Four Essays on Return Behaviour and Market Microstructures: Evidence from the Saudi Stock Market

A thesis submitted for the degree of
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Abstract

This dissertation is divided into an introductory chapter and four essays. Chapter one discusses the importance of the study and describes the development and growth of the market as well. The first part (Chapters 2 & 3) examines stock returns behaviour and trading activity around earnings announcements. The second part (Chapters 4 & 5) examines price impact asymmetry and the price effects of block trades in the market microstructure context. Each essay addresses some aspects of market microstructure and stock returns behaviour in order to aid researchers, investors and regulators to understand a market which lacks research coverage.

The research provides empirical evidence on issues such as the efficiency of the market, information asymmetry, liquidity and price impact of block trades. In first part of the thesis, event study and regression analysis were used to measure the price reaction around earnings announcements and to examine trading activity, information asymmetry and liquidity. In second part the determinants of the price impact of block trades were examined with regard to trade size, market condition and time of the day effects using transaction data. Liquidity and information asymmetry issues of block trades were also studied in this part.

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chapter 1 **: Saudi Stock Market- An Introduction**

1.1 Motivation and Importance

The thesis is motivated by many factors: first, I investigate the Saudi stock market (hereafter, SSM) to provide out-of-sample evidence regarding the on-going debate about Post-Earnings Announcements Drift (PEAD) and the way in which it can be explained, because the nature of this anomaly is not well understood. I also extensively examine and provide evidence on trading activity, information asymmetry, market liquidity, and price impact of block trades. There is almost no evidence on block trades in emerging markets, this is the first study to analyse the price impact of block trades in the SSM and in the region.   Second, the SSM is dominated by retail investors, more than 90% of its total trading is individual trading, which provides an ideal setting for studying how investors react to informational events. Third, the SSM has certain characteristics which distinguish it from many developed and emerging markets (e.g., high government ownership, larger market capitalisation and company size coupled with relatively few listed companies, highly active trading and finally lack of options , short selling and institutional investment). Moreover, few analysts follow the market and reports are scarce and not regularly published, which makes the level of information asymmetry high.   Fourth, the SSM has experienced remarkable structural change implemented by the newly establish capital market authority (CMA). Unlike most previous studies, we use data that is more recent which reflect those changes.

It is of great value to both academics and practitioners to study the effect of these unique aspects of the SSM on stock trading and return behaviour especially in a market that lacks research coverage which is my primary objective of this thesis.

1.2 Contribution

The research is divided in four essays. Essay one is titled "How Markets React to Earnings Announcements in the Absence of Analysts and Institutions" and is organised in two parts. In part one, I document the functionality of the SSM and compare it with those of developed markets. The objective of this part is to describe the differences of the SSM and how these differences might affect its behaviour. In part 2, I use standard event study to measure price reaction to earnings announcements where I find post-earnings announcement drift (PEAD).   I further analyse the market reaction using different measures of abnormal returns and constructing various portfolios and event windows. I also conduct sector-level analysis to examine whether government ownership and company size can have effects on the magnitude of the price drift. The results of this study strongly suggest the predictability of subsequent returns especially around earnings announcement.

Essay two is titled "Information Asymmetry, Trading Activity and Investor Behaviour around Quarterly Earnings Announcements". Covering 2,437 earnings announcements, it analyses the variation in stock returns, trading activity, volatility, information asymmetry and liquidity caused by earnings announcements for the period 2002-2009. I also examine traders' placement strategy around earnings announcements through constructing Order Imbalance where I classify investors into small and large. I first use standard event study to measure informativeness of earnings news and I then construct various measures of abnormal trading activity, information asymmetry, and volatility around earnings announcements. These measures were then compared to non-event measures "control period" to analyse changes in various event windows. Overall, this essay shows higher level of private information acquisition in the pre-announcement period and persistent information asymmetry in post-announcement period which can be attributed to the difference in investors' ability to interpret news .I further use regression analysis to investigate the magnitude of the cumulative abnormal returns (CAR) around earnings announcements. I also investigate the bid-ask spread in general and the information asymmetry component in particular using cross-section regression.

The third essay is titled "Bid-Ask Spread and Price Impact Asymmetry of Block Trades". In this essay, I investigate the price impact of block trades in the SSM for the period 2005-2008. Using a unique dataset of intraday data consisting of 2.3 million block buys and 1.9 million block sales, I document an asymmetry in the price reaction between buyer-and seller-initiated block trades. The price impact asymmetry indicates that buy block trades have persistent impact while sell blocks do not. The larger block trades have even higher permanent price impact asymmetry between purchases and sales. The price impact asymmetry still persists even when using prices that are purged of bid-ask spread biases suggesting order-driven markets such as SSM may not be able to deal with informed trading without designated market makers.

The final essay explores the determinants of price impact of block trade and liquidity in the market and is titled "Liquidity and Price Impact of Block Trades". In this essay, I empirically analyse three types of price impacts using intraday trade data for all stock transactions in the period 2005-2008. I investigate further the price impact using, trade size category, trade sign and market condition. I also compare the intraday patterns of liquidity and price impact using time of the day dummy variables. The bid-ask spread was decomposed using

Huang and Stoll model (1997). Price impact and information asymmetry follow the inverse J-shaped pattern through the day. The study also reveals that the price impact asymmetry is an increasing function of trade size.

Numerous obstacles had to be overcome to carry out this research. For example, the data had to be collected and compiled from different sources, especially historical firm-level and intraday data. A significant amount of research efforts were devoted to data collection and manipulation. Data regarding earnings announcements were recorded manually from the stock exchange website, documenting date and content of each announcement. Data regarding daily stock prices were obtained from the stock exchange (Tadawul). Intraday data which have been used extensively in this thesis were constructed with programming capability which stores and processes all historical data because data vendors don't provide historical trade and intraday data. Some of these data were obtained using personal networks of private chartists and programmers.

Overall, our results contribute to our understanding of the behaviour of emerging markets where certain characteristics distinguish these markets (i.e., high information asymmetry level, weaker corporate governance and disclosure practices, lower level of analysts coverage and inactive institutional investing).Chapters two and three provide evidence regarding the efficiency of the market. In the absence of analysts, the SSM undereacts to good news and overreact to bad news in the first week of earnings release date, then a price drift (reversal) is observed for good (bad) news firms. The levels of information asymmetry and trading activity are high around the time of earnings announcement and remain high in the post announcement period which can be attributed to the difference in investors' ability to interpret news. In other words, some investors can turn public news into private.

Chapters four and five produce results from market microstructure prospective. Price impact asymmetry has been documented in the SSM between buy and sell block trades. The asymmetry in price reaction is an increasing function of trade size indicating that informed traders prefer to trade a large amount at any given price. On average, the price effect of a block trade is small and short-lived suggesting that resiliency is high in the market. Moreover, price discovery is very quick; the five minutes prior to a block trade contain a significant portion of the price impact. When analysing time of the day effect, we find Information asymmetry is higher in the beginning of the day (after the open) then shows diurnal pattern through the day followed by a slight increase toward the end of the trading day.

1.3 The Saudi Stock Market (background)

The literature overwhelmingly agrees that emerging markets, in general, are characterised by less information efficiency, weaker corporate governance, lack of shareholders' rights and enforcements, higher volatility and greater information asymmetries (Harvey, 1995; La Porta et al., 1998; and Bekaert and Harvey, 2002). Moreover, Lasfer et al. (2003) find that post-shock abnormal performances are significantly larger for emerging markets.

Bekaert and Harvey (2002) summarise the academic evidence into three main points: 1) higher autocorrelations in emerging market indices; 2) information leakage prior to public announcements; and 3) high returns to cross-sectional characteristic trading strategies in emerging markets. All these attributes surely create acute information problems in less developed markets.

The last 20 years have seen the focus by investors , mutual funds and academics alike shifting to the emerging markets, with the availability of more stock and trading data. However, there is still a need for more research to enable us to understand how these markets work. The SSM is no stranger to these problems, as it is relatively new and started to attract attention only at the start of the new millennium with the rapid growth in its market capitalisation, trading volume and number of companies.

Only a few studies have attempted to cover some behavioural aspects of the SSM, owing to the lack of market data. However, though some of the issues which have arisen cover a range of subjects, most of the focus has been from an accounting standpoint, more precisely the timeliness and usefulness of financial statements and investors' valuation methods. While we do not intend to list all the studies which have been made of the SSM, some studies worth mentioning include those of (Butler and Malaikah, 1992, for market efficiency; Abdeslalam, 1990; Al-bogami et al., 1997; and Alsehali and Spear, 2004, for the usefulness of financial statements and investors' attitudes to them; Al-Suhaibani and Kryzanowsky, 2000a and 2000b, for market microstructure studies; and Alsubaie and Najnad, 2009, for trading volume and volatility).

Most of the previous research on the SSM has primarily extracted data of the time span preceding the introduction of the CMA in 2004, which was a milestone in the SSM's development. Data analysed after the creation of CMA will be of significance not only to the

CMA's existence itself but to the rules, developments and changes which have faced the SSM since then.

Table 1-1. Major SSM Development and Events for the period 1985-2008

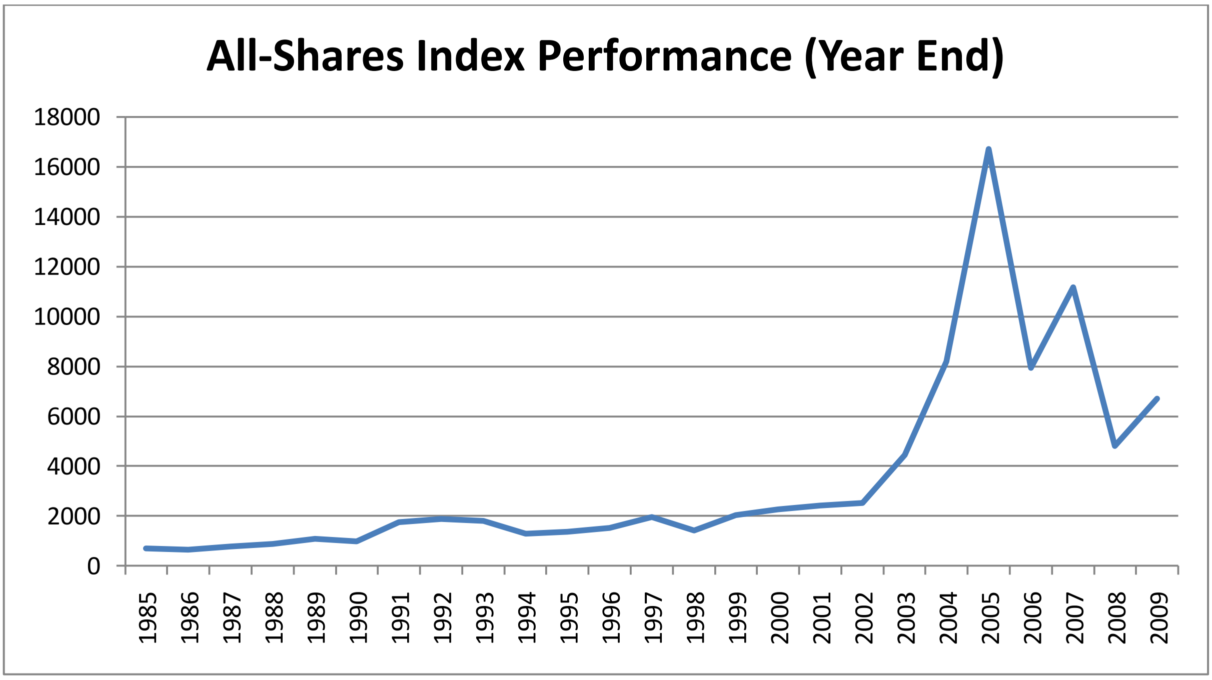
Event	Date
• Official start of the Saudi stock market.	1985
• ESIS (Electronic Security Information System).	1990
• Earning Announcements posted on the Exchange website with time and date recorded.	2001
• Introduction of Capital Market Law.	2003
• Establishment of Capital Market Authority (CMA).	2004
• Foreign (residing in Saudi) Investors Access to the Market. • New corporate governance guidance. • Stock Split for the whole market (5:1) to reduce par value and market value. • Changing of trading time (one session per day instead of two sessions).	2006
• Change in the calculation of the index to reflect only free-floating stock excluding major ownership (Government, foreign partner and 10% ownership) • Swap Agreements with non-resident foreign investors (broker retains legal ownership, foreign investor has the economic benefits).	2008

Notes: this table summarises the major developments that have taken place and are believed to have affected the market in general for the period 1985 -2008. Since the establishment of the CMA, very great changes have been enforced in the market. Its disclosure practice has become timely and is closely monitored by the CMA.

Development and Growth

The SSM has in recent years grown impressively, in terms of market value, number of listed firms and trading volume. For example, the number of shares traded and number of transactions have grown remarkably in the period 2000-2006, averaging around 192% and 212% per year, respectively. The SSM has some unique characteristics among developed and emerging markets (e.g., a high percentage of government ownership, larger market capitalisation and company size, highly active trading market, regulations against options and short selling and finally being dominated by individuals).

Figure 1-1 :Tadawul All Shares Index (TASI) performance for the period (1985-2009)



Notes: Figure (1) shows the market index performance for the period 1985-2009. The graph clearly shows that the SSM has grown rapidly since 2002, coinciding with oil price movement. The high growth is mainly attributed to the growth of GDP and other economic indicators, such as money supply and credit. However, some of it can be ascribed to irrational exuberance, due to the entry into the market of new, less informed and less sophisticated investors each year.

Table 1-2 : Summary of Some of the Main Market and Economic Indicators in Saudi Arabia

Year	GDP Billion	No. of Investors '000	N0. of Shares traded Million	No. of transactions '000	Market Value in Billions	Index (Value-weighted)
2002	707	N/A	1,735	1,033	280	2,518
2003	804	N/A	5,565	3,763	589	4,437
2004	938	1,383	10,298	13,319	1,148	8,206
2005	1,182	2,573	12,281	46,607	2,438	16.712
2006	1,335	3,577	54,440	96,095	1,225	7,933
2007	1,430	3,669	57.829	65,665	1,946	11,176
2008	1,758	3,954	58,727	52,135	924	4,803
2009*	N/A	N/A	37,950	22.591	1,074	5,964

Notes: Source: Saudi Central Bank (SAMA), 45th Annual Report .The Saudi Arabian Riyal is effectively pegged to the dollar at a value of USD1=SAR 3.75.
*2009 data for the first 6 months only.

Institutional setting of the SSM

The SSM is a pure order-driven market where most of the activities taking place are initiated by private and not by institutional investors. In fact, more than 90% of trading is individually initiated. The presence of institutional investors is still new and hesitant. Moreover, foreign direct investment is restricted and does not confer full ownership of the shares bought. Only common stocks are traded with options and short selling is not allowed in the market. Nonetheless, it is a very active market in terms of trading volume and market capitalisation compared with other regional markets. [1]

Ownership structure in the SSM is highly concentrated; government funds, foreign partners and major business families with 10% ownership have a stake in the market of more than 65%. However, the market lacks the presence of institutional investment, because government funds and other mentioned parties usually follow a buy-and-hold strategy. Even though only 38% are free floating stocks (tradable stocks), trading volume is high in the SSM compared with other markets. The turnover ratio for the SSM in 2008 is the highest of all Arab markets, the value of traded shares to GDP standing at 212% compared with an average of 70% of the value of traded shares relative to GDP for the other 15 Arab markets. The SSM, however,

1 The SSM is by far the biggest stock exchange in the Middle East. According to the Arab Monetary Fund's annual report for the year 2008, which provides statistics for 15 stock markets, the capitalisation of the SSM represents 41% of the total market capitalisation of all these markets, while the value traded of the SSM represents 67% of the total value traded in the markets of all the members.

suffers from the absence of financial analysts who issue regular reports, recommendations and forecasts for each security. The SSM provides a natural experimental setting to test for all the previous factors (e.g., no short selling, individual dominance, absence of analysts' forecasts). It is interesting to study the effect of these unique aspects of the SSM on stock trading and returns, especially around earnings announcements.

Since mid 2001, the stock exchange bulletin (Tadawul) provides a medium in which all companies must post their earnings announcements on its official website before any other medium. Investors actively search for private information during the period before each announcement, but investors rarely have any method for anticipating news and earnings. Some investors rely on informal sources, such as Internet forums which are very active in speculating on companies' earnings, forecasts and news; this is a time when wild rumours are rife. Some large investors may depend on insider information and react to information leakage ahead of an announcement. The disclosure and corporate governance practices of SSM are still weak, compared to more developed markets. It is notable for showing unusual trading activities, in terms of volume and abnormal returns, in some stocks before an announcement is officially made. More recently, investment houses and brokerage companies, which are newly established entities, have begun to issue reports and recommendations which could help investors to reach more informed decisions.

Table 1-3 :Main SSM Structural Elements Compared with those of Developed Markets.

Feature	Developed countries	Developing countries (SSM)
Regulation	Established	Early stage of establishment (undergoing development)
Financial institution	Investment banks, Commercial banks, Consulting and brokerage houses	-Commercial banks exercise most of the functions. -Recently brokerage firms have begun to operate in the market, but are not yet important players.
Market maker	Specialists, Brokers and dealers	Not found (liquidity supplied by limit order traders)
Analyst forecasts	Available	Weak presence (a few reports, not regular)
Earning announcements	Scheduled	Allowance period after each quarter (2 weeks) but no specific date
Number of participating firms	Many	A few
Information asymmetry	Exists	Evidence of high level of information asymmetry
Institutional investors	Varieties (mutual funds, pension funds, other funds, individuals)	-A few large inactive government funds and some commercial mutual funds. -Large number of active individual investors.
Market Design	Quote-driven market makers. Examples: NYSE.	-Order-driven market. -Only stock traded, no options , short sales or any other financial instruments.

chapter 2 : **How Markets React to Earnings Announcements in the Absence of Analysts and Institutions**

2.1 Introduction

This paper makes several contributions. First, we test the existence of Post-earnings announcement drift (PEAD) in a comprehensive sample in a less developed market. Second, we provide a perspective on the way in which a market reacts to earnings announcements in the absence of analysts' forecasts and institutions. We test for PEAD effects not only in general, but also across industries on the stocks listed on the Saudi stock exchange. Third, the Saudi Stock Market (hereafter, SSM) is dominated by retail investors, which provides a perfect setting for studying investor behaviour and reaction to informational events. Fourth, the SSM has certain characteristics which distinguish it from many developed and emerging markets (e.g., high government ownership, larger market capitalisation and company size, highly active trading, lack of options and short selling and finally a market that is dominated by individuals)[2]. It is interesting to study the effect of these unique aspects of the SSM on stock trading and returns, especially in regard to earnings announcements.

What is interesting to investigate is how a market might behave without strong presence of information intermediaries such as financial analysts. Many stock markets in developing countries such as Saudi Arabia have no financial analysts who – regularly – follow stocks and issue forecasts and recommendations. We can assume the level of information asymmetry in such markets to be high. There is supporting evidence of high information asymmetry in developing stock markets which can be attributed to many other factors, including information intermediaries and corporate disclosure practice. To our knowledge, no-one has examined the impact of earning news on market behaviour if there are no financial analysts providing information to investors (that is to say, analysts and informed traders are essential for the efficient market to work, as they are believed to facilitate and speed the impounding of information into stock prices). Would the market be better off without analysts' forecasts? Would natural market forces (demand and supply) have an effect on the market without the influence of analysts? Could the market reaction to news be the best explanation of the surprise factor?

Any attempt to measure market reaction to news in the SSM is essentially measuring retail investors reaction because they dominate the markets. We aim in this study to examine how the absence of analysts can impact the behaviour of the market. If there is no price drift in the market, we can infer that PEAD is caused by analysts herding and bias. However, if the price

[2] Individual trading exceeds 92% in 2008.

drift is larger in magnitude, we can safely infer that analysts are important agents for the price impounding process to take place and for the market efficiency in general

Throughout the study, we form two portfolios of positive and negative news based on the earnings announcement return (EAR) methodology suggested by Brandt et al. (2008) among others. We evaluate portfolios in reaction to news and overall performance by computing both cumulative abnormal return (CAR) and buy-and-hold abnormal returns (BHAR).

It is found that market-adjusted abnormal returns continue to drift upward for the good news firms (companies which react positively on the announcement date) and market-adjusted abnormal returns reverse their price movements after one week of the announcements for the bad news firms (companies which react negatively on the announcement date).

2.2 Literature Review

One of the most puzzling tendencies in capital markets is the drift in prices after particular corporate events (earnings announcements, mergers, stock splits, etc). Studies which focus on the drift in prices, such as event studies, are considered to be joint test studies for the price model chosen (the model of expected rate of return) and for market efficiency.

In other words, if prices continue to drift we either question the model used, such as CAPM, or the efficiency of the market. The continuous drift in prices in particular after the earnings announcement is called the Post-Earning Announcement Drift (PEAD). PEAD is a phenomenon which has been overwhelmingly confirmed and is now widely accepted among researchers. However, there is no agreed theoretical explanation for such a phenomenon. Moreover, most of the price reaction studies are conducted in the more developed stock markets where agents play an important role in formulating prices and channelling information. We focus on the behaviour and reaction of the SSM to earnings announcements for many reasons. We aim to provide a different perspective by focusing on a less developed market which has some unique characteristics and structure. We study, indirectly, the impact of different market characteristics (the SSM being, for example, a market less followed by analysts, with inactive institutional investors and where short sales are not allowed) on market behaviour in regard to earnings news. We believe that the SSM is distinct from other developed and emerging markets in that it lacks active presence of analysts who are important information intermediaries in the market. Because the functionality of developed markets, such as the NYSE and other markets is well documented in the literature, we first describe this benchmark functionality briefly and then compare it with the current functions of the SSM.

In the following section, we describe how capital markets work in terms of price anticipation and the role of analysts in the market. Then we compare price anticipation and the role of information intermediaries in mature capital markets with those in the SSM.

Anticipation of news and post earnings announcement drifts (PEAD)

Information plays a vital role through having the potential to change investors' beliefs regarding investment strategies and behaviour. Investors naturally require information to aid them in their evaluating and investment decisions. Beaver (1998) indicates that there are various sources of information, including financial reports, announcements, analysts' reports, newspaper articles and other publicly available information which can alter investors' beliefs about the value of an asset. How investors perceive, interpret and react to news has been an active area of research since the seminal work of Ball and Brown (1968). They empirically investigated the association between accounting earnings as the core information in financial statements and stock returns in order to assess the usefulness of accounting information. They were the first to report a drift in the stock returns after earnings announcements, a phenomenon which was later given the name of the Post-Earnings Announcement Drift (PEAD). Since then, many researchers have confirmed the robustness of PEAD using different techniques and different data (e.g., Bernard and Thomas, 1998, 1990; Ball, 1992; Ball and Bartov, 1996; and Chordia and Shivakumar, 2005). Capital market research findings suggest that earnings announcements contain information which is believed to alter investors' opinion about the value of stocks through the process of impounding information on prices.

The earnings-returns studies can be classified into two groups: event studies and association studies. In the latter, the focus is on the long term association between earnings and stock prices, while in the former, short-window returns are usually examined, to verify the market reaction to earnings announcements. Recently, event studies have gained popularity over other methods as a credible method for measuring the economic impact of earnings announcements on stock returns (Kothari and Warner, 2007).

Liu et al. (2003) define PEAD as "cumulative abnormal returns for stock, announcing extreme positive (negative) unexpected earnings drift upward (downwards) for an extended period after the announcement". The price drift is the result of a persistent underreaction to earnings news. It suggests that the market underreacts to information on earnings announcements and hence that future returns are somewhat predictable.

This phenomenon refers to generating continuous returns over and above the expected return, as measured by a valuation model, such as capital asset pricing model (CAPM). PEAD is considered one of the most robust stock market anomalies in the financial literature. The Efficient Market Hypothesis (EMH) states that prices should fully and instantaneously reflect all publicly available information.[3] Hence, an efficient market should incorporate all information (factual or predicted) into prices in a quick and unbiased way. A price drift in general indicates that the market fails to translate the information into prices. For this reason, many researchers consider price drift to be a serious empirical challenge to the EMH.

While most of the PEAD studies concentrated first on US markets and data, more recent studies have expanded the coverage to other European and emerging markets worldwide. However, the mainstream evidence comes from US data and other stock markets have attracted little research (Liu et al., 2003). Naturally, the UK market has become the second most studied market in terms of price drift but beyond this only a few other European or Asian markets have been the subject of studies, a mere handful, and other markets in the Middle East and North Africa have hardly been studied at all. The studies which have been conducted in non-US markets include but are not limited to those by (Hew et al., 1996; Liu et al., 2003, for the UK market; Gajewski and Quéré, 2001, for the French market; Forner et al, 2008, for the Spanish market and Booth et al., 1996 , for the Finnish market). Since most of these studies have found a similar pattern in the price drift in different markets, it can be called a global pattern. The most common pattern found is that stock returns continue to drift upwards (downwards) for stocks with unexpected positive (negative) earnings announcement surprises.

