures 5.2, 5.3 and 5.4 show the cumulative average abnormal returns for the Upper and Lower price limit hits over the event window for the two regimes.

Figure 5-2: Cumulative average abnormal returns for the upper limit hit for the two regimes

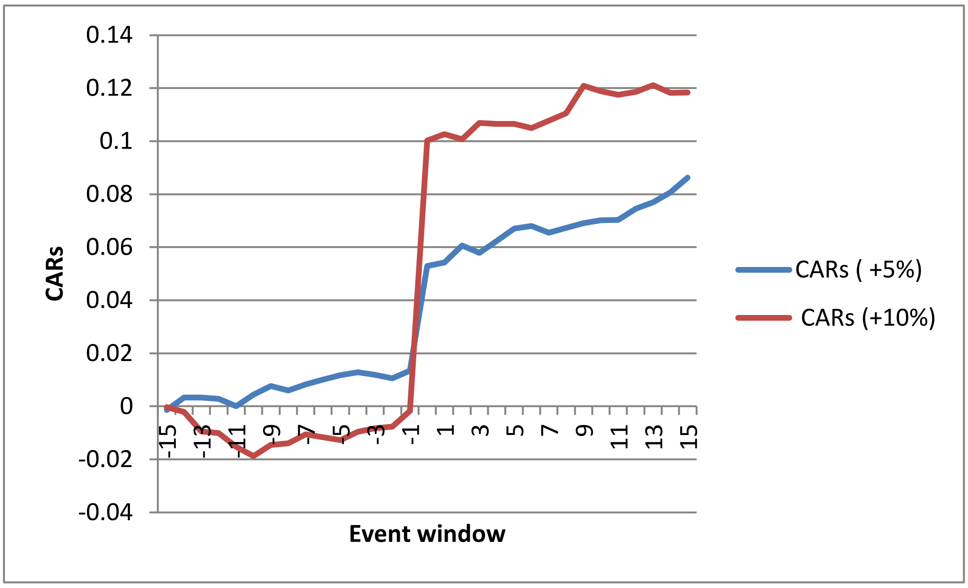


Figure 5-3: Cumulative average abnormal returns for the lower limit hit for the two regimes

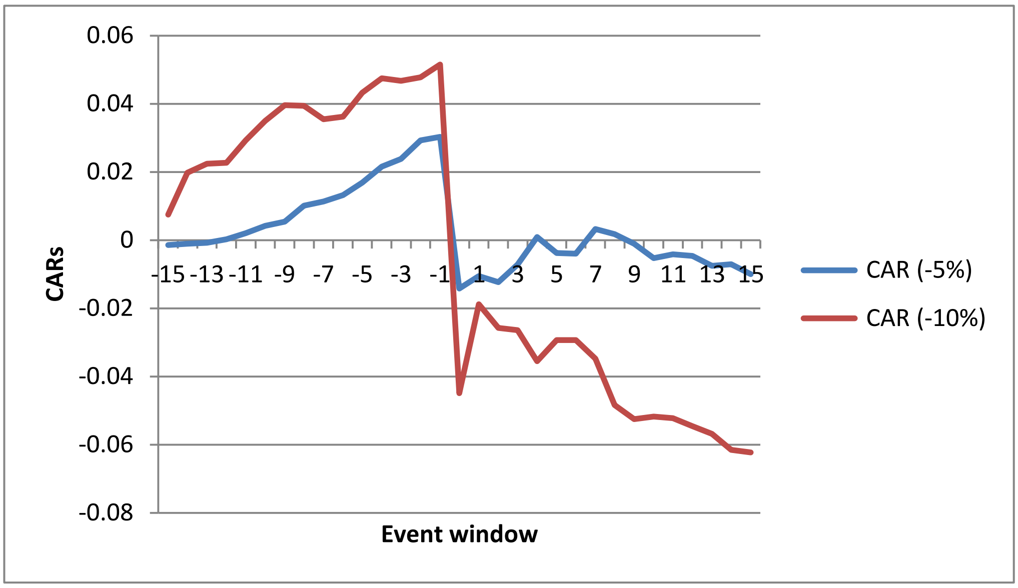


Figure 5-4: Cumulative average abnormal returns (CAARs) for the upper and lower price limit hits over the event window for the two regimes

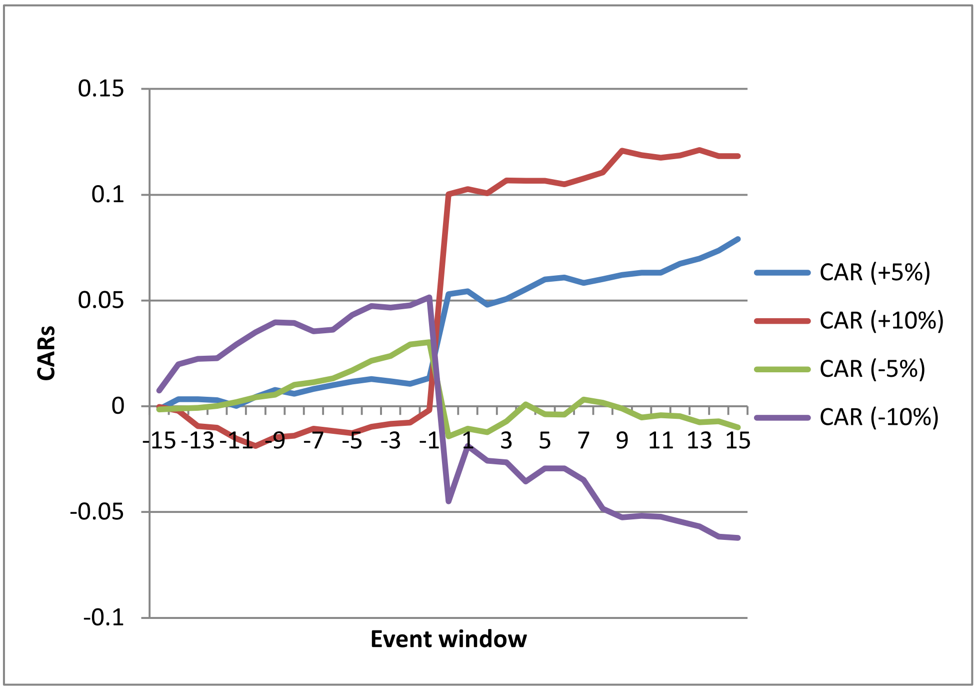


Figure 5.2 shows that there are no significant price reversal patterns either for the Strict Price Limits or for the more relaxed Circuit Breaker regimes in the case of the Upper limit hits (although we notice negative and insignificant abnormal returns one and three days subsequent circuit breakers and strict price limits regimes respectively). This suggests that price continuation patterns are expected post-Upper limit hits. The jump in the cumulative average abnormal returns on Event date within circuit breakers regime is wider – as expected – post-event compared with those of pre-events.

On the other hand, for the Lower limit hits, figure 5.3 shows that there is a significant price reversal pattern for the CB regime on day one following limit hits. However, there is an insignificant price reversal pattern for the SPL regime. The event day drop in the CAARs between the two regimes is again wider for the CB regime.

To sum up, the above figures show that there is price reversal pattern for the Lower limit hits (bad news) within the two regimes. In addition, there is price continuation pattern (momentum behavior) for the Upper limit hits (good news) within the two regimes.

In conclusion, these results support the overreaction hypothesis in the case of bad news (Lower limit hits) and suggest the presence of a leverage effect in the Egyptian stock market within the two regimes.

5.5.1.5 Overreaction hypothesis: the size effect

To investigate the effect of firm size[27] on the overreaction hypothesis under different regulatory policies, Table 5.6 presents the average abnormal returns and the cumulative average abnormal returns for the strict (+5%) Upper limit hits (good news) for Small and Big portfolios.

The results presented in table 5.6 (Upper limit hits) show that there is price continuation behaviour for small portfolios for two days following event day (limit hit). Price reversals occur on day three following the event. These results are consistent with Huang (1998) as we are interested in the sign (direction) rather than the significance of the abnormal returns; however we notice positive and marginally significant abnormal returns one day following the event.

Table 5.6 also reports that price reversal for big portfolios occurs on the second day following the event for the Upper limit hit. The leakage of information is clear for big portfolios in cases of Upper limit hits (good news) as highly significant and positive cumulative abnormal returns are detected for two days pre limit hits. A possible

[27] Following the literature of the overreaction hypothesis and price limits, I use market capitalisation as a proxy for firm size as all the firms included in the sample are listed in the EGX. None of the literature used other measures i.e. total assets due to the drawback of accounting measures.

interpretation of this result is the vast majority of investors are actively involved in analysing the news of big firms.

Table 5.6: Average abnormal returns for the upper limit hits for Big and Small portfolios within SPL regime

Upper limit hits +5%								
Days	Small portfolio				Big portfolio			
	AR(%)	CAR(%)	t(AR)	t(CAR)	AR(%)	CAR(%)	t(AR)	t(CAR)
-15	-0.3628	-0.3628	-0.9109	-0.9109	0.1285	0.1285	0.4165	0.4165
-14	1.1477	0.7849	2.6569***	1.5510	0.3629	0.4914	1.4986	1.8737*
-13	-0.7191	0.0658	-1.6397*	0.1611	0.2636	0.755	1.4876	2.3366**
-12	0.5414	0.6072	1.9375*	1.1319	-0.2198	0.5352	-1.0585	1.2286
-11	-0.7107	-0.1035	-1.4020	-0.1628	0.0365	0.5717	0.1285	1.0401
-10	0.8820	0.7785	1.9968**	0.9402	0.3271	0.8988	1.0941	1.4539
-9	0.6619	1.4404	1.7361*	1.3823	0.2668	1.1656	1.0184	1.5516
-8	-0.2919	1.1485	-0.8285	1.0858	0.1483	1.3139	0.8344	1.5656
-7	0.2745	1.423	0.4719	1.2900	0.4210	1.7349	1.5200	1.3301
-6	-0.7047	0.7183	-1.9739**	0.6218	0.0268	1.7617	0.1200	1.3558
-5	0.1271	0.8454	0.1583	0.4836	0.0858	1.8475	0.2709	2.3573**
-4	0.2510	1.0964	0.6533	0.5566	-0.1743	1.6732	-0.9536	1.9856**
-3	0.2510	1.3474	0.6533	0.4151	-0.1743	1.4989	-0.9536	2.2870**
-2	-0.3751	0.9723	-0.5475	0.2103	0.2724	1.7713	1.9596**	2.0891**
-1	0.0678	1.0401	0.0978	0.1977	0.3615	2.1328	1.9604**	2.2447**
0	**3.8801**	**4.9202**	**6.1000*** **	**2.9372*** **	**3.7326**	**5.8654**	**13.3678*** **	**5.3084*** **
1	0.0778	4.998	0.0583*	1.2906	0.1048	5.9702	0.1755	4.434***
2	0.7752	5.7732	0.7695	1.0854	-1.2117	4.7585	-2.4622**	3.2049***
3	-0.3761	5.3971	-0.4428	1.1963	0.4813	5.2398	0.894	3.7437***
4	0.3922	5.7893	0.4325	1.3891	0.2277	5.4675	0.4061	3.3547***
5	1.0838	6.8731	1.9944**	1.5849	-0.0854	5.3821	-0.1715	3.1556***
6	1.4037	8.2768	2.0287**	1.8153*	-0.4670	4.9151	-1.1201	2.7652***
7	-0.4326	7.8442	-0.7240	1.6311	-0.5090	4.4061	-1.3056	2.5228**
8	-0.6800	7.1642	-0.8938	1.5577	-0.2555	4.1506	-0.7500	2.4402**
9	0.1946	7.3588	0.2943	1.6454*	0.9579	5.1085	2.8107***	2.7367***
10	0.6032	7.962	0.9669	1.8512*	0.3398	5.4483	0.6603	3.0451***
11	0.8317	8.7937	1.0101	1.8084*	-0.1059	5.3424	-0.2685	3.3089***
12	-0.2078	8.5859	-0.3158	1.6886*	0.6081	5.9505	1.7028	3.6141***
13	0.9613	9.5472	1.5074	1.8712*	-0.0209	5.9296	-0.0863	3.6537***
14	0.8263	10.3735	1.5167	1.8924*	-0.0017	5.9279	-0.005	3.9516***
15	0.6163	10.9898	1.2618	1.9369*	0.3798	6.3077	0.8430	4.2100***

***, **,* indicate significance at the 1%, 5% and 10% levels. The number of observations varies across time. It ranges from 180-251 companies and the total number of events is 4221 events.

Table 5.7 presents the average abnormal returns and the cumulative average abnormal returns for the strict (-5%) Lower limit hits (bad news) for Small and Big portfolios.

Table 5.7 reports that price reversal for small portfolios occurs on the third day following the event (Lower limit hits). We notice positive and highly significant abnormal returns for small portfolios on days three and four following the event. However, price reversal for big portfolios occurs on the second day following the event. The leakage of information is not clear for both Small and Big portfolios.

Table 5.7: Average abnormal returns for the lower limit hits for Big and Small portfolios within SPL regime

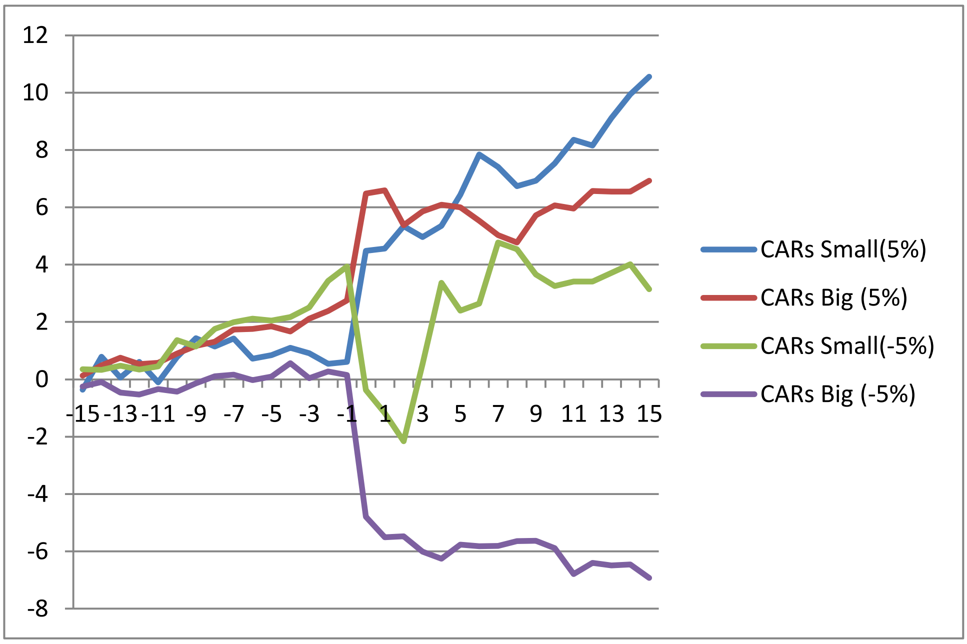
Lower linit hits -5%								
Days	Small portfolio				Big portfolio			
	AR(%)	CAR(%)	t(AR)	t(CAR)	AR(%)	CAR(%)	t(AR)	t(CAR)
-15	0.3520	0.3520	0.6964	0.6964	-0.2510	-0.2510	-0.6794	-0.6794
-14	-0.0243	0.3278	-0.0600	0.4210	0.1595	-0.0915	0.4657	-0.1547
-13	0.1485	0.4763	0.5712	0.6308	-0.3701	-0.4616	-1.1573	-0.8320
-12	-0.1330	0.3432	-0.4052	0.3833	-0.0729	-0.5345	-0.1947	-0.6543
-11	0.1058	0.4491	0.5046	0.4441	0.1909	-0.3436	1.0285	-0.3812
-10	0.9216	1.3706	2.1811**	1.0331	-0.0899	-0.4335	-0.2389	-0.4252
-9	-0.2312	1.1394	-0.4048	0.7610	0.2933	-0.1402	1.0392	-0.1205
-8	0.6140	1.7533	1.1886	0.9167	0.2425	0.1023	0.6663	0.0870
-7	0.2348	1.9882	0.7034	1.0167	0.0601	0.1624	0.1439	0.1110
-6	0.1290	2.1172	0.2511	0.9107	-0.1922	-0.0298	-0.5011	-0.0234
-5	-0.0703	2.0469	-0.1680	0.8068	0.1234	0.0936	0.2269	0.0754
-4	0.1268	2.1737	0.2704	0.8246	0.4688	0.5624	1.0389	0.4067
-3	0.1268	2.5031	0.2704	0.8908	0.4688	0.0379	1.0389	0.0257
-2	0.9282	3.4314	2.0186**	1.0771	0.2310	0.2690	0.3852	0.1848
-1	0.4986	3.9300	0.9355	1.1235	-0.1157	0.1533	-0.2225	0.0933
0	**-4.3080**	**-0.3780**	**-10.2560***	**-0.1036**	**-4.9465**	**-4.7932**	**-22.048***	**-2.7439***
1	-0.7945	-1.1725	-1.6235*	-0.3095	-0.7171	-5.5103	1.1773	-2.2732**
2	-0.9835	-2.1560	-2.2162**	-0.5835	0.0376	-5.4727	-0.0614	-2.4389**
3	2.6901	0.5341	1.9817**	0.2217	-0.5376	-6.0103	-1.3276	-2.8949***
4	2.8364	3.3705	1.9825**	0.9592	-0.2411	-6.2514	-0.8844	-2.8865***
5	-0.9755	2.3951	-1.9136*	0.7427	0.4912	-5.7602	1.1370	-2.6105***
6	0.2461	2.6412	0.6696	0.8276	-0.0559	-5.8161	-0.1248	-2.4556**
7	2.1338	4.7750	0.8127	0.9084	0.0070	-5.8091	0.0193	-2.5287
8	-0.2399	4.5351	-0.5887	0.8640	0.1656	-5.6435	0.4210	-2.4596**
9	-0.8771	3.6580	-1.5489	0.7450	0.0178	-5.6257	0.0500	-2.4672**
10	-0.4041	3.2539	-0.9203	0.6715	-0.2660	-5.8917	-0.6671	-2.7143***
11	0.1545	3.4084	0.4715	0.7001	-0.8966	-6.7883	-2.6559***	-3.5623***
12	0.0002	3.4087	0.0005	0.7375	0.3842	-6.4041	0.9133	-2.7968***
13	0.3077	3.7164	0.7227	0.7928	-0.0889	-6.493	-0.1721	-2.3969**
14	0.2926	4.0090	0.5418	0.8557	0.0313	-6.4617	0.0614	-2.4342**
15	-0.8617	3.1473	-2.5813***	0.6938	-0.4662	-6.9279	-1.4975	-2.7522***

***, **,* indicate significance at the 1%, 5% and 10% levels. The number of observations varies across time. It ranges from 180-251 companies and the total number of events is 4221 events.