Ball (1992) assumes that the post-earnings announcement drift in mature markets may differ by the level of disclosure. This is confirmed for an emerging market (Helsinki Exchanges) by Schadewitz et al. (2005), who suggest that similar patterns may exist in other emerging markets.

[3] A theory stating that stock prices reflect all available information at any given time; see Fama (1965) "Random Walks in Stock Market Prices".

Why stock prices drift after the earnings announcement

While the PEAD is well documented in the literature, the reasons for the persistent underreaction to earnings announcements are not well understood .This phenomenon can be explained with a number of hypotheses, but two competing hypotheses and explanations dominate the debate. The first is the rational explanation and the second comes from the behavioural school which suggests that investors are irrational. Advocates for the rational and efficient market claim that PEAD can be explained by the inaccuracy of the tools used by researchers to detect the price drift, an inaccuracy which may stem from returns mismeasurement, risk mismeasurement or methodological biases in general. They also attribute rational risk premium and transaction cost as important causes for the drift. This rational explanation views the price drift anomaly as a compensation for risk associated with shocks in the earnings news. For instance, Ball et al. (1993) discuss pricing models which ignore the change in equity risk, since news is positively associated with risk. Garfinkel and Sokobin (2006) assert that the price drift is related to the risk factors attributed to the divergence in investors' opinions.

Kothari (2001) in a review of capital market research concludes that the literature has exposed the drift anomaly to a battery of tests, but a rational, economic explanation for it remains elusive.

The difficulty in explaining the PEAD by an argument consistent with market efficiency has caused much research effort in seeking an alternative explanation for the price drift when the rational explanation was not satisfactory. This effort has led to the second set of explanations for financial anomalies, behavioural explanations. The price drift is attributed to irrational factors which result from financial behaviour and this sort of explanation has gained some prominence in the financial literature.[4] Behavioural finance generally argues that irrationality in the form of one or more cognitive biases has led to observed patterns of abnormal returns. Because of shared human attributes, such as overconfidence, greed or fear, people make errors of judgment, which are a deviation from the assumption of rational expectations in economics and the Efficient Market Hypothesis. Findings suggest that PEAD is related to investors' underraction or overreaction to earning news (see, for example, DeBondt and Thaler, 1985; Bernard and Thomas, 1998; and Daniel et al., 1998). A common explanation for this phenomenon is that

4 Contrary to traditional finance, behavioural finance asserts that some agents in the market are not fully rational which can explain financial phenomena .See Barberis and Thaler (2004) for a review of behavioural finance.

investors underreact to earnings news and they also fail to recognise the serial autocorrelation patterns in quarterly earnings (Bernard and Thomas, 1990; Ball and Bartov, 1996).

More recent studies have sought a more broadly rational explanation. For example, Chordia and Shivakumar (2005) argue that the post-earnings announcement drift is related to investors' underestimation of the impact of expected inflation on future earnings growth.

Another line of research, more relevant to our paper, is aimed to distinguish between individual trading and institutional trading. Several studies suggest that institutional trading is more sophisticated than individual trading and accordingly that individual trading may be more closely related to the PEAD than institutional trading (see, for instance, De Franco et al., 2007). Accordingly, individual trading may be more responsible for the PEAD than institutional trading is. Hirshleifer et al. (2008) call it the individual trading hypothesis. Bhattacharya (2001) and Battalio and Mendenhall (2005) provide evidence consistent with the conjecture that individuals cause the PEAD.

The magnitude of the drift may differ for good and bad news. Management plays an important part in explaining overreaction and underreaction to news. When there is good news, it is announced immediately. It benefits the management to announce all positive news. However, when there is negative news, management tends to announce it at some point in time but maybe to delay it (see, for example, Hong et al., 2000), in other words, when withholding negative news from the public can no longer be postponed. At the event, all positive news would have been announced but not all negative news would have been announced. Some managements believe that they can turn news from negative to positive before it is announced and do not see why they should announce something too soon which will damage their reputation. Moreover many management and influential agents may benefit from withholding negative news by selling at a higher price before it is announced.

2.2.1 The role of the financial analyst as financial intermediary

Financial analysts are those professional persons or bodies who analyse financial data (news, disclosures, reports and private information) and interpret it in order to forecast the future prospects of the assets being analysed to ultimately issue recommendations regarding investments to buy, hold or sell the stock. The role of analysts' forecasts in the market and the way in which their opinions are reflected in prices were early recognised by Douglas (1933); he states, "even though an investor has neither the time, money, nor intelligence to assimilate the mass of information in the registration statement, there will be those who can and who will do so, whenever there is a broad market. The judgment of those experts will be reflected in the market price."

Financial analysts are important players in the stock market. They add value to the market through collecting, processing and aggregating information from diverse sources and then producing added value information and communications through earnings forecasts and stock recommendations. Regulators and other market participants view analysts' activities and the competition between them as enhancing the information efficiency of security prices, specifically, how analysts can speed up the reflection of public information in stock prices (Frankel et al., 2006).

The SEC acknowledges on its website that "Research analysts study publicly traded companies and make recommendations on the securities of those companies. Most specialize in a particular industry or sector of the economy. They exert considerable influence in today's marketplace."

Studies of the value of intermediaries mainly focus on financial analysts. Academic studies focus on the information provided to investors from two summary measures produced by analysts – earnings forecasts and buy/hold/sell recommendations. Overall, the evidence indicates that financial analysts add value in the capital market .Prior research confirms that analysts' reports and forecasts, in general, convey information to the capital market which speeds up the price impounding of information into prices (e.g., Fried and Givoly, 1982; Francis and Soffer, 1997; Hong et al., 2000).

No doubt, analysts' forecasts play an important role in the capital market by conveying information (presumably valuable information) to investors. However, the properties of the analysts' forecasts – whether individual or consensus – have been questioned and tested in many studies.[5] Analysts are not perfect financial intermediaries because they too can be irrational (e.g., too optimistic, over-reacting to some information and under-reacting to other information).[6]

[5] Kothari' review (2001) of the subject was a section on his paper "Capital market research in accounting"
[6] See Schipper (1991) and Brown (1993) for comprehensive reviews.

2.2.2 Market Expectation proxy (the Earning Surprise)

One of the main activities of the capital market research is the branch which associates financial statement information with security returns. This type of literature often uses a model of expectation for earnings to isolate the surprise component of earnings from the anticipated components (Kothari, 2001). Kothari emphasises that the degree of return-earnings association is crucially affected by the accuracy of the proxy set by the researcher for the unexpected earnings.

It has been standard for most market reaction studies to measure standard unexpected earnings (SUE), which are defined as actual earnings minus expected earnings. Unexpected earning is considered the independent factor in the regression analysis which enables us to understand why the market reacts in such a way.

Many measures have served as proxies for unexpected earnings or the surprise component of earnings, the two most popular of which are the time-series property of earnings and analysts' forecasts. Time-series forecasts of earnings (yearly or quarterly) emerged first as a proxy which researchers often used to model expected earnings (see, for instance, Foster, 1977; and Brown, 1993). These studies typically use a time-series model to predict earnings, forming two portfolios, one composed of companies with higher earnings than predicted and the other of companies with lower earnings than predicted by the time-series model. Analysts' forecasts are nowadays the most frequently followed proxy for unexpected earnings. Many researchers agree that it is a better substitute proxy for market expectations than forecasts generated by time-series models; see, for example, Fried and Givoly (1982) and Kothari (2001). Consensus forecasts are often used where the average of analysts' forecasts is considered to be the market expectation of earnings. However, despite the growing dependence on analysts' forecasts, there are major issues related to the accuracy of these forecasts, such as underreaction and incentive bias. Often these forecasts are optimistic and made by sell-side analysts who are, typically, working in an investment bank which has a business relationship with the firm whose security is being analysed. It has indeed been established that analysts' earnings forecasts are biased and optimistic (see, for instance, Brown, 1993; Dugar and Nathan, 1995).

In capital market research, a relatively new measure has been used, namely, Earning Announcement Returns (hereafter, EAR). The scarcity of analysts in the SSM creates the need for EAR to be used as a proxy for market expectations for earnings.[7] The actual market reaction to the information contained in the announcement could be the best estimator of the surprise. Assuming investors' rationality and in line with the market's "Efficiency", the market on the aggregate level should react to the earning announcements in the same direction. For example, if a firm announces a large increase in earnings growth, the stock price should move upward to reflect this change in the firm's fundamental value. When the market does fail to fully react to the information disseminated in the earnings announcement, we expect the anomaly of "PEAD" to occur. The EAR can be extended to a multi-period event window. The logic for constructing more than a one-day earnings announcement window is that announcements are sometimes made public toward the end of the day or there could be a leakage in the market before the announcement is due.

Cumulative abnormal return (hereafter, CAR) is the tool used to capture the market reaction to the information content of the earning announcements. Brandt et al. (2008) have used this measure and call it the earnings announcement return (EAR). In their study, they find the post earnings announcement drift for EAR strategy is stronger than post earnings announcement drift for SUE. We follow the methodology of Chan et al. (1996) in using the cumulative abnormal market adjusted return around the announcement date. They accumulate the returns over a four-day period (-2 to +1) to account for the possibility of a delayed stock price reaction to earnings news and use it as a measure of the earnings surprise to predict subsequent returns. They also believe this to be a clean measure of earning surprise because it is free of the bias which is typically associated with earning expectation models. They find that this proxy predicts subsequent returns roughly as well as the seasonal random walk model. This proxy for earning surprise has also been used by many others (see, for example, Garfinkel and Sokbin, 2006; Shivakumar, 2006;Lerman et al., 2008).

[7] Recently, some regional and local investment banks have started to issue general forecasts for major companies, but these forecasts tend to be general, few and irregular.

2.3 The Saudi Stock Market: characteristics and structure

SSM is a relatively new and still emerging market, operating formally only since 1985. However, long before this, many public companies were traded in an informal and unregulated market through unlicensed dealers and trade offices.

In 1985, the responsibility for the regulation of the market was delegated to the Ministry of Finance, the Ministry of Commerce and Industry and the Saudi Central Bank. Each ministry or agency has a different function: the Ministry of Commerce and Industry regulates the primary market through which new company listings are made; the Ministry of Finance determines the market's general policy; while the central bank (the Saudi Arabia Monetary Agency, SAMA) operates and manages the market.[8]

SAMA established the Security Control Department (SCD), which was responsible for the day-to-day operations of the market and, in addition, all related issues such as disclosure requirements and market statistics. Under this scheme, only commercial banks were given the privilege of stock intermediation function. Settling and clearing facilities for all equity transactions, together with central regulation facilities for joint stock companies, were introduced with the establishment of the Saudi Share Registration Company (SSRC) in 1985 (source: Saudi Arabian General Investment Authority).

The SSRC coordinates all buying and selling orders from different banks through a central clearing house.[9] Potential buyers and sellers have to go to the bank and fill out an Order form (Buy). Then the bank has to meet the order on the other side (Sell) from other traders in its own listing. If no match can be found, the bank has to contact other banks via telephone or telex. It is possible to witness transactions of the same stocks taking place in different banks at different prices, as banks prefer to match the order within their own listing of traders or clients. Moreover, a delay (of days or weeks) in fulfilling orders used to be common, as banks are not allowed to buy or sell shares for their own accounts or maintain an inventory for trading purposes. Clearly, a lack of official liquidity providers or market makers made an opportunity for a group of investors to be, unofficially, the market makers. These market makers provide liquidity through posting their own bid-ask prices and trade for their own account.

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[8] Source: Saudi Arabian General Investment Authority.

[9] The SSRC was established with equal ownership by the twelve commercial banks.

Electronic Securities Information System (ESIS)

One of the major developments in the SSM occurred in 1990, when SAMA introduced the new electronic screen-based trading system called the Electronic Securities Information System (ESIS). This overcomes all the previous issues and obstacles in the old system and provides operational efficiency, accuracy in trading process and rapid settlement. Following this development, banks established Central Trading Units (CTU), at some of their branches, which are all linked to the central system at SAMA.

An advanced version of the ESIS, Tadawul, was introduced in October 2001, as the new service system for the trading, clearing and settlement of shares in enabled real-time share trading, as well as same day settlement and clearing of transactions .

Investment in the SSM was not open to foreigners, except indirectly through subscription in designated mutual funds. Recently, the market opened to foreign investments through equity swaps bought through local brokers.

Capital Market Authority

The capital market environment in Saudi Arabia had lacked independent legislative and control bodies which regulate the market and delegate its operation to a sub-unit (currently Tadawul). Based on the need for such bodies, the Capital Market Authority was established by the Capital Market Law, issued by Royal Decree No. M/30, dated 16th June, 2003. The Capital Market Law has created the legal environment for establishing the Capital Market Authority, CMA, with a five-member governing board (appointed in July 2004), a Committee for the Resolution of Securities Disputes and a Saudi Arabia Stock Exchange with the status of a joint-stock company[10]. This company consists of Tadawul, the electronic share trading system hitherto run at the central bank (SAMA).

The CMA is a government organisation with financial, legal and administrative independence. It reports directly to the Prime Minister. The CMA’s function is to regulate and develop the Saudi market. It issues the required rules and regulations for implementing the provisions of Capital Market Law, aimed at creating an appropriate investment environment.

[10] Owned initially by the Pubic Investment Fund and then will be offered partially to the public.

Development and growth

Since 2000, the SSM has achieved impressive growth in terms of market capitalisation, volume and value of the stocks traded. The Tadawul All-Share Index, TASI, grew in athree-year period more than five-fold; it rose from 2,518 points by the end of 2002 to 16,715 points by the end of 2005.

The stock market has witnessed an increase in the number of individual portfolios created and even in the number of companies listed (from 67 companies in 2002 to 134 companies by September 2009). Oil prices are the main incentive for Saudi economic growth; when they go up, the whole economy anticipates growth. However, the SSM is a very volatile market; for example, in 2006 it collapsed by 62% after briefly reaching an all-time high of over 20,966 points in February, 2006. The market is fairly new compared to other developed markets and it is still undergoing many changes.

The period 1985-2000 was an inactive stable market which does not accurately reflect the economic activities of the Saudi economy. This period is characterised by less market participation and investment, lower disclosure practices and slow but steady growth. Starting with the new millennium, the SSM experienced an unprecedented boom in investments and trading activities. This boom was mainly attributed to the liquidity generated by higher oil prices. Then the SSM started to attract the attention of wealthy business families and individuals alike. The years 2001-2007 witnessed an average annual growth of 22% and 29% for the market capitalisation and the index, respectively. The number of participating investors in this period increased four-fold. During this period, average annual growth for the value of traded shares amounts to 58% whereas the average annual growth in the number of transactions was 84%. The high growth is mainly attributed to the growth of GDP and other economic indicators, such as money supply and credit. However, some of it can be ascribed to irrational exuberance, due to the entry into the market of new, less informed and less sophisticated investors each year.

2.3.1 Number and concentration of Listed Shares

In 1999, 74 different companies were traded on the Saudi stock market, compared to an average of 350 companies in other emerging markets (Bakheet, 1999). One of the main reasons for the low number is that the government imposes rigorous requirements for companies wishing to be publicly listed corporations, in order to encourage only large, efficient and well-established companies to have this privilege. The market has a higher degree of concentration as the top ten companies represent 60-70 percent of the overall market, measured by any indicator: size, turnover or profit (Bakheet , 1999). The government has a majority ownership stakes in major companies such as SABIC, Saudi Electricity and the Riyadh Bank, of 71%, 76% and 43%, respectively. Moreover, approximately 44% of the total market value of shares listed in the market are not traded because they are owned by government or semi-governmental entities (i.e. the Pensions Fund and GOSI), or by foreign partners and other joint stock companies. [11]

Although the SSM is the largest stock market in the Middle East, representing 47 per cent of the total capitalization of Arab stock exchanges, the number of listed stocks and the size of the free-float of shares is small.[12] Therefore, it is considered a thin market in comparison with more developed and mature markets.

The SSM is dominated by a few leading major companies which have significant share holdings either by government or by certain families, business houses and joint venture partners. This high level of holdings saps the free float available for trading. Ultimately, it leads to a low market turnover ratio. However, the repatriation of capital from the West after 9/11 and new companies listing have attracted more liquidity into the market and this raised the average turnover ratio to a level of 71% in 2006. Overall, the number of listed stocks and the size of the free-float of shares in the SSM are small, giving the government strong control over the stock market. However, these features of the SSM are changing; for instance, the number of companies grew at an exceptionally high rate in 2006 and 2007. Moreover, more small and family companies have been listed on the market. Finally, starting in April 2008, the CMA has changed the way of calculating the general Index so as to reflect only floating stocks, which represent 36.76% of the total outstanding stocks.

2.3.2 Characteristics of Saudi stock market (Microstructure)

Despite the growth and development which the SSM has witnessed over the last decade, it has been regarded as more thinly traded, less liquid and less efficient than developed stock markets .

[11] (Saudi Stock Market Review, SABB, 2003).
[12] http://www.ameinfo.com/78125.html

The stock exchange lacks depth, as the shares listed are limited to a few large industrial companies and domestic companies, mainly banks. Currently, there are 134 publicly traded companies, whereas some experts claim that the market can accommodate 200 companies at least, considering the size of the economy and the number of registered private companies in Saudi.[13]

In a recent country assessment report by the IMF (2006), the Saudi equity market is regarded as buoyant,[14] with significant turnover but with limited provision of investment information. Butler and Malaikah (1992) were the first to study the efficiency in the SSM in a study which also covered the Kuwaiti market; they find huge one-day negative autocorrelations of -0.47 and attribute the market inefficiency to many institutional factors ,some of which include illiquidity, market fragmentation, trading and reporting delays and the absence of official market makers.

Awwad (2000) states that the financial systems in the country are bank dominated, with several large institutions exerting significant influence on the pattern and structure of market activities. He concludes that the absence of non-bank intermediaries within the financial system has meant that the Saudi market is structurally less developed. Al-Abdulqader (2003) finds that the SSM can be described as 'weak-form inefficient' and investors can earn excess returns by using trading strategies such as filter rules and moving averages. Moreover, investors use mainly fundamental analysis when valuing shares. However, technical analysis is also employed by a sizable number of those surveyed. He concludes that large shareholders appear to be relatively sophisticated when valuing shares.

Alsubaie and Najand (2009), in a study of volatility/volume relationship and using different measures of volatility and information arrival, find that the sequential reaction to information suggests that asset price volatility is potentially forecastable with knowledge of trading volume.

A few studies have attempted to cover some microstructural aspects of the Saudi stock market (i.e., Al-Suhaibani and Kryzanowsky, 2000a, 2000b). The study by Al-Suhaibani and Kryzanowsky (2000a) of the microstructure of the SSM analyses the patterns in the order book, the dynamics of order flow, the time of execution and the probability of executing limit orders. These writers examine the behaviour of market participants in order to understand the effect of order placement on market liquidity and to identify some trading patterns. Some of the main findings are as follows:

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[13] As of September 2009.

[14] A market in which prices have a tendency to rise easily with a considerable show of strength.

- Intraday patterns are similar to those found in other markets, even those with a different structure. These patterns include U-shaped patterns in traded volume, number of transactions and volatility.
- When measured by width and depth, as it commonly is, liquidity is relatively low on the SSM. Nevertheless, liquidity is exceptionally high when measured by immediacy.[15]
- Limit orders when priced reasonably, have on average a shorter expected time to executions and have a high probability of subsequent execution.

Al-Suhaibani and Kryzanowsky in another study (2000b) assess the information content of a newly submitted order and investigate not only the order size effect but also the information content of orders with different levels of aggressiveness. They find that:

- Larger and more aggressive orders are more informative.
- A large amount of asymmetric information is present in the SSM.
- The relative measure of order informativeness implies that private information is more important for infrequently traded stocks.

Most of the previous research on the SSM has primarily extracted data of the time span preceding the introduction of the CMA in 2004, which was a milestone in the SSM's development. Data analysed after the creation of CMA will be of significance not only to the CMA's existence itself but to the rules, developments and changes which have faced the SSM since then. We will briefly explain some of the main characteristics of the SSM and highlight the aspects needed to understand its structure.

Sustainable Liquidity (specialists and market makers)

There are no designated market makers in the SSM; large investors sustain the liquidity of the market with large orders which reflect their own investment strategies. In extreme circumstances, it is common to witness Buy (Sell) orders only, with no quantity of stocks supplied (demanded) on the other side. The stock exchange imposes on all stocks listed a daily price cap to limit price movement to 10 per cent. Occasionally, trading in a stock stops if the price hits its daily limit, a situation called limit-up or limit-down, depending on direction. Traders cannot place limit orders at a price beyond the daily limit; hence, trading stops

[15] Immediacy refers to the speed of order execution with specific quantity and cost.

temporarily because there are no traders willing to take the other side in the trading. This kind of situation generally accompanies extremely good or bad news.

Large trades may set the direction of the market because large investors can manipulate prices easily with large orders, due to the absence of market makers and institutional investors. Al-Rodhan (2005) states in his paper that hyping, dumping and rumoured investing are all too common in the Gulf Countries, including Saudi. Moreover, although short selling and margin trading are not allowed in the market, investors can borrow from banks against their holding of stocks.

Institutional Investors

There are a few open-end mutual funds run by commercial banks whose investment strategies are not known. They publish only their weekly returns. By the end of 2007, the number of investors participating in bank-managed mutual funds was around 426,100. In addition, the autonomous government institutions (AGIs),[16] together with the specialised credit institution (Public Investment Fund), have equity ownership in many of the listed companies in the SSM. They play an important role as institutional investors in the market. Nevertheless, these institutions are not active traders in the secondary market.

The limited participation of institutional investors in the secondary market, with buy-and-hold strategies, constrains the intermediation of information and an effort to encourage such services could be an important method of ensuring that more investors act on the basis of real fundamentals rather than rumours (IMF, 2006).

The SSM lacks the presence of major institutional players, who usually form the backbone of such markets, and foreign investors are not allowed direct market participation.

Analysts' forecasts

Analysts' forecasts play an important role in any market by conveying information to the public of the expected earnings and performance of companies; many investors rely on these in making their investment decisions. Moreover, these forecasts are considered as a communication channel from the professional world to the public. Without independent analysts, less information is conveyed to the public, as happens in the case of the SSM. Alsehali and Spear (2004) describe the SSM as weakly monitored by analysts and other stakeholders.

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[16] There are three AGIs: the Pension Fund, the General Organization for Social Insurance (GOSI) and the Saudi Fund for Development (SFD).

This situation could promote more dependence on informal and unreliable sources, such as rumours and Internet forums. Some investors turned to international consultant houses to seek advice and reports regarding investment opportunities in the SSM. Other investors lost the whole concept of investment and dropped fundamental analysis entirely. Many traders adopted short-time investment strategy (speculating), focusing on techniques and news which help to achieve returns in the short run, regardless of company financial performance. For all these reasons, the SSM is very volatile and dominated by waves of speculation which are fuelled by news and rumours. Clearly the lack of institutional investments worsens the situation. According to Tadawul monthly reports, individual trading in the SSM in 2008 amounted to 92% of all trading in the market.

Anticipation of news

News regarding earnings and other issues of importance to investors is announced on the official website of the stock exchange. There are no scheduled events or expected announcement dates. However, all listed companies must announce the annual and quarterly reporting of financial results. They are required to submit quarterly financial statements within 2 weeks from the end of each quarter. Annual financial statements reviewed by auditors are to be submitted within 40 days of the end of the financial year.

Before the announcement day, investors in general have no means of anticipating news and earnings. Some investors rely on informal sources such as Internet forums, which are very active in speculating companies' earnings, forecasts and news.[17] Some large investors could depend on insider information and react to information leakage in advance of announcements. It is notable in the SSM to see unusual trading activities, in terms of volume and returns, in some stocks before announcements are officially made. More recently, investment houses and brokerage companies, which are newly established entities, have begun to issue reports and recommendations which could help investors make more informed decisions.

In general, disclosure norms and announcement practices in the SSM are poor, in particular regarding items of voluntary disclosure, such as earning forecasts and management activities. Al-Bogami et al. (1997) investigate the timeliness of publishing and reporting in the SSM. Covering 39 Saudi listed companies from the first quarter of 1987 to the end of 1991, they calculate the number of days from each company's quarter-end to the release of the quarterly financial statement in the local newspaper. Companies on average publish their fourth quarter's

[17] Personal correspondence with Remal IT www.remal.com (one of the biggest software companies in Saudi which manages and maintains Internet forums and sites) reveals that the number of daily visitors to economic and share Internet forums in Saudi ranges between 200k and 300k. One forum alone has 45-60k daily visitors.

reports within 108 days of the quarter end and publish their first three quarterly statements within 50 days after the end of the quarter. In a more recent study Aljabr (2007) shows that Saudi publicly listed firms have taken less time to publish their annual reports since the establishment of the CMA. He finds on average that the number of days between the end of the financial year and the publication of annual reports decreased to 28 in 2005. The CMA recently started to take action against companies which failed to meet the deadline for either quarterly or yearly statements, de-listing them temporarily or permanently. Moreover, publishing practice has greatly improved with automation and Internet access being available to all investors. As mentioned earlier, the Tadawul website carries announcements and news facilities which allow companies to announce their news promptly and efficiently. Furthermore, the CMA recently suspended two stocks from being traded in the market because those two companies made losses exceeding 75% of their capital.[18]

AL-Bogami et al. (1997) observe that stock returns do not seem to respond to announcements of the first three quarters but respond significantly to the fourth quarter announcement. Al-sehali and Spear (2004) investigate the decision relevance and timeliness of accounting information in the SSM, using a sample period during 1995-1999 and covering 52 firms' annual financial reports. They suggest that the publication of accounting earnings leads individual investors to revise their security holdings. They also suggest that earnings are timely in terms of their association with security returns

Access to the market

All citizens of Saudi and the Gulf States (GCC) can invest in the SSM. Foreigners who reside in Saudi have recently (since 2006) been allowed to invest directly in the market but it is closed to foreign direct investors and institutional investors. However, there are some mutual funds which allow foreign investors to buy shares in funds which invest in the SSM (the SAIF is a closed-end fund listed on the London Stock Exchange and is managed by SAMBA). Investment by foreigners who live outside the country is restricted by a scheme called "Equity Swap", under which they can buy shares in Saudi companies through a local broker who retains the legal ownership (i.e., voting rights), giving the foreign investor only entitled to the economic benefits (e.g., dividends and equity issuance) Some officials and analysts believe that the CMA is working toward full opening of the market in the future.

[18] According to the regulations of the Capital Market Act, 2004.

Brokerage and Dealership

The SSM is purely an order-driven market with no physical trading floor, regulated brokers or market makers (Al-Suhaibani and Kryzanowski, 2000a). It runs only on automated systems which allow commercial banks through their trading units to receive orders to buy and sell with different types of specifications (limit order vs. market orders). Trading units in commercial banks at Saudi are like discount brokers who transact buy and sell orders at a reduced commission, but provide no investment advisory service, unlike a full-service broker.

Recently, the CMA has granted some companies licences to operate in the market, which vary in the services they are authorised to provide. Moreover, commercial banks are not permitted to provide brokerage service directly. Instead Commercial banks were allowed to establish separate entities for their brokerage activity like any other broker in the market, however, brokerage companies that are owned by commercial banks still enjoy the majority of the market share. Some of the newly established brokerage firms exercise full licence, including advice, dealing and the management and custody of funds. Others hold licenses which cover one area only. Brokerage and dealership firms have already started to operate, some of which issue reports and general forecasts about market prospects or recommendations;[19] however, these forecasts tend to be general in nature and cover only a few "blue chip" companies. Moreover, they are not managed in a timely way, unlike their counterparts in developed markets, where each stock is followed by a group of analysts who issue timely reports and revise them in the light of new information as it emerges.

Expectations

As we have seen from the literature discussion section, analysts' forecasts play an important role in disseminating information to the market and speeding up the stock price impounding of information. Moreover, many characteristics of the SSM have been discussed regarding the interactions between different agents in the market, showing how strong is the element of individual trading. The absence of market makers, coupled with inactive institutional investing, may be expected to increase the level of information asymmetry in the SSM. Information asymmetry can make patterns of financial anomaly such as PEAD more persistent as price adjustments to information will take longer and show predictable patterns in stock returns, such as momentum trends.

[19] The CMA has granted licences to 80 brokers and dealers.

All the previous factors lead us to hypothesise that PEAD exists in the SSM. Moreover, the magnitude of the drift is expected to be higher than in other developed markets, while the longer persistence of the drift is consistent with Lasfer et al. (2003), who find that emerging markets respond much more strongly to market shocks than developed markets do. We also expect higher price drift in industries that have small sized firms in general and low share holding by institutional investors and government.

2.4 Data and Descriptive Analysis

The dataset covers all companies in the SSM but excludes new companies which have not so far made any earnings announcements. It includes 89 companies (banking =10, industry =35, cement=8, service=23, electricity=1, agriculture=9, telecommunication=2 and insurance=1). It covers quarterly earnings announcements for listed companies in the SSM during the period between the first quarter of 2001 and the third quarter of 2007. 1667 earnings announcements were documented from the Tadawul website after removing those announcements for which the exact timing and date of dissemination to the market could not be verified. Data regarding stock daily prices were provided by the official stock exchange. They include the following fields: Close, High, Low, Volume, Value and Trades for the seven-year period 2001-2007 where the following values obtain:

Prices: the daily closing prices for all stocks in the market and the daily high/low.

Volume : the total number of shares traded over a given day, as reported by all market participants

Value : the total Saudi Riyal value (1$=3.75SR, fixed rate) of all shares traded over a given day, as reported by all market participants.

Trades (transactions) : the total number of trades reported in one day.

2.4.1 Characteristics of Earnings Announcements

The Saudi Stock Market normally disseminates earnings information through the official website, www.tadawul.com.sa and later in other media. Three kinds of quarterly earnings report are published: first, the quarter's income "forecast" or guidance by the company or the company executives in the official website. Normally, this is published before or toward the end of the quarter; second, the official announcement of the earnings in Tadawul; and third, the completed interim (quarterly) report which is also published in the stock exchange official website and published to newspapers. The first type of announcement, which is management forecast or guidance, is often precise;[20] recently, in particular, the forecast has been almost identical to an official announcement. Given that forecasts contain the same income figures as the official announcements do, effectively the announcement date is the date of issue of the company management's guidance, if it exists. However, such management guidance is not issued by all companies and as a rule it is an abstract of the official earnings announcement. It usually contains the gross revenue and net income, with no further details. We treat the management guidance day as the announcement day. Alternatively, if no forecast was made, we use the date of the official announcement. The official earnings announcement usually contains more details of the revenue, income and costs. Later, after the announcement day, companies publish their interim statements in different media channels (the stock exchange website, the company's own website and newspapers).

All listed companies in the SSM are required to publish their announcements within two weeks of the end of the quarter, but the exact timing of the announcement is not known until it is published. End-of-year announcements must be made within the first forty days of the end of the company's financial year.

There is no standard format to which companies should adhere in their announcements; each company has its own style of wording and has control over the content. In general, the announcements contain the current quarter's sales, operating profit and any extraordinary or non-recurring items which might affect its earnings. The current quarter's earnings are usually compared (in percentages) with the previous quarter or the equivalent quarter in the previous year (the most common). Some companies include general future expectations of the company's earnings.

It should be noted that companies tend to give better and more detailed treatment of positive news than negative news, e.g., the percentage of an increase in earnings is usually mentioned whereas the percentage of a decrease is omitted sometimes.

Moreover, some companies announce accumulated earnings up to date, i.e., they announce earnings as an accumulated figure without specifying what percentages or proportion should be attributed to each quarter (i.e., a figure for the earnings in all quarters of the financial year without breaking them down into quarterly numbers). Readers must refer to previous

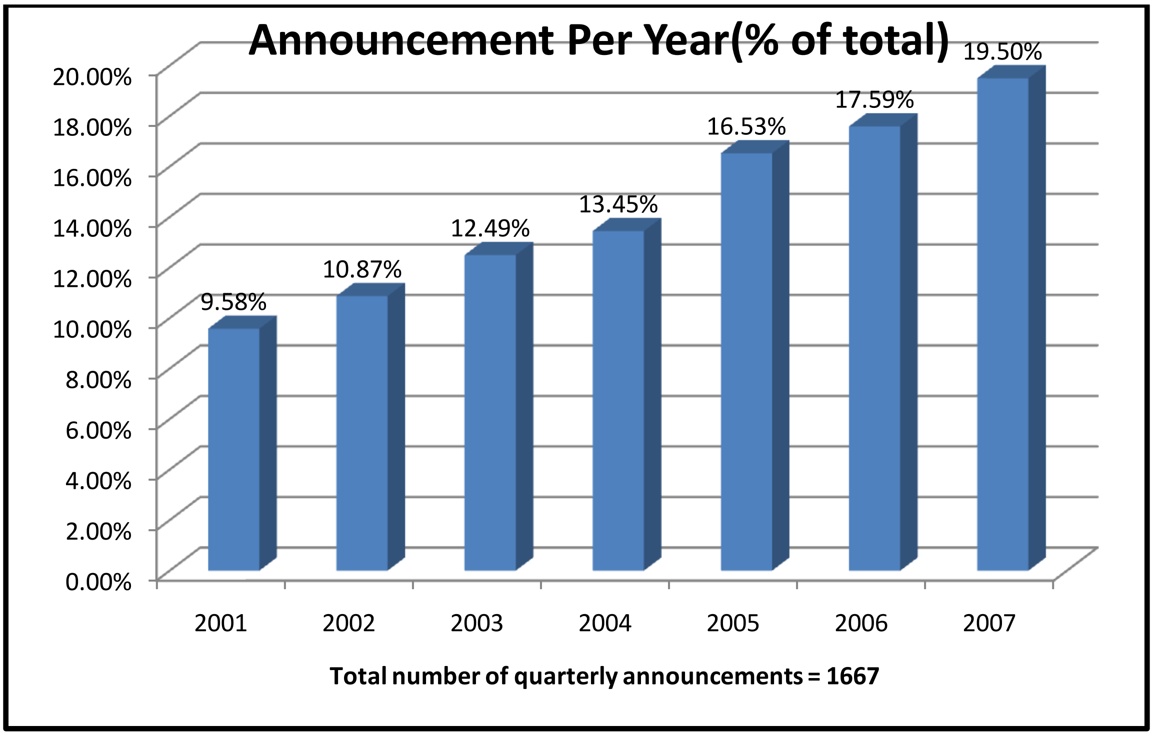
[20] A few loss companies have disputes with the auditing firms, usually announcing a forecast which could be different later in the completed report because accounting standards and treatment applied. These companies are usually small, loss and few in number.

quarters to know the exact figures for them all; such a method could be misleading and confusing, whereas the quarter net contribution figure could easily be shown. A company may have done better in the aggregate number, but worse in the last quarter or vice versa. We look at any systematic bias which could be associated with the announcements practice in the SSM, such as the clustering or overlapping of events and timing patterns of the announcments. In the following section, we look at the yearly, weekly and daily distribution of the earnings announcement dates.

Announcements per year

From Figure 2-1, we can see clearly that the number of announcements has increased, with last recorded year making up one-fifth of all announcements, though it covers only the first three-quarters of the year 2007. This growth trend can be attributed to three factors. First, recent years have witnessed an increase in the number of listed companies (new IPOs). Second, the increased investment awareness of the importance of timely and accurate information has created pressure on firms to announce theirs in a timely manner. Third, the capital market authority (CMA) established and enforced disclosure laws and regulations. For instance, the CMA started to impose fines for companies which announced their earnings late. Previously, some companies could announce their quarterly or yearly earnings after a long delay (which could extend to months), allowing for speculation and insider trading to benefit from this private information. A company could publish its announcement only in a local newspaper, thus favouring geographically local investors. Information can take a long time to reach all market participants. Since the beginning of 2001, however, Tadawul has made announcements on its website which the whole public can access. This is the main reason that we concentrate on data starting from 2001.

Figure2-1: Distirbution of Announcement Dates Per Year.

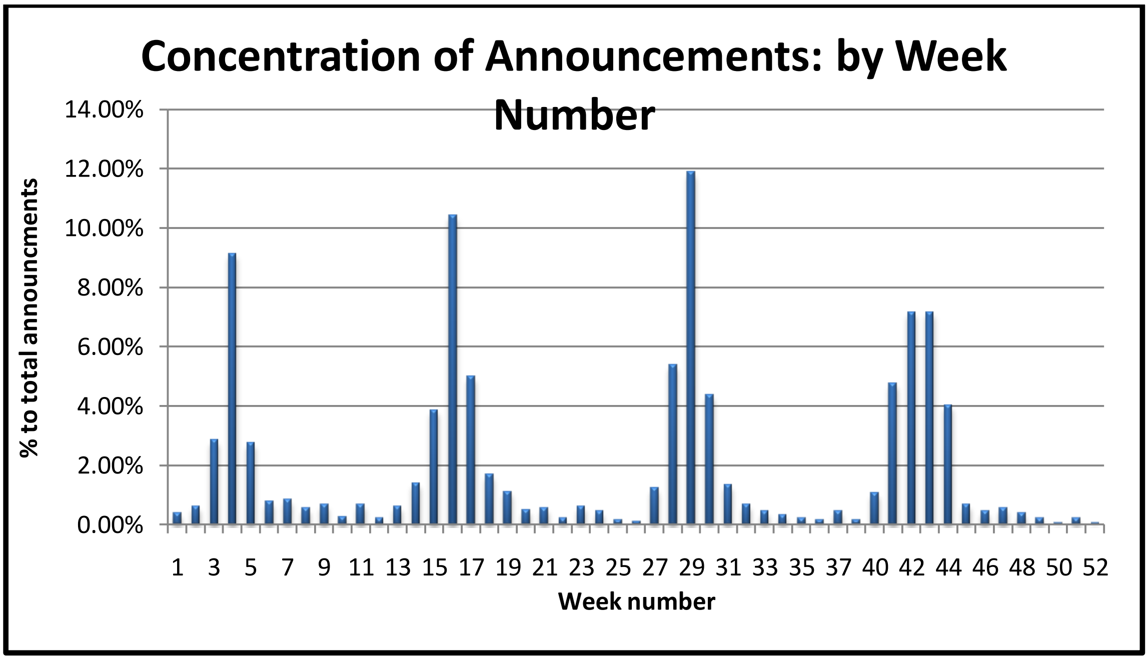


Notes : Figure 2-1 exhibits the development of announcement practice. Recent years show a higher percentage of announcements. In 2007, almost all companies have announced their earnings on time, whereas in 2001 the practice was not strict. Some of the observations were dropped from 2001-2002 because the exact time of the announcement cannot be verified. Moreover, more observations are added to the sample each year because of new companies listing on the market.

Announcements by week number

Announcements were fairly evenly distributed in all weeks throughout the year. Weeks 4,16,30,43 and 44 have the highest frequency, as they occur at the same distance from the end of each quarter in turn. A careful look at the dates of events in Figure (2-2) shows, however, that many announcements are made outside these specified weeks. Announcements are made almost evenly throughout the announcments period allowed by the Capital Market Authority (a two-week period from the end of each company's quarter end for the quarterly statements and a 40-day period from the end of the year for the yearly statements).

Figure 2-2: Clustering of Announcements per Week.



Notes: This figure shows the distribution of earnings releases by the week number. Some week numbers, typically, have a higher percentage of announcements because these weeks fall in the announcement period (after the end of the quarter). The total number of observations is 1667 earnings announcements.

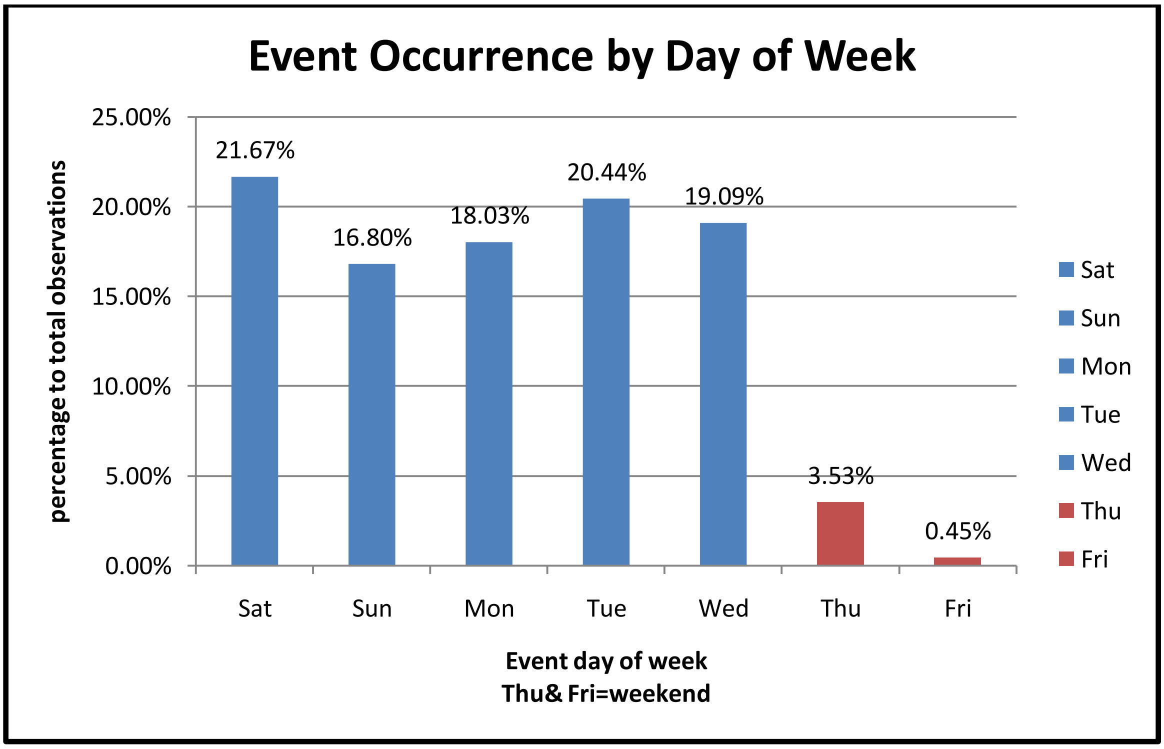
As mentioned earler, there are no scheduled announcements for companies in the SSM. However, an announcment period of 2 weeks starting from the last day of each firm's quarter is the period in which each company should report its earnings, or face a penatly levied by the CMA. The fact that companies have longer announcement periods helps us to better interpret normal returns results, since not all announcement are clustered around any particular date.

Day of the week analysis

The announcements data were further investigated for any pattern which could be of interest, such as the day of the week effect. One of the implications of the day of the week effect is that news announced on a Friday, which is the last trading day of the week in any developed market, or Wednesday in the case of the SSM, might not attract investors' attention at the time and might therefore produce a delayed reaction. Moreover, many researchers (e.g., Damodaran, 1989, Defusco et al., 1993) have suggested that managements tend to release negative news regarding their companies at the weekend.

Events were categorised by the day of the week when they occurred, including events announced at the weekend. The SSM used to operate from Saturday through Thursday, with Friday as the weekend. With effect from 15/06/2006, the weekend was extended to two days (Thursday and Friday), after the cancellation of trading on Thursdays. In September 2006, also, the trading hours were reduced from two sessions (morning and evening) to one. Before this date, it was customary for firms to make their announcement between sessions. As seen in Figure (2-3), announcements occur fairly evenly throughout the week. Only 4% of annoucnments were made at weekends, which indicate the lack of evidence of when managements time their annouuncements.

Figure 2-3 : Announcements by the Day of the Week



Notes: this figure plots event occurrence by the day of the week. Starting from September 2006, Thursday and Friday became non-trading days. The number of observations of quarterly earnings announcements is 1667. Only 67 earnings news reports were made at the weekend, with the rest being reported throughout the week and no day showing a significantly higher number of earnings announcements than any other.

2.5 Methodology

In order to measure the market reaction to the earnings announcements, we use event study methodology (see Kothari , 2001, for comprehensive review) . Event studies techniques were used in variety of studies, for example, earnings announcements, mergers and acquisitions, investment decisions, new laws and regulations effects. The aim of the event study is to measure the economic impact of an event on a firm or asset value. This measurement is done through econometric techniques which emphasis on the flow of the analysis or procedures that are needed to conduct event studies. Most event studies suggest similar procedures or flow of analysis (See for instance, MacKinlay ,1997; Binder, 1998 ; Kothari and Warner,2007). The general steps in event studies are listed briefly below then our own event study steps are discussed in more details:

1. **Identify the Event and the relevant Event Window**. Events should be clearly identified and date of event should be investigated to be certain, as the assumption here is that the event date is clearly known to the researcher or at least within reasonable range. In this step the researcher should decide on the appropriate event window which could extend to more than one period or day. Moreover, the length of the estimation window, which could be before or after the event, should be decided and identified. An estimation period should be long enough to produce asymptotic properties of the parameters. Issues such as daily or weekly assets returns should be considered also here.

2. **Estimate normal return using a Return Expectation Model.** The choice of the model could be a crucial step because event studies are joint tests of market efficiency and the model used. Results leading to market inefficiency could be attributed to the bad model chosen. Two main categories of models are often used; statistical models and economic models where the latter have economic assumption regarding the behavior of the assets and the former depends on statistical assumptions regarding the assets return (MacKinlay, 1997).

3. **Analysing abnormal returns and average abnormal returns**. Calendar dates are converted to event calendar where t=0 is defined to be the event day or announcement day for all companies regardless of their calendar announcements dates. Once abnormal returns ***AR*** are computed for all firms in the sample, average abnormal returns ***AAR***, typically are computed over all events so the researcher can easily infer and generalise the results to the whole sample and to eliminate specific company movement that is unrelated to the event. It is common for most event studies to classify assets or stocks returns to Good (positive) and Bad (negative) news portfolios as each one should, in theory, react in different direction.

4. **Cumulative Average Abnormal Return (CAAR) or Buy-and-Hold-Abnormal Returns (BHAR)**. Cumulating the effects of the event by summing or compounding all the abnormal returns for specific periods gives an indication of the wealth formation and how portfolios would have performed over multiple periods. The cumulating process can be used also to measure the anticipation of the news or leakage of information in the market.

5. **t-statistics.** To test whether the average abnormal returns or the cumulative abnormal returns would be statistically significant or different than zero, parametric or non-parametric tests are used for this purpose. The standard test is to compute the standard deviation of all excess returns of the firms in the sample (cross –section) or pre-event standard deviation of the time-series of the excess returns.

Return generating Model (Expected Returns)

In event study methodology, the interest is to measure the performance of a security following an "event". An important step in this process is to define what a "normal" or expected performance is or should be, then it will be a matter of computation to realise what can be considered as "abnormal" performance. The Abnormal return represents the difference between the "expected" return and the actual return. Several methods are used in prior research to estimate expected or normal return; Mean Adjusted Model, Market Adjusted Model, Market Model, the Capital Assets Pricing Model (CAPM) and more recently Fama-French Three Factor Model. The essence of all these models is to subtract the actual performance from the expected performance. In other words, abnormal returns are the differences between event returns and non event returns (expected returns unconditional on the event). To show this concept, we can use the following equation:

$$\boldsymbol{AR_{it}} = \boldsymbol{R_{it}} - \boldsymbol{E(R_{it})} \qquad (1)$$

Where:

$\boldsymbol{AR_{it}}$ Is the abnormal return for firm *i* over time interval *t*,

$\boldsymbol{R_{it}}$ Is the actual return for firm *i* over time interval *t*,

$\boldsymbol{E(R_{it})}$ Is the expected / predicted return for firm *i* over time interval *t*.

What differ among these models are the assumptions about the expected return $E(R_{it})$ and the risk for the security with regards to the market portfolio reflected in the coefficients. For example, in both mean adjusted model and CAPM: It is assumed each stock has an expected return which is a constant over some period of time; however this expected return varies across firms. In practice, the gains from using more sophisticated models are limited because the variance of abnormal return is not reduced significantly by choosing the more sophisticated model (Brown and Warner, 1980, 1985).

It is common to find an event study using two or three models simultaneously. The choice over which model should be used usually doesn't matter a lot .Brown and Warner (1980) test three methods of calculating the expected return: 1)Mean adjusted returns,2)Market adjusted returns, and3) market and risk adjusted returns .They indicate that even though mean adjusted return is perhaps the simplest model, it often yields similar results to those more advanced models and it is as effective as the other methods. Precisely, they find that the market and market-adjusted models perform better than the mean-adjusted model when there is a clustering of event dates.

Kothari and Warner (1997) use all four methods for their return generating process that is ;1) Market-adjusted return model ,2) Market model ,3) Capital assets pricing model (CAPM) , and 4) Fama–French three factor model. MacKinlay(1997) evaluate in depth the alternative models and classify them in either statistical or economics models. He states that the insensitivity to the model chosen could be accredited to the fact that when choosing more sophisticated models, they often do not reduce the variance of abnormal return.