The results presented in tables 5.6 and 5.7 support the effect of firm size on the overreaction hypothesis for the Lower limit hits for small firms in particular. This can be explained in the light of the literature as volatility is more likely to be higher for small firms (Huang (1998).

Figure 5.5 plots the cumulative averages abnormal returns for Big and Small portfolios within the Strict Price Limits +-5% Upper and Lower limit hits. It is clear from figure 5.5 that price reversals are prevailing for small firms in case of strict (-5%) price limit.

Figure 5-5: Cumulative averages abnormal returns for Big and Small portfolios for the upper and lower limit hits within SPL regime



Tables 5.8 and 5.9 present the average abnormal returns and the cumulative average abnormal returns for Small and Big portfolios within the CB Upper and downward (10%) limit hits respectively. It is clear from the tables that within the Upper and Lower 10% limit hits, price reversals occur one day following the event (limit hits day) for both Big and Small portfolios. However, these reversals are highly significant for small firms for the

Upper limit hits and big firms for the Lower limit hits. Furthermore, the leakage of information is clear for small firms as a highly significant abnormal return is reported one day pre-event for the Upper limit hits.

Table 5.8: Average abnormal returns for the upper limit hits for Big and Small portfolios within CB regime

	Upper limit hits +10%							
Days	Small portfolio				Big portfolio			
	AR(%)	CAR(%)	t(AR)	t(CAR)	AR(%)	CAR(%)	t(AR)	t(CAR)
-15	0.0230	0.0002	0.0189	0.0189	0.2203	0.2203	0.4366	0.4366
-14	0.3370	0.0036	0.6734	0.2334	-0.8836	-0.6633	-2.5796***	-0.9326
-13	-1.6317	-0.0127	-3.9772***	-0.9564	0.3462	-0.3172	0.7803	-0.3943
-12	0.7860	-0.0049	1.7593*	-0.4379	-0.3317	-0.6488	-0.6099	-0.6411
-11	-1.0335	-0.0152	-2.0605**	-1.2686	-0.2290	-0.8779	-0.4606	-0.6437
-10	0.2641	-0.0126	0.3938	-0.7754	-0.0334	-0.9113	-0.0673	-0.5798
-9	0.8586	-0.0040	1.9247*	-0.2375	0.5631	-0.3482	1.2414	-0.1923
-8	0.3144	-0.0008	0.6263	-0.0449	0.8693	0.5211	2.4041**	0.2675
-7	-0.0042	-0.0009	-0.0105	-0.0465	0.1585	0.6796	0.3907	0.3476
-6	-0.2591	-0.0035	-0.5209	-0.1649	0.3124	0.9920	0.6129	0.4647
-5	-0.2184	-0.0056	-0.5331	-0.2681	-0.7859	0.2061	-1.1043	0.1105
-4	-0.8265	-0.0139	-1.2501	-0.5995	1.3715	1.5776	2.2880**	0.7740
-3	-0.8265	-0.0136	-1.2501	-0.5277	1.3715	2.1136	2.2880**	0.9423
-2	-0.2851	-0.0164	-0.2861	-0.5202	0.8154	2.9290	1.0346	1.0771
-1	2.0326	0.0039	2.1044**	0.1159	-1.3659	1.5631	-1.0650	0.4591
0	**11.9821**	**0.1237**	**21.1858*****	**3.6754*****	**10.1940**	**11.7571**	**11.2760*****	**3.6214*****
1	-3.9895	0.0838	-4.8058***	2.3055**	-0.9499	10.8072	-0.8447	3.3666***
2	0.9464	0.0933	0.6173	2.3764**	-0.1755	10.6317	-0.1717	3.0765***
3	-0.0105	0.0932	-0.0158	2.4136**	-0.3207	10.3111	-0.5933	2.8026***
4	0.9056	0.1022	0.7328	2.6762***	-0.2861	10.0250	-0.4533	2.8377***
5	3.2954	0.1352	1.8201	2.9140***	0.1720	10.1969	0.2277	2.7993***
6	-1.5100	0.1201	-1.2351	2.4623**	0.4639	10.6608	0.5073	2.6286***
7	2.2880	0.1430	0.9667	2.3354**	0.6128	11.2736	0.7652	2.8261***
8	-0.3055	0.1399	-0.4681	2.4765**	-0.5101	10.7635	-0.7909	2.6929***
9	2.8493	0.1684	1.5158	2.3437**	-1.1072	9.6564	-1.5432	2.3683**
10	1.2279	0.1807	1.0446	2.2890**	0.1206	9.7770	0.1915	2.5123**
11	0.3237	0.1839	0.4907	2.3531**	-1.6492	8.1278	-1.8445	1.9064*
12	-2.2213	0.1617	-1.6006	2.4211**	0.5156	8.6434	0.5108	2.3353**
13	-0.2452	0.1593	-0.3736	2.2961**	-0.1473	8.4960	-0.2412	2.2837**
14	-0.9861	0.1494	-1.4756	2.2416**	-0.8235	7.6725	-1.3231	1.8705*
15	-0.3968	0.1454	-0.4544	2.3859**	-0.3389	7.3336	-0.4192	1.8312*

***, **,* indicate significance at the 1%, 5% and 10% levels. The number of observations varies across time. It ranges from 180-251 companies and the total number of events is 4221 events.

Table 5.9: Average abnormal returns for the upper and lower limit hits for Big and Small portfolios within CB regime

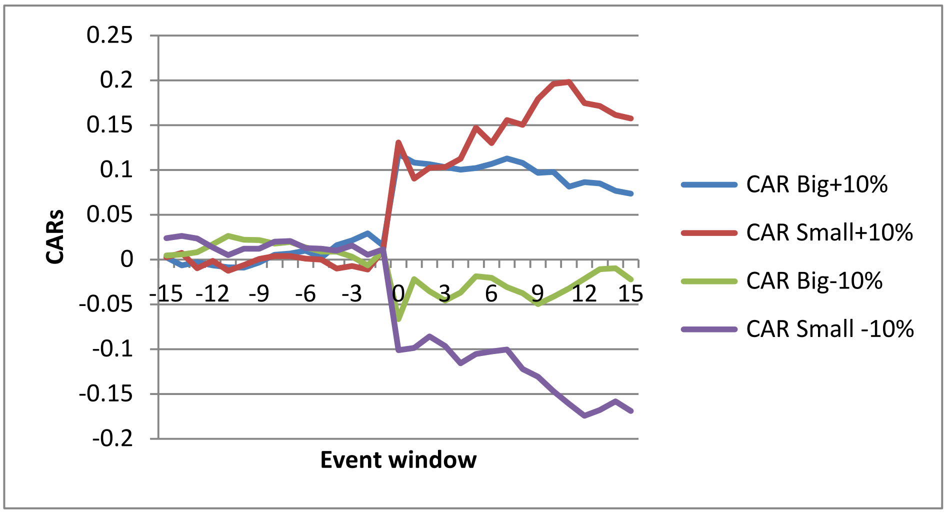
Lower limit hits -10%								
Days	Small sized portfolio				Big sized portfolio			
	AR(%)	CAR(%)	t(AR)	t(CAR)	AR(%)	CAR(%)	t(AR)	t(CAR)
-15	2.3637	2.3637	1.3984	1.3984	0.4387	0.4387	0.8998	0.8998
-14	0.2721	2.6357	0.4462	1.3198	0.1276	0.5663	0.3126	1.0189
-13	-0.3024	2.3334	-0.4000	1.3910	0.2504	0.8166	0.3876	0.7924
-12	-1.0080	1.3254	-1.4911	0.6828	0.8922	1.7089	1.9430*	1.4483
-11	-0.8538	0.4717	-1.0516	0.2010	0.9058	2.6147	1.8833*	2.1399**
-10	0.7254	1.1971	0.4910	0.3944	-0.4132	2.2015	-1.5097	1.9101*
-9	-0.0102	1.1868	-0.0085	0.3256	-0.0339	2.1676	-0.0804	1.9666**
-8	0.8040	1.9909	0.9015	0.5127	-0.4043	1.7633	-1.5907	1.4895
-7	0.0789	2.0697	0.0674	0.5385	0.1785	1.9418	0.4517	1.4396
-6	-0.7880	1.2817	-0.6720	0.3260	-0.6130	1.3288	-1.0243	0.8624
-5	-0.0874	1.1943	-0.1089	0.2878	-0.4531	0.8757	-1.0928	0.5774
-4	-0.2045	0.9898	-0.2792	0.2227	-0.0153	0.8604	-0.0280	0.5701
-3	-0.2045	1.5429	-0.2792	0.3253	-0.0153	0.2956	-0.0280	0.1797
-2	-1.0182	0.5247	-0.9959	0.1102	-0.9721	-0.6765	-1.4695	-0.3702
-1	0.5944	1.1191	0.3527	0.2299	1.6311	0.9547	2.7069***	0.4790
0	**-11.2329**	**-10.1138**	**-8.9462***	**-2.1427**	**-7.6231**	**-6.6684**	**-6.3750***	**-2.8245***
1	0.2354	-9.8785	0.2371	-1.8729*	4.4624	-2.2060	3.8610***	-0.7539
2	1.3024	-8.5761	0.8968	-1.6109	-1.3305	-3.5365	-1.7616*	-1.3486
3	-1.0993	-9.6754	-1.2649	-1.9779**	-1.0512	-4.5877	-1.3126	-1.7083*
4	-1.9053	-11.5808	-1.5797	-2.1336**	0.8758	-3.7119	1.4234	-1.4249
5	1.0256	-10.5552	1.0104	-2.0436**	1.8371	-1.8748	2.9406***	-0.6304
6	0.2712	-10.2840	0.3895	-2.1216**	-0.1722	-2.0471	-0.4245	-0.7125
7	0.2394	-10.0446	0.4581	-2.0873**	-1.0398	-3.0868	-1.9040*	-1.0431
8	-2.1925	-12.2371	-1.2813	-2.1864**	-0.6933	-3.7801	-0.7307	-1.2956
9	-0.8417	-13.0787	-0.9092	-2.2535**	-1.1947	-4.9748	-1.9592**	-1.7038*
10	-1.6071	-14.6859	-1.8575*	-2.5001**	0.8214	-4.1534	1.0468	-1.2910
11	-1.4261	-16.1120	-1.8654*	-2.8093***	0.9363	-3.2171	1.1676	-0.9404
12	-1.3349	-17.4468	-1.1400	-3.0846***	1.0451	-2.1720	1.5368	-0.6068
13	0.6416	-16.8053	0.4889	-2.8946***	1.0910	-1.0810	1.4690	-0.2913
14	0.9747	-15.8305	1.2816	-2.6729***	0.0852	-0.9958	0.1975	-0.2620
15	-1.0714	-16.9019	-1.2455	-2.7000***	-1.2359	-2.2317	-1.3426	-0.6072

***, **,* indicate significance at the 1%, 5% and 10% levels. The number of observations varies across time. It ranges from 180-251 companies and the total number of events is 4221 events.

Results presented in tables 5.8 and 5.9 do not support the effect of firm size on the overreaction hypothesis within the circuit breakers regime as price reversals occur one day following the event. Therefore there is no evidence of the volatility spillover hypothesis within circuit breakers regime; this result is consistent with Kim and Rhee (1997) .

Figure 5.6 plots the cumulative averages abnormal returns over the event window for the Big and Small portfolios within the CB (10%) Upper and Lower limit hits.

Figure 5-6: cumulative averages abnormal returns over the event window for the Big and Small portfolios within the CB regime



5.5.2 Volatility Spillover hypothesis

To investigate the Volatility Spillover (VS) hypothesis, for each event (price hits the Upper or the Lower limit), I identify days (events) where the high price during the trading session matches its previous day's closing price plus the symmetric price limit (-/+5%) or (-/+ 10%) (Kim and Rhee 1997).

For Upper limits I assume:

$$H_t = C_{t-1}(1 + SPL_t) \tag{8}$$

And for lower limits I assume:

$$L_t = C_{t-1}(1 - SPL_t) \tag{9}$$

where:

H_t is day's high price.

L_t is day's low price.

C_{t-1} is previous day's closing price.

SPL_t is the symmetric price limit for day (t) (+/-5% or +/-10%) according to the regime in operation (SPL or CB).

To test the volatility spillover hypothesis and following Kim and Rhee (1997), I examine volatility during 21 days (-10, +10) around event day. The event for a particular stock occurs when its price hits its Upper or lower price limit (+/-5% or +/-10%) in a particular day. In event time, this day is t=0.

I define daily price volatility in the fashion of Kim and Rhee (1997) as in equation 10:

$$V_{tj} = R_{tj}^2 \qquad (10)$$

where: V_{tj} is the volatility of stock (j) on day (t).

R_{tj} is the close-to-close return for stock j on day t, measured by the log of the firm's price ratio i.e.

$R_t = \ln P_t / P_{t-1}$ where P_t is the closing price of the stock on day (t).

In order to examine the volatility spillover hypothesis in post limit days for each regime (SPL +/-5% or CB +/-10%) within the two categories (upward and downward movements), I calculate the daily price volatility R_{tj}^2 for each stock in the four categories (upward and downward +/-5% or +/-10%) and then take the daily averages.

To overcome potential bias in volatility estimation I include only non-overlapping event windows; the inclusion of consecutive events would bias the post-event window. To compare volatility levels for upward and downward price movements, I use the nonparametric Wilcoxon signed–rank test (Kim and Rhee, 1997). I assume that the sample distribution of the difference between the matched pairs is symmetric. The null hypothesis is "The distribution is centered on zero difference".

To investigate the volatility spillover hypothesis, table 5.10 presents stock returns volatility around the event (limit hit day) for the Upper and Lower limit hits within the two regimes. I exclude from the analysis the multiple overlapping events to minimise the pre-limit day volatility bias arising from the inclusion of the consecutive events as independent events (Kim and Rhee 1997). This reduces the sample size for the stocks that hits their limits by 19.20% (from 4221 to 3542).

It is clear from the table 5.10 that the highest volatility is reported on event day for both Upper and lower price movements for the two regimes. For the Upper limit hits for instance, we notice a large drop in volatility on day one from 2.5 to 1.57 for the strict (+ 5%) price limit regime and from 10 to 0.81 for the (+ 10%) circuit breakers regime.
However, for the lower price limits we also notice a large drop in volatility on event day from 2.5 to 1.28 and from 10 to 0.89 within Strict Price Limits (SPL) and circuit breakers (CB) regimes respectively. Ma et al. (1989) explain this as the cooling effect of price

limits, however Kim and Rhee (1997) and Lee et al. (1994) conclude that volatility measures will naturally decline when stocks hit their limits. To support this result, I re-estimated the volatility spillover hypothesis for other categories of stocks that nearly hit their limit 90% and 80% of Upper and Lower limit, and found similar results.

Table 5.10: Volatility Spillover Hypothesis

Days	Upper price movements			Lower price movements		
	+5%		+10%	-5%		-10%
-10	0.1768		0.1291	0.2200		0.2241
-9	0.1653		0.2984	0.2190		0.2216
-8	0.0827		0.2414	0.2813		0.2450
-7	0.1095		0.2422	0.1933		0.2936
-6	0.0957		0.2490	0.2071		0.3542
-5	0.1349		0.2239	0.2373		0.2214
-4	0.1110		0.2568	0.2398		0.2440
-3	0.1333	<	0.2644	0.2430		0.3259
-2	0.2667		0.3379	0.2541	<	0.4071
-1	0.4072		0.5560	0.3674	<<	0.6695
0	**2.5000**	<<	**10.0000**	**2.5000**	<<	**10.0000**
1	**1.5723**	>>	**0.8088**	**1.2797**	>>	**0.8947**
2	**1.2739**	>>	**0.7680**	0.3649	<	0.4448
3	0.2427	<<	0.3895	0.2962	<<	0.4770
4	0.1107	<	0.2857	0.1309		0.2409
5	0.1277		0.2572	0.1727		0.2115
6	0.1586		0.2876	0.2138		0.2883
7	0.1432		0.3813	0.1735		0.4051
8	0.1745		0.3598	0.1752		0.2809
9	0.1326		0.3249	0.1400		0.3169
10	0.1343		0.2779	0.2005		0.2590

>> and > implies that the left hand figure is significantly greater than the right hand figure at 0.01 and 0.05 significance levels respectively using Wilcoxon signed-ranked test.
Volatility is measured by squared stock returns multiplied by 1000.
The number of observations varies across time. It ranges from 180-251 companies and the total number of events is 4221 events.

By comparing the volatility within the two regimes, we notice that for the Upper and Lower events, the volatility within the CB regime is greater than those of the SPL regime over the entire event window except for the first two days subsequent to the Upper limit hits and for the first day post-event for the Lower limit hits.

Volatility of the Upper (+ 5%) SPL for the first two days post-event (limit hits) is greater than those of CB by 93%, and 65% respectively. However, volatility of the Lower SPL (-5%) is greater than those of the CB regime by 43.82% only during the first day post-event. This suggests that within the SPL regime, stocks that hit their Upper and Lower limit continue to experience greater volatility during the first 1-2 days post-event compared with the CB regime.

These results are consistent with the volatility spillover hypothesis as price discovery mechanism is disrupted when stocks experience greater volatility for a few days post limit hits, therefore stock prices are prevented from reaching their equilibrium levels for the following few days post-event. These deviations from the true prices are expected to prevail within the SPL (+-5%) regime as trading session is suspended until the following day (trading session) when the prices hit their Upper or lower limits. However, within wider bands of limits (- +10%) followed by trading halts investors have chance to adjust their portfolio positions within the same trading session. Therefore, the volatility spillover is expected to be higher within the SPL regime.

To support the analysis I compare between volatility levels pre and post each regime. We notice that within the Upper and Lower price limit regimes, volatility post limits is greater than those of pre limits for two and three days for Lower and Upper price limits respectively, for example, within +5% SPL, post limit volatility is greater than those of pre limit volatility for the first three days post limits by 286%, 377% and 82%. Similarly, within +10% CB regime, post limit volatility for the first three days is greater than those of pre-limit hit by 45%, 127% and 47%. This result supports the volatility spillover hypothesis. Finally, the Wilcoxon signed–rank test shows that the differences between the two regimes are significantly different from zero at the 0.01 and 0.05 levels on event day and over the three days post-event.

To conclude, results show that price limits do not decrease volatility as intended in both regimes (SPL and CB). However, volatility is found to be higher within the CB regime. On the other hand, within the SPL regime, volatility is spread out over the following two days subsequent to limit hit day. These results support the volatility spillover hypothesis in the Egyptian stock exchange consistent with findings of Kim and Rhee, (1997) and Lee et al (1994). Figures 5.7 and 5.8 present the daily price volatility around event day.

Figure 5-7: Daily price volatility for the Upper limit hits for the two regimes around event day

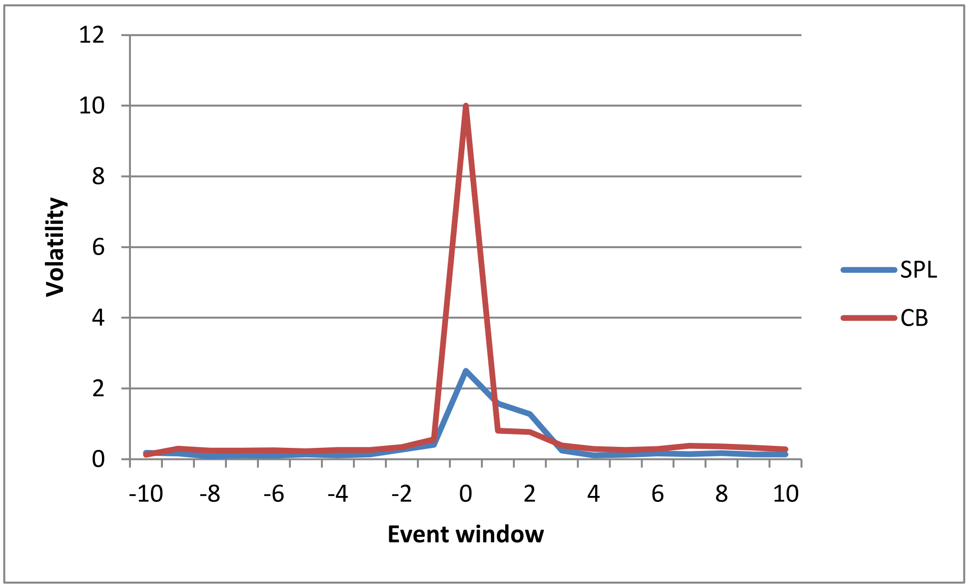
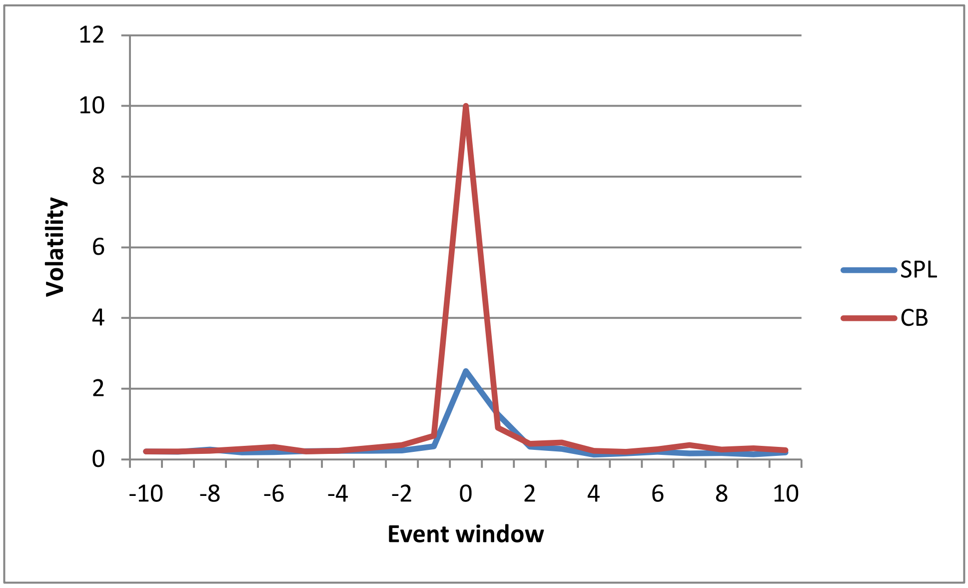


Figure 5-8: Daily price volatility for the Lower limit hits for the two regimes around event day



Figures 5.9 and 5.10 present the cumulative average volayility (CAV) for the Upper and Lower limit hits for the two regimes.

Figure 5-9: Cumulative average volatility (CAV) for the Upper limits hits for the two regimes

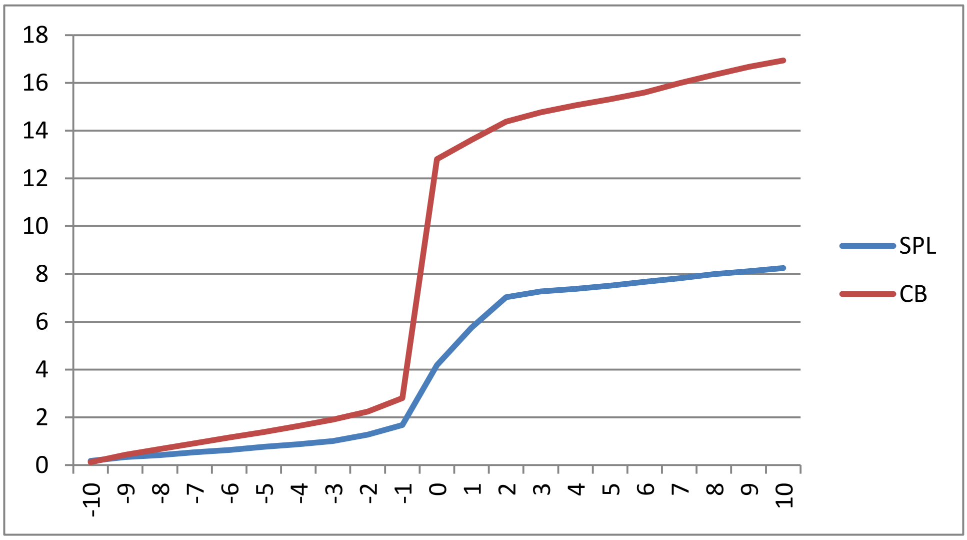
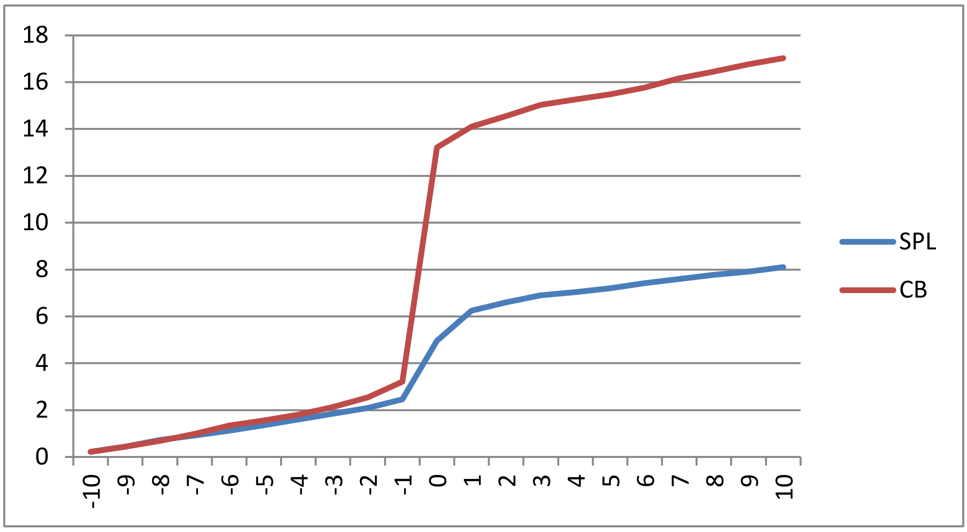


Figure 5-10: Cumulative average volatility (CAV) for the Lower limits hits for the two regimes



5.5.3 The delayed price discovery hypothesis

According to the Delayed Price Discovery (DPD) hypothesis there will be positive overnight returns for stocks which hit their Upper limits and negative overnight returns for stocks which hit their Lower limits (Kim and Rhee 1997).

To investigate these claims I estimate the following two returns series: open-to-close returns on the limit day, namely $R(O_0C_0) = \ln(C_0 / O_0)$ and close-to-open returns between the event day and the following day, namely $R(C_0O_1) = \ln(O_1 / C_0)$, where C_0 is the closing price on day (t) and O_1 is the opening price on day (t+1). As stock returns can be positive, negative or zero, we have nine return series (+, +), (+, 0), (0, +), (0, -), (0. 0), (+, -), (-, +), (-, -) and (-, 0) as shown in table 5.11 below.

The first return symbol represents the open-to-close returns on the limit day $R(O_0C_0) = \ln(C_0 / O_0)$ and the second return symbol represents the close (in event day)-to-open (in event day +1) $R(C_0O_1) = \ln(O_1 / C_0)$.

Stocks often experience either price continuation or price reversal based on overnight returns. I compare the price behaviour of the two regimes (SPL and CB) so that if price continuation behaviour within SPL is greater than those of the CB regime then, we can infer that the efficient price discovery mechanism is much delayed within the strict price limit regime and the opposite is correct.

In other words, I argue that price continuation behaviour prevents stock price from reaching their equilibrium levels (Kim and Rhee, 1997), since otherwise we should observe price reversals or overreactive behaviour (Roll, 1983). I examine the immediate stock price movement subsequent to price-limit hit on event day for both regimes (SPL and CB) by estimating the frequencies of price continuation, price reversal and no changes, as in the following table 5.11.

Table 5.11 Frequencies of price continuation and price reversal for the two regimes

	Upper limit	**Lower limit**
Price continuation	(+, +) and (0, +)	(-, -) and (0, -)
Price reversal	(+, -), (0, -), (-, +), (-, 0) and (-, -)	(-, +), (0, +), (+, -), (+, 0) and (+, +)
No change	(+,0) and (0,0)	(-, 0) and (0, 0)

Note: The first return symbol represents the open-to-close returns on the limit day $R(O_0C_0) = \ln(C_0 / O_0)$ and the second return symbol represents the close-to-open $R(C_0O_1) = \ln(O_1 / C_0)$

The number of observations varies across time. It ranges from 180-251 companies and the total number of events is 4221 events.

Following Kim and Rhee (1997) and Bildik, and Gulay (2006), consecutive event days are not excluded from the analysis as they will underestimate the frequencies of price continuation and price reversals. As can be seen from Table 5.11 I classify both (+, +) and (0, +) categories as price continuation for the Upper Limit hits. The (0, +) category is classified as price continuation because these stocks experience an overnight price increase (stocks open at the Upper limit and remain unchanged over the event day). The same concept applies to the lower limits as I classify (-, -) and (0, -) categories as price continuation for the Lower limit, Kim and Rhee (1997) and Bildik, and Gulay (2006).

On the other hand, I classify – following Kim and Rhee (1997) (+, -), (0, -), (-, +), (-, 0) and (- , -) as price reversal for the Upper limits. I include (-, +), (-, 0) and (-, -) categories as price reversal as the first negative sign (open-to-close returns) implies price reversal before the end of trading session in event day (Kim and Rhee (1997) and Bildik, and Gulay (2006)). The same concept applies on the lower limits as I classify (-, +), (0, +), (+, -), (+, 0) and (+, +) categories as price reversals for the Lower limit. Finally, I consider (+, 0) and (0, 0) as no-change categories for the Upper limit hits and the (-, 0) and (0, 0) as no-change categories for the Lower limit hits (Kim and Rhee (1997) and Bildik, and Gulay (2006)).

I use the following standard nonparametric binomial Z-test to examine for significant differences between the two regimes with respect to price continuations and price reversals (Kim and Rhee (1997) and Bildik, and Gulay (2006)).

$$z = \frac{(x_{hitsSPL} - px_{hitCB} * N_{hit})}{\sqrt{px_{hitCB}(1 - px_{hitCB}) * N_{hit})}} \qquad (11)$$

where:

$x_{hitsSPL}$: Number of price continuations or price reversals events that stocks experience within SPL regime.

px_{hitCB}: Percentage of price continuations or price reversals events that stocks experience within CB regime x_{hitCB} / N_{hitCB}.

N_{hit}: sample size for stocks hit the limit within the SPL and CB regimes.

As the sample is large the Z-statistic is normally distributed (Olkin, Gleser, and Dermam, 1980 pp. 244-253).

I now discuss the empirical results of the delayed price discovery hypothesis. Table 5.12 presents the frequencies of price continuations, price reversals and no change events for stocks that hit their Upper and/or lower price limits for the two regimes over the period 1999-2009.

For the Upper price limit hits, table 5.12 shows that price continuation occurs 74.7% and 51.04% immediately following the event (limit hit day) for SPL and CB regimes respectively. However, price reversals occur 24.88% and 47.15% immediately following the event for SPL and CB regimes respectively over the same period. The no change events occurs 0.42% and 0.81% immediately following the event for SPL and CB regimes respectively. For the Lower price limit hits, price continuation occurs 69.15% and 47.58% immediately following the event for SPL and CB regimes respectively.

However, price reversals occur 30.15% and 52.40% immediately following the event for the SPL and CB regimes respectively.

We notice that price continuation occurs more frequently within the SPL regime; however, price reversals occur more frequently within the CB regime immediately following the event. This result is consistent with the delayed price discovery hypothesis as price limits prevents stock prices from reaching their equilibrium levels, in particular within a strict price limit regime. The nonparametric binomial Z test show that there are significant differences between the two regimes regarding price continuations and price reversals.

Table 5.12: Delayed price discovery: price continuation and reversal

Price Behaviour	Upper price movements			Lower price movements		
	SPL (%)	CB (%)	SPL-CB (z- stat)	SPL (%)	CB (%)	SPL-CB (z-stat)
Price Continuation	74.70	51.04	5.7737***	69.15	47.58	7.9097***
Price Reversal	24.88	47.15	-8.9936***	30.15	52.40	-5.3111***
No. change	0.42	0.81	-1.2568	0.70	0.02	1.5987

The table presents the limit hit frequencies for the two regimes. The number of observations varies across time. It ranges from 180-251 companies and the total number of events is 4221 events.