Market-Adjusted Model (method chosen)

This model takes into account the market return as a benchmark to determine the normal return of a particular stock at point of time t. The market-adjusted model assumes the expected returns are equal across all stocks at a point of time t, but not necessarily constant for a stock at different times. The abnormal return for a stock is defined to be the residual which is calculated as the difference between the return on the stock $\boldsymbol{R_{it}}$ and the return on the market portfolio$\boldsymbol{R_{mt}}$ written as:

$$\boldsymbol{AR_{it} = R_{it} - R_{mt}} \tag{2}$$

This model has been used in many event studies for its simplicity and easiness of calculation. MacKinlay(1997) shows that Market adjusted model can be regarded as a restricted market model with coefficients $\alpha = 0$, and $\beta=1$. Such restriction of beta equals to one assumes that each security has the same systemic risk as the market. Because the coefficients are pre-specified, there is no need for an estimation period prior to the event period in order to find parameter estimates. Such situation could happen when new IPO's are introduced to the market. The Market-Adjusted Model assumes stocks have the same property for average returns and risk as the market. It is plausible in our data to use the Market-Adjusted Model where the bias in the model is mitigated through sample selection of the firms that nearly represent the whole Market. Binder (1998) when evaluating this model concludes that, in large sample the bias will usually average to zero if the average beta of the sample firms is one. We choose the Market-Adjusted Model because it is the most appropriate model that could accommodate the nature of our data. SSM is relatively a new growing market with many IPOs introduced each year. For example in the first quarter in the data (1^{st} quarter of 2001), there are 55 observations whereas in the last quarter in the data (3rd quarter of 2007), there are 85 observations. It would be impractical to choose any other model that requires pre –event estimation data which is not available in such situation.

For each company, calendar time of the announcement is converted to event time by defining the date on of announcement (t=0). For announcements on Thursday and Friday (when the markets are closed) and on stock exchange holidays, we use the next available trading day as the event day, t=0.

Next, we calculate the daily stock returns of the listed companies from 2001 to 2007 and the daily returns of the Tadawul All Share Index (TASI), by using historical prices obtained from Tadawul as shown below;

$$\boldsymbol{R_{it}} = \frac{\boldsymbol{P_{it}} - \boldsymbol{P_{it-1}}}{\boldsymbol{P_{it-1}}}, \boldsymbol{and} \quad \boldsymbol{R_{mt}} = \frac{\boldsymbol{T_t} - \boldsymbol{T_{t-1}}}{\boldsymbol{T_{t-1}}}, \tag{3}$$

Where $\boldsymbol{P_{it}}$ is the stock price of the *i*th firm at time *t*, $\boldsymbol{R_{it}}$ refers to its rate of return, $\boldsymbol{T_t}$ represents TASI(index) value at time *t* , and $\boldsymbol{R_{mt}}$ is its rate of return.

Aggregating abnormal returns

We aggregate abnormal returns across several stocks and events for selected time intervals to form an overall inference about the impact of the event being studied on the market in general, since individual stocks historically show higher variance and could be subject to other factors than the event itself. We aggregate the abnormal returns across two dimensions, across events or firms (Cross-section) and across a time interval [t1, t2].

Cross-Section Aggregation

The abnormal returns are aggregated through two dimensions: cross-sectional aggregation and time aggregation. Abnormal returns are calculated over a 40-day period which extends from event days -19 to +20 (-19, +20), using the Market-Adjusted Model : $\boldsymbol{AR_i = R_{it} - R_{mt}}$ to obtain residuals which we call Abnormal Returns. In the cross-sectional aggregation, AR_i are averaged across the N firms in the sample on each day *t* to form the average abnormal returns AAR, as can be shown in the following equation:

$$\boldsymbol{AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{it}} \qquad (4)$$

AAR_t = The average abnormal return across event observations N (number of companies)

Time Aggregation

One drawback of examining AARs in an event study is that they do not accurately reflect the return realized by actual investors, as Fama (1998) suggests. There are two common ways of calculating the impact of the event on the returns of security and an investor's wealth: cumulative abnormal returns (CARs) and buy-and-hold abnormal return (BHARs). BHAR is calculated by compounding each period's abnormal return (subtracting the stock returns from the benchmark or market returns). Abnormal returns are calculated into a buy-and-hold measure to accurately reflect the change of investor wealth:

$$\mathbf{BHAR_{i,t} = \prod_{t=0}^{T}\left[1 + AR_{i,t}\right]} \qquad (5)$$

Barber and Lyone (1997) favour the use of BHAR, showing that CARs suffer the bias of not reflecting the experience of investors. However, BHAR suffer from a rebalancing bias in long-run studies, when using equally-weighted reference portfolios with periodic rebalancing.

CAR measures the investor wealth change around the event by summing each period's abnormal return over the event window. Many studies suggest using CAR, e.g. Fama (1998) and Mitchell and Stafford (2000), as this is judged to be a better, less biased method in particular in long-run returns. Lyon et al. (1999) indicate that CARs might be used because they are less skewed and less problematic statistically. The BHAR method can exaggerate over- or under -

performance even in one single period, as the compounding effect will show up in subsequent periods. But CAR can eliminate the compounding effect associated with BHAR for single-period abnormal returns. It is worth noting that both methods suffer some biases and drawbacks, in particular in long horizon event studies. These biases could be skewness (long-term abnormal returns are positively skewed), survival-related bias, rebalancing bias (benchmark portfolio returns are calculated assuming periodic rebalancing) and new listing bias (new firms entering the benchmark, index and portfolio in each period or year). However, most of these biases are found in long-run events. In short-horizon event studies, this study included, CAR seems to be an appropriate choice. Simply put, most short-run tests are well specified while most long-run tests are not. The latter are more susceptible to bias in the method of calculating and testing the abnormal returns.

Kothari and Warner (1997) find that long-horizon event studies suffer misspecification in the test statistic, due to the methods of calculating abnormal returns and their standard deviations. Kothari and Warner (2007) state that the results of short-horizon tests are more reliable than long-horizon tests. They emphasise that short-horizon event study methods are relatively straightforward and trouble-free.

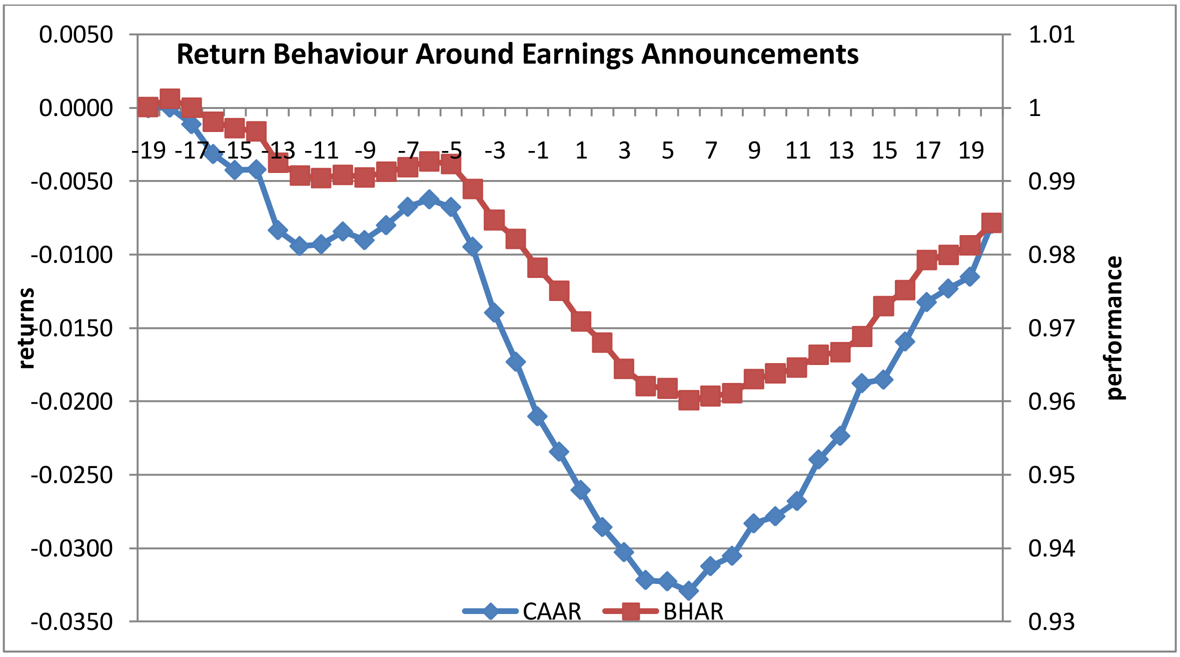
To estimate a performance measure for any time interval or event window for the total sample, CAAR, the Cumulative Average Abnormal Return is computed. It is a measure of abnormal performance which adds up each day's average abnormal return $\mathrm{AAR_t}$. In other words, CAAR corresponds to the way in which an investor (sample) portfolio would perform around the event window in terms of wealth change. Tests using CAAR can also be used to infer the market efficiency as systematic non-zero cumulative abnormal returns following an event which contradicts the market efficiency hypothesis. Furthermore, one could hypothetically benefit by trading on this anomaly (ignoring trading costs). **CAAR** is defined as:

$$\boldsymbol{CAAR(t_{1,}t_2) = \sum_{t=t_{1,}}^{t_2} AAR_t} \tag{6}$$

Where $\boldsymbol{CAAR(t_{1,}t_2)}$ represents the cumulative market -adjusted abnormal return on a portfolio of N events over the time period t_1 to t_2. For example, $CAAR(-1,+1)$ is the cumulative average abnormal return across event observations from day $t_1 = -1$ to day $t_2 = +1$.

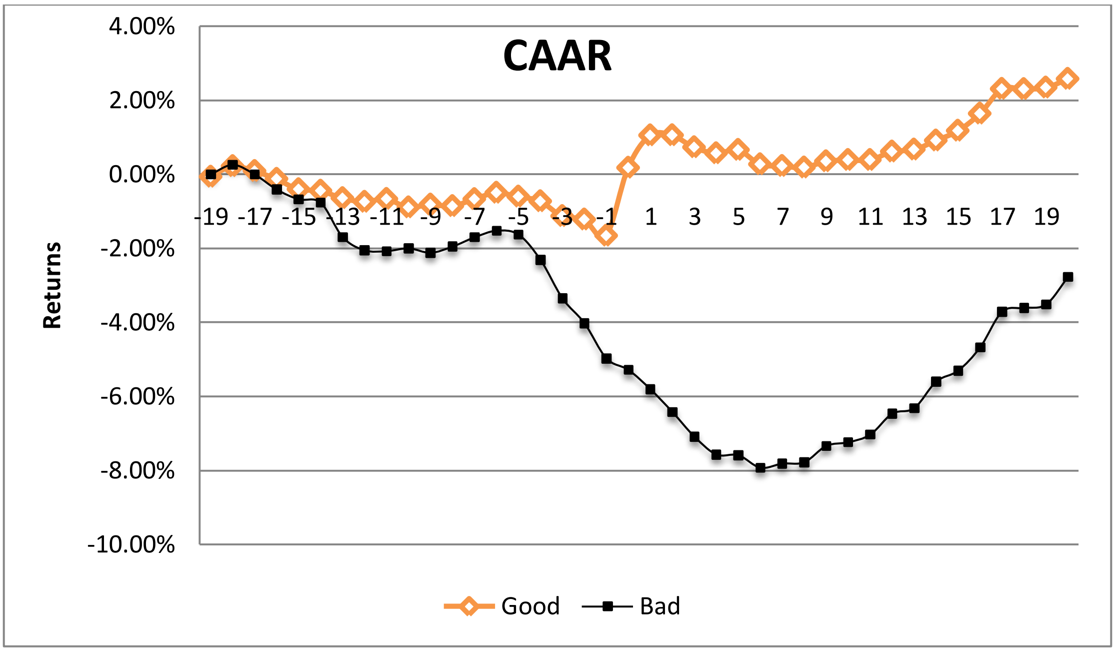
2.6 Results

Figure 2-4 : Cumulative Average Abnormal Returns (CAAR) and Buy-and-Hold Returns (BHAR).



Notes: Figure (2-4) reports daily cumulative abnormal returns for an all-firms equally-weighted portfolio for the period (-19, +20). BHAR reports the compounding performance of an all-firms weighted portfolio for the same period. Anticipation of news starts from the pre-announcement date which indicates information leakage in the market. We can see that CAAR is continuing to react in the same direction up to day 6, when price reversal takes place forming a U-shaped pattern of CAAR and BHAR for the period (-5,+19).There seems to be an overreaction to news at first followed by price reversal . On average, one Saudi Riyal invested 20 days prior to the announcement day in the market portfolio is worth only 96% 6 days after the announcement and is worth 98.5% of its original value 20 days after the announcement day. However, it is necessary to split the portfolio in event studies into two samples, (positive) good news firms and negative (bad) news firms, to show the effect of the news on returns. The question arises whether the price drift magnitude will be similar for the two portfolios?

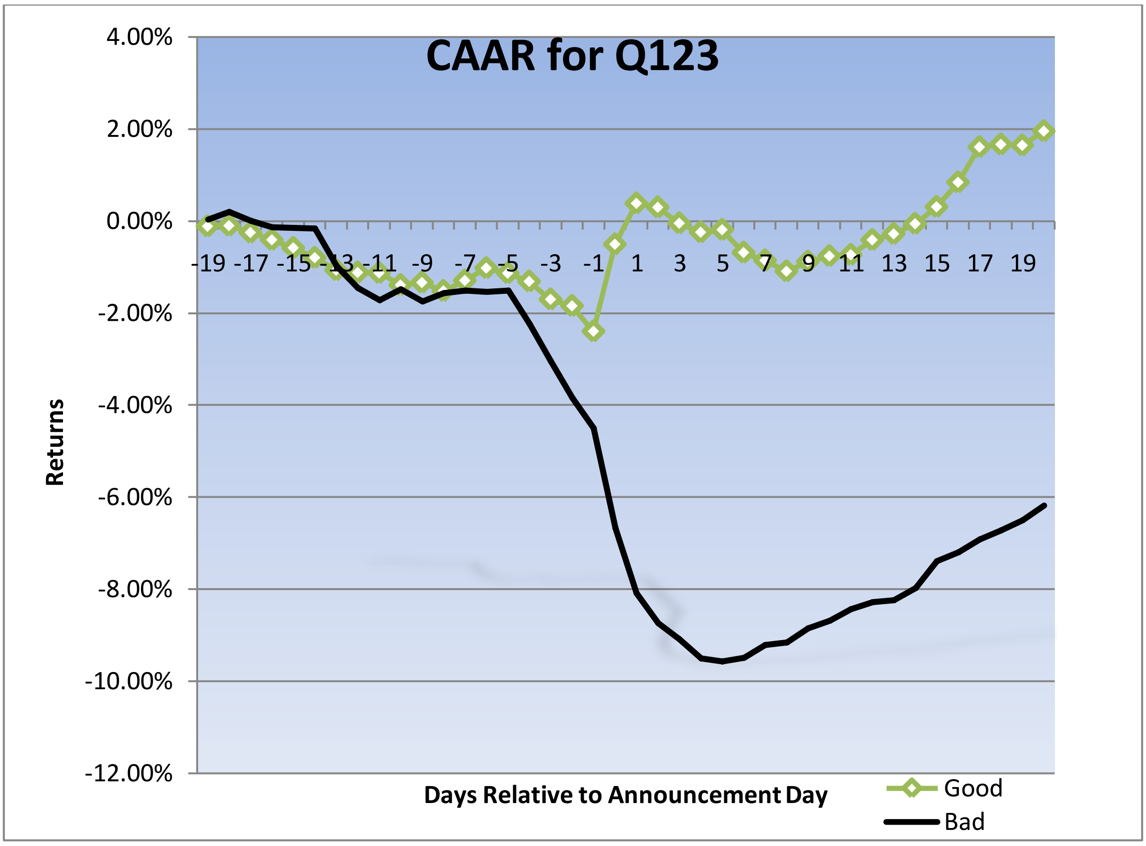
Figure 2-5: Good and Bad News (CAAR) for Event Window (-19, +20).



Notes: Figure (2-5) shows CAAR performance for Good and Bad news portfolios. We follow Garfinkel and Sokobin (2006), who use only the abnormal return at the time of the earnings announcement to control for earnings surprise. The good news portfolio (708 observations) is those companies who report positive abnormal returns on announcement days (0, +1). A Bad news portfolio (959 observations) consists of companies which report negative abnormal earnings returns on the announcement days (0, +1). On the graph, the Good news portfolio does not show strong anticipation to news in the pre-announcement period. However, the bad news portfolio exhibits some reaction to news in the pre-announcement period which can be observed in the period (-14,-5), an indication of some information leakage. Moreover, the Good news firms show similar PEAD pattern found in many other markets. Conversely, the bad news portfolio seems to overreact to news at first in the period (-5, +7), before a price reversal pattern forms.

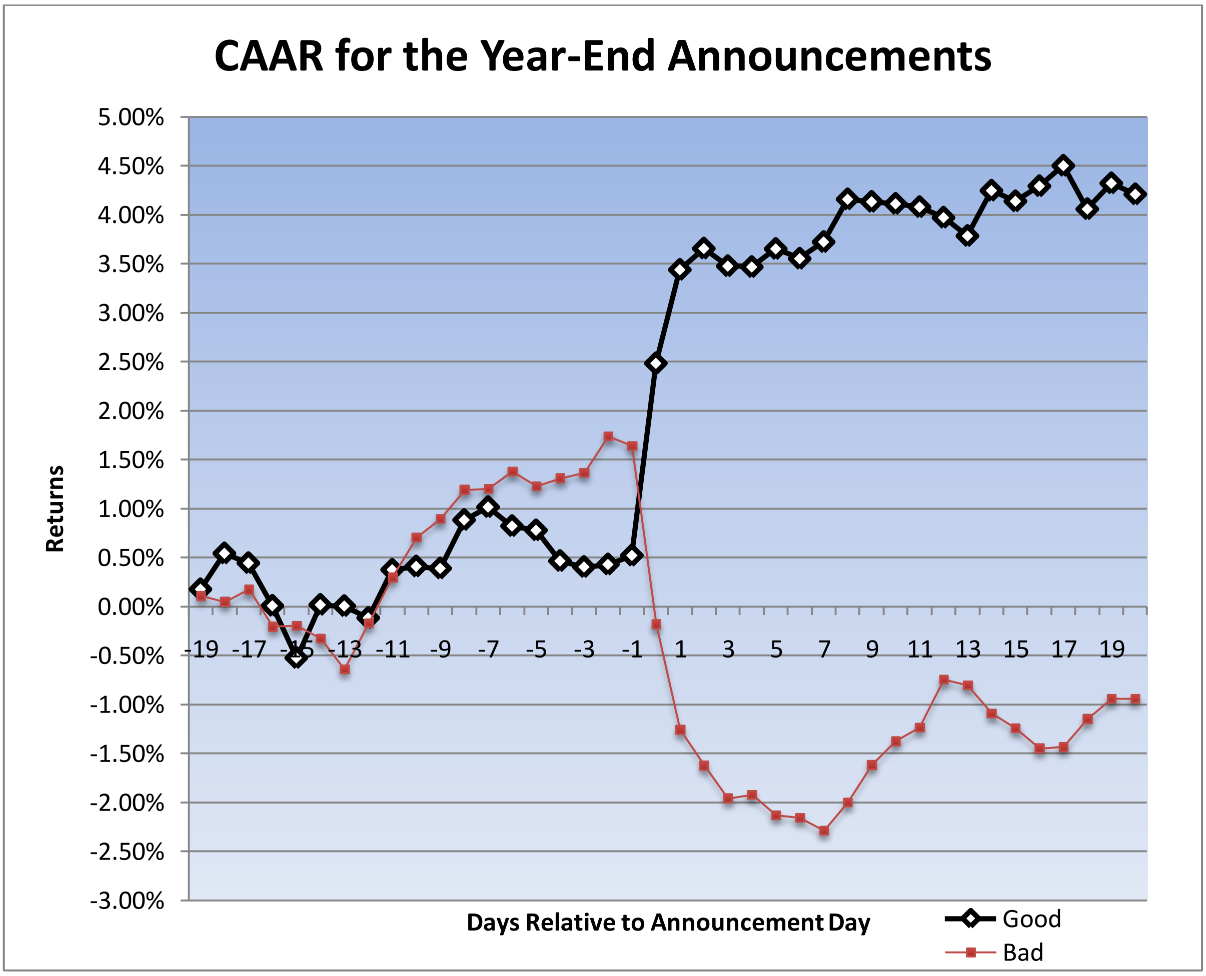
AL-Bogami et al. (1997) suggest that investors in the SSM do not react to quarterly statements; he finds that stock returns do not seem to respond to the announcement of the first three quarters but respond significantly to the fourth quarter announcement. To investigate whether investors would respond differently for quarterly announcements than for year-end announcements, we plot earnings announcements stock returns for quarters 1, 2 and 3 on the next graph and then in a separate graph we show stock returns around earnings announcements of end-of-year news.

Figure 2-6: Cumulative Average Abnormal Returns (CAAR) for First Three Quarters.



Notes: The figure shows the performance of Good and Bad news portfolios for the first three quarters (Q1, Q2 and Q3). Good news portfolio (561 observations) = companies achieving positive returns on the announcement days (0, +1). Bad news portfolios (779 observations) = companies achieving negative returns on the announcement days (0, +1). Both portfolio performances show anticipation of the news before the announcement day; however, Bad news firms seem to raise the anticipation of news. The first three quarters were analysed here to examine whether the market could react in a different way for the fourth quarter, when year-end financial reporting is required. By law, the earnings in the first three quarters in the SSM are announced shortly after the quarter's end, whereas the fourth quarter's announcement can be extended to 40 days after the end of the financial year.

Figure 2-7: Year-End Earnings Announcements CAAR



Notes : Figure 2-7 shows Cumulative average abnormal returns (CAAR) performances over 40 trading days around earning announcements (-19, +20) for the Year-end announcements. The figure shows CAAR for Good news portfolios (144 observations) and Bad news portfolios (208 observations). Good news exhibits upward price drift that starts in the pre-announcement period and continues for the 4 weeks following announcements. Bad news shows upward trend in its returns before announcements that is corrected once announcements have been made public and then forms volatile patterns. It seems bad news is harder to interpret by investors because usually it contains higher accruals and "earnings management" figures.

Our results for the fourth quarter announcements (Year End) show higher price reaction in the good news firms and lower price reaction in the bad news firms than quarterly results. Al-bogami et al. (1997) suggest that investors in the SSM respond more strongly to the year-end results than to those in the first three quarters. Our findings support theirresults for the good news category and contradict them for the bad news category. The year-end good news firms show higher and more persistent upward price drift while the bad news exhibit more volatile returns than returns of quarterly bad news.

The year-end result is more authentic than quarterly results, because it is mandatory for the year-end result to be audited by an accounting firm; this makes it more credible for the investors and creates a strong incentive for investors to be actively searching and anticipating news. In contrast, quarterly earnings announcements are reviewed but not audited by accounting firms, which make these announcements less effective. Moreover, good year-end results are usually followed by other good news announcements (i.e., stock splits and dividends) which explain the stronger price reaction for good news year-end results. Conversely, companies usually release quarterly bad news without "earnings management" whereas, year-end bad news is subject to a lot of earnings management practices which could reduce losses and hence the price reaction to these losses. The good news signal current and future firm's performance to investors in the markets.

Testing Abnormal Returns for Significance (test-statistics)

Based on the efficient market hypothesis, all tests of statistical significance are tests of the null hypothesis that abnormal returns are zero over any event window. However, rejecting this null hypothesis indicates the possibility of achieving predictable abnormal returns and outperforming the market.

To test whether there is any significant change in firms' value around the announcement day, we use aggregated returns, over firms and cumulative over time, since individual stock returns typically have higher variance, which could affect the power of the test. Usually, in event studies, a sample of firms which have made the same type of announcement are selected; each firm's announcement would naturally have been made on a different calendar day. The benefit of this approach is that it increases the likelihood that no other effect (information) beside the event under study is being picked up, as any unexpected information that is announced on a different day by a different firm will cancel out other information.

In event studies, the standard assumption is that returns are independent and normally distributed. Brown and Warner (1985) prove that departing from normality will be less pronounced for cross-sectional mean excess returns than for individual security excess returns. By the Central Limit Theorem and assuming that the announcement period returns for the sample firms are independently and identically distributed, consequently, average abnormal return is normally distributed with a zero mean.