Figures 5.11 and 5.12 illustrate the frequencies for price continuation and price reversal within the two regimes.

Figure 5-11: Frequencies for price continuation and price reversal for the Upper limit hits within both regimes.

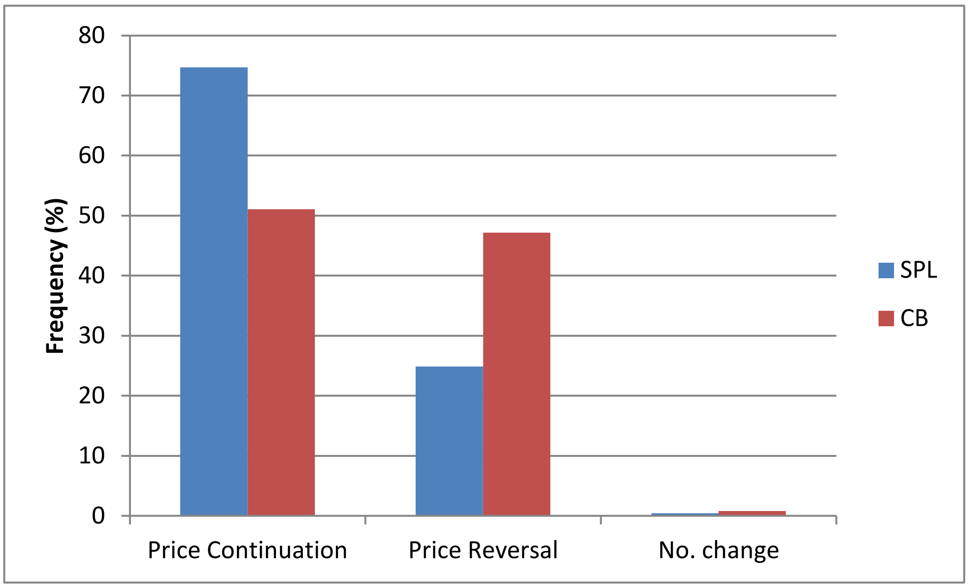
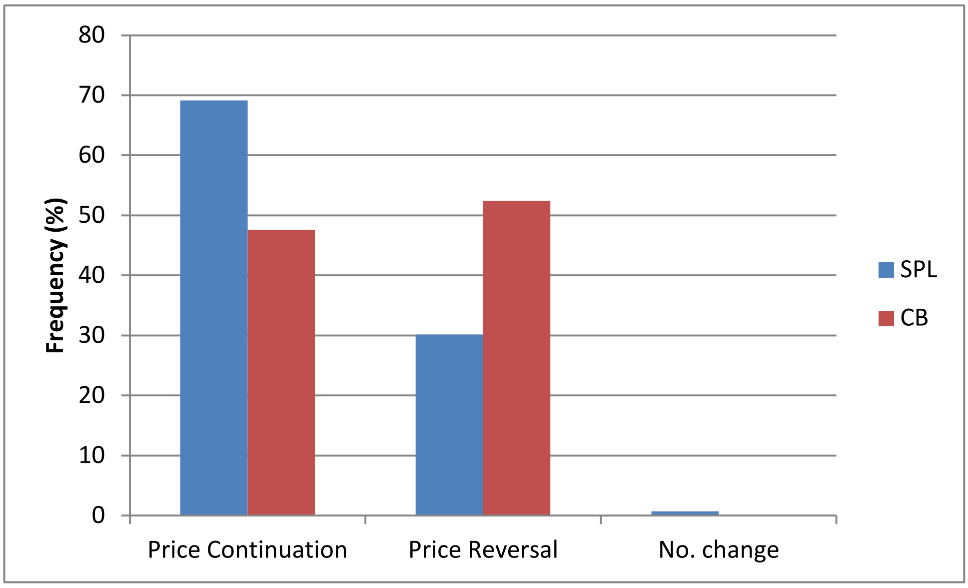


Figure 5-12: Frequencies for price continuation and price reversal for the Lower limit hits within both regimes.



To summarise, price continuation behaviour occurs more frequently within the SPL regime immediately following the event (limit hit day). This implies that price discovery mechanism is delayed by the Strict Price Limits. This result supports the delayed price discovery hypothesis. Price reversal behaviour seems to occur more frequently within the CB regime compared to the SPL regime immediately following the event. This implies that Strict Price Limits delay or prevent - to some extent - the overreactive behaviour, compared to the circuit breakers regime.

5.5.4 The Trading Interference hypothesis.

The Trading Interference (TI) hypothesis claims that trading volume (as a proxy for trading activity) will be higher for stocks that hit their Upper or Lower limits for a few days post-event (Bildik, and Gulay (2006)). As we expect that price limits will prevent rational trading on the event day, therefore trading volume is expected to continue increasing over the post-event days (Kim and Rhee (1997).

To investigate the trading interference TI hypothesis around limit-days, following Kim and Rhee, (1997) and Cressy and Farag (2011), I calculate the percentage change in the turnover ratio as a proxy for trading activity in the window (-10 to +10 days): as follows:

$$\%\Delta TA_{jt} = \ln(TA_{jt} / TA_{jt-1}) \quad (12)$$

$$TA_{jt} = Vol_t / No. of\ shares \quad (13)$$

where:

TA_{jt} is the turnover ratio as a proxy for trading activity of stock (j) at time (t).

Vol_{jt} is a daily trading volume for stock (j) at time (t).

I calculate the percentage change in the turnover ratio for each stock in the two regimes (± 5% SPL) and (± 10% CB) and then take averages for each day for each window (-10, +10); I exclude the consecutive events during the limit window (-10, +10) to be consistent with volatility spillover (VS) hypothesis analysis (Kim and Rhee, (1997). We are interested in the daily percentage change in turnover ratio because liquidity (trading) interference hypothesis is mainly concerned with the daily change in trading activity (Bildik, and Gulay (2006)).

Table 5.12 presents daily percentage change in turnover ratio as a proxy for trading activity over a 21-day window (-10 to +10) around the event (limits hit ± 5% and ± 10%) for both SPL and CB regimes.

It is clear from the table that there is sharp increase in trading activity on event day (limit hit day) for both the SPL and CB regime. For the upward price movement, table 5.13 reports that the percentage increases in trading activity on event day are 51.26% and

77.03% for SPL and CB respectively. In addition, the trading activity on event day (limit hit day) is significantly greater than those within the first 8 days of trading window.

The increase in trading activity lasts for two days (45.15% and 36.69%) subsequent to the event within the SPL and lasts only for one day (40.50%) following the event within the CB regime. Trading activity within the CB regime is higher than those of the SPL four days pre-event.

For the Lower price movements, the highest trading activity – as expected – is reported on event day; 42.84% and 67.15% for the SPL and CB respectively. We also notice that the increase in trading activity lasts only for one day (24.89%) following the event within the SPL regime. In addition, we find a significant decrease in trading activity one day following the event within CB regime. Trading activity within the CB regime – on average – is higher than those of the SPL for four days pre-event.

I interpret these results as follows: within the SPL regime, traders are unable to obtain their desired positions on event day. In addition, traders are unable to adjust their portfolios' positions – when prices hit the limit – and are forced to wait until the following day. Therefore Strict Price Limits interfere with trading activity.

On the other hand, within circuit breakers regime, trading activity on average is significantly higher than those of Strict Price Limits as price limits are widened to ± 10%. Investors within the CB regime have the chance to adjust their portfolios positions during the same trading session. However, not all investors are informed about the suspension of trading due to the lack of informational efficiency in the emerging markets. Therefore, only one day following the event (in case of Lower limit hits) may be required to adjust portfolios' position.

Table 5.13: Trading interference hypothesis: Turnover ratio

Days	Upper price movements			Lower price movements		
	+5%		+10%	-5%		-10%
-10	-0.0498		0.0227	-0.0380		0.0012
-9	-0.0462		0.0249	-0.0354		-0.1074
-8	-0.0716		-0.1658	0.2126	>	0.1201
-7	0.1791	>	0.0855	0.0274		-0.0336
-6	-0.0151		0.1044	-0.1268		0.1127
-5	-0.1385		-0.1485	0.1669		-0.0172
-4	0.0569		0.1480	-0.0857		-0.0704
-3	0.0511		0.1052	-0.0368		0.0583
-2	-0.0475		0.0958	0.1470	<	0.1701
-1	0.2578	<	0.4053	-0.1330		-0.0453
0	**0.5126**	<<	**0.7703**	**0.4284**	<<	**0.6715**
1	0.4515	>>	0.4050	0.2489	>>	-0.3751
2	0.3669	>>	-0.2302	-0.1296		0.0618
3	-0.1578		0.1976	0.0929		0.1522
4	-0.0168		-0.0079	0.0722	<<	0.1550
5	-0.1162		-0.0345	-0.0526		-0.0355
6	-0.1133		-0.0236	-0.0563	<<	0.1122
7	-0.0534	>>	-0.1374	0.0607		0.0935
8	-0.1176		0.0078	-0.0568		-0.0183
9	-0.0256	<<	0.1283	0.1099		-0.0457
10	0.0179		0.0686	-0.1377	<<	-0.0461

>> and > implies that the left hand figure is greater than the right hand figure at 0.01 and 0.05 significance respectively using Wilcoxon signed-ranked test. The number of observations varies across time. It ranges from 180-251 companies and the total number of events is 4221 events.

This result suggests that price limits interfere with trading activity and negatively affect the investors' liquidity positions within the two regimes. Moreover, these results are consistent with Lehmann, (1989) and Kim and Rhee (1997). Figures 5.13 and 5.14 present the trading activity ratio (TAR) for the Upper and Lower limit hits respectively.

Figure 5-13: Trading activity ratio (TAR) for the Upper limit hits

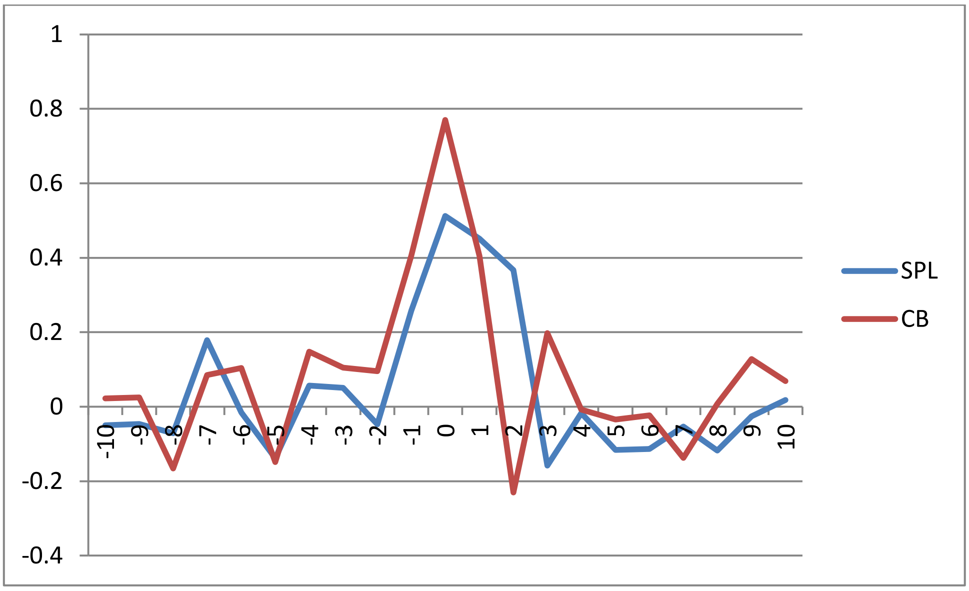
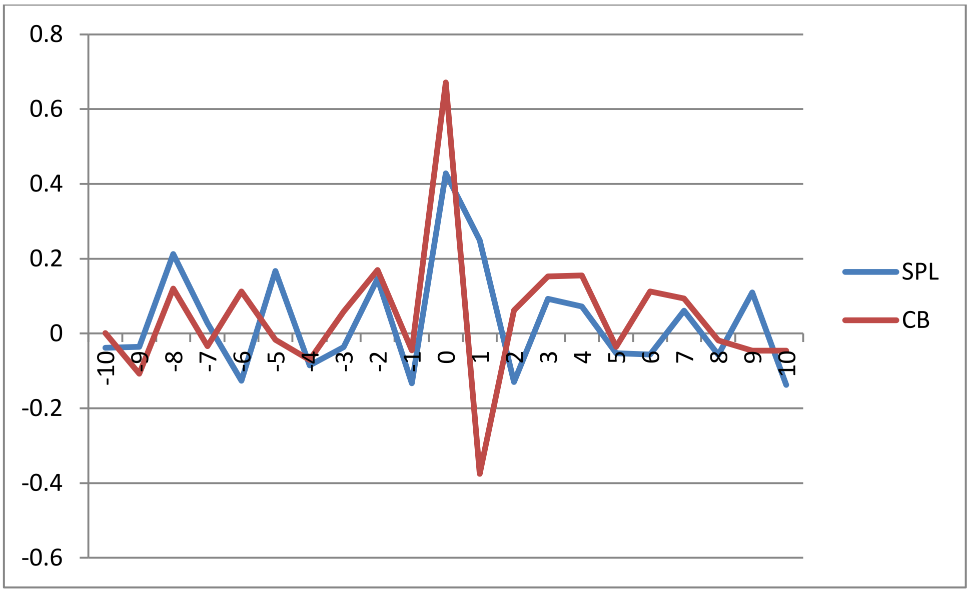


Figure 5-14: Trading activity ratio (TAR) for the Lower limit hits



5.5.5 Regulatory policies and volume-volatility relationship.

In this section I investigate the relationship between regulatory policies and volume-volatility dynamics. It is well documented that there is a positive relationship between trading volume and stock price volatility which is often explained by the Mixture of Distributions Hypothesis of Clark (1973) subsequently developed by Epps and Epps (1976) and Tauchen and Pitts (1983). An alternative explanation is provided by the Sequential of Information Arrival hypothesis (SIAH) of Copeland (1976Farag and Cressy (2011).

To explore further the Trading Interference hypothesis, I run a regression (following Kim and Rhee, 1997) for the 21-day window for both the Upper and Lower limits within the two limit regimes as in equation 14. I exclude the consecutive events for the sake of consistency with the volatility spillover analysis.

$$V_j = \alpha + \beta_1 (TA)_j + \beta_2 CB_j + \varepsilon_j \qquad (14)$$

where:

V_j : Squared stock returns as a measure of price volatility.

TA_j : The percentage change of turnover ratio as a proxy of trading activity.

CB_j : A dummy variable that equals 1 for stocks that reach Upper or Lower limit within CB regime, and equals 0 within SPL regime.

I use the turnover ratio as a proxy for trading activity instead of trading volume per se as Farag and Cressy (2011) found that there is an endogeneity problem between trading volume and stock price volatility (each determines the other). I estimate the above equation for each day of the 21-day window for both Upper and Lower limit hits.

According to the literature, I expect a positive relationship between trading activity and stock price volatility during the 21-day window. However, in day 0, I do not expect this relationship to continue, as price limits interfere with trading activity according to the trading interference (TI) hypothesis. The sign of the CB – dummy is expected to be positive and significant around event day. This implies an increase in stock price volatility due to regime switch from Strict Price Limits to circuit breakers.

To investigate the relationship between regulatory policies and the volume volatility relationship, tables 5.14 and 5.15 report the results of the OLS regressions for the Upper and Lower price movements as in equation 14. The two models are well specified as the F stat is highly significant and the adjusted R squared is reasonably high on event day.

As expected, tables 5.14 and 5.15 report a positive relationship between turnover ratio (as a proxy for trading activity) and stock price volatility over the 21-day window for the Upper and Lower price movements. This suggests a positive relationship between trading volume and stock price volatility. However, this volume–volatility relationship is much stronger and highly significant around event day for the Lower and Upper price movements respectively[28].

Interestingly, I find an insignificant volume–volatility relationship on event day (limit hits day) and on the first day subsequent to the event or both Upper and Lower limit hits. This suggests that regulatory policies (Strict Price Limits and circuit breakers) disrupt trading activity according to the trading interference hypothesis.

[28] Although the adjusted R squared is quite low in table 5.14, however, this is consistent with Kim and Rhee (1997) as we are interested in the direction (sign) of the volume-volatility relationships not in the explanatory power of the model. However we notice that F-statistics are highly significant.

Table 5.14: Volume volatility relationship for the Upper limit hits

Day	Intercept	CB	TR	Adj R^2	F.value
-10	0.0013*** (0.0002)	0.0004** (0.0002)	0.00004 (0.0001)	0.0074	2.6455*
-9	0.0014*** (0.0002)	0.0007*** (0.0003)	0.0002* (0.0001)	0.0208	5.7050***
-8	0.0015*** (0.0001)	0.0010*** (0.0002)	0.0003*** (0.0001)	0.0773	19.544***
-7	0.0012*** (0.0001)	0.0006*** (0.0002)	0.0002** (0.0001)	0.0341	8.8236***
-6	0.0017*** (0.0002)	0.0011*** (0.0003)	0.0003 (0.0002)	0.0560	14.146***
-5	0.0013*** (0.0001)	0.0006*** (0.0002)	0.0004*** (0.0001)	0.0239	6.4277***
-4	0.0014*** (0.0002)	0.0008*** (0.0002)	0.0003** (0.0003)	0.0379	9.7202***
-3	0.0140 (0.0843)	0.0834 (0.1092)	0.1182*** (0.0417)	0.0150	4.3669**
-2	0.0012*** (0.0001)	0.0006*** (0.0002)	0.0004** (0.0004)	0.0403	10.290***
-1	0.0030*** (0.0003)	0.0025*** (0.0003)	0.0006*** (0.0001)	0.1669	45.363***
0	**0.0177*** (0.0004)**	**0.0152*** (0.0005)**	**0.0002 (0.0002)**	**0.6544**	**78.36*****
1	0.0037*** (0.0002)	0.0024*** (0.0003)	0.0004 (0.0003)	0.1531	41.030***
2	0.0014*** (0.0002)	0.0006*** (0.0002)	0.0003*** (0.0001)	0.0163	4.6628***
3	0.0012*** (0.0001)	0.0004*** (0.0002)	0.0002*** (0.0001)	0.0279	7.3632***
4	0.0016*** (0.0002)	0.0008*** (0.0002)	0.0002*** (0.0001)	0.0369	9.4785***
5	0.0014*** (0.0001)	0.0005*** (0.0002)	0.0002*** (0.0001)	0.0323	8.3821***
6	0.0018*** (0.0002)	0.0010*** (0.0003)	0.0002** (0.0001)	0.0377	9.6817***
7	0.0011*** (0.0001)	0.0004** (0.0002)	0.0001* (0.0001)	0.0153	4.4516**
8	0.0017*** (0.0002)	0.0011*** (0.0003)	0.00002 (0.0001)	0.0324	8.4281***
9	0.0014*** (0.0001)	0.0008*** (0.0002)	0.0003*** (0.0001)	0.0640	16.153***
10	0.0012*** (0.0001)	0.0004*** (0.0002)	0.0001* (0.0001)	0.0213	5.8159***

The table presents the results of equation 14 for the Upper limit hits.

$$V_j = \alpha + \beta_1 (TA)_j + \beta_2 CB_j + \varepsilon_j$$

where, V_j : Squared stock returns as a measure of price volatility, TA_j : The percentage change of turnover ratio as a proxy of trading activity, CB_j : dummy variable equals 1 for stocks that reach Upper or Lower limit within CB regime, and 0 within SPL regime. ***, **,* indicate significance at the 1%, 5% and 10% levels. The number of observations varies across time. It ranges from 180-251 companies and the total number of events is 4221 events.

Table 5.15: Volume volatility relationship for the Lower limit hits

Day	Intercept	CB	TR	Adj R^2	F.value
-10	0.0010^{***}	0.0003^{*}	0.00003	0.0045	1.7904
	(0.0001)	(0.0001)	(0.0001)		
-9	0.0012^{***}	0.0005^{***}	0.00001	0.0140	3.4804^{**}
	(0.0001)	(0.0002)	(0.0001)		
-8	0.0010^{***}	0.0003^{**}	0.0001^{*}	0.0229	5.1069^{***}
	(0.0001)	(0.0001)	(0.0001)		
-7	0.0017^{***}	0.0010^{***}	0.0003^{*}	0.0327	6.9245^{***}
	(0.0002)	(0.0003)	(0.0001)		
-6	0.0019^{***}	0.0013^{***}	0.0001	0.0283	6.0977^{***}
	(0.0003)	(0.0004)	(0.0002)		
-5	0.0014^{***}	0.0008^{**}	0.00003	0.0109	2.9250^{*}
	(0.0002)	(0.0003)	(0.0001)		
-4	0.0011^{***}	0.0006^{***}	0.0001	0.0291	6.2441^{***}
	(0.0001)	(0.0002)	(0.0001)		
-3	0.0038^{***}	0.0032^{***}	0.00004^{**}	0.0174	4.1070^{**}
	(0.0008)	(0.0011)	(0.0002)		
-2	0.0020^{***}	0.0012^{***}	0.0005^{**}	0.0289	6.2000^{***}
	(0.0003)	(0.0004)	(0.0002)		
-1	0.0054^{***}	0.0046^{***}	0.0004^{**}	0.0410	8.4796^{***}
	(0.0008)	(0.0011)	(0.0002)		
0	**0.0180^{***}**	**0.0151^{***}**	**-0.0002**	**0.5732**	**36.00^{***}**
	(0.0005)	**(0.0007)**	**(0.0003)**		
1	0.0021^{***}	0.0010^{***}	0.0002	0.0411	8.5066^{***}
	(0.0002)	(0.0003)	(0.0002)		
2	0.0023^{***}	0.0016^{***}	0.0002^{**}	0.0717	14.519^{***}
	(0.0002)	(0.0003)	(0.0001)		
3	0.0018^{***}	0.0010^{***}	0.000^{**}	0.0417	8.6144^{***}
	(0.0002)	(0.0002)	(0.0001)		
4	0.0013^{***}	0.0006^{***}	-0.0001^{*}	0.0425	8.7626^{***}
	(0.0001)	(0.0002)	(0.0001)		
5	0.0012^{***}	0.0005^{**}	0.0001	0.0137	3.4380^{**}
	(0.0001)	(0.0002)	(0.0001)		
6	0.0018^{***}	0.0010^{***}	0.0001	0.0275	5.9499^{***}
	(0.0002)	(0.0003)	(0.0001)		
7	0.0015^{***}	0.0009^{***}	0.0002	0.0175	4.1251^{**}
	(0.0002)	(0.0003)	(0.0002)		
8	0.0008^{***}	0.0001	0.0001	-0.0016	0.7234
	(0.0001)	(0.0001)	(0.0001)		
9	0.0012^{***}	0.0004^{**}	0.0002^{*}	0.0134	3.3710^{**}
	(0.0002)	(0.0002)	(0.0001)		
10	0.0013^{***}	0.0006^{*}	0.0002	0.01165	3.0476^{**}
	(0.0002)	(0.0003)	(0.0001)		

The table presents the results of equation 14 for the Lower limit hits.

$$V_j = \alpha + \beta_1 (TA)_j + \beta_2 CB_j + \varepsilon_j$$

where, V_j : Squared stock returns as a measure of price volatility, TA_j : The percentage change of turnover ratio as a proxy of trading activity, CB_j : dummy variable equals 1 for stocks that reach Upper or Lower limit within CB regime, and 0 within SPL regime. ***, **,* indicate significance at the 1%, 5% and 10% levels. ***, **,* indicate significance at the 1%, 5% and 10% levels. The number of observations varies across time. It ranges from 180-251 companies and the total number of events is 4221 events.

On the other hand, I also find a positive and significant relationship between the dummy variable (CB) and stock price volatility within the Upper and Lower limit hits. This suggests that switching from Strict Price Limits to circuit breakers does increase short-term stock price volatility rather than cooling down the market as was intended by the regulator. These findings are consistent with the volatility spillover hypothesis as regulatory policies (not trading activity) cause volatility to spread out few days subsequent to limits hit.

5.5.6 Long term volatility and regime switch

To further investigate the long-term effect of regime switch on stock price volatility, I estimate the Exponential Asymmetry GARCH model (EGARCH of Nelson (1991)) for the EGX30 market index over the period 1999-2009 (5 years within SPL regime and 5 years within CB regime) and augment it by adding a price limit dummy variable as in equation 15. The EGARCH model has many advantages over the symmetric GARCH as the estimation has no negative parameters ($\log(\sigma_t^2)$ is positive), and so, no non-negativity constraints need be imposed on the model parameters as in TARCH-GJR model. The EGARCH formula is presented in equation 15 below.

Leverage effect (the effect of positive and negative shocks on the future conditional volatility) is allowed and the parameter γ is expected to be negative in sign if the relationship between return and volatility is negative. The leverage effect in the EGARCH model is exponential rather than quadratic and can be tested by the hypothesis that $\gamma < 0$. The impact is asymmetric if $\gamma \neq 0$. The volatility persistence is measured by β to examine whether big (small) shocks are followed by bigger (smaller) shocks.

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\mu_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] + \eta \, CB_t \qquad (15)$$

where:

$\ln(\sigma_t^2)$ is the conditional variance of return at time (t)

$\beta \ln(\sigma_{t-1}^2)$: is the conditional variance at time (t-1)

$\alpha \left[\frac{|\mu_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right]$ is the effect of the shock (i.e. new information arrival) on conditional volatility.

$\gamma \frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}^2}}$ is the effect of positive and negative shocks on conditional volatility (leverage effect).

CB_t is a dummy variable takes the value of 1 if the CB regime is in operation on day t; and zero if the SPL regime is in operation.

Importantly for our empirical analysis, the sign of η will be positive or negative as switching regimes increase or decrease volatility. Nelson (1991) assumed that the error term follows the Generalized Error Distribution (GED). This is defined by

$$I(\Theta)_t = \ln\left(\frac{v}{\lambda}\right) - \left(\frac{1}{2}\right)\left|\frac{\varepsilon_t}{h_t \lambda}\right|^v - \left(1 + \frac{1}{v}\right)\ln(2) - \ln\left(\Gamma\left(\frac{1}{v}\right)\right) - 0.5\ln(h_t^2) \qquad (16)$$

where $\lambda = \exp((-1/v)\ln(2) + (1/2)\ln(\Gamma(1/v) - (1/2))\ln(\Gamma(3/v)))$, and v is a tail thickness parameter. When v = 2, u_t has a Standard ormal distribution. Finally, I use the Berndt-Hall-Hall-Hausman (BHHH) technique to maximize the log likelihood function of the GED.

To investigate the effect of long-term volatility on regulatory policies, table 5.16 presents the results of the augmented EGARCH model. The model is well specified as the log likelihood estimation is big compared to the symmetric GARCH model. This suggests that the EGARH model fits the daily returns time series of the EGX30 and the temporal dependence of return volatility can be captured by the model.

The volatility persistence coefficients α and β are highly significant, however β is greater in magnitude than α ; this implies that the bigger the market shocks the relatively smaller revision expected volatility.

Table 5.16: Augmented EGARCH Estimation

	ω	β	γ	α	η
EGX30	-0.4949*** (0.0704)	0.9686*** (0.0068)	-0.0281* (0.0167)	0.0371*** (0.0135)	**0.0296** (0.0142)**
Log likelihood	5680				
Ljung-Box $Q_{(20)}$	35.831				
Ljung-Box $Q^2_{(20)}$	18.634				
LMARCH	1.1435				

The table presents the results of the augmented Exponential Generalized autoregressive GARCH model as in equation 15. ***, **,* indicate significance at the 1%, 5% and 10% levels.

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\mu_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] + \eta\, CB_t$$

The number of observations varies based on the number of trading days in the EGX across years.

The leverage effect is negative as expected; this suggests that negative shocks have greater effect on conditional volatility in the EGX. Most importantly, the CB coefficient is positive in sign and highly significant; this suggests that the switch from SPL to CB increases future volatility. This result is consistent with the previous analysis. Furthermore, we can reject the null that the residuals are serially uncorrelated and homoskedastic. The results of the Ljung-Box $Q_{(20)}$ and Ljung-Box $Q^2_{(20)}$ for serial correlation and the LMARCH for heteroskedastisity are insignificant.

The results of the volatility spillover and delayed price discovery hypotheses in addition to the asymmetry EGARCH models show that switching from the SPL to the CB did increase stock price volatility in the Egyptian stock market. A potential interpretation to this result is as follows: based on the volatility spillover hypothesis, price limits prevent speculative traders from responding to the new information and to adjust their portfolios. This implies a remarkable delay in price discovery mechanism as current prices are away from their equilibrium levels (Farag and Cressy (2011).

I claim that the price discovery mechanism in the Egyptian stock market varies between SPL and CB. Within the SPL as prices hit the limit, trading is suspended until the end of the trading session, therefore volatility is expected to spread out over the following day(s), Meanwhile, investors have more time (until the following day) to analyse and to react to the new information and then adjust their portfolios accordingly. On the other hand, within the CB regime, when prices hit the limit, trading is suspended for 30 minutes. During this relatively short time investors have to adjust their portfolios based on the new information arriving in the market (Farag and Cressy (2011).

I argue that since herding behaviour and noise trading are dominant behaviours in emerging markets, intense trading activity is continued by some speculative traders when a trading session is resumed. In addition, the media coverage plays an important role in affecting investors' belies within a trading halt period (Lee et al. 1994) and (Farag and Cressy (2011).

However, due to the lack of informational efficiency in the Egyptian stock market not all investors are being informed with the new information. Therefore investors are unable to reveal their demand during the halt period. This suggests that stock prices are expected to be much noisier post halt period and significantly different from their equilibrium levels. As a result, higher volume and volatility are expected when trading is resumed (Lee et al. (1994) and Farag and Cressy (2011)[29].

5.6 Summary and conclusion

The main objective of this chapter is to investigate the effect of regulatory policies (price limits, circuit breakers) on four main hypotheses, namely, the overreaction hypothesis, volatility spillover hypothesis, the delayed price discovery hypothesis and the trading interference hypothesis in the Egyptian stock market. In addition, the chapter examines the effect of the regime switch (from Strict Price Limits to circuit breakers) on the long-term volatility. Moreover, the chapter introduces a comprehensive literature review of price limits as well as the theoretical background about the evolution of the different types of regulatory policies.

The dataset consists of daily open, high, low and closing prices for all listed shares in the Egyptian stock exchange during the period 1999-2009, in addition to trading volumes as a proxy for trading activity and market capitalisation as a proxy for size. Moreover, I use the EGX30 - a free-float market capitalisation-weighted index - as a benchmark.

[29] These results have been published in the European Journal of Finance (forthcoming) based on my earlier work in this chapter.

The Egyptian stock exchange (EGX) has unique price limit regimes; this makes studying the EGX - amongst a few other stock exchanges i.e. Korean stock exchange - interesting. The regulator in the EGX has imposed strict (+-5%) price limits (SPL) for all the listed shares since 1996. The limit is activated for a particular stock only when stock return hits the Upper or Lower limit, then the trading on this share is suspended to the end of the trading session. In 2002 the regulator commenced a new price ceiling system, namely, circuit breakers (CB) in which the price limits have winded to (+-20%) for the most actively traded shares in the EGX. Within the new CB regime, trading is halted for 30 minutes when stock return for a particular stock hits (+-10%).

The results of the overreaction hypothesis show that there is price reversal pattern for the Lower limit hits (bad news) one and two days following the event within the two regimes SPL and CB respectively. In addition, there is a price continuation pattern for the Upper limit hits (good news) within the SPL regime over the event window. This result supports the overreaction hypothesis in case of bad news (Lower limit hits) while also suggesting the leverage effect in the Egyptian stock market within the two regimes.

Moreover, the results support the effect of firm size on the overreaction hypothesis for the Lower limit hits for small firms in particular. This can be explained in the light of the literature as volatility is more likely to be higher for small firms (Huang (1997 and (1998)). The results do not support the effect of firm size on the overreaction hypothesis within the circuit breakers regimes.

The findings of the volatility spillover hypothesis conclude that price limits do not decrease volatility as intended in both regimes (SPL and CB). However, volatility is found to be higher within the CB regime whereas, within the SPL regime, volatility is spread out over the following two days subsequent to limit hit day.

These results are consistent with the volatility spillover hypothesis as the price discovery mechanism is disrupted when stocks experience greater volatility for a few days post limit hits, therefore stock prices are prevented from reaching their equilibrium levels for the following few days post-event. These deviations from the true prices are expected to prevail within the SPL (+-5%) regime as a trading session is suspended until the following day (trading session) when the prices hit their Upper or lower limits. However, within wider bands of limits (- +10%) followed by trading halts, investors have chance to adjust their portfolios position within the same trading session. Therefore the delay in the price discovery process is expected to be higher within the SPL regime. These results are consistent with Kim and Rhee, (1997) and Lee et al (1994).

The results of the delayed price discovery hypothesis show that price continuations behaviour occurs more frequently within the SPL regime immediately following the event (limit hit day). This implies that the price discovery mechanism is delayed by the Strict Price Limits. This result is consistent with the delayed price discovery hypothesis. Price reversal behaviour seems to occur more frequently within the CB regime compared to the SPL regime immediately following the event, thus implying that Strict Price Limits delay or prevent the overreactive behaviour, compared to the circuit breakers regime.

The results of the trading interference hypothesis show that there is a sharp increase in trading activity on event day (limit hit day) for both SPL and CB regimes for the Upper and Lower price movement. In addition, the trading activity on event day (limit hit day) is significantly greater than those within the rest of trading window. This increase in trading activity lasts for 1-2 days subsequent to the event.