Brown and Warner (1985), Corrado and Zivney (1992), Beneish and Gardner (1995) and many others have used the following test statistics, assuming abnormal returns are independent across securities. In this test statistic, the mean excess return is divided by its estimated standard deviation, which is estimated from the time-series of mean excess returns. The test statistic for any event day "t" is as follows:

$$\textbf{test} - \textbf{statistics} = \frac{\boldsymbol{AAR_t}}{\boldsymbol{s_{AAR_t}}^{\mathbf{2}}} \tag{7}$$

Where $\boldsymbol{AAR_t}$ is the average abnormal return at time t for N events and $\boldsymbol{s_{AAR_t}}$ is the estimated standard deviation the time-series of mean excess returns for a pre- or post-event estimation window. An estimate of the variance of this series (an equally-weighted portfolio variance), $\boldsymbol{s_{AAR_t}}$ is estimated over 21 trading days (-40, -20). The variance estimate is:

$$\boldsymbol{s_{AAR_t}} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{N}-\mathbf{1}}(\boldsymbol{AAR_t} - \overline{\boldsymbol{AAR_t}}\ )^{\mathbf{2}}} \quad \rightarrow \ \boldsymbol{s_{AAR_t}} \tag{8}$$

Where $\boldsymbol{AAR_t}$ is the average abnormal return at time t for N events and $\overline{\boldsymbol{AAR_t}}$ is the sample mean average abnormal return for an interval of K days from $t_1\ to\ t_2$. For an estimation period of 21 days, the standard deviation $\boldsymbol{s_{AAR_t}}$ is calculated as:

$$\boldsymbol{s_{AAR_t}} = \sqrt{\frac{\mathbf{1}}{\mathbf{20}}(\boldsymbol{AAR_t} - \overline{\boldsymbol{AAR_t}}\ )^{\mathbf{2}}} \tag{9}$$

The expected values of $\boldsymbol{AAR_t}$ and $\mathbf{CAAR}(\mathbf{t_{1,}t_{2}})$ are zero in the absence of an abnormal return. For the cross sectional averaged abnormal returns, we can form our hypothesis as follows:

H_o**: Expected average abnormal return is zero or** $\boldsymbol{AAR_t} = \mathbf{0}$ **.**
H_1**: Expected average abnormal return is different from zero or** $\boldsymbol{AAR_t} \neq \mathbf{0}$ **.**

Table 2-1: shows Average Abnormal Returns (AARs) with their t-tests and Average Performance Indices (APIs).

Days Relative to Announcements	A: Positive Return Portfolio AAR (%)	t-test	API	B: Negative Return Portfolio AAR (%)	t-test	API
-19	0.09%	-0.642	1.001	-0.07%	0.620	0.999
-10	-0.08%	-1.255	0.999	0.33%	3.311***	1.000
-5	0.07%	1.116	1.001	0.11%	1.320	1.001
-4	-0.07%	-0.124	1.000	-0.26%	-2.609***	0.998
-3	-0.04%	-1.855*	1.000	-0.34%	-2.093**	0.995
-2	-0.01%	-0.882	1.000	-0.24%	-1.522	0.993
-1	-0.18%	-2.043**	0.998	-0.05%	-0.247	0.992
0	1.83%	14.145***	1.016	-2.12%	-18.273***	0.971
1	-0.30%	-7.494***	1.013	-0.49%	-15.105***	0.966
2	-0.01%	-1.014	1.013	-0.33%	-3.870***	0.963
3	-0.18%	-0.005	1.011	-0.18%	-3.292***	0.961
4	-0.07%	-0.579	1.010	-0.22%	-2.285**	0.959
5	0.5%	0.947	1.011	-0.02%	-0.490	0.959
10	0.01%	0.350	1.014	0.27%	0.461	0.974
20	0.12%	0.204	1.036	0.18%	0.387	0.984

Notes: The table reports the average stock price response to the earnings announcements around the event day (0, +1). The T-test was conducted in the traditional way $t = \frac{AAR_t}{(var\,(AAR_t))^{1/2}}$. The table provides a standard test for whether the average abnormal return AARt is significantly different from zero. The positive return portfolios are reported in Panel A (708 firms) and negative return portfolios (959 firms) are reported in Panel B. Portfolios were formed on the basis of the earnings announcement returns during an extended period of two days (0, +1). We extend the announcement period to two days to capture any market reaction for announcements made after or toward the end of the trading day. Positive (negative) returns were formed into Good (Bad) portfolios. The average performance index (API) uses a buy-and-hold strategy to calculate returns. $API = \prod_{t=0}^{T}[1 + AR_{it}]$ Was calculated to show wealth formation changes around earnings announcements. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

It can be observed from panel A that AARs for the Good news portfolio are statistically significant around the announcement day and most of the AARs in the pre-announcement period are negative numbers. Our finding is that there is strong evidence to support rejection of the null hypothesis that there is no daily abnormal return for the -3, -1, 0 and 1 days in the event window (-19, +20). The higher significance levels are found at Day 0 and Day 1 where a 1% significance level is shown. This is expected, as these are considered the initial market reaction to the positive news. AARs for the four days following the event day are of the wrong or opposite sign. This may point to some underreactions to the event which is later being corrected by the fact that the AARs from day +5 until day +20 start to pick up again with positive returns.

For the negative news portfolio, AARs are significant for the following days: -10,-4,-3, 0,1,2,3 and 4. Most of these AARs are significant at the 1% level with negative t-tests. This suggests that the market overreacts to bad news, starting even before the announcement day. Negative AARs starts from day T-5 up to day T+5; after this, the market reverses its direction and corrects its movement to a level where it would regain almost all its losses. The average performance index API, which reflects the actual investors' wealth change, shows us clearly that an investor who invested initially in the specified portfolio on day t-20 could lose, on average, up to 5% if he was to liquidate his bad news investment 5 days after the announcement day. However the same investor would regain his losses and reach near break-even point 20 days after the announcement. In general, It appears that prices underreact (overreact) to positive (negative) news for the first week after the announcement, then prices reverse for both portfolios achieving higher positive returns which drift upward for the next two and a half weeks; that is, T+5 to t+20. Interestingly, the magnitude of the news impact on prices is phenomenal, suggesting that someone could constantly outperform the market by utilising the under-/over-reaction and price reversal patterns in the SSM.

Aggregating the mean abnormal returns over time produces cumulative average abnormal returns (CAAR) which allow us to test the persistence of the effect of the event during an event window $(T_2 - T_1)$ where $T_1 < t < T_2$. CAAR can also be tested by standard test statistics where the CAAR is divided by an estimate standard deviation of the time series of average abnormal returns aggregated over event window K. As K periods increase for the CAAR estimation window, the variance also increases.

$$\mathbf{t-statistics} = \frac{\boldsymbol{CAAR(t_{1,}t_2)}}{\sqrt{(\boldsymbol{K}+\mathbf{1})\boldsymbol{s_{AAR_t}}^2}} \qquad (10)$$

We need only to adjust the variance for the accumulation of time where K is the total number of event time (days) observations used to calculate CAAR. The focus of this model is to test whether or not the average return on the sample during the event window is statistically different from the average return during a non-event period, which is expected to be zero. It is crucial to make sure that events are not clustered or overlapping; if they are, they will hinder any inference from the test statistics.

We hypothesise that CAAR = 0. In other words, investors' wealth will not experience abnormal returns merely because of investment decision made conditionally on the event. We can state our hypothesis in the following format:

H_o **: If the expected cumulative average abnormal return is zero, CAAR=0.**
H_1 **: If the expected cumulative average abnormal return is other than zero, CAAR≠0.**

The assumption that the abnormal returns of each individual stock are uncorrelated in the cross section allows us to infer something about the cumulative average abnormal returns without regard for the covariance between the individual CARs. All CAARs are tested for being significantly different from zero.

Table 2-2 : Positive and Negative news portfolios' performances using CAAR.

Event Window (week number)	CAAR (in days)	Good news	Bad news
A:Pre-Announcement period			
Weeks (-4,-1)	**CAAR (-20,-2)**	**-0.65%****	**0.39%**
Weeks (-2,-1)	**CAAR(-11,-2)**	**-0.21%**	**0.40%***
Week (-1,-1)	**CAAR(-5,-1)**	**-0.66%*****	**-0.51%****
Day (-1,-1)	**CAAR(-1,-1)**	**-0.23%**	**-0.03%**
B: Announcement day(s)	**CAAR (-1,+1)**	**2.30%*****	**-2.96%*****
C: Post-announcement period			
Week (+1,+1)	**CAAR (+2+5)**	**0.14%**	**-0.96%*****
Week (+1,+2)	**CAAR (+2+11)**	**0.41%****	**-0.40%****
Week (+1,+4)	**CAAR (+2,+20)**	**2.11%*****	**1.24%*****
D: Whole period (40 days)	**CAAR (-19,+20)**	**3.77%*****	**-1.33%*****
No. of Firms		**708**	**959**

Note: this shows CAARs and their test statistics for Positive and Negative news. The table reports the positive and negative news performances over different time intervals to show how events are anticipated in the pre-event period and to examine the market reaction to news over different event windows. Event periods were divided into four panels. Panel A reports the pre-announcement cumulative returns, Panel B shows the announcement day(s) returns, Panel C the post-announcement period and Panel D the whole period (40 days). Good news firms increase on average by 3.77% over CAAR (-19, +20), while Bad news firms decrease on average by -1.33% over CAAR (-19, +20). The statistical significance of the average stock price response to the earnings announcements around different event windows is shown below:

$$\text{t} - \text{statistics} = \frac{\text{CAAR}\,(t_1,t_2)}{\sqrt{(K+1)s_{AAR\,t}{}^2}}.$$

* Estimate significant at the 10% level,** Estimate significant at the 5% level,*** Estimate significant at the 1% level.

For the cumulative average abnormal return CAARs, we construct different CAAR windows to capture any unusual activities around earnings announcements. Event windows were divided into four periods; pre-announcement, announcement day, post-announcement and the whole period; their results are presented in Panels A, B, C and D, respectively. Panel A shows an event window which starts 20 days before the announcement and continues until the announcement day. The pre-announcement period shows any anticipation or leakage of news. We can observe statically significant cumulative abnormal returns in the period (-5, -1) for portfolios of both Good and Bad news, indicating the importance of examining this period carefully and testing whether this period could explain returns in subsequent periods. For the good news portfolio, CAAR (-5,-1) interestingly shows a negative return (-0.66%) which is significant at the 1% level. For the Bad news portfolio, the pre-announcement CAAR (-11,-2) and CAAR (-5,-1) show statistical significance at both the 5% and 1% levels, which could indicate a leakage of information to the market because it shows the reaction starting from Day t = -10 with a negative sign of CAAR. A loss-averse investor is more highly motivated to anticipate bad news to avoid losses incurred by these announcements.

In panel B, which captures market reaction around the announcement day, the CAAR for the three days (-1 to +1) shows the good news reports price impact with a 2.3% increase which is significant at the 1% level. Conversely, the CAAR (-1, +1) for the Bad news portfolio reports the highest price impact, with an almost 3% decline which is significant at the 1% level. The strongest part of the price reaction takes place in the event window (-1, +1), which suggests that the SSM is somehow efficient to an extent in impounding the new information into the prices.

The post-announcement period in Panel C exhibits interesting patterns of returns, while the Good news portfolio clearly indicates predictability in its returns, which are characterised by initial underraction. The Bad news portfolio does not reverse its return sign until a week after the announcement is made.

In the Good news portfolio, CAAR (+2, +5) shows no statistical significance, which confirms our previous analysis of the AARs that the market underreacts to Good news for the first five days after the announcement is made and then the market starts to form a post-earnings announcement drift for certain days (+2, +11). This is also confirmed by the CAAR (+2, +20) which is significant at the 1% level. Around 74% of the cumulative returns in the post-announcement period originated in weeks 3 and 4, while weeks 1 and 2 contribute only 26% of the CAAR in this period. One explanation of this underreaction at first followed by a price drift pattern is that most investors in the SSM are individuals who lack the ability to interpret news properly. Moreover, there are no analysts following the market who could issue recommendations and forecasts; thus it takes investors more time to react to positive news later on, when interpretation and analysis can be found in newspapers, TV interviews and Internet forums. In the behavioural finance literature, this kind of behaviour is called “Investors’ Attention”. The Bad news portfolio shows continuous reaction in the first week after the announcement day and then a price reversal which almost compensates for all the losses incurred because of the announcement. Positive CAAR in the period (+2,+20), as compared to negative CAARs in (+2+5) and (+2+11) indicate a strong price correction of the initial negative returns in the first week after the earnings announcement. CAARs for the post- announcement periods (+2+11) and (+2,+20) report statistical significance at both the 5% and 1% levels, with negative returns for first period mainly because week 1 is negative, then followed by positive returns for the second period. This confirms our previous analysis of overreaction in the first week followed by price reversal in the weeks 2, 3 and 4 after the announcements being released.

Overall, CAAR (-19, +20) reports 3.77% abnormal returns for the positive news firms and (-1.33%) abnormal returns for the negative news firms that are all significant at the 1% level. The price impact of earning news is persistent in the good news firms while much of the price reaction in the bad news is reversed shortly after the earnings being released.

Does PEAD differ by industry?

We test for price reaction differences between various industries to examine whether industries have different PEAD properties. This industry-level analysis is addressed because we believe that there are certain characteristics associated with certain industries. For example, the banking and industrial sectors tend to have larger than average company size, higher government ownership and higher institutional ownership. In contrast, the service and agriculture sectors can be described as having low market capitalisation, higher volatility in stock prices and earnings, a lower level of disclosure and many loss firms. We use the stock exchange classification of industries where companies are grouped into eight sectors: banking, industrial, cement, service, electricity, agriculture, telecommunication and insurance. Some sectors have a higher number of earnings announcements due to the high number of firms (e.g., the banking and industry sectors which report 235 and 622 earnings announcements, respectively). We believe that reporting average and cumulative abnormal returns around earnings announcements by industry may reveal some explanation for the PEAD based on firm characteristics.

We expect companies of small size with fewer institutional investors to have a stronger price reaction, either in the form of a delayed price reaction or an initial overreaction followed by a price reversal. It is very well established in the literature that small companies which are less often followed by analysts tend to show a higher PEAD pattern in their returns around earnings announcements; hence, we expect the drift to vary by size as well. Our selection of industries can also serve as a proxy of size because large firms tend to be in the banking and industrial sectors. Tables (2-3) and (2-4) report the average abnormal returns (AAR) and cumulative average abnormal returns (CAAR) around earnings announcements by sector type.

Table 2-3: Average Abnormal returns (AARs) across Firms, Relative to the Announcement Day.

Industry	Banking		Industrial		Cement		Service		*Electricity*		*Agriculture*		*Telecommunication*		*Insurance*	
Days	**Good**	**Bad**	**Good**	**Bad**	**Good**	**Bad**	**Good**	**Bad**	***Good***	***Bad***	***Good***	***Bad***	***Good***	***Bad***	***Good***	***Bad***
-5	**0.001**	**0.000**	**0.000**	**0.002**	**0.000**	**0.000**	**-0.002**	**0.000**	**-0.015**	**-0.002**	**0.000**	**0.005**	**0.004**	0.**005**	**-0.004**	**0.006**
	(0.79)	(-0.41)	(-0.26)	(1.25)	(-0.15)	(0.05)	(-0.97)	(-0.23)	(-1.60)	(-0.48)	(-0.07)	(1.35)	(0.60)	(1.25)	(-0.53)	(1.93)
-4	**0.001**	**0.000**	**-0.001**	**0.000**	**-0.001**	**-0.001**	**-0.006**	**-0.001**	**0.003**	**0.000**	**-0.012**	**-0.007**	**0.003**	**-0.001**	**0.003**	**0.004**
	(0.89)	(0.09)	(-0.47)	(-0.03)	(-0.46)	(-0.83)	(-1.97)	(-0.57)	(0.37)	(-0.09)	(-1.91)	(-1.76)	(0.53)	(-0.45)	(0.48)	(0.83)
-3	**-0.004**	**-0.001**	**-0.003**	**-0.002**	**-0.001**	**0.000**	**-0.006**	**0.001**	**-0.021**	**-0.002**	**-0.003**	**0.000**	**-0.004**	**0.009**	**-0.002**	**0.012**
	(-2.45)	(-0.81)	(-1.38)	(-1.45)	(-0.87)	(-0.29)	(-1.99)	(0.27)	(-1.69)	(-0.52)	(-0.59)	(-0.08)	(-0.84)	(2.49)	(-0.42)	(0.63)
-2	**0.001**	**0.001**	**-0.003**	**-0.002**	**-0.002**	**-0.001**	**-0.009**	**0.001**	**-0.003**	**0.005**	**-0.003**	**-0.001**	**0.007**	**0.007**	**-0.002**	**0.031**
	(0.52)	(0.51)	(-1.350	(-1.19)	(-1.09)	(-0.82)	(-2.62)	(0.41)	(-0.25)	(0.62)	(-0.47)	(-0.14)	(0.75)	(2.07)	(-0.29)	(2.39)
-1	**-0.002**	**0.002**	**-0.001**	**0.000**	**0.000**	**0.000**	**-0.003**	**-0.003**	**-0.001**	**0.004**	**-0.007**	**-0.001**	**0.000**	**0.006**	**-0.007**	**0.010**
	(-1.16)	(-0.85)	(-0.30)	(-0.11)	(0.14)	(-0.13)	(-1.23)	(-1.39)	(-0.18)	(0.57)	(-1.02)	(-0.16)	(0.03)	(1.52)	(-0.86)	(1.36)
0	**0.011**	**-0.011**	**0.019**	**-0.018**	**0.012**	**-0.009**	**0.027**	**-0.018**	**0.015**	**-0.011**	**0.027**	**-0.023**	**0.021**	**-0.010**	**0.015**	**-0.02**
	(6.62)	(-9.71)	(9.04)	(-12.7)	(6.76)	(-6.76)	(8.56)	(-9.99)	(2.64)	(-1.50)	(4.94)	(-8.18)	(3.51)	(-2.62)	(7.72)	(-1.86)
1	**0.008**	**-0.009**	**0.013**	**-0.017**	**0.006**	**-0.008**	**0.019**	**-0.018**	**0.011**	**-0.010**	**0.020**	**-0.024**	**0.003**	**-0.012**	**0.008**	**-0.005**
	(4.71)	(-8.32)	(6.32)	(-12.3)	(3.49)	(-6.77)	(5.46)	(-10.1)	(1.24)	(-1.41)	(3.81)	(-7.93)	(0.49)	(-3.10)	(0.91)	(-0.66)
2	**-0.001**	**-0.002**	**0.001**	**-0.004**	**-0.001**	**-0.001**	**0.005**	**-0.006**	**-0.004**	**-0.008**	**0.011**	**-0.007**	**-0.012**	**0.010**	**0.003**	**-0.001**
	(-0.58)	(-1.29)	(0.56)	(-2.64)	(-0.71)	(-0.49)	(1.45)	(-2.75)	(-0.58)	(-1.07)	(1.58)	(-1.64)	(-2.42)	(1.69)	(0.42)	(-0.13)
3	**0.003**	**0.001**	**0.004**	**-0.005**	**-0.002**	**-0.004**	**0.001**	**-0.002**	**-0.010**	**-0.006**	**-0.007**	**-0.007**	**-0.003**	**0.004**	**0.005**	**-0.01**
	(1.61)	(0.45)	(1.74)	(-3.12)	(-1.07)	(-2.45)	(0.29)	(-0.98)	(-1.23)	(-1.42)	(-1.17)	(-2.03)	(-1.30)	(0.70)	(0.76)	(-1.28)
4	**-0.001**	**-0.001**	**-0.001**	**-0.002**	**-0.001**	**-0.003**	**0.000**	**0.001**	**0.007**	**-0.003**	**0.000**	**-0.008**	**-0.002**	**0.000**	**0.002**	**-0.004**
	(-0.36)	(-0.56)	(-0.76)	(-1.26)	(-0.40)	(-2.00)	(0.13)	(0.25)	(1.22)	(-0.78)	(0.00)	(-1.96)	(-0.61)	(0.03)	(0.59)	(-0.97)
5	**0.000**	**-0.001**	**-0.001**	**0.000**	**0.001**	**0.002**	**0.002**	**0.000**	**0.002**	**0.001**	**-0.002**	**0.001**	**0.009**	**-0.004**	**0.003**	**0.007**
	(0.19)	(-0.42)	(-0.70)	(-0.18)	(0.37)	(1.10)	(0.52)	(0.22)	(0.25)	(0.29)	(-0.36)	(0.19)	(1.81)	(-1.53)	(2.89)	(0.66)

This table reports the average abnormal returns AARt across industries for different days around earnings announcements. A T-test was conducted in the traditional way.

$\mathbf{t} = \frac{\mathbf{AAR_t}}{(\mathbf{var}(\mathbf{AAR_t}))^{1/2}}$. AARt were broken down by sector (Industrial, Cement, Service, Electricity, Agriculture, Telecommunication and Insurance). Positive (negative) Returns were formed into Good (Bad) portfolios for each industry .t-statistics are reported in parentheses.

Table 2-4: Cumulative Average Abnormal Returns (CAAR) by Sector.

Event window	Banking (n=235)		Industrial (n=622)		Cement (n=216)		Service (n=397)		*Electricity* (n=31)		*Agriculture* (n=164)		*Telecom* (n=38)		*Insurance* (n=21)	
Panel A: CAAR	G	B	G	B	G	B	G	B	G	B	G	B	G	B	G	B
(-20,-1)	0.000	0.001	-0.004	0.008 **	-0.018 ***	-0.010 ***	0.019 ***	0.024 ***	-0.036 ***	0.015 ***	0.005	0.042 ***	0.008	0.013 ***	-0.011	0.052 ***
(-10,-1)	0.002 ***	-0.001	-0.004	0.010 ***	-0.006 ***	-0.004 ***	0.014 ***	0.006 **	-0.029 ***	-0.002	-0.015 ***	0.032 ***	-0.020 ***	0.015 ***	-0.019 ***	0.057 ***
(-5,-1)	-0.002 *	0.001	-0.007 ***	-0.003	-0.003 **	-0.003 *	0.007 **	-0.007 ***	-0.037 ***	0.004 *	-0.025 ***	-0.003	0.009 **	0.025 ***	-0.011 **	0.064 ***
(0,+1)	0.001 ***	-0.020 ***	0.032 ***	-0.036 ***	0.018 ***	-0.016 ***	0.046 ***	-0.036 ***	0.026 ***	-0.021 ***	0.047 ***	-0.047 ***	0.025 ***	-0.022 ***	0.024 ***	-0.025 ***
(+2+5)	0.001	-0.003 **	0.002	-0.011 ***	-0.003 *	-0.006 ***	-0.021 ***	0.005 *	-0.005	-0.016 ***	0.002	-0.022 ***	-0.008 **	0.010 ***	0.013 ***	-0.007 *
(+2+10)	-0.002 ***	0.000	0.008 ***	-0.008 ***	-0.009	-0.005 ***	-0.027 ***	-0.001	-0.008 *	-0.022 ***	0.003	0.000	-0.035 ***	0.000	0.057 ***	-0.003
(+2,+20)	-0.005 ***	-0.006 ***	0.030 ***	0.012 ***	0.002 **	-0.003 *	-0.026 ***	-0.003	0.061 ***	-0.054 ***	0.036 ***	0.033 ***	-0.030 ***	-0.001	0.071 ***	0.017 **
Panel B: ***BHAR (-20,+20)***	1.037	0.976	1.059	0.984	1.001	0.971	1.038	0.986	1.05	0.941	1.09	1.02	1.002	0.989	1.086	1.042

Table 2-4 shows cumulative average abnormal returns (CAAR) and buy-and-hold-abnormal returns (BHAR) broken down by sectors. Positive (negative) returns are reported for each industry in two portfolios Good and Bad. The letter G represents the Good news portfolios while B represents the Bad news portfolios. The table reports the positive and negative news performances over different time intervals to show how events are anticipated in the pre-event period and to examine the market reaction to news from different industries. *Significant at the 10% level, ** Significant at the 5% level and *** Significant at the 1% level.

The service and agriculture sectors report the highest earnings announcement returns (EAR) on days (0,+1), confirming our expectation that small companies will show a strong price reaction due to the higher volatility and risk associated with this type of company. Table (2-3) shows all AARs to be significant at the 1% level for all industries except electricity, which contains only one company and has fewer earnings announcements. Moreover, blue chip sectors (i.e., banking, industry, cement) show lower AAR in the days preceding the announcement day, indicating that the level of information leakage or price anticipation in general is lower in these sectors than in sectors where the companies are small and less often followed by investors and the media.