I interpret these results as follows: within the SPL regime, traders are unable to obtain their desired positions on event day. In addition, traders are unable to adjust their portfolios' positions - when prices hit the limit - and are forced to wait until the following day. Therefore Strict Price Limits interfere with trading activity.

On the other hand, within circuit breakers regime, trading activity on average is significantly higher than those of Strict Price Limits. Investors within the CB regime have the chance to adjust their portfolio positions during the same trading session. However, not all investors are informed about the suspension of trading due to the lack of informational efficiency in emerging markets. Therefore only one day following the event may be required to adjust their portfolios' position. This result suggests that price limits interfere with trading activity and negatively affect the investors' liquidity positions within the two regimes. Moreover, these results are consistent with Lehmann, (1989) and Kim and Rhee (1997).

The results of the volume volatility relationship show that there is a positive relationship between turnover ratio (as a proxy for trading activity) and stock price volatility over the 21-day window for the Upper and Lower price movements. However, this positive volume–volatility relationship is much stronger and highly significant around event day for the Lower and Upper price movements respectively.

Interestingly, I find insignificant volume–volatility relationship on event day (limit hits day) and on the first day subsequent to the event for both Upper and Lower limit hits. This suggests that regulatory policies (Strict Price Limits and circuit breakers) disrupt trading activity according to the trading interference hypothesis.

On the other hand, I also find a positive and significant relationship between the dummy variable (CB) and stock price volatility within the Upper and Lower limit hits in the short run. In addition, I investigate the effect of regulatory policies on the long-term conditional volatility, using the augmented EGARCH model. I find that the CB coefficient (dummy variable in the conditional variance of the EGARCH model) is positive in sign and highly significant, thus suggesting that the switch from SPL to CB increases future volatility.

To conclude, the above results of the volatility spillover and delayed price discovery hypotheses in addition to the asymmetric EGARCH model show that switching from the SPL to the CB did increase stock price volatility in the Egyptian stock market. A potential interpretation to this result is as follows: based on the volatility spillover hypothesis, price limits prevent speculative traders from responding to the new information and to adjust their portfolios. This implies a remarkable delay in price discovery mechanism as current prices are away from their equilibrium levels (Farag and Cressy (2011).

I claim that the price discovery mechanism in the Egyptian stock market varies between SPL and CB. Within the SPL as prices hit the limit, trading is suspended until the end of the trading session, therefore volatility is expected to spread out over the following day(s). Meanwhile, investors have more time (until the following day) to analyse and to react to the new information and then adjust their portfolios accordingly. Within the CB regime, when prices hit the limit, trading is suspended for 30 minutes. During this relatively short time investors have to adjust their portfolios based on the new information arriving in the market (Farag and Cressy (2011).

I argue that since herding behaviour and noise trading are dominant behaviours in emerging markets, intense trading activity is continued by some speculative traders when trading session is resumed. In addition, the media coverage plays an important role in affecting investors' belies within trading halt period (Lee et al. 1994) and (Farag and Cressy (2011).

Due to the lack of informational efficiency in the Egyptian stock market not all investors are being informed with the new information. Therefore investors are unable to reveal their demand during the halt period. This suggests that stock prices are expected to be much noisier post halt period and significantly different from their equilibrium levels; as a result higher volume and volatility are expected when trading is resumed (Lee et al. (1994) and Farag and Cressy (2011).

Table 5.17: Summary of the literature on price limits and circuit breakers

Authors, date and title	**Study objective(s)**	**Sample description, study period and methodology**	**Summary of empirical finding and conclusion**
Gerety, M. & Mulherin, J. (1992) Trading Halts and Market Activity: An Analysis of Volume at the Open and the Close.	Investigate the performance of the daily trading volume under trading halts at the open and the close of the trading day.	They used hourly trading volume data of three market indices - the New York Stock Exchange (NYSE) from 1933-1988, the Down Jones (DJ) 30 industrial index from 1933-1940 and the Dow Jones 65 Composite Index over the period 1941- 1988. They estimated of expected and unexpected volatility following Brock and Kleidon (1992), and Davidian and Carroll (1987).	They found that circuit breaker leads to an overreaction phenomenon rather than cooling the market down as was intended. In addition they found that the trading volume at a closing hour is highly related to the previous day's trading volume at the opening hour.
Santoni, G. & Liu, T. (1993) Circuit Breakers and Stock Market Volatility.	Looked at the volatility of the NYSE under circuit breakers and whether or not price limits reduced stock price volatility.	Daily data were collected for the S&P 500 over the period July 1962 - May 1991 and using the ARCH model.	They found that imposing circuit breakers did not reduce the stock price volatility in the US.
Lauterbach, B and Ben-Zion (1993) Stock Market Crashes and the Performance of Circuit Breakers: Empirical Evidence.	To analyze the behaviour of stock prices for small firms after the imposition of circuit breakers for a selected number of stocks during the stock market crash of 1987.	They used a short window (form 13^{th} to 28^{th} October) of daily stock prices, firm characteristic and order imbalances data around the stock market crash (1987) from the Tel Aviv Stock Exchange (TASE). They regress the order imbalances on firm specific characteristics.	They found no evidence that circuit breakers affected the magnitude of the decline but concluded that they might have smoothed fluctuations in prices, i.e. reduced volatility. In addition, they found that during the crash (1987) the selling pressure were concentrated on both higher beta and larger companies.

Lee, C, Ready, M, and Seguin, P. (1994) Volume, Volatility, and New York Stock Exchange Trading Halts.	To investigate the effect of trading halts on stock price volatility and trading volume.	They used a sample of 852 trading halts of 449 firms on NYSE during 1988 and followed the price-matched case control methodology to isolate the volume volatility effects of the price impact. In addition, they controlled for firm-specific time-of-day effects, the amount of information released and the relationship between media coverage and posthalt activity.	They found that trading halts increase both trading volume and stock price volatility by 230% higher than following nonhalt control. In addition they found little evidence that the flow of information is not facilitated by the trading halts. Finally they argued that media coverage played an important role in explaining the posthalt price behavior due to the increase heterogeneity of investors' beliefs.
Subrahmanyam, A. (1994) Circuit Breakers and Market Volatility: A Theoretical Perspective.	Examined the effect of circuit breakers (price limit + trading halts) on stock return volatility in New York Stock Exchange (NYSE) and Dow Jones Industrial Average.	Daily date of New York Stock Exchange (NYSE) and Dow Jones Industrial Average (DJIA). Linear equilibrium and optimization in addition to market models.	Imposing circuit breakers increases stock return volatility rather than cooling the volatility as intended. In addition these regulatory policies are not consistent with maximising market liquidity objectives.
George, T. & Hwang, C.-Y. (1995) Transitory Price Changes and Price-Limit Rules: Evidence from the Tokyo Stock Exchange.	Investigated the stock returns volatility during 24 hours for the most actively traded against the least traded shares listed in Tokyo stock exchange (TSE).	Open and close price data were collected over the period from January 1975 to December 1989. They used the Generalized Method of Moments (GMM).	They found the price limits prevent share prices from reaching to the equilibrium level when changes in share value is associated with order imbalance. Therefore, the most actively traded shares are exhibited price continuation with high trading volumes.

Lee, S. & Chung, J. (1996) Price limits and stock market efficiency.	Investigated the effect of price limit on the market efficiency in the Korean Stock Exchange KSE.	They used a sample of thirty active individual stocks over the period from January 1990 to December 1993, and the conditional heteroscedasticity to test the efficient market hypotheses.	The main findings of this paper is that the KSE seems to be inefficient due to the price limit regime as opening prices reflects all the information that was not fully reflected during the previous session due to the limits.
Kim, K. & Rhee, S. (1997) Price Limit Performance: Evidence from the Tokyo Stock Exchange.	To examine the price limit mechanism and to investigate three main hypotheses namely volatility spillover, delayed price discovery, and trading Interference hypotheses.	Daily stock prices date from Tokyo Stock Exchange (TSE) over the period 1989-1992. They used the squared stock returns as a measure of volatility for all the listed shares in the TSE for a 21-day window for three different events namely; stock hitting the limit, stocks hitting 0.90 and 0.80 of the limits.	The main finding of this paper is that imposing price limits leads to volatility spillover, as price limits prevent larger price changes. Therefore price limits do not cool off volatility but just spread the volatility over the subsequent days. In addition they found evidence for the price continuation hypothesis as well as trading inference hypothesis.
Lee, S. & Kim, D. (1997) Price Limits and Beta.	Investigated the effect of price limits on the parameters of the market model particularly on beta in the Koran stock exchange.	They used the methodology of restricted regression analysis together with the two-pass regression analysis (suggested by Cohen et al. 1983) to investigate whether the estimation of bets is bias or not. The data set consists of all listed shares in the Korean Stock Exchange over the period 1990-1993.	The found that the stochastic process of the returns and the parameters of market models are significantly affected by the price limits. In addition, they found that the estimation of beta is biased and unstable over the time.

Arak, M. & Cook, R. (1997) Do Daily Price Limits Act as Magnets? The Case of Treasury Bond Futures.	The main objective is to investigate whether price limits destabilise price behaviour or act as a magnet in the U.S. Treasury bond futures market.	Daily price data were collected for the US treasury Bonds over the period from 1980 to April 29 1987. In order to include a day into the data set, the absolute value of the overnight price change should be twice as the standard deviation. Two empirical models were used to examine the effect of the price limits or news on the change in price.	They found that price limits lead to small price reversal behaviour; this suggests the role of price limits as a stabilizer in the US futures market.
Kryzanowski, L. & Nemiroff, H. (1998) Price Discovery around Trading halts on the Montreal Exchange using trade –by- trade data.	To examine whether the relationship between price discovery and the regulatory polices (trading halts) are stable over time.	Using 823 trading halts from the Montreal stock exchange over three- six month sub periods arbitrarily chosen over the period 1988-1989. They used the mean –adjusted generating model to measure the Abnormal Returns for stocks that experienced trading halts.	They found that both volatility and trading volume tend to increase significantly around trading halts over the two days subsequent to trading halts.
Shen, C.-H. & Wang, L.-R. (1998) Daily serial correlation, trading volume and price limits: Evidence from the Taiwan stock market.	To examine the effect of price limits on the stock return autocorrelation, and trading volume.	Daily date from Taiwan stock exchange over the period from November 1988 to December 1995, and using generalized autoregressive conditional heteroscedasticity (GARCH) and the (GMM).	They found evidence of the impact of price limits on stock autocorrelation; however the UpperUpper limit has positive and stronger impact than o Lower limit.
Chen, H. (1998) Price Limits, Overreaction, and Price Resolution in	Investigated the overreaction hypothesis and the effect of price resolution in the futures markets.	The data set consists of daily prices for 19 futures contracts. They used the event study methodology following Ma et al. (1989, 1990) and Gay et al.	The main results of this paper relatively support the futures market efficiency with regard the information dissemination. In

Futures Markets.		(1994).	addition, little evidence of overreaction hypothesis is found in the US futures markets.
Huang (1998), Stock Price Reaction to Daily Limit moves: Evidence from the Taiwan Stock Exchange.	Investigated the overreaction hypothesis following up and down limit moves.	The data set consists of all listed shares in the Taiwan stock exchange over the period 1971-1993. They used the market model in the context of the event study methodology.	They found highly significant price reversals following up and down limit moves; in addition, these reversals are not due to size effects. Therefore the overreaction hypothesis is dominated in the Taiwan Stock Market under the price limit regime.
Phylaktis, K., Kavussanos, M. & Manalis, G. (1999) Price limits and stock market volatility in the Athens Stock Exchange.	Investigated effect of price limits of stock price volatility in the Athens Stock Exchange (ASE). In addition the paper examined the information and overreaction hypotheses.	The dataset consists of daily and monthly closing prices for the most active 10 stocks in the ASE over the period from January 1990 to June 1996. They used the serial correlation of the daily returns and the time varying models (GARCH).	They found that no effects of price limits on stock price volatility, in addition their results supported the information and the overreaction hypotheses in the ASE.
Kim, K. & Limpaphayom, P. (2000) Characteristics of stocks that frequently hit price limits: Empirical evidence from Taiwan and Thailand.	Looked at the characteristics of shares that frequently hit the limit in Taiwan and Thailand stock exchanges.	The data set consists of daily and monthly returns over four years 1990-1993. They used the generalized method of moments (GMM) following Gallant (1987) and Ogaki (1993).	They found that it is highly likely for the share to hit the limits if it has small market capitalisation (small firm effect), high volatility, and high trading volume.

Corwin, S. & Lipson, M. (2000) Order Flow and Liquidity around NYSE Trading Halts.	Looked at the trading behaviour, stock price volatility and shares liquidity around halts in the NYSE.	The data set consists of 469 intraday trading halts for the listed shares over the period 1995-1996. They compared the normal trading activity (non halts sessions) with those of trading halts for 10 days before and after the halt.	They found consistent results with Lee et al. (1994) as volatility tends to be higher following trading halts as liquidity is decreased around trading halts. In addition they found higher volume of order submission and cancellation around trading halts; this suggests that investors are trying to adjust their portfolios during the halt period.
Ackert, L., Church, B. & Jayaraman, N. (2001) An experimental study of circuit breakers: The effects of mandated market closures and temporary halts on market behaviour.	Investigated the relationship between circuit breakers and both trading volume and price dynamics in the NYSE futures markets.	They used experimental methods on nine different markets to analyse and compare the behaviour of prices under three regulatory policies namely; temporary halt, no limit effects and market closure.	The main finding of this paper is that circuit breakers significantly affect trading volume as trading activities tend to be higher the closer the limit hits. In addition they found no impact of temporary trading halts on trading profits.
Huang, Y., Fu, T.-W. & Ke, M.-C. (2001) Daily price limits and Stock price behaviour: evidence from the Taiwan stock exchange.	To investigate the information and overreaction hypothesis in the Taiwan stock market.	The data set consists of all Upper and downward limits for consecutive three days for all listed shares in the Taiwan stock exchange over the period 1990-1996. In addition the study extended the analysis to further investigate the intraday limit moves and near-limit cases. They used the market model in the context of the event study	The main findings of the paper supported both the information and the overreaction hypotheses as continuation pattern is found in the overnight period following the limit moves and price reversal behavior is reported in the subsequent trading days due to noise trading.

		methodology to examine the overnight and trading time Abnormal Returns.	
Holder, M, Ma, C. and Mallet, J. (2002) Future price limits moves as option.	To investigate the information and the overreaction Treasury bond future prices in the US futures market.	Simulation models were used on the Treasury bond futures prices data were collected from the Chicago Board of Trade (CBOT) over the period 1980-1988.	They concluded that the price limit moves can be predicted three hours prior to the first limit move as the true futures prices deviate from the actual prices In addition they found evidence that the overreaction hypothesis better explain stock prices around price limits than the information hypothesis in the US future market.
Christie, W., Corwin, S. & Harris, J. (2002) Nasdaq Trading Halts: The Impact of Market Mechanisms on Prices, Trading Activity, and Execution Costs.	The main objective of the paper is to examine the effect of two different reopening mechanisms on stock prices, transaction costs, and trading activity.	Data set consists of a sample of 714 news –related halts in Nasdaq over the period 1997- 1998 and using a matched sample of trading halts and non trading halts days.	They found that the market liquidity can be enhanced during market closure as trading halts allows the dissemination of information. They also found highly significant increase in the trading volume and stock price volatility during the 90 minutes following halts reopened in the following morning.
Cho, D., Russell, J., Tiao, G. & Tsay, R. (2003) The magnet effect of price limits: evidence	Investigated the 'magnet' effect of imposing price limits in Taiwan stock exchange.	Intraday data from Taiwan stock exchange (5-min return series on all the listed companies from January 3, 1998 to March 20, 1999). They tackle	They found evidence of ceiling magnet effect but only a weak evidence of floor magnet effect. They argue that magnet effect is

from high-frequency data on Taiwan Stock Exchange.		the deterministic volatility pattern by standardising the 5-min returns by its standard deviations.	strong evidence against overreaction hypothesis so that price limits fail as a tool for the control of price overreaction.
McDonald, C & Michayluk, D. (2003), Suspicious trading halts	To Examine the type of trading halts that stimulates investors to take advantage due to Paris Bourse imperfection.	The data set consists of daily transactions, quotes and orders of all continuously traded shares listed on the Paris Bourse during 1997-1998. They used Wilcoxon rank sums test and ANOVA F-test.	They found that closing price in the Paris Bourse can be manipulated by some noise traders using trading halt mechanism and this leads to dramatic decrease in the market liquidity for the rest of the trading session.
Chen, A, Chiou, S and Wu, C (2004), Efficient learning under price limits: evidence from IPOs in Taiwan	Investigated the learning behaviour by rational investors and the role of past information within price limits regime (7%) in Taiwan.	Daily data of 362 IPOs were collected over the period 1991-1998. They adopted the methodology of Bossaerts and Hillion (2001) and using Fama and French 3 factor model to estimate the IPO's benchmark return.	They found significant and positive abnormal return four months after IPO. This suggests underreaction behaviour due to the delayed information hypothesis under price limits.
Naughton, T. & Veeraraghavan, M. (2004) Stock Exchange Are Price Limits Priced? Evidence from the Taiwan.	Investigated whether or not price limits are priced in the Taiwan stock exchange (TSE).	The data set consists of monthly stock returns over the period 1975-1996 and using the Fama and French three-factor model and augmented it by the price limit factor.	They found that size and price limits factors significantly explain cross section of stock returns in Taiwan. In addition, they found that shares that hit the limit less frequently have significant returns and risk premium as well.
Chung, J. & Gan, L. (2005) Estimating the	Investigated the relationship between price limits and the	The sample consists of 69 continuously traded stocks over the	They found evidence that imposing price limits leads to cooling effect