Table (2-4) lists all industries' CAARs in Panel A, while Panel B shows how returns around the earnings announcement impact investors' wealth formation, when using the BHAR method. In Panel A, CAARs for different industries vary and the upward price drifts seem to be more persistent for industrial, agricultural and insurance firms in the Good news portfolios. In the Bad news portfolios, the banking, industrial, cement and electricity sectors show persistent downward price drift which is consistent with the literature, whereas the service, agriculture, telecommunication and insurance sectors show contradicting results of negative initial reaction to bad news followed by positive reaction in the weeks following earnings announcements.

Panel B reports returns on both Good and Bad news portfolios of 1 S.R. invested equally in all industries using buy-and-hold-abnormal returns method for the period between – 20 and +20. Agriculture and insurance sectors report the highest returns on their Good news portfolios at 9% and 8%. Electricity and banking report the highest losses for the same period of investment (-20 to +20). Interestingly, the insurance and agriculture sectors report positive returns for the bad news portfolios at 4.2% and 2%, respectively. It should be mentioned that, due to their relatively small size, these sectors are always the target of very speculative waves which make their prices deviate very widely from their fundamental values.

Robustness test

It is natural to assume that the magnitude of the drift is closely related to unexpected earnings or the earning surprise (i.e., the difference between the actual earnings and the market's expectations of earnings). We have discussed previously the many possible proxies to have been used for the earnings surprise, which can generally be categorised into time-series models, analyst forecast models and earnings announcement returns (EARs).

In this study, we assume that that market is directionally efficient, meaning that if a company announces earnings which are higher (lower) than expected, the stock should react positively (negatively) on the announcement day. We use EAR as our measure of surprise and group all companies which produce positive (negative) EARs into two portfolios, namely, Good (Bad) news portfolios. Many papers in the literature use consensus forecasts or the average of analysts' forecasts as a measure of the earnings surprise. The SSM lacks publicly available analysts' forecast; hence, for a robustness check, we use the time-series property of quarterly earnings as another measure of earnings surprise and to compare with our EAR surprise measure. To model for unexpected earnings, we apply a naive time-series model which predicts that this quarter's earnings will be the same as they were in the same quarter of last year's earnings, i.e. earnings follow a random walk with a drift. This model is called the seasonal random walk model**:**

$$\boldsymbol{EPS_{q,i} = \alpha + EPS_{q,i-4} + \delta_i} \qquad (11)$$

where EPS_q is the earnings per share in the current quarter and EPS_{q-4} is the earnings per share of the same quarter in the previous year and $\boldsymbol{\delta_i}$ is the drift. If actual earnings are higher than predicted by the model, then we consider that their earnings quarter in the Good news portfolio and Bad news portfolio is allocated for firms whose earnings are below the level of predicted earnings.

Table 2-5 : Average Abnormal returns (AARs) and Average Performance Index APIs.

	Good news Portfolios			Bad news Portfolios		
Days Relative to Announcements	AAR (%)	t-test	API	AAR (%)	t-test	API
-19	**0.016%**	0.178	**1.0002**	**-.11%**	-1.42	**1.0048**
-10	**0.13%**	1.41	**1.0007**	**0.05%**	0.63	**1.0007**
-5	**0.09%**	1.013	**1.005**	**0.02%**	0.20	**1.0070**
-4	**-0.15%**	1.645*	**1.003**	**0.10%**	1.10	**1.005**
-3	**-0.04%**	0.456	**1.003**	**-0.158%**	-1.71*	**1.001**
-2	**-0.03%**	0.331	**1.002**	**-0.002%**	-0.02	**0.999**
-1	**-0.16%**	1.625*	**1.0023**	**0.143%**	1.31	**0.996**
0	**-0.27%**	2.602***	**1.0031**	**0.072%**	-5.43***	**0.99**
1	**-0.53%**	-5.233***	**1.00045**	**-0.51%**	-4.77***	**0.984**
2	**-0.16%**	-1.640*	**0.9993**	**-0.19%**	-1.69**	**0.982**
3	**-0.19%**	-1.96**	**0.9968**	**-0.02%**	-0.23	**0.981**
4	**-0.13%**	-1.475	**0.9945**	**-0.10%**	-1.17	**0.980**
5	**-0.08%**	-0.916	**0.9942**	**-0.03%**	-0.31	**0.981**
10	**0.07%**	0.855	**0.999**	**0.18%**	1.06	**0.985**
20	**0.12%**	1.327	**1.009**	**0.35%**	3.1***	**1.005**

Notes: The table reports the average stock price response to the earnings announcements around the event day (0, +1). T-test was conducted in the traditional way $t = \frac{AAR_t}{(var\,(AAR_t))^{1/2}}$. The table provides a standard test for whether the average abnormal return AARt is significantly different from zero. The Good news portfolio is reported in Panel A (985 observations) and the negative returns portfolio (330 observations) is reported in Panel B. Portfolios were formed on the basis of expected earnings according to the following rule: If ESP>E(EPS)= Good news portfolio; and If EPS<E(EPS)= Bad news portfolio. The average performance index (API) uses buy-and-hold strategy to calculate returns. $API_t = \prod_{t=1}^{40}[1 + AR_{it}]$ was calculated to show wealth formation changes around earnings announcements. *Significant at the 10% level,** Significant at the 5% level and*** Significant at the 1% level.

When using the times-series forecast model (Seasonal Random Walk Model with Drift) to measure the earning surprise, we get similar results to the EAR measure. Underreaction to higher actual earnings than expected is observed in the Good news firms, resulting in an upward price drift for the following weeks. The Bad news firms show overreaction to earnings news in the first week, followed by a price reversal which also continues to drift upward in the following weeks (+2,+4), a pattern similar to the one found using the EAR surprise measure. However, the magnitude of the drift is lower for the earnings which are forecasted using the random walk model. The model seemed to underestimate the expected earnings, in particular when average EPS for the whole market rose more than four-fold during the time of the study. The two portfolios react differently but eventually they produce similar returns for the event window (-19 to +20).

Figure 2-8: Buy and Hold Abnormal Returns (BHAR) for the Earnings Surprise using a Time-Series Earnings Forecast.

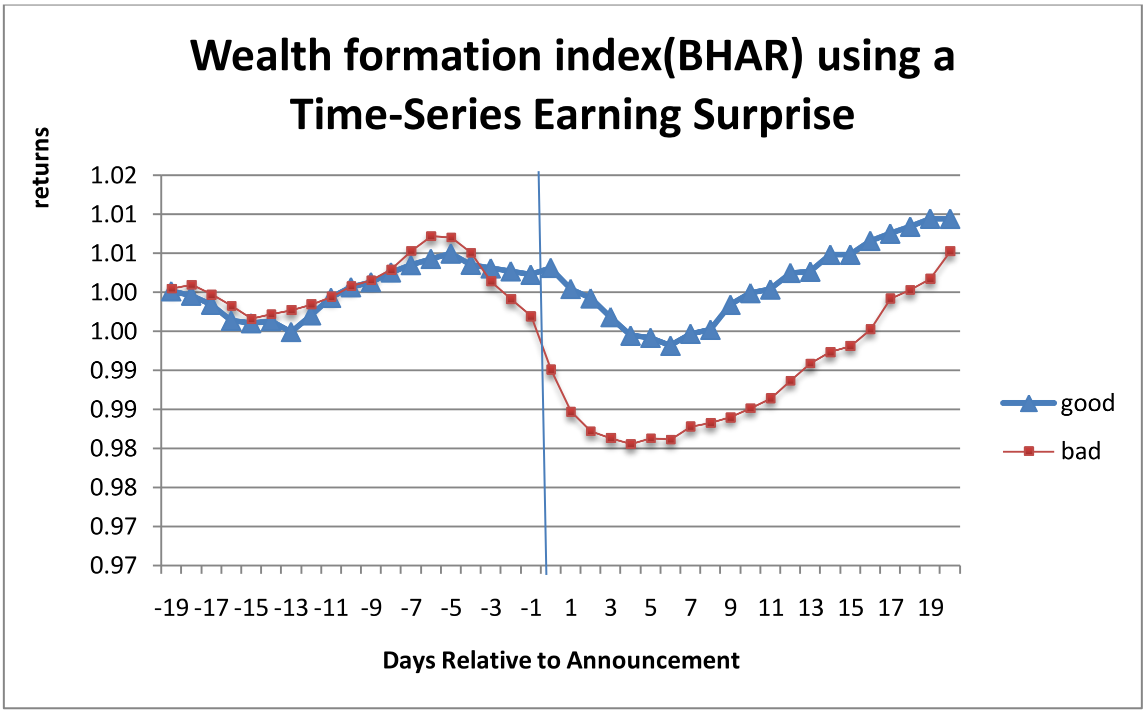


Figure (2-8) shows BHAR performances over 40 trading days around earnings announcements (-19, +20). The Good news portfolio (985 observations) = companies achieving higher earnings than expected by the time-series forecast model. The Bad news portfolio (330 observation) = companies achieving lower earnings than expected by the time-series forecast model. Portfolio performance is calculated using :$\mathrm{BHAR_t} = \frac{1}{N}\sum_{i=1}^{n}(\prod_{t=0}^{T}[1 + R_{i,t}] \; - \prod_{t=0}^{T}[1 + MR_t])$. One Riyal invested in either portfolio 20 days before the earnings announcement will eventually produce similar results at the end of the period (20 days after the announcement). While Good news firms exhibit clear underreaction to the news, Bad news firms show overreaction to the news, followed by an upward price drift which starts in the second week after the announcement and continues through weeks 3 and 4.

2.7 Summary

In this paper, we show the existence of PEAD in the SSM, using announcement returns as proxy for the earnings surprise. Disregarding transaction costs, it is possible in the SSM to outperform the market constantly by adapting the market reaction patterns and through the use of PEAD. The results pose a challenge to the efficiency of the SSM. The SSM seems to underreact to positive news for the first five days and then a positive reaction tends to be stronger for the following weeks, indicating the existence of a post-earnings announcement drift. In contrast, the SSM overreacts to negative news in the first five days and then reverses its direction and reports an upward post-earnings announcement drift. Our results suggest that the market is slow in adjusting to new information when there is good news and reacts irrationally to bad news. The results are robust using different earnings surprises EAR and time-series earning expectation models. The absence of analysts' forecasts and an individually dominated market are the main explanation of this underreaction to positive news and overreaction to negative news. It is confirmed by higher PEAD in sectors containing smaller firms and where there is lower government and institutional ownership.

Transaction costs have been highlighted by many researchers as a limitation of the arbitrage strategy of riding the PEAD wave (e.g., Bernard and Thomas, 1989, 1990; Bhushan 1994). However, our results are in line with the more recent study by Ng et al (2008), who explain the existence PEAD by means of the transaction cost. They find that transaction costs constrain informed trades which are necessary to incorporate earnings information into price. They suggest that there is a weaker returns response at the time of the announcement and a higher subsequent return drift for firms with higher transacting costs. We confirm that this constraint on behaviour owing to transaction cost exists in the SSM, in particular for Good news small firms.

Our results confirm the uncertain information hypothesis suggested by Brown et al (1988), who postulate that rational, risk-averse investors may underreact to positive news and overreact to negative news. We document a return reversal pattern for the Bad news firms starting one week after the initial announcement is made. We find an upward post-earnings announcement drift for both positive and negative news firms, which are confirmed through statistically significant CARs around earnings announcements and in the four weeks following the event.

Interpretation of the different reactions for Good and Bad news firms, where a Good news portfolio shows an initial underreaction to positive news and a Bad news portfolio shows strong overreaction, can easily be linked to the literature. This kind of behaviour has been well documented and explained in many ways. Lim and Kong (2004) have explained this behavioural pattern in different ways. First they trace it to the Prospect Theory of Kahneman & Tversky (1979) and to the Conservatism Theory (see Edwards, 1968), which have frequently been referred to in the field of behavioural finance. Both these theories suggest that investors are risk and loss averse. This attitude makes investors value gains and losses differently, leading to quick and strong reactions to any potential losses; whereas they are more careful in taking decisions related to optional gains due to the risk involved. Second, the conservatism theory provides another element which is in harmony with the former theory: this postulates that investors are slow to update their beliefs in the face of new information. The underreaction to good news is more consistent with the conservatism theory. Within this context, investors would sell any Bad news stock early and buy any Good news stock late, creating the underreaction to good news and overreaction to bad news, a behaviour which is observed in the SSM and supported by prospect and conservatism theories. This explanation is modelled in Barberis et al. (1998) in the underreaction and overreaction hypothesis, under which conservative investors underreact to good news. Their model of investors' sentiments is motivated by varied psychological evidence and displays the heuristic of representativeness. When investors face an adverse event (here, bad news), they will overreact by selling the asset rapidly and even at a very low price, which suggests that investors overreact to bad news announcements and underreact to positive news announcements.

In conclusion, the SSM shows predictable returns around earnings announcements. It is possible in the SSM to outperform the market constantly by adapting the market reaction patterns using PEAD investment strategy. Disregarding transaction cost, for a holding period of (-19, +20) an investor would achieve 3.77% abnormal market-adjusted returns for positive news firms, which is 15% annually, and (-1.33%) abnormal market-adjusted returns for the negative news firms, which is (-5.32%) annually.

chapter 3 : **Information Asymmetry, Trading Activity and Investor Behaviour around Quarterly Earnings Announcements**

3.1 Introduction

This chapter examines stock returns and trading activities around earnings announcements for listed companies in the Saudi stock market (SSM). Specifically, we examine the levels of stock liquidity, trading activity, volatility, bid-ask spread, asymmetric information and investor trading behaviour around earnings announcements for all firms in the market for the period 2002-2009. We also examine trading behaviour among small and large investors in the market through constructing order imbalance measures. The magnitude of the cumulative abnormal returns and liquidity around earnings announcement are investigated using regression analysis.

Our study is motivated by many factors: first, we investigate the Saudi stock market to provide out-of-sample evidence regarding the on-going debate about Post-Earnings Announcements Drift (PEAD) and the way in which it can be explained, because the nature of this anomaly is not well understood. Second, the SSM is dominated by individual investors, 90% of its total trading, which provides an ideal setting for studying how investors react to informational events. Third, the SSM has unique institutional characteristics which make it suitable to test for these characteristics on stock returns and trading activities. For instance, it allows neither short selling nor derivatives trading. Moreover few analysts follow the market and reports are scarce and not regularly published, which makes it hard to anticipate earnings and news in the market. Finally, the SSM is an order-driven market; thus, analysing traders' placement strategies around earnings announcements provides an insight which is applicable to other order-driven markets.

All these factors motivate us to study how information content affects trading behaviour around earnings announcements. It is of great value to both academics and practitioners to study the effect of these unique aspects of the SSM on stock trading and return behaviour.

Following previous studies (see, among others, Bradshaw and Sloan, 2002; Chiang and Wang, 2007 and Lakhal, 2008), we measure the information content of quarterly earnings announcements, using abnormal returns, abnormal trading volume, abnormal volatility and abnormal trading activity around the dates of quarterly earnings announcements. We also estimate and observe the change in bid-ask spread and investors' trading behaviour around the quarterly releases of earnings.

3.2 Literature review

For over 40 years, researchers have consistently documented the phenomena in stock markets where stock prices tend to drift in the direction of the earnings surprise following earnings announcements; this phenomenon is called Post-Earnings Announcements Drift (PEAD). PEAD has been found in the SSM (see Chapter 2, above). In this chapter, we explore the trading activities around earnings announcements with the aim of examining how investors and the market in aggregate level behave around earnings announcements. This behaviour is reflected in trading volume, volatility, bid/ask spread, abnormal returns, order imbalance and other factors. A vast body of research has documented the tendency of stock price returns to show a continuous drift after the release of earnings announcement (see, for example, Ball and Brown, 1968; Bernard and Thomas, 1989, 1990; Fama, 1998; and Garfinkel and Sokobin, 2006). The systematic increase in price returns around earnings announcements can be observed in periods either before or after earnings announcements (see, for example, Beaver, 1968; Garfinkel and Sokobin, 2006; Cohen et al., 2007; and Frazzini and Lamont, 2007). Early event studies even document that the information content of earnings announcement not only affects returns, but other stock characteristics of trading, such as higher abnormal trading volume surrounding announcements (Beaver, 1968; Kiger, 1972; and Morse, 1981).

Many researchers have confirmed the robustness of PEAD using different techniques and different data (e.g., Bernard and Thomas, 1998, 1990; Ball, 1992; Ball and Bartov, 1996; and Chordia and Shivakumar, 2005). Findings of research on the capital markets suggest that earnings announcements contain information which is believed to alter investors' opinion about the values of stocks, through the process of impounding information into prices.

PEAD is typically explained by the magnitude of the earnings surprises , the unexpected component of the earnings. The higher the surprise (the difference between anticipated earnings and actual earnings), the higher the drift found. Early studies measure the earnings surprise using the seasonal random walk model, while later studies focus on analyst-based earnings surprise, since it is deemed a better substitute proxy for market expectation. More puzzling is that recent studies find that the drift which is associated with analyst-based surprise is even larger than that associated with the seasonal random walk surprise (Livnat and Mendenhall, 2006; and Doyle et al., 2006).

In attempting to explain the drift, many studies have distinguished between individual trading and institutional trading and suggest that institutional trading is more sophisticated than individual trading. On this basis, individual trading may be more closely related than institutional trading is to market inefficiencies in general and PEAD in particular (see, for instance, De Franco et al, 2007). Frazzini and Lamont (2007) indicate that the earnings announcement premium is driven by buying from uninformed investors and relate the price pattern to a temporary increase in trading volume around the announcement release date.

Berkman et al. (2009) and Trueman et al. (2003) find that the prices of certain stocks tend to increase only temporarily before the announcement, but do the opposite after the announcement. They also suggest that retail investors are a likely source of the temporary surge in buying and stock prices.

However, recent research provides some evidence that even relatively more sophisticated investors have difficulty in processing financial information which could delay the price reaction to news (e.g., Bushee 2001; Ke and Petroni 2004). While we do not intend to review all the literature on PEAD drift, we intend to show that this phenomenon is poorly understood; as Livnat and Mendenhall (2006) argue, “if researchers do not understand how the magnitude of the drift depends on the specification of earnings surprise, they stand little chance of understanding the nature of the anomaly.”

Research on the capital market has established that when earnings announcements are released, a substantial increase is observed, not only in return volatility and trading volumes as found in earlier studies, but even in the concentration of trading activity**.** Analysing trading activities around earnings announcements should provide us with a clearer picture of the way in which different aspects of the market respond in general, not only the stock returns. The persistent increase of stock returns can be induced by factors other than the earnings surprise. Liquidity, level of information asymmetry, trading volume and order imbalance can all have major effects on price drift.

Trading volume and volatility

In general, stock returns and trading volume tend to be positively correlated. Stocks tend to rise on high volume and decline on low volume.[21] Most of the theories explaining the volume-return relationship emphasise the dispersion of beliefs among investors. In Miller's theory (1977), in an environment of short selling constraint and dispersion of opinion, prices will be biased upward because only the optimistic traders will buy the stock and the pessimistic ones are kept out of the market. Earnings announcements provide an ideal environment to test the volume effect on returns, because they are frequent, exogenous, generate substantial volume and have almost fixed intervals (Frazzini and Lamont, 2007).

Past empirical work shows that stock returns around earnings announcements are usually associated with an increase in trading volume and volatility. Trading volume usually increases in response to earnings announcements, due to the reduction of information uncertainty among investors. In addition, as some researchers suggest, investors have different levels of ability to process information and may interpret earnings news differently, hence respond differently (Karpoff, 1986; Demski and Feltham, 1994; and Kim and Verrecchia, 1994, 1997).

Other researchers have explained the relationship between volume and returns in the context of noise traders. Higher trading volume indicates the presence of irrational or noise traders, who push up prices (Baker and Stein, 2004). Other similar explanations have focused on the "attention-grabbing hypothesis", under which individual traders have limited attention and rarely use short selling. If a stock attracts their attention, they are likely to buy it, regardless of the nature of the news good or bad. This hypothesis predicts that stocks in the news have both high volume and high net buying by individuals (Lee, 1992; Gervais et al. , 2001; and Barber and Odean, 2008).

Kandel and Pearson (1995) demonstrate that volume rises on earnings announcements for all types of news, whether good, bad or without significance. Frazzini and Lamont (2007) find that, around earnings announcements, stocks with high volume have subsequently both high premiums and high imputed buying by individual investors. They invoke the "attention-grabbing" hypothesis, causing stocks in the news to be usually associated with higher trading volume and net buying by individuals. They also show that the anomaly cannot be arbitraged

[21] See, among others, Karpoff's review of the subject (1987)

away due to the costly trading volume needed and the highly idiosyncratic volatility around earnings announcements, which deters traders from diversifying.

If new information is believed to either increase or decrease uncertainty in the market, then we can safely assume that volatility will also change around earnings announcements. Many research papers have documented the increase in return volatility and trading volume around earnings announcements compared with non-announcement periods (Beaver, 1968; Bamber, 1986). However, the relationship property between volatility in the post-announcement period and the content or precision of the earnings announcement cannot be exactly defined. Kim and Verrecchia (1991), for example, suggest that the private information-gathering characteristics in an economy play an important role into determining the volatility around earnings announcements.

Acker (2002) links volatility with the content of the earnings announcement and documents a time asymmetry in volatility according to the information processing reaction. If an announcement is easy to interpret or contains good news, an increase in volatility is usually observed on the day of the announcement, while bad news or difficult-to-interpret news has a delayed price and volatility reaction until the following day.

Liquidity and information asymmetry

If various groups of investors differ in their ability to interpret information or if they do not have the same access to information, then one would assume that earnings announcements may be of different degrees of usefulness to them and that the information content of announcements differs from one investor to another. This notion has been established for some time; for example, Hakansson (1977) shows that if investors differ in their information acquisition abilities or resources, different patterns of information acquisition and processing emerge. In making investment decisions, investors with low information processing skills or resources (small investors) tend to rely on public information, whereas more sophisticated investors with better information processing skills or resources rely on pre-disclosure information. Many researchers suggest that since some investors are asymmetrically informed before the anticipated announcement, they may respond to it differently (Kim and Verrecchia, 1991; Demski and Feltham, 1994). The Behavioural school argue that irrationality, in the form of one or more cognitive processing biases, can be the major source for these financial anomalies. It is also argued that individual investors behave less rationally than institutional investors (Daniel et al., 1998).

The information content of public disclosures can be observed through stock returns and changes in trading volume around the date of announcement, among many other variables. Announcements which cause more change in abnormal returns and trading volume are believed to contain more information than announcements whose effects are milder (Bamber and Cheon, 1995). While abnormal returns are closely linked to the information content of the announcement, trading volume is normally associated with the level of information asymmetry in the market such that it captures the willingness of investors to hold or sell the stock, according to beliefs.

Akerlof (1970) provides a framework in which corporate disclosures aim to reduce the informational gap between investors and the effect of information asymmetry by which informed investors gain when trading with uninformed ones. Glosten and Milgrom (1985) introduce the notion that a higher presence of informed traders on the market will widen the bid-ask spread to compensate the market maker for additional adverse selection cost. Diamond and Verrecchia (1991) suggest that these adverse selection costs may reduce liquidity and affect the cost of capital to firms. It is often argued that the level of information asymmetry in the market is reduced after the announcement (Lee et al., 1993). Handa et al. (2003) argue that spread serves also as a proxy of information asymmetry in an order-driven market, because it is a function of adverse selection and also of difference in valuation.

Furthermore, the literature on market microstructure has shown the positive impact of earnings announcements on stock market liquidity (Diamond and Verrecchia, 1991; Coller and Yohn, 1997; and Bushee et al., 2003). Demsetz (1968) proposes the bid-ask spread as a measure of liquidity where the spread reflects the adverse selection costs entailed by asymmetric information among investors. Higher information asymmetry would increase the adverse selection cost and this is reflected in a wider bid-ask spread. The market microstructure literature usually decomposes the spread into three components, namely, order processing, inventory and adverse selection components. More recent papers have shown that adverse selection or information asymmetry component represents a significant portion of the spread and that increased adverse selection cost is the dominant factor affecting bid-ask spread around earnings announcements. Kim and Verrecchia (1994) argue that, due to the different levels of ability of market participants to process information, information asymmetry should not only increase on the day before the announcement, but should also stay at a high level in the post-announcement period, since some investors are better able to interpret news than other. Some participants, for example, process the public information (earnings announcements) into private information about a firm's performance and make better informed judgements.

Affleck-Graves et al. (2002) find that, on the day of the announcement, the adverse selection component of the spread increases. They also find this component increases even before the announcement day and suggest that spread is used as a proxy for both information asymmetry and market liquidity. Heflin et al. (2005) show that high quality disclosures enhance market liquidity by increasing the quoted depth and reducing effective spreads. Healy et al. (1999) conclude that companies which show sustained growth at the level of information disclosure exhibit higher liquidity through a lower relative bid-ask spread. Both Heflin et al. (2005) and Healy et al. (1999) use relative spread as a proxy for market liquidity. Demsetz (1986), Tinic (1972) find a negative relationship between trading activity and the bid-ask spread. Yet Glosten and Harris, (1988) among many others, suggest that spreads are negatively associated with trading volume and share price but positively associated with return volatility.