effect of price limits on limit-hitting days.	underlying equilibrium prices on limit-hitting days. In addition the paper examined the two main effects namely; Ceiling and Cooling off (Heating up) effects.	period 1987-1997. They used the maximum likelihood estimation of the effect of price limits on five randomly selected shares as well as for all listed shares in the Taiwan stock exchange. In addition to the mixture normal density and the Mixture of Distributions Hypothesis (MDH).	on average stock returns. In addition they found significant effect of price limits on stock return volatility assuming that stock returns follow simple normal density function. However these effects disappear if the mixture normal density function is used.
Chan, S, Kim, K and Rhee, J. (2005). Price limit performance: evidence from transactions data and the limit order book	Investigated the effect of imposing wider price limits on price discovery mechanism, information asymmetry and order imbalance in Kuala Lumpur Stock Exchange (KLSE) of Malaysia.	They used order flow data and real-time transaction data over the period from Jan. 1995 to Dec.1996. Using the methodology of Madhavan and Smidt (1991) and Choi and Subrahmanyam (1994), they identified two main groups namely limit-hit group and non-hit group and comparing the pre- and post-hit periods.	They found no evidence that price limit enhance information asymmetry, in addition they found that price limits delay the information flow and lead to order imbalance.
Chen, G.-M., Kim, K. & Rui, O. (2005) A note on price limit performance: The case of illiquid stocks.	To investigate whether illiquid stocks are highly affected by price limits and more vulnerable to hitting the limit more frequently than liquid shares.	Daily data of 83 firms (A-shares and B-shares) over the period from July 1999 to December 2002 from the Chinese stock exchange. Following the methodology of Kim and Limpaphayom (2000), they run a regression to examine the relationship between the wider bid-ask spread and the frequency of limit hitting for liquid and illiquid stocks.	They found that B-shares are less liquid and have wider bid-ask spread than those of A-shares this may lead to hitting the price limit more frequently than those of A-shares. They also found positive and systematic relationship between bid-ask spread and tendency to hit the limits.

Chou, P.-H., Lin, M.-C. & Yu, M.-T. (2005) Risk aversion and price limits in futures markets.	Investigated the relationship between price limits and default risk and whether price limits can reduce the effective margin requirements and to minimise default risk in the Taiwan futures market.	Using optimization problem and the extended Brennan (1986) model on a numerical example from Taiwan stock exchange.	They found evidence that price limits can actually reduce the cost of contracts and the margin requirements only for low risk aversion investors. In addition they found that price limit is not an efficient tool to cool down the futures market price volatility for risk averse investors.
Chou, P.-H., Li, W.-S. Lin, J.-B. &Wang, J.-S. (2006) Estimating the VaR of a portfolio subject to price limits and non-synchronous trading.	To investigate the potential bias at the VaR estimation due to the infrequent trading and price limits.	Using daily stock returns of all listed shares in the Taiwan Stock Exchange (TSE) together with the Over the counter market over the period 1998-2003 they estimated the Value at Risk (VaR) using the two-limit type Tobit model and following the methodology of Scholes and Williams (1977).	They found that the simulation models were reasonably well specified in TSE except for the OLS even in case of higher volatility when prices hit the limits.
Madura, J., Richie, N. & Tucker, A. (2006) Trading Halts and Price Discovery.	Investigated the consequences of the trading halts and investors' reaction pre, during and post trading halts in NASDAQ.	Data of 656 trading halts were collected in NASDAQ in 1998. They compared the price behaviour pre, during and post trading halts in order to examine investors' reaction to the halts.	They found significant Abnormal Returns pre and during the halts period in NASDAQ, in addition they found no significant Abnormal Returns post trading halts.
Bildik, R. & Gulay, G. (2006) Are Price Limits Effective? Evidence from the Istanbul Stock	Iinvestigated the effects of price limits on the volatility spillover, delayed price discovery, and	The data were collected from Istanbul stock market over the period 1998 – 2002. They used the methodology of	They found that volume weighted average prices (VWAP) provide stronger evidence for the volatility spillover, delayed price discovery,

Exchange.	trading interference hypotheses.	Kim and Rhee (1997).	and trading interference hypotheses compared with limit moves.
Abad, D & Pascual, R. (2007) On the Magnet Effect of Price Limits.	Investigated the magnet effect of the price limits in the Spanish stock exchange (SSE).	Data were collected for 114 listed shares over the period from 2001-2003. They compared trading sessions with limits hit with other normal trading sessions (no limit hits).	Using FGLS they found that regime switch does not create magnet effect of price limits in the Spanish stock exchange.
Kim, H, Yague, J. & Yang, J. (2008). Relative performance of trading halts and price limits: Evidence from the Spanish Stock Exchange.	Looked at the trading activity, liquidity, stock price volatility in addition to price discovery mechanism in the Spanish stock exchange around trading halts and price limit hits.	The dataset consists of daily returns, trading volume for the listed shares in the Spanish Stock Exchange over the period January 1, 1998, and April 30, 2001. They analysed the Abnormal Returns over 10 days around trading halts.	They found that both trading volume and volatility increases immediately after trading halts. However, liquidity tends to be higher within trading halts.
Kim, Y. & Yang, J. (2008) The effect of price limits on intraday volatility and information asymmetry.	Investigated the relationship between price limits and both information asymmetry and intraday price volatility by investigating the information and the overreaction hypotheses in the Taiwan Stock Exchange (TWSE).	They used transaction data for all listed shares in the TWSE during 2000 to calculate stock returns and variances during 5-minute in either 30 or 15 min before and after the limit hits.	They found that there is a dramatic decrease in price volatility following consecutive limit hits; in addition they found that price limits are unable to reduce information asymmetry in the TWSE.
Wong, W., Liu, B. & Zeng, Y. (2009) Can price limits help when the price is falling?	Investigated the intraday dynamics of magnet effect (ceiling and floor) of the price limits in the Shanghai	Intraday (5-min price returns half an hour prior to the limit hits) data were collected over the period January 2002 to December 2002. They used the	They found evidence of trading activity acceleration and higher volatility when prices approach to limit hit, in addition they found

Evidence from transactions data on the Shanghai Stock Exchange.	Stock Exchange (SHSE).	methodology of Du et al. (2005).	asymmetric price limit effect between ceiling and floor limit hits as trading volume tends to be lower when stock prices approach the floor limits.
Hsieh, P.-H. & Yang, J. (2009) A censored stochastic volatility approach to the estimation of price limit moves.	They examined stock returns under price limits as equilibrium prices are unobservable when share prices hit the limit.	Data were collected form a sample of two actively traded shares in the Taiwan stock exchange TSE in addition to two futures contracts in the Chicago Board of Trade CBOT. They used the censored stochastic volatility model.	They suggested that portfolio managers may use the CSV model to model return time series under price limits to obtain better estimates for risk.
Jiang, C, Mclnish, T. & Upson, J. (2009). The information content of trading halts.	Investigated the effect of trading halts on the informationally related shares in the NYSE.	The dataset consists of daily stock returns for the halted shares in the NYSE over the period 2003-2005. They used the methodology of Spiegel and Subrahmanyam (2000).	They found direct impact of liquidity and high correlation between halted and reference stocks. In addition the effect of the liquidity is found to be more significant for small firms.
Hsieh, P. & Kim, J. & Yang, J. (2009). The magnet effect of price limits: A logit approach.	Investigated the magnet effect using new approach, namely, the logit approach to control for the macroeconomic variables in the Taiwan stock market.	Transactional data are collected for all listed shares in the Taiwan stock exchange TWSE. They used the logit model to control for the microstructure variables and stock price behaviour.	The main findings of this paper supported the magnet effect in the Taiwan stock exchange as they found significant increase of the conditional probability of stock prices when the prices reach their Upper limits and the opposite is correct when prices approach the

			lower limits.
Kim, K. & Park, J. (2010) Why Do Price Limits Exist in Stock Markets? A Manipulation-Based Explanation.	Investigated the relationship between the levels of corruption together with the quality of public enforcement of the likelihood of adopting price limits regime.	Corruption data were collected as a proxy of market manipulation a sample of stock exchange all over the world.	They found high direct relationship between the level of corruption together with low-quality public enforcement and the likelihood of adopting price limits. In addition they found no significant relationship between the information asymmetry and price limits regime.
Farag, H. and Cressy, R. (2011) Stock Market Regulation and News Dissemination: Evidence from an Emerging Market.	Investigated the relationship between the changes in regulatory policies namely the switch from Strict Price Limits to circuit breakers on stock price volatility. In addition, they investigate the relationship between regulatory policies and the information arrival modes using two competing hypotheses, namely, the Mixture of Distributions Hypothesis (MDH) and the Sequential of Information Arrival Hypothesis (SIAH).	Data for the market index EGX30 and trading volumes were collected from the Egyptian stock exchange over the period 1999-2009.	They found that the mixture of distributions hypothesis is prevailing within the Strict Price Limits; however the sequential of information arrival hypothesis is prevailing within the circuit breakers regime. In addition, the switch from the SPL to CB leads to an increase in volatility due to the information inefficiency and noise trading in the Egyptian stock market.

Chapter 6 : Conclusions

6.1 Introduction

This chapter includes summary and main conclusions of the study. In addition, I present the main policy implications of the findings as well as suggestions for future research.

This study investigates both short and long-term overreaction phenomenon. Moreover, the study examines the role and the effect of regulatory policies (price limits/circuit breakers) on the overreaction hypothesis in the Egyptian stock market. The Egyptian Stock market is considered one of the leading emerging markets in the Middle East and North Africa region (MENA) according to the statistics of the WFE (World Federation of Exchanges).

The literature survey revealed that the overreaction phenomenon is regarded one of the newly added stock market anomalies. De Bondt and Thaler (1985) are the first to empirically examine the overreaction hypothesis in the finance literature. De Bondt and Thaler argue that price reversals can be predicted using only past return data. Therefore stock returns are predictable and this implies a clear violation of the weak-form market efficiency. Therefore the overreaction hypothesis is "Loser portfolios constructed using past information (stock returns) outperform those of Winners".

De Bondt and Thaler (1985) argue that large stock price movements will be followed by price reversals in the opposite direction. This suggests that stock returns exhibit negative serial correlation over longer horizon, therefore investors may earn abnormal return by exploiting this long-term mispricing.

Chapter two of this thesis presents a comprehensive literature survey of the overreaction phenomenon in both developed and emerging stock markets. The literature survey shows that the overreaction hypothesis has been extensively investigated in developed markets. However, few studies have been carried out on emerging markets. Emerging stock markets are regarded as less efficient, and therefore there is a possibility to achieve abnormal returns by exploiting market imperfection.

Chapter three investigates the short-term overreaction using a novel methodology, namely, the dynamic panel data model using system GMM. Moreover, the chapter introduces a comparison between the traditional size portfolios and the so called fixed effects portfolios. In addition, chapter three investigates the unobservable factors which cause the company heterogeneity.

Chapter four on the other hand, investigates the long-term overreaction phenomenon for all listed shares in the Egyptian Stock exchange. I present in chapter four the theoretical arguments of the abnormal returns measurements in addition to the alternative explanations of the long-term overreaction phenomenon. Moreover, chapter four investigates the relationship between regulatory policies and long-term overreaction. I augment the traditional Fama and French three-factor model by including the contrarian factor and the unobservable (fixed effect) factor based on the company heterogeneity.

Chapter five introduces a comprehensive literature review of the different types of regulatory policies (price limits and circuit breakers) as well as the theoretical background about the evolution of the different types of regulatory policies. The chapter also examines the effect of regime switch (from Strict Price Limits to circuit breakers) on the four main hypotheses, namely, overreaction, volatility spillover, the delayed price discovery and the trading interference hypotheses in the Egyptian stock market. The chapter also investigates the impact of regulatory policies on the dynamic relationship between volume volatility relationships. Finally, the chapter examines the effect of the regime switch on the long-term conditional volatility.

6.2 Summary of the main findings

Chapter two of the thesis includes a comprehensive literature survey of the overreaction phenomenon. I present the literature on the short- and long-term overreaction in both developed and emerging markets. Moreover, I analyse the possible interpretation to the overreaction phenomenon, namely, the variation of risk (beta), seasonally and size effects, bid-ask spread and the tax hypothesis. In addition, I analyse the overreaction to specific events such as the overreaction to corporate actions (merger, acquisition and earnings and dividends announcements), overreaction to rumors and overreaction to the international sport championships results. Finally, I critically discuss the main arguments of the opponents of the overreaction phenomenon.

I find that both short- and long-term overreaction phenomenon have been extensively investigated in developed markets in the 1980s and 1990s using both cumulative average abnormal return (arithmetic and rebalancing method) and the buy and hold method. However, a new strand of literature has recently investigated the overreaction phenomenon in emerging markets. The literature survey shows that there is a debate about the existence of the overreaction phenomenon itself and whether or not the change in risk factor (beta), firm size, seasonality, and bid-ask spread are the main sources of contrarian profits.

The existing body of the literature has investigated the overreaction phenomenon using either cross section or time series dimension. However, none of the existing studies has combined the two dimensions using panel data model cross section time series (CSTS). Ignoring time dimension may lay the estimation open to bias (Cressy and Farag (2011). Moreover, none of the existing studies has investigated the overreaction phenomenon using the dynamic panel data model and system GMM in particular.

Regulatory policies (price limits and circuit breakers) play an important role in cooling down stock market volatility in both developed (trading halts) and emerging markets. However, none of the existing body of the literature on the overreaction has investigated the link between regulatory policies and overreaction hypothesis. The above mentioned gaps in the literature are the main motivation for this thesis.

Chapter three empirically investigates the short-term overreaction hypothesis using a novel methodology, namely, dynamic panel data. In this chapter I compare the traditional and dynamic panel data models to investigate the short-term overreaction and price reversal phenomena in the Egyptian stock market. Using daily price data from the Egyptian stock market on a sample of 100 companies which experienced dramatic one-day price change as the result of main four events over the period 2003 to 2009, I find negative and significant abnormal returns as the result of terrorist attacks for the subsequent three days post-event. However, the Lebanon war as a proxy for the tension in the Middle East region has no effect on the average abnormal returns in the Egyptian stock exchange.

There is no significant average abnormal return as the result of the announcement of the constitutional change and the formation of the new government. In addition, I find that past Losers significantly outperform past Winners over 120 days post-events. Therefore investors can beat the market and exploit market imperfection to achieve abnormal return. The traditional fixed and random effects models show that the sign of lnmcap (our proxy for firm size) is positive for both Losers and Winners. This suggests the underlying company heterogeneity in the data and a biased estimation of the OLS regressions.

The system GMM results are consistent with the estimation of the two-way fixed effects model and in contrast with the cross-sectional regressions; this confirms the concealed company heterogeneity and the biased estimation of the OLS. I find also evidence of the leverage effect as size coefficients are highly significant for Losers (negative shocks) but insignificant for the Winners (positive shocks). Moreover, I find evidence of insider information and market inefficiency as the leakage of information variable is found positive in sign and highly significant for all the events.

Most importantly, I find that low fixed effects portfolios outperform high fixed effects portfolios as the dummy variable DumQ (our proxy of company heterogeneity) is found negative for all events and highly significant for the Losers.

One of the main contributions of this chapter is to construct the so called fixed effects (unobservable) portfolios. I find that low fixed effects portfolios for Losers not only outperform those of high fixed effects, but also outperform small and big size portfolios. In addition, the arbitrage portfolio LMH (fixed effects) outperforms the SMB portfolios on average. High fixed effects Winners outperform low fixed effects portfolios on average, however small size portfolios outperform those of big size on average. This result is new to the literature as I argue that the portfolio formation based on fixed effects may be used as a new profitable construction strategy to achieve higher abnormal return than the traditional size portfolios.

To identify the potential unobservable factors, I found a positive and significant relationship between the political connections of the board members and the company heterogeneity in addition and, interestingly, I found an inverse relationship between both management quality and corporate governance compliance with the company heterogeneity. This suggests that the better the management quality the lower the company heterogeneity and the more efficient the share price.

To conclude, investors can exploit the Egyptian market imperfection and achieve abnormal returns as a result of major events. Past Losers significantly outperform past Winners post-events over the event window. The panel data approach adds a new dimension to the existing models and offers interesting insights and reveals the importance role of unobservable firm-specific factors in addition to the observable size in the analysis of the overreaction phenomenon. Finally, constructing portfolios based on some unobserved factors i.e. management quality, corporate governance and political connections of board members significantly outperform traditional portfolios based on size.