The inconclusive evidence of information asymmetry and liquidity behaviour around earnings announcements has been explained by Krinsky and Lee (1996), who investigate the spread components around earnings announcements and find an offsetting effect. While other components decrease because of higher trading volume, adverse selection costs increase because some traders have a superior capacity to estimate firm performance.

Because the SSM is an order-driven market, we also study the traders' order placement strategies around the release of this accounting information by classifying traders into two categories, large and small. The different analyses allow us to infer the effect of earnings announcements on the level of information asymmetry and market liquidity among different types of investor.

Since earnings announcements convey new information to the market as observed through a reduction in information asymmetry, some investors will actively seek information in the pre-disclosure period which will be reflected in the concentration of trading activities before the earnings announcement. Trading activities can be examined by various groups of variables (i.e., trading volume, bid/ask spread and number of buy and sell orders in the market). On the basis of the earlier arguments, we expect quarterly earnings announcements in the SSM to exhibit significant abnormal returns, higher abnormal trading volume, a wider bid-ask spread and more net buying by small traders. We also assume that the stock market reaction occurs even before the day of the earnings announcement, for some investors will be actively seeking information in this period and this will increase the information asymmetry before the expected release date.

Like Lakhal (2008), we conjecture that, in an order-driven market such as the SSM, earnings announcements are likely to narrow the subsequent bid-ask spread and to increase trading volume around the day of the announcement, thus improving market liquidity and reducing information asymmetry. We also anticipate that the spread increases before the announcement is made, because liquidity traders widen the spread in order to compensate for their potential losses from trading with informed traders.

3.3 Data

We use three sets of data:

1) Earnings announcements data which are recorded manually from the official stock exchange bulletin (Tadawul) with their time and date stamped. We document 2,437 quarterly earnings announcements covering the period between Q1 in 2002 and Q2 in 2009. After removing announcements whose time or date cannot be verified or announcements coinciding with those of other corporate events, we are left with 2170 earnings announcements. For each observation, we document the date, earnings and nature of the news as good or bad, compared either with the reaction of prices to the news on the announcement day or to a seasonal ranking walk surprise measure. Ninety-five listed firms are included in the sample, which each have at least six observations (earnings announcements). [22]

2) Data regarding stock daily prices for all stocks and market index were provided by the official stock exchange bulletin, Tadawul. It includes the following fields: Close, High, Low, Volume, Value and Trades for the eight-year period of 2002-2009.

3) Intraday data for all trades stamped to the nearest minute for the same period with the same field for the daily stock data. These data are extracted with a programming capability which stores and processes all historical data. Current high frequency data providers in the SSM provide data only for the last 25 days. These data were used for estimating the bid- ask spread,

[22] The sample firms represent around 96% of the total market value , only newly-found firms which haven't made operating earnings were excluded.

calculating order imbalance, classifying traders into small and large, computing the number of buyer and seller initiated trades and finally for computing intraday volatility.

All the listed companies in the SSM are required to publish their earnings in the fortnight starting from the last day of the quarter, but the exact timing of announcements is not known until they have been made public. At the end of each financial year, announcements must be made in the first forty days from the end of each company's financial year.

Our unique datasets allow us to precisely investigate trading activities around earnings announcements in more detail, since intraday data has never been used in this market .

3.4 Methodology (Event Study)

We first use standard event study to capture the informativeness of earnings announcements through estimating daily abnormal returns, trading activity measures, volatility and spread over time.[23] To compute abnormal return (AR) and cumulative abnormal return (CAR), we use an expected return generating process as follows: $\boldsymbol{AR_{it}} = \boldsymbol{R_{it}} - \boldsymbol{E(R_{it})}$,

Where $\boldsymbol{AR_{it}}$ is the abnormal return for firm *i* over time interval *t*,
$\boldsymbol{R_{it}}$ is the actual return for firm *i* over time interval *t*,
$\boldsymbol{E(R_{it})}$ is the expected / predicted return for firm *i* over time interval *t*.

We consider the following two return generating models (i.e., models for 'normal returns'):

A) Market-adjusted return model

$$\boldsymbol{AR_{it}} = \boldsymbol{R_{it}} - \boldsymbol{R_{mt}} \qquad \textbf{(1)}$$

where the abnormal return is the difference between the raw return R_{it} and the market return (TASI index) R_{mt} at time t,

B) Market model where returns are estimated using the following equation:

$$\mathbf{E(R_{it}) = \boldsymbol{\alpha}_i + \boldsymbol{\beta}_i\,(R_{mt})} \qquad \textbf{(2)}$$

[23] For reviews of the subject and event study econometrics, see MacKinlay (1997) , Binder(1998), and Kothari and Warner (2007).

Then estimated returns are subtracted from the raw returns $\boldsymbol{R_{it}}$ to formulate the abnormal returns $\boldsymbol{AR_{it}}$.

If an earnings announcement occurs within trading hours, then the announcement day is labelled day 0. If an announcement is made after the close of the day, then day 0 is the next trading day. The abnormal return for a given day is computed as the difference between the realised returns predicted from the market model and the raw returns R_{it}. Abnormal returns are then aggregated across two dimensions, across events or firms (cross-section) and across a time interval [t1, t2]. Within the event window sample, the cross-sectional averages of all stock returns and other measures are constructed for each day and then a time series of cross-section averages is computed for the whole event window. To construct a control sample, the time series for each stock [-100,-11] relative to the day of the earnings announcement (day 0) is formed, to estimate the parameters. The time-series averages of these cross-sectional measures are then calculated to arrive at a single number which represents the control for comparison purposes for the measures of trading activity.

Cumulative Abnormal Returns (CARs) are then computed for various windows around the event day. We define our event period to be various event windows [-10, +10], [-5, +5] and [-1, +1], so as to fully capture the earnings announcements effects. We focus on stock returns and trading activity during the 21-, 11- and 3-day event windows around earnings announcements.

Measures of trading activities and information asymmetry

For trading activates, like Berkman et al. (2009), we assign our "normal period" for trading activities to be days [-30,-11]. We then construct our measure of abnormal trading activity for each day in the event window relative to our "normal" control period. Following Jarrell and Poulsen (1989) and Bajo (2009), we compare the behaviour pattern of each variable around the earnings announcement to its "normal behaviour" estimated from the non- announcement control period (benchmark period). For each variable chosen, the abnormal measure is normalised and defined as:

$$\frac{\boldsymbol{V_{event}} - \boldsymbol{\bar{V}_{benchmark}}}{\sqrt{\boldsymbol{Var}(\boldsymbol{\bar{V}_{benchmark}})}}$$

where V_{event} is the event period interval, $\bar{V}_{benc\,hmark}$ is the mean value over the benchmark period intervals [-30,-11] and $\sqrt{Var(\bar{V}_{benc\,hmark})}$ is the standard deviation over the control period [-30,-11]. Because we are interested in observing the change in trading activity around corporate events, we do not focus on the level of trading activity, but rather in recognising unusual activity. The deviation from normal trading activity is measured through normalising these trading activities.

We use various measures of trading activates which have been used in the literature to capture the market behaviour before, during and after the earnings announcement day. We consider three different measures of trading activity; trading volume (TV) in SAR, share turnover (Turnover) which is computed as a percentage of the daily volume traded relative to outstanding shares and the number of trades (NT), since these measures have been used frequently to proxy for the level of trading activity. For the remaining variables, we define each variable and document how it is computed below.

For the volatility measure we use the intraday high-low price range. For the liquidity and information asymmetry, we use three measures: the bid-ask spread, order imbalance and overnight indicator. We define each variable and document according to the way in which it is computed.

Volatility (VOL) is measured as daily High and Low prices scaled by Low prices. The market volatility is expected to increase around the date of the earnings announcement due to the release of price-sensitive information. We compute our volatility measure similar to those of Bushee et al. (2003); and Lakhal (2008) which can be written as follows:

$$\boldsymbol{VOL_{i,t}} = \frac{\boldsymbol{P^{H}_{i,t} - P^{L}_{i,t}}}{\boldsymbol{P^{L}_{i,t}}} \qquad \textbf{(3)}$$

where $P_{i,t}$ denotes respectively the highest (H) and the lowest (L) prices for firm i and day *t*.
Bid-ask spreads are used as a proxy for both information asymmetry and liquidity. Spreads are commonly considered a proxy for information asymmetry (Glosten and Milgrom, 1985). The wider spreads reflect the higher adverse selection cost, as suggested by many researchers (see, for example, Coller and Yohn, 1997; Affleck-Graves et al., 2002; and Heflin et al., 2005). The order processing and inventory components reflect the liquidity while the adverse selection

component reflects the information asymmetry. We follow Affleck-Graves et al. (2002), who suggest using the bid-ask spread as proxy for both the liquidity and information asymmetry.

Since quote data are not directly available in the SSM, we estimate the spread using high frequency data (with one-minute intervals). We make use of the covariance model of George et al. (1991) which shows how the first-order auto-correlation in stock returns and quotes can be used to estimate the bid-ask spread.

They estimate the informational asymmetry component of the bid-ask spread, $\emptyset_{\mathrm{i,m}} = 1 - \pi_{\mathrm{i,m}}$ which is that part of the spread which is derived from the information asymmetry of firm i and time m . George et al (1991) used daily prices, but we use intraday prices at one-minute intervals; hence, we give the time period the subscription m. Furthermore, $\pi_{\mathrm{i,m}}$ rep-represents that part of the spread which is not due to information asymmetry. The spread estimation equation can be written as follows:

$$\boldsymbol{\pi_{i,m}} = \frac{\mathbf{2}\sqrt{-\boldsymbol{cov}\left(\boldsymbol{RD_{i,t}}, \boldsymbol{RD_{i,t-1}}\right)}}{\boldsymbol{S_{i,d}}} \tag{4}$$

where $RD_{i,t} = RD_{iTt} - RD_{iLt}$ is the difference between the intraday returns of the transaction prices RD_{iTt} and bid prices RD_{iLt} (intraday Low prices) ,$RD_{i,t-1}$ is the one- minute lag of $RD_{i,t}$, RD_{iTt} is the 1-minute intraday return of firm i using the transaction prices of the time interval between t-1 and t, RD_{iLt} is the 1-minute intraday return of firm i using bid prices computed between time t-1 and time t, $S_{i,d}$ is the average of intraday bid-ask spreads of all transactions recorded for firm i on day d and finally $cov\left(RD_{i,t}, RD_{i,t-1}\right)$ is the serial covariance of $RD_{i,t}$.[24]

The overnight indicator (ONI) of Gallo and Pacini (2000) is used to measure the disagreement and dispersion of opinion among investors regarding the fundamental value of a stock. ONI represents the surprise between the closing of one day and the opening of the next day; we find this a good proxy for information asymmetry and arrival in the SSM.[25] It is calculated as follows:

[24] Van Ness et al. (2001) have examined several spread decomposition models and concluded that no single model appears to perform better than the others.

[25] Gregoriou et al. (2005) and many others have used the variance of analysts' forecasts as a proxy for the diversity of opinion amongst investors. However, in the SSM, it is not possible to obtain such data.

$$ONI_t = \left| log \frac{Open_t}{Close_{t-1}} \right| \qquad (5)$$

In principle, there should be no increase of information arrival in the immediate pre-announcement period beyond that of the non-announcement period. The SSM has few reports which publicly forecast and publish future anticipated sales and earnings; therefore, the overnight indicator should provide us with a precise measure of information asymmetry and informational arrival.

In our study, we also use Order Imbalance (OI) as another proxy for information asymmetry and examine the way in which it influences volume and returns. Order imbalance has frequently been used in the market microstructure literature as a proxy for informed trading and for liquidity asymmetry (see, e.g., Chan and Fong, 2000; Chordia et al, 2002; and Su et al, 2009). OI is the excess of net buying or selling orders at one time which reflect the forces behind the orders. The OI is then classified by types of investor, whether small or large. We adopt Chan and Fong's definition of order imbalance (2000): the net of the numbers of buyer-vs.-seller initiated trades. Any large positive order imbalance in the stock indicates excess buying, while a large negative order imbalance indicates excess selling. For this purpose we use Lee and Ready's "Tick Rule Test" (1991), which infers trade direction using trade to trade prices. The Tick Rule Test compares trade price changes relative to previous trade price. If the price change between trades is positive, then the transaction is coded as a buy-initiated trade. A negative price change yields a sell-initiated trade. Like Shanthikumar (2004), we define order imbalance as follows:

$$OI_{i.x.t} = \frac{Buys_{i,x,t} - Sells_{i,x,t}}{Buys_{i,x,t} + Sells_{i,x,t}} \qquad (6)$$

where we add all buyer and seller initiated trades for firm i and investor type x at time t. A positive OI indicates net-buying while negative outcome indicates net-selling. We classify investors into small and large, according the value of the transaction. We use two primary cut-offs to classify investors of type x with a buffer between small and large trades to reduce noise, a method which has been used by Shanthikumar (2004), and Chiang and Wang (2007). The lower cut-off is all trades with a value of SAR 75,000 or lower (USD 20,000) and the higher cut-off is all trades with a value of SAR 250, 000 or higher (USD 66,666).

Statistical Tests

To examine whether trading activity measures, bid-ask spreads, overnight indicators and volatility are significantly different in the period surrounding earnings announcements from "normal" times, a difference of means test is used. To gauge the prevalence of increases in returns, volume, volatility, bid-ask spreads and information asymmetry across the sample of earnings announcements, the frequency of increases in each metric is recorded for each day in the event window (-5, +10). Then a Student t-statistic is calculated for each variable on each day in the event window to test whether the event window variable is greater than the normal value. The significance of t-statistics is assessed using two-tailed critical values.

3.5 Event study results

We first show results which examine the informativeness of earnings announcements measured by stock price reaction in the event window, more precisely by cumulative abnormal returns, CARs, around earnings announcements. We calculate abnormal returns using two models, the market model and the market adjusted model. Once we have computed the abnormal returns, we construct two event windows [-5,+5] to measure CAR in the eleven days around the announcement day (0) and a smaller event window[-1,+1] to measure immediate reaction to public announcements.

Table 3-1 : Cumulative Abnormal Returns (CARs) around Earnings Announcements.

Panel A: Market model $AR_{it}-(R_{it}=\alpha_i+\beta_i R_{mt})$	***All (N= 2133)***	***Good (N=790)***	***Bad (N=1003)***	***Neutral (N=338)***
CAR(-5,+5)	-.01633 *** (.0018) -8.91	0.0111*** (.0030) 3.66	-.0397*** (.0027)-14.63	-.0112*** (.0028)-3.98
Car(-1,+1)	-.0110*** (.0013)-7.29	.01354 *** (.0023) 5.83	-.0314 *** (.0019) -16.31	-.01002 *** (.0020)-4.82
Panel B: Market adjusted returns $AR_{it}=R_{it}-R_{mt}$	***All (N=2179)***	***Good (N=961)***	***Bad (N=1218)***	***Neutral (N=247)***
CAR(-5,+5)	-.00079*** (.0002) -3.69	0.01194*** (0.0003)	-.01180 *** (.0003) -30.61	-.0003*** (.00007) -4.55
Car(-1,+1)	-.00462*** (0.0012) 3.67	.04006 *** (.0014)26.89	-.0398 *** (.0011) -33.70	0.0002 (.0001) 0.13

Notes: reports the cumulative abnormal returns (CARs) along with the test statistic for Good, Bad and Neutral portfolios and across different event windows (-5,+5) and (-1,+1). The statistical significance of the average stock price response to earnings announcements around different event windows is shown as follows: $t-\text{statistics}=\frac{CAAR\,(t_1,t_2)}{\sqrt{(K+1)s_{AAR\,t}^{\ 2}}}$ Estimated standard errors are reported in parentheses after each CAR, along with t-statistics values. Significance levels are reported as *** p<0.01, ** p<0.05, * p<0.1.

Portfolios were constructed on the basis of the earnings announcement return (EAR) on days (0, +1). A positive EAR belongs to the good news portfolio, whereas a negative EAR is in the bad news portfolio and the neutral portfolio is one which contains all the stocks that have the lowest 10% absolute EAR during the announcement day (0, +1). In general, it was found that market reaction was negative in the days around earnings announcements, but this could be a reflection of the higher incidence of bad news at the time of the study. The CARs in panel A were computed using the market model, which produces different behaviour of CARs than the ones computed using the market adjusted model in Panel B. The latter assumes the expected return is changing ,however, is constant among firms and discounts the matching market return with the firm raw return, while the former measures the linear relationship between a stock and a market return and discounts only that relationship from the raw returns. However, all CARs are statistically significant at the 1% level, indicating that the market in general reacts positively (negatively) to good (bad) news and that public earnings announcements change the perceived value of a stock. Panel A reports asymmetry in the price reaction between good and bad news portfolios for both event windows (-5, +5) and (-1, +1). The bad portfolio shows a higher CAR at (-3.9%) and (-3.2%) for both event windows while a good portfolio exhibits an averages of 1.1% for one window and 1.3% for the other windows. The different price reactions to bad news and good news have been found in many studies (see Hayn, 1995, for example). The underreaction to good news has been established and explained in Chapter 2 of this thesis. When using market adjusted returns, the asymmetry of CAR disappears altogether; we see a similar reaction to good and bad news at 1.1% (-1.1) and 4% (-3.9%) for good (bad) portfolios in the event windows (-5, +5) and (-1, +1), respectively.

3.5.1 Abnormal Trading activity

In Table (3-2), we present average abnormal returns (AARs) along with three measures of abnormal trading (AT). We have discussed abnormal returns around the earnings announcement in the previous table; nonetheless, we list abnormal returns to link them to abnormal trading (AT). We focus on AT, by taking each daily measure of trading activity during the event window (-5, +10), subtracting the mean and dividing by the standard deviation over the control period, (- 30, -11).

Under the null hypothesis that the abnormal returns or trading activities of the event window have the same distribution as non-event (control period) returns or trading activity, we test for differences between each daily trading activity in the event window against the average of the control period of the event window [-30,-11]. Abnormal dollar (riyal) trading volumes are highly significant; however, there is mostly negative reaction in the five days before the event day (0). A higher than average significant positive reaction is experienced one day before the announcement and stays mainly positive until day 7. This pattern of a negative trading activity reaction in the pre-announcement period followed by a positive one is also observed in the turnover and number of trades. Turnover is negative and significant in days (-3) and (-2). The number of trades is also negative and significant in all of the week before the announcement day, but both the turnover and the number of trades shows positive and significant reaction during and after the announcement day. However, the positive reaction is more persistent in the dollar trading volume and turnover than in the number of trades.

In general, this result indicates that daily trading activity during the event period significantly exceeds the mean daily activity over the control period [-30,-11]. These findings suggest that there is systematic evidence of informed trading before the release of earnings announcements. The substantial increase in trading activity subsequent to the announcement on the event day (0) in particular is consistent with the finding in cumulative abnormal returns where the market reaction to new information indicates the informativeness of these announcements.

Table 3-2 Abnormal Returns and Trading Activity around Earnings Announcements.

Days	Abnormal Returns %	Abnormal Dollar Volume	Turnover	Number of trades
-5	**0.04**	**- 0.45**	**-0.41**	**-0.014****
	(0.61)	(-1.22)	(-0.97)	(-2.53)
-4	**- 0.11***	**-0.49 *****	**-0.40**	**-0.004**
	(-1.80)	(-2.65)	(-1.28)	(-1.34)
-3	**- 0.09**	**- 0.45 *****	**-0.39***	**-0.015*****
	(-1.33)	(-3.03)	(-2.20)	(-2.70)
-2	**- 0.07**	**-0.45 ****	**-0.38*****	**-0.015*****
	(-1.04)	(-2.23)	(-2.74)	(-2.74)
-1	**- 0.10***	**1.42 ***	**0.39 ****	**-0.011*****
	(-1.70)	(-1.85)	(1.98)	(-2.20)
0	**- 0.17****	**1.10 *****	**0.45 ***	**0.041*****
	(-2.34)	(6.15)	(1.61)	(4.65)
1	**- 0.26*****	**0.85**	**0.39**	**0.045*****
	(-3.65)	(1.29)	(0.03)	(5.01)
2	**- 0.09**	**0.52**	**0.37*****	**0.022*****
	(-1.67)	(-1.38)	(2.10)	(2.20)
3	**- 0.06**	**0.43*****	**0.37 *****	**0.010**
	(-0.90)	(-2.84)	(3.69)	(0.66)
4	**- 0.08**	**0.32 *****	**0.38 *****	**-0.005**
	(-1.34)	(-2.64)	(2.96)	(-0.07)
5	**0.05**	**0.18 *****	**0.38 *****	**-0.004**
	(0.94)	(-3.52)	(2.59)	(-0.10)
6	**- 0.01**	**0.10**	**0.37 *****	**0.004**
	(-0.24)	(-1.13)	(-3.51)	(0.13)
7	**0.20 *****	**0.03 *****	**0.39 ****	**-0.007****
	(3.25)	(-3.48)	(-2.18)	(-1.69)
8	**0.03**	**- 0.03****	**0.39 ***	**-0.003**
	(0.34)	(2.22)	(-2.00)	(-0.26)
9	**0.29*****	**-0.01****	**0.42**	**0.007**
	(4.87)	(2.44)	(-0.14)	(0.29)
10	**0.25*****	**-0.04****	**0.41**	**-0.003**
	(4.09)	(2.22)	(-0.47)	(-1.14)

Notes: Average Abnormal Returns (AARs) represent the daily average cross-section market adjusted returns. The three measures of trading activity (TA) are dollar trading volume, turnover and number of trades. TA measures are normalised by the average and standard deviation of the estimation period[-30,-11], as follows $\frac{V_{event} - \bar{V}_{benchmark}}{\sqrt{Var\,(\bar{V}_{benchmark}\ )}}$.For both Abnormal returns and TA measures, all hypotheses were accepted or rejected according to the t-statistic, formulated as follows: $t = \frac{AAR_t}{(var\,(AAR_t))^{1/2}}, \frac{TA_t}{(var\,(TA_t))^{1/2}}$, respectively. The t-statistics are reported in parentheses and are based upon the null hypothesis that AAR (TA) is equal to 0($\overline{AT}$) and the alternative hypothesis which states that AAR (AT) is not equal to zero ($\overline{AT}$).
*, **, *** denote statistical significance at the 10%, 5%,1% levels, respectively.

3.5.2 Liquidity and information asymmetry

Table (3-3) reports the volatility, overnight indicator and bid-ask spreads around earnings announcements as measures of investors' disagreement and information asymmetry in the market. The variable spread is closely related to the liquidity level in the markets, whereas the overnight indicator should measure the arrival of information and disagreement between investors regarding the value of a security. We measure price volatility by the difference between the highest and lowest prices scaled by lowest prices for every day in the event window (-5, +10). The overnight indicator (ONI) developed by Gallo and Pacini (2000) measures the dispersion of opinion among investors regarding the fundamental value of a stock. The ONI represents the surprise between the closing of one day and the opening of the next day; we find it a plausible proxy for information asymmetry and the arrival of information, as most corporate events and announcements happen toward the end of the trading day. The bid-ask spread is estimated from transaction prices using the model of George et al. (1991); hence, it may not reflect the actual quoted bid-ask spread. All variables were computed for every day in the event window (-5, +10) and compared with the averages for the non-event window [-30,-11].

Under the null hypothesis that information symmetry and the liquidity of the event window has the same distribution as those of the non-event (control period), we test for differences between each daily measure of liquidity and information asymmetry in the event window against the average of the control period of the event window [-30,-11].

Volatility and the overnight indicator are higher at the time of the announcement and the days immediately following it. They steadily increase in magnitude over the five days before the announcement and peak on the day of the announcement and the day after (days 0 and +1). In the subsequent days, volatility declines but remains above the pre-announcement levels. The highest volatility in prices is found on the announcement day at 5%, which indicates different opinions and interpretation of news on the part of different types of investor. If investors in the market were homogeneous, then we should anticipate a lower level of volatility, at least in the announcement day. The t-statistics indicate that volatility is significantly higher than it is in the control period [-30,-11].

The ONI measures the rate of arrival of information in the market. It shows the highly significant arrival of information for every day in the pre-announcement period, indicating informed trading and engagement in private information seeking. The highest level of information arrival is found on day (1) and not on day (0), which can be explained by the fact that most of the news is made after the closing hour of day (0). The ONI declines substantially only 2 days after the announcement is made, to a lower level than before the announcement. Overall, bid-ask spreads increase around earnings announcements; however, they substantially decrease on the two days around the earnings announcement before they bounce back to the same level as in the pre-announcement period. Spread is significant on days (0) and (1) only, but shows no significant level in the week before or after the announcement period; however it remains high after the announcement period. Our spread results are opposite to those recorded by Coller and Yohn (1997), who found an increased spread only on the day of the management forecast release and the day after it, but not in the period before management forecast. They explain the failure of the spread to increase in the pre-release period by the fact that these management forecasts are unanticipated by investors. Even though earnings announcements in the SSM are not scheduled, evidence from trading activity and information asymmetry suggests that announcements can be anticipated by some market participants. Many studies found no significant changes in spread surrounding earnings announcements, despite evidence that the adverse selection component of the spreads widens significantly (see Morse and Ushman, 1983; Venkatesh and Chiang, 1986; Lee et al, 1993; Krinsky and Lee, 1996; and Affleck-Graves, 2002).

Since spread has three components and each component is induced by different factors, many previous researchers have suggested that these factors may have opposite directional effect and that this could explain the lack of evidence of changing spread around earnings announcements which some studies find (Krinsky and Lee, 1996). For example, trading volume reduces the spread, due to lower order processing cost, while private information induces the adverse selection component of the spread, hence increasing the spread. Obviously, a high number of trades surrounding earnings announcements in the SSM will reduce inventory and order processing costs, which eventually narrows the spread.

The pre-release information asymmetry level indicates disagreement between market participants about the content and implication of forthcoming earnings announcements, whereas the persistence in volatility after the announcement compared to the volatility of a non-event period suggests that different market participants have different levels of ability to process the content of the earnings announcements and supports the assumption that some investors convert public information into private. Since the dates of announcements are not predictable in the SSM, most imminent days before earnings announcements show significant levels of information asymmetry, indicating a higher incidence of private acquisition of information.

These results support the hypothesis suggested by Kim and Verrecchia (1994), who explain the persistence of adverse selection problems after the announcement day by the varying abilities of investors to process corporate disclosure. An informed judgement based on earnings release increases the information asymmetry between different traders in the market.

Table 3-3: information asymmetry and liquidity around earnings announcements

Days	Volatility	Overnight(ONI)	Spread
-5	**4.0**	**0.11 ****	**3.17**
	(0.51)	(2.18)	(0.25)
-4	**4.1****	**0.14 *****	**3.16**
	(2.15)	(5.07)	(0.81)
-3	**4.0**	**0.18 *****	**3.08**
	(1.56)	(4.80)	(0.31)
-2	**4.2*****	**0.18 *****	**3.14**
	(4.08)	(5.47)	(0.28)
-1	**4.5*****	**0.20 *****	**3.19**
	(6.49)	(5.37)	(1.62)
0	**5.0*****	**0.21 *****	**3.07****
	(12.97)	(5.27)	(2.00)
1	**4.8*****	**0.25*****	**3.13***
	(9.93)	(6.20)	(1.65)
2	**4.7*****	**0.14 *****	**3.18**
	(8.54)	(2.44)	(0.68)
3	**4.4*****	**0.12***	**3.19**
	(6.26)	(1.70)	(0.21)
4	**4.4*****	**0.09**	**3.22**
	(5.66)	(0.45)	(0.15)
5	**4.2*****	**0.14***	**2.19**
	(3.76)	(1.69)	(0.34)
6	**4.1*****	**0.10**	**3.21**
	(2.72)	(0.30)	(0.38)
7	**4.2*****	**0.10**	**3.18**
	(3.05)	(0.10)	(0.75)
8	**4.1***	**0.01**	**3.22**
	(1.90)	(1.25)	(0.77)
9	**4.0**	**0.07**	**3.14**
	(1.36)	(0.06)	(0.70)
10	**4.0**	**0.04 ***	**3.20**
	(0.92)	(1.70)	(0.83)

Notes: this table reports the volatility, overnight indicator and estimated bid-ask spread along with their t-statistics. All variables are averaged cross-sectionally for all days in the event window (-5, +10). Volatility is measured by difference between highest and lowest prices per day, scaled by lowest prices, the overnight indicator is the absolute log of opening prices to the previous day's closing prices and spread is estimated using the serial covariance model of George et al. (1999).

All hypotheses were accepted or rejected according to the t-statistic, formulated as follows:

$$t = \frac{\mathrm{Volatility}_t}{(\mathrm{var}(\mathrm{Volatility}_T))^{1/2}}, \frac{\mathrm{ONI}_t}{(\mathrm{var}(\mathrm{ONI}_T))^{1/2}}, \frac{\mathrm{Spread}}{(\mathrm{var}(\mathrm{Spread}_T))^{1/2}}.$$

The t-statistics, reported in parentheses, are based upon the null hypothesis that the daily cross-section average is equal to its time-series average in the estimation window [-30,-11]. The alternative hypothesis states that the daily average is not equal to the normal period average.

* denotes statistical significance at the 10% level

** denotes statistical significance at the 5% level

*** denotes statistical significance at the 1% level

3.5.3 Investors' behaviour around earnings announcements

In this section, we analyse different types of investor and the ways in which they react to news. The aim is to examine any pattern in buying or selling and whether this pattern differs according to the type of investor. In other words, we investigate who is buying around earnings announcement dates. Many studies suggest that small investors are less rational and become net buyers around earnings announcements. Panel A in Table (3-4) reports order imbalance according to the type of investor. Assuming that different investors have different levels of ability and resources of information regarding the true value of a security, we use the value of trades to separate small and large investors. If this assumption is valid, we should observe different behaviour between the two groups. It is worth mentioning that because event window (-5,+10) is relatively short, we do not aim to examine trading strategy followed by investors , but instead examine immediate reaction to news.

The small investors order imbalance in Panel A indicates that they tend to buy more than sell around earnings announcements, whereas large investors tend to sell immediately after the announcements; they buy every day and sell on days (-3,-2, 1, 2 and 5). Panel B shows the order imbalance split further by type of news. Good news is reported in subgroup (1) and bad news in subgroup (2). The good news portfolio shows interesting results: while large investors are mainly net-buyers in the pre-announcement period and net-sellers in most days after the announcement, small investors are net-buyers in the days immediately following the release of the news. The bad news portfolio in subgroup (2) indicates concentrated selling for small investors in days (1), (2) and 3), while large investors show no strong pattern of selling around earnings announcements. The evidence suggests that small investors are less sophisticated in acquiring pre-announcement information and in interpreting news. Good news shows strong buying from small investors, while bad news shows strong selling by small investors. Conversely, large investors show that they buy shares in good news firms even before the announcement day and sell them afterwards. Moreover, large investors show a buying pattern on the day of bad news announcements and the next day. The evidence suggests informed trading and a higher ability to interpret news among large investors in the SSM. Our results are in some ways similar to those reported by Barber and Odean (2008), who surmise that individuals tend to be net-buyers whether the news is good or bad. Their buying behaviour is motivated by the attention-grabbing hypothesis, under which any stock in the news experiences higher abnormal buying. This finding is supported by Lee (1992) and Hirshleifer et al. (2008). Our order imbalance results are also similar to those found in Shanthikumar (2004) and Chiang and Wang (2007), who use similar methodology and find that small investors in general react more strongly to earnings surprises than do large investors. Moreover, our results suggest that informed trading is associated with the size of the trades, evidenced by the buying of good news stocks by large investors in the pre-announcement period.

Table 3-4: Order Imbalance by Type of Investor and by Type of News.

Days	Order Imbalance (small investors)	Order Imbalance (Large investors)
Panel A: Order imbalance by type of investor		
-5	-0.031	0.023
-4	-0.034	0.020
-3	0.026	-0.019
-2	0.025	-0.009
-1	0.015	0.020
0	0.023	0.028
1	0.016	-0.009
2	0.026	-0.012
3	0.025	-0.017
4	0.030	0.021
5	-0.035	-0.015
6	-0.027	0.020
7	0.028	0.032
8	0.028	0.023
9	0.035	0.024
10	0.032	0.020

	Panel B: order imbalance for Good and Bad news			
	(1) Good News		(2) Bad news	
	Small investors	Large investors	Small investors	Large investors
-5	-0.76	4.08	1.04	1.29
-4	-0.52	3.45	-0.15	2.22
-3	-0.63	4.27	0.96	1.61
-2	0.90	3.25	0.65	-2.03
-1	-0.15	3.35	0.54	0.84
0	0.79	4.26	0.47	1.88
1	0.00	3.19	-1.67	0.92
2	1.40	-1.10	-0.08	-2.98
3	0.58	-2.21	-0.80	1.18
4	0.90	-1.98	0.71	-2.80
5	-0.70	3.73	0.33	1.95
6	-0.35	-2.83	1.70	-1.37
7	-0.64	-2.00	1.00	0.31
8	1.62	2.71	-0.45	0.46
9	1.22	3.98	0.01	1.14
10	-0.66	-2.49	-0.39	-1.91

Notes: This table presents the results of raw order imbalance, measured as follows:

$$OI_{i.x.t} = \frac{Buys_{i,x,t} - Sells_{i,x,t}}{Buys_{i,x,t} + Sells_{i,x,t}}$$

Where all orders are classified into buy or sell initiated orders, then counted for firm i, investor type x (small or large) and date t. Panel A reports the order imbalance for each group of investors. Panel B report an order imbalance for each group of investors and for type of news, either good or bad. Order imbalance is computed for all days in the event period (-5, +10) to show how different types of investors react to good and bad news.

3.6 Regression

I attempt to explain the magnitude of cumulative abnormal return, CAR (-1, +1) by estimating Equation (7). OLS linear regression was used to test the hypothesis that the pre-announcement stock behaviour and level of trading activity have an effect on the magnitude of the abnormal returns on the announcement day. I use Cumulative Abnormal Return (CAR) in the window (-1, +1) to capture the market reaction of the announcement. Then, I regress CAR on a set of variables which are expected to affect the magnitude of the stock return. For the pre-announcement explanatory variables, I include the price trend in the stock returns (momentum), cumulative overnight indicator, average abnormal volume. All the previous variables are computed using a time frame of the three weeks before the announcement day, that is, 15 trading days. I also include two firm characteristics; size measured in market value and the earnings surprise of the current quarter compared to same quarter of the previous year. Good (Bad) news portfolios contain all the companies which have positive (negative) CAR (-1, +1).

The aim is to test whether the level of pre-announcement trading activity or firm characteristic would have predictive power to explain the magnitude of the earnings announcement returns.

We expect a positive relationship, positive (negative) coefficient estimates for the good (bad) subsamples for pre-announcement trading activity and the earnings surprise with regard to abnormal return. At the same time, we expect a negative relationship between firm size and the magnitude of price reaction CAR that is a negative (positive) coefficient sign for the good (bad) subsamples.

A cross-sectional model, similar to that adopted by Jackson and Madura (2003), is used to investigate the association between the absolute CARs and a set of pre-announcement variables covering trading activity and firm characteristics (Size and SUE) specific to the event observation. The model is constructed as follows:

$$\boldsymbol{CAR_i = \alpha + \beta_1 Momentum_{i,t} + \beta_2 ONI_i + \beta_3 \overline{Abvol}_i + \beta_4 SUE_{i,t} + \beta_5 Size_{i,t} + \varepsilon_{i,t}} \quad \textbf{(7)}$$

where:

1-Momentum is defined as the compounded stock returns for the past three trading weeks before the earnings announcement, where: $Momentum_{i,t} = \prod_{t=1}^{15} R_{i,t}$ and $R_{i,t}$ is the daily stock return for firm i and day t in the window [-16,-2].

2-ONI is the summation of overnight indicators over the period [-16,-2] calculated as:

$$ONI_i = \sum_{t=1}^{15} \left| log \frac{Open_t}{Close_{t-1}} \right| \quad \textbf{(8)}$$

3- $\overline{Abvol}$ is the average normalised abnormal volume which was first used by Jarrell and Poulsen (1989). It is computed as the residual of daily volume less mean daily volume scaled by trading volume standard deviation during the three weeks before an announcement [-16,-2] as follows:

$Abvol_{i,t} = \frac{TV_{i,t} - \overline{TV}_{i,t}}{\sigma_{i,t}}$, where $\overline{TV}_{i,t} = \frac{1}{20}\sum_{t=1}^{20} TV_{i,t}$, is the average trading volume for 20 days over the window of [-36,-17] and $\sigma_{i,t} = \sqrt{\frac{1}{20}\sum_{t=1}^{20}\left(TV_{i,t} - \overline{TV_{i,t}}\right)^2}$, is the standard deviation of trading volume during the estimation period [-36,-17]. The daily estimated Abvol is then averaged as follows:

$$\overline{Abvol_i} = \frac{1}{15}\sum_{t=1}^{15} Abvol \quad \textbf{(9)}$$

4- Standard unexpected earnings (SUE) are measured by scaling the unexpected earnings (seasonal random walk with a drift) to its standard deviation. The SUE for each firm *i* at quarter *t* is given by:

$$SUE_{i,t} = \frac{e_{i,t} - E(e_{i,t})}{\sigma_{i,t}} \quad \textbf{(10)}$$

where $e_{i,t}$ represents actual earnings and $E(e_{i,t})$ is the expected earnings computed using a random walk model with drift $E(e_{i,t}) = e_{t-4}^{i} + \delta^{i}$, where δ^{i} is the seasonal drift in a firm's earnings and $\sigma_{i,t}$ is estimated using the figures for the previous 8 quarters' earnings.

5- Finally, *Size* variable is the market value of each firm at the time of the announcement. We multiply the number of outstanding shares by the closing price immediately before the earnings announcement day.

Table 3-5 : Cross-sectional Regression of Cumulative Abnormal Returns on Pre-announcement trading activity and Firm Characteristics.

VARIABLES	(1) Good News	(2) Bad News
Momentum	**0.0140***** (0.00538)	**-0.00840**** (0.00416)
ONI	**0.000215**** (0.000101)	**-0.000218***** (4.67e-05)
$\overline{\boldsymbol{Abvol}}$	**0.000328**** (0.000128)	**-0.000272**** (0.000109)
SUE	**-0.000153*** (5.95e-05)	**0.000134***** (4.26e-05)
size	**-0.00130***** (0.000403)	**0.00126***** (0.000327)
Constant	**0.0402***** (0.00907)	**-0.0394***** (0.00733)
Observations	**860**	**1131**
R-squared	0.058	0.065

Note: This table presents regression coefficients of the earnings announcement returns CAR (-1, +1) on trading activity and firm characteristics for two types of disclosure (Good and Bad news portfolios) for 95 firms during the period 2002-2009 with 1991 as the total number of observations. Good (bad) news firms are defined according to the price reaction during the event window (-1, +1), while positive (negative) CARs are placed in the good (bad) news portfolios. *** p<0.01,*p<0.05, * p<0.1. Standard errors are in parentheses.

As expected, all trading activity variables have a positive relationship with CAR for both types of news, good and bad. The price trend (momentum) has a positive relationship, positive (negative) coefficients with good (bad news) firms. The momentum was selected to show any pre-announcement trend in informed trading. A company which exhibited a price trend before the release of its earnings shows higher cumulative abnormal returns. However, the coefficient is higher for the good news firms at 1.4%, suggesting that traders in the good news firms engage actively in private information seeking. The ONI, which is a measure of investors' disagreement and information asymmetry in the market, also has a positive relationship with abnormal returns. In the two portfolios, the abnormal volume increases CAR and is significant at 5%. SUE shows a bizarre negative relationship which is not expected, for the good news firm with significant coefficients at 10% .However, the bad news firms show a predicted positive coefficient for SUE that is significant at 1%. SUE was measured using the seasonal random walk model, since analysts' forecasts are not available in the SSM. The time-series model has proven to be inaccurate, more precisely in the case of the Saudi market, where during the period of our study, the price of oil and earnings per share (EPS) for the whole market rose to more than 400% between 2002 and 2009. Consequently, SUE might not be good predictor for earning surprise in a boom economy. Finally size, as expected, is negatively related to the cumulative abnormal returns, with positive (negative) coefficients for the bad (good) news which are significant at 1%. Larger companies in the SSM have substantial government and institution ownership and have better disclosure practices, which reduces information asymmetry and the reaction to news for such stocks. In general, pre-announcement trading activity and information asymmetry (momentum, overnight indicator and volume) have a positive relationship with cumulative abnormal returns. However, firm characteristics (SUE and Size) have a negative relationship with CAR.

3.6.1 Liquidity, Information asymmetry around earnings announcement

We first examine the change in liquidity (models 1 & 2 in table 3-6) around earnings announcements using an approach similar to that of Venkatesh and Chiang (1986) and Chan and Li (2005), who examine the change in adverse selection cost around earnings announcements. We use the estimated bid-ask spread as a proxy for liquidity. Model (1) uses the effective estimated spread from the model of George et al. (1991) and model (2) uses a relative estimated spread which deflates the spreads relative to prices. We use the estimated information asymmetry component of the spread in model (3), where we distinguish adverse selection cost behaviour with regard to good news and bad news firms.

For each earnings announcement, we estimate the following regression model:

$$\boldsymbol{BAS_{it} = \alpha + \beta_1 Volatility_{it} + \beta_2 Price_{it} + \beta_3\, Volume_{it} + \beta_4 D1_{it} + \beta_5 D2_{it} + B_6 D3_{it} + \varepsilon_{it}} \qquad \textbf{(11)}$$

where:

$BAS_{it} =$ Estimated Bid-Ask spread of firm i on day t;
$Volatility_{it}$ = High to low price range divided by low prices for firm i on day t;
$Price_{it}$= closing stock prices of firm i on day t;
$Volume_{it}$ =Ln (number of shares traded of firm i on day t multiplied by $Price_{it}$);
D1it =1 for days -20 to - 2; zero otherwise (pre-announcement period);
D2it =1 for days - 1 to +1; zero otherwise (announcement period);
D3it =1 for days +2 to +20; zero otherwise (post-announcement period).

Following the research design of Venkatesh and Chiang (1986) and Chan and Li (2005), volatility, price and volume are used in the model to measure the inventory and order processing cost, as suggested by the literature. Dummy variables measure the change in information asymmetry in the period before, during and after earnings announcements. An increase in the volatility of a stock will increase its market risk, which would be reflected in market makers/participants increasing the spread. Therefore, in line with the literature, we expect volatility to widen the spread because the SSM is an order driven market which has no designated market makers. Price is assumed to have a negative relationship with regard to spread because order-processing costs are disproportionately higher for lower priced stocks (Demsetz, 1968). We also expect a negative relationship between the "Saudi Riyal" trading volume and the spread, because inventory and liquidation cost will decline with higher trading. The dummy variables are constructed to test how the information asymmetry component would affect the spread around earnings announcements. After controlling for other components of the spread, namely, the inventory and order processing costs, the higher level of information asymmetry should be reflected in positive coefficients between the bid-ask spread and the dummy variables.

Table 3-6: Liquidity and Information Asymmetry around Quarterly Earnings Announcements.

VARIABLES	(1) Spread	(2) Relative Spread	(3) Information Asymmetry	
			Good	Bad
Volatility	**-2.062*****	**-0.0407*****		
	(0.0206)	(0.000756)		
Price	**-0.00478*****	**-0.000175*****		
	(1.48e-05)	(5.43e-07)		
Volume	**-0.0177*****	**-0.000121*****		
	(0.000457)	(1.68e-05)		
D1	**-0.000505**	**-7.88e-05**	**0.0291*****	**-0.00746**
	(0.00158)	(5.79e-05)	(0.00884)	(0.00869)
D2	**0.00991*****	**0.000312*****	**0.0303****	**0.0148**
	(0.00247)	(9.09e-05)	(0.0128)	(0.0127)
D3	**0.00961*****	**0.000271*****	**0.0175***	**-0.0171****
	(0.00157)	(5.79e-05)	(0.00889)	(0.00864)
Constant	**1.216*****	**0.0266*****	**0.370*****	**0.754*****
	(0.00755)	(0.000278)	(0.0444)	(0.0459)
Observations	105827	105827	58965	58110
R-squared	**0.573**	**0.531**	**0.651**	**0.689**

Notes: This table presents the estimated coefficients of the liquidity and information asymmetry components of volatility, stock price, volume and time dummies, representing the pre-announcement (D1), announcement (D2) and post-announcement periods (D3). Model (1) is run for the estimated spread, Model (2) uses relative spread (spread/price) and Model (3) uses the estimated adverse selection component of the spread as a dependent variable, which was run separately for the good and bad news portfolios.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses

As expected, spread is negatively associated with stock price and “Saudi Riyal” trading volume. However, volatility deviates from expectation and shows a negative coefficient too which could be a reflection of noise trading. A lot of noise trading is expected during this time.

Controlling for the previous variables should mainly control for the inventory and order processing components of the spread. The dummy variables show an increasing information asymmetry around and after earnings announcements (D2 and D3) with positive coefficients of around 0.01 which are significant at the 1% level. The information asymmetry in the pre-announcement period (D1) shows negative coefficient, but this is not significant. In general, information asymmetry remains at a high level after the announcement. These results are consistent with previous literature, maintaining that the different levels of ability among traders to interpret news aggravate the information asymmetry between them.

Model (3) was used to confirm our original model of the spread around earnings announcements; this model uses dummies to control for the adverse selection component. In the information asymmetry model, we use an adverse selection component which was estimated using the model of George et al (1991) and run the same model again on time dummies. We show whether this component would differ from or confirm the behaviour of the spread and time dummies in models 1 and 2. The behaviour of the information asymmetry component of the spread is reported for three periods, the pre-announcement period (D1), announcement period (D2) and post-announcement (D3). Regression was run separately for good news and bad news. Good and bad news firms were defined according to the earnings announcement return (EAR). Positive (negative) EAR is allocated in good (bad) groups. Because we are interested only in the information asymmetry component around earnings announcements, we report the dummies' coefficients and ignore the other coefficients of volatility, price and volume.

The behaviour of information asymmetry differs slightly in model (3) from that in the previous models, where information increased around and after the date of the earnings announcement. When we run the information asymmetry component and take into consideration the nature of the news, new and interesting results emerge. The good news firms show an increasing positive relationship of information asymmetry relative to the time of the announcement: information asymmetry gradually increases in the 20 days event window before the news and then peaks at the announcement period. Information asymmetry is then reduced after the announcement to the lowest level in the 20 days event window. The time dummy coefficient is statistically significant at the 1%, 5% and 10 % levels for D1, D2 and D3, respectively. Information asymmetry is reduced substantially in the post-announcement period, suggesting that earnings announcements reduce uncertainty in the market. The bad news firms show different behaviour patterns for information asymmetry. Information asymmetries are at their highest level during the announcement period D2; the other two periods exhibit lower levels of information asymmetry. However, only period D3 shows a negative coefficient of (-.017) which is significant at the 1% level.

The difference between good and bad news information asymmetry supports our conclusion in the price reaction regression, where we find that traders engage more actively in information seeking activities in the good news firms. The evidence suggests that while other components of the spread, inventory and order processing are reduced around the time of earnings announcements, information asymmetry increases around this time.

Our results are consistent with those of Chan and Li (2005), who also find evidence of an increase in adverse selection cost around earnings announcements, using similar time dummies to show an information asymmetry reaction to earnings news.

3.7 Summary

This study analyses abnormal returns, trading activity (dollar volume, turnover and number of trades), and liquidity and information asymmetry for the Saudi stock market around its quarterly earnings announcements. We use a sample of 2,437 quarterly earnings announcements which covers all listed and operating firms in the period from 2002-2009. We examine the market reaction to news through computing market adjusted abnormal returns over various event windows. We also examine the changes in different measurements of trading activity, liquidity, volatility, asymmetric information and in the traders' order placement strategies. In general, we find a significant increase in abnormal returns, increases in trading volume, a significant shift in systematic risk, widening bid-ask spread and above average stock price variability.

The highly significant abnormal returns around earnings announcements indicate the importance and informativeness of the information content of these announcements. We observe a rise in trading activities and volatility around earnings announcement with a higher information asymmetry which gradually reduces in the 20 days following the announcement date. The persistence of volatility and information asymmetry in the post announcement period can be explained by the heterogeneity in investors' ability to process the information in the public announcement, which indicates that investors may respond differently to news. These results are consistent with such different levels of ability, a notion suggested by Karpoff, 1986; Demski and Feltham, 1994; and Kim and Verrecchia, 1994, 1997, among others.

When examining trading behaviour among small and large investors in the market through order imbalance measures, we find that large investors are more sophisticated and show higher informed trading before earnings announcements, whereas smaller investors show a stronger reaction to news. Moreover, small investors show a buying pattern which is consistent with the earnings surprise. Our investors trading placement behaviour around earnings announcements is similar to that found by Chiang and Wang (2007), Barber and Odean