Chapter four investigates the long-term overreaction for all listed shares in the Egyptian Stock exchange and whether or not the overreaction phenomenon can be attributed to size, length of formation period, time varying risk and seasonality effects. Based on the results of chapter three that the fixed effects portfolios outperform traditional size portfolios, I investigate whether the contrarian and the unobservable (fixed effect) factors are priced or not by using the augmented Fama and French three-factor model and the Carhart (1997) four-factor model.

The chapter also investigates the academic debate regarding the measures of the long-term performance (CARs vs BAH) in addition to the different types of biases and measurement errors in contrarian strategies i.e. bid-ask spread, Survivorship bias, data- snooping bias, data mining bias, look-ahead bias, rebalancing bias and the non-synchronous trading bias. Following Fama (1998) I adopted the rebalancing RB CARs approach as it implies fewer theoretical and statistical problems than long-term Buy and Hold. In addition, Roll (1983) argues that using monthly returns is less likely to be affected by the choice of CARs or BH. Dissanake (1994) argues that the BH approach may lead to less benefit from diversification in the longer term. Moreover, Loughran and Ritter (1996) claim that there is a little difference between BH and CARs in test period returns calculations, and they argue that the results of Conrad and Kaul (1993) are affected by the survivorship bias.

I find evidence of genuine long-term overreaction in the Egyptian stock market and this phenomenon is not attributed to size effect. Past Losers outperform past Winners for Big and Small firms. Therefore investors can earn significant abnormal returns by buying Losers and selling Winners. In addition, the findings suggest that the overreaction phenomenon in the Egyptian stock market is not sensitive to the length of the formation period.

One of the main contributions of this chapter is the first to link the overreaction phenomenon with regulatory policies. Results show that within the strict price limit regime, there is no significant market-adjusted abnormal return by adopting the contrarian strategy (for the two non-overlapping portfolios) as Losers continue to be Losers and Winners continue to be Winners and thus there is no positive abnormal return for the arbitrage portfolio.

On the other hand, the overreaction phenomenon is clear during the circuit breaker regime for both short (two years) and longer (four years) test periods. Results show positive and highly significant market-adjusted abnormal returns for the arbitrage portfolio. The main interpretation for this is the delayed price discovery hypothesis as imposing price limits prevent stock prices from reaching their equilibrium levels (Kim and Rhee, 1997).

The stability of beta results shows that beta for Loser portfolios – in the aggregate test period- are highly significant and outperform those in the rank period. This suggests that Losers are more risky during the test period. On the other hand, betas of the Winner portfolios in the rank periods significantly exceed those of test periods. The change in beta from rank to test period is negative and highly significant. We also notice that betas of the Losers are greater than those of Winners in the aggregate test period. This suggests that beta is not constant over time throughout the rank and the test periods. These results are consistent with Chan (1988) and Gaunt (2000).

I also find evidence of the January effect in the arbitrage portfolio, as we notice positive and highly significant abnormal return in January and negative and highly significant abnormal returns in December. This result is consistent with the literature on the calendar effect and the tax–loss hypothesis as investors tend to sell Losers by the end of December to increase the capital losses and to reduce the tax burden at the end of the financial year followed by buying Winners in January. I also find significant and positive abnormal return in June and July as the vast majority (84%) of the listed companies in the Egyptian stock exchange have June as the end of their financial year. This suggests that the significant abnormal return resulting from the overreaction phenomenon in the Egyptian stock market is not mainly due to the seasonality effect.

The results of the augmented Fama and French and the Carhart (1997) models show that the HML loadings are positive in sign for the Losers and negative for the Winners. This suggests that value stocks (high book-to-market ratio) outperform growth stocks (low book- to-market ratio) for the Losers and the opposite is correct for the Winners. In addition, the contrarian factor LMW is positive for the Losers and negative for the Winners. This implies that Losers outperform Winners. Interestingly, HMLFE (High minus Low fixed effects) is negative in sign for both Winners and Losers; this suggests that lower fixed effects portfolios are positively correlated with portfolios return. This result is consistent with main findings of the system GMM of chapter three. Finally, size effect has a minor role in explaining portfolio returns in the Egyptian stock exchange.

To conclude, results show evidence of genuine long-term overreaction phenomenon in the Egyptian stock market. The contrarian profits of the arbitrage portfolio cannot be attributed to the small firm effect, formation period length, or seasonality effect. In addition, the study highlighted the strong relationship between regulatory policies and the long-term contrarian profits. Results show no evidence of contrarian profits within the Strict Price Limits, however there are clear contrarian profits within circuit breakers regime. I find that the contrarian factor LMW is positive for the Losers and negative for the Winners. This suggests that Losers outperform Winners. Moreover, HMLFE is negative for both Winners and Losers and this suggests that lower fixed effects portfolios outperform higher fixed effect portfolios and are positively correlated with the portfolios return.

Chapter five investigates the effect of the regime switch (from Strict Price Limits to circuit breakers) on the overreaction, volatility spillover, the delayed price discovery and the trading interference hypotheses in the Egyptian stock market. The chapter also examines the effect of the regime switch on the long-term conditional volatility.

The results of the overreaction hypothesis show that there is price reversal pattern for the Lower limit hits (bad news) one and two days following the event within SPL and CB regimes respectively. However, there is a price continuation pattern for the Upper limit hits (good news) within the SPL regime over the event window. This result supports the overreaction hypothesis in cases of bad news (Lower limit hits). Moreover, the results support the effect of firm size on the overreaction hypothesis for the Lower limit hits for small firms in particular. This can be explained in the light of the literature as volatility is more likely to be higher for small firms (Huang (1998). However, results do not support the effect of firm size on the overreaction hypothesis within the circuit breakers regimes.

The results of the volatility spillover hypothesis show that price limits do not decrease volatility as was intended in both regimes. However, volatility is found to be higher within the CB regime. Within the SPL regime, volatility is spread out over the following two days subsequent to limit hit day. These results are consistent with the volatility spillover hypothesis as price discovery mechanism is disrupted when stocks experience greater volatility few days post limit hits, therefore stock prices are prevented from reaching their equilibrium levels for the following few days post-event.

These deviations from the true prices are expected to prevail within SPL (+-5%) regime as the trading session is suspended until the following day (trading session) when the prices hit their upper or lower limits. However, within wider bands of limits (- +10%) followed by trading halts investors have chance to adjust their portfolios position within the same trading session. Therefore the delay in price discovery process is expected to be higher within the SPL regime. These results are consistent with Kim and Rhee, (1997) and Lee et al (1994).

The results of the delayed price discovery hypothesis show that price continuations behaviour occurs more frequently within the SPL regime. This implies that price discovery mechanism is delayed by the Strict Price Limits. This result is consistent with the delayed price discovery hypothesis. Price reversal behaviour seems to occur more frequently within the CB regime compared to the SPL regime, which suggests that strict price limit delays or prevents the overreactive behaviour, compared to the circuit breakers regime.

The results of the trading interference hypothesis show that there is sharp increase in trading activity on event day (limit hit day) for both the SPL and CB regimes for the Upper and Lower price movement. In addition, the trading activity on event day (limit hit day) is significantly greater than those within the rest of trading window. This increase in trading activity lasts for one-two days subsequent to the event.

I interpret these results as follows: within the SPL regime, traders are unable to obtain their desired positions on event day. In addition, traders are unable to adjust their portfolios' positions - when prices hit the limit - and are forced to wait until the following day. Therefore Strict Price Limits interfere with trading activity.

On the other hand, within the circuit breakers regime, trading activity on average is significantly higher than those of Strict Price Limits. Investors within the CB regime have the chance to adjust their portfolio positions during the same trading session. However, not all investors are informed about the suspension of trading due to the lack of informational efficiency in emerging markets. Therefore only one day following the event may be required to adjust portfolios' position. This result suggests that price limits interfere with trading activity and negatively affect the investors' liquidity positions within the two regimes. Moreover these results are consistent with Lehmann, (1989) and Kim and Rhee (1997).

The results of the volume volatility relationship show that there is positive relationship between turnover ratio (as a proxy for trading activity) and stock price volatility over the 21- day window for the Upper and Lower price movements. However, this positive volume volatility relationship is much stronger and highly significant around event day for the Lower and Upper price movements respectively. Interestingly, I find an insignificant volume–volatility relationship on event day (limit hits day) and on the first day subsequent to the event for both Upper and Lower limit hits. This suggests that regulatory policies disrupt trading activity according to the trading interference hypothesis.

On the other hand, I find a positive and significant relationship between the dummy variable (CB) and stock price volatility within the Upper and Lower limit hits in the short term. This suggests that volatility is found to be higher within the CB regime. In addition, I investigate the effect of regulatory policies on the long-term conditional volatility, using the augmented EGARCH model. I find that CB coefficient (dummy variable in the conditional variance of the EGARCH model) is positive in sign and highly significant, thus suggesting that the switch from SPL to CB increases conditional volatility.

To conclude, the above results of the volatility spillover and delayed price discovery hypotheses in addition to the asymmetric EGARCH model show that switching from the SPL to the CB did increase stock price volatility in the Egyptian stock market. A potential interpretation to this result is as follows: based on the volatility spillover hypothesis, price limits prevent speculative traders from responding to the new information and to adjust their portfolios. This implies a remarkable delay in price discovery mechanism as current prices are away from their equilibrium levels (Farag and Cressy (2011).

I claim that the price discovery mechanism in the Egyptian stock market varies between SPL and CB. Within the SPL as prices hit the limit, trading is suspended until the end of the trading session, therefore volatility is expected to spread out over the following day(s), Meanwhile investors have more time (until the following day) to analyse and to react to the new information and then adjust their portfolios accordingly. Within the CB regime, when prices hit the limit, trading is suspended for 30 minutes. During this relatively short time investors have to adjust their portfolios based on the new information arriving in the market (Farag and Cressy (2011).

I argue that since herding behaviour and noise trading are dominant behaviour in emerging markets, intense trading activity is continued by some speculative traders when trading session is resumed. In addition, the media coverage plays an important role in affecting investors' beliefs within the trading halt period (Lee et al. 1994) and (Farag and Cressy (2011).

However, due to the lack of informational efficiency in the Egyptian stock market not all investors being informed with the new information. Therefore investors are unable to reveal their demand during the halt period. This suggests that stock prices are expected to be much noisier post halt period and significantly different from their equilibrium levels and as a result higher volume and volatility are expected when trading is resumed (Lee et al. (1994) and Farag and Cressy (2011).

6.3 Contribution of the study

The study contains many methodological contributions. The main contribution of chapter three is the use of the dynamic panel data model in investigating the overreaction phenomenon. Panel data approach adds a new dimension to the existing models and offers interesting insights and reveals the importance role of unobservable firm-specific factors in addition to the observable size in the analysis of the overreaction phenomenon (Cressy and Farag 2011). I use the unobservable factors (fixed effects) as a new methodology to construct portfolios compared with the traditional size portfolios. The chapter investigates the potential unobservable factors and concludes that management quality, corporate governance and political connections of the board of directors are the main unobservable factors which may add new insight to the existing panel data models. This chapter is the first in the literature to investigate the relationship between firms' corporate governance compliance as well as the political connections of the board of directors and the overreaction phenomenon.

The main contribution of chapter four is that it is the first to link the long-term overreaction phenomenon with the change in regulatory policies, namely, the switch from Strict Price Limits to circuit breakers. In addition, this study is the first to augment the Fama and French three-factor model and the Carhart (1997) four-factor model by including the contrarian factor and the unobservable factor based on the company heterogeneity.

The main contribution of chapter five is that it is the first to investigate the effect of regime switch (from Strict Price Limits to circuit breakers) on the overreaction, volatility spillover, the delayed price discovery and the trading interference hypotheses.

Finally, this study is the first to empirically investigate both the short- and long-term overreaction phenomenon and the relationship between regulatory policies and the volatility spillover, the delayed price discovery and the trading interference hypotheses in the Egyptian stock market as one of the leading market in the Middle East and North Africa region (MENA).

6.4 Research limitations

The vast majority of the well-documented and most influential studies of the overreaction phenomenon are focused in developed markets (US and UK). This is due to the availability and the reliability of the data from different sources and data bases. Emerging markets are considered less informationally efficient and transparent. This feature makes conducting research on emerging markets rather difficult. The sources of the data in this thesis are from a range of sources, namely the Egyptian stock exchange, Egypt for Information Dissemination Company (EGID) and the Capital Market Authority in addition to the companies' annual reports. There is no published intraday (hourly) trading data available to the researcher; this kind of data would have enabled one to investigate intraday volatility and its relationship with regulatory policies. In addition, there is no published data on both bid and ask prices in addition to margin buying data. Finally, the Egyptian stock market is considered a thinly traded market and less liquid compared with developed markets, and this limits valid comparison of results to other markets.

6.5 Policy implication of the findings

The thesis has clear policy implications; firstly, from the viewpoint of investors, it provides clear evidence of stock market imperfection, namely, stock market overreaction. Investors and fund managers in particular are trying to explore a potential violation of efficient market hypothesis and to exploit emerging market imperfection to achieve abnormal returns on their portfolios. The opportunities are limited in well developed markets. Therefore, emerging markets are essential for the international portfolio investments. The long- and short-term overreaction phenomenon in the Egyptian stock markets encourages both local and international investors and fund managers to well diversify their portfolio risk and to achieve abnormal returns. The Egyptian stock market provides a suitable investment environment to investors all over the world as there is no tax on either dividends or capital gains, in addition to the strong legal and regulatory institutional settings compared with other emerging markets.

Since the short selling strategy, which is not widely used in the Egyptian stock market, investors may adopt one of the following two trading strategies base on the overreaction hypothesis. Firstly, at the end of each trading day, investors may buy shares that experience a particular event and to sell it at the end of the following trading session, Brown et al. (1988) and Lob and Rieks, (2011). Secondly, investors may buy Losers based on stocks past performance or unobservable factors and sell Winners at the end of particular investment holding period.

From the perspective of regulators, exploring market imperfections and a potential market anomaly works as an early warning system to the regulator. Emerging stock markets are known to be more volatile and less efficient than well established markets. In particular, thinly trading markets are likely to be more risky and therefore the effect of shocks is greater than in larger, established markets.

The regulatory authorities in all markets are trying their best to raise the level of market efficiency and to make sure that stock prices do not depart from their true economic values. The vast majority of emerging markets are thinly traded markets; therefore raising the level of market efficiency encourages share buying and increases the market liquidity. Most importantly, market efficiency facilitates the process of resource allocation in the economy, and it gives a message to the current management (Fama, 1976).

On the other hand, due to the greater volatility of emerging markets, the regulator adopts price limits and circuit breakers to cool markets down during times of panic and to reduce excessive price volatility. However, despite the potential benefits of price limits and circuit breakers, much recent empirical research in this area finds that they are not fit for purpose: they do not reduce volatility. This is found to be true for both developed and developing markets. See for example, Santoni, and Liu (1993), Subrahmanyam (1994), Kim and Rhee (1997), Phylaktis et al. (1999), Lee and Chung (1996), Ryoo and Smith (2002) and Kohers et al. (2004).

Following Lee and Chung (1996) and Ryoo and Smith (2002) I argue that the Weak Form market efficiency hypothesis is violated in the Egyptian stock exchange due to the effect of price limits. The thesis finds consistent results with Lee and Chung (1996) as closing prices do not fully reflect all the information arriving in the market when prices hit the limits. Therefore price limits prevent prices from reaching their equilibrium levels. There is an obvious policy implication beyond this as we can firstly, identify the right band of price limits. Secondly and most importantly, the regulator should consider the potential tradeoff between market efficiency and the excessive volatility.

6.6 Suggestions for future research

Several suggestions for future research can be identified. Firstly, examine empirically the profitability of different trading strategies such as selling Winners short and buying Losers (the disposition effect). This could be done by collecting data on the short selling transactions on the Egyptian stock exchange. Secondly, more attention could be given to comparing the profitability of both contrarian and momentum strategies. Momentum strategy – by contrast of overreaction hypothesis- assumes that Losers continue to be Losers and Winners continue to be Winners and thus the disposition effect does not exist.

Thirdly, to investigate the generalisability of the results of the dynamic panel data model by using data from other emerging and developed markets; in particular those emerging markets which have similar characteristics of regulatory policies i.e. the Korean stock exchange.

Fourthly, the potential definitions of the unobservable factors (management quality, corporate governance compliance and political connections of the board members) might be taken into consideration when estimating the GMM model. Controlling for these factors may lead to better explanation to the overreaction phenomenon and to overcome the potential omitted variables problem.

Fifthly, as there are few stock markets that have the regime switch features, i.e. Korean stock market, future research might compare the effect of regime switch on the volatility spillover, delayed price reaction and the trading interference hypotheses. Furthermore, more attention should be given to those stock markets which operate from Sunday-Thursday while the vast majority of the well developed markets are closed. This creates the notion of the 24/7 trading phenomenon. Finally, investigating the relationship between regulatory policies and the intraday volatility is another future research suggestion.

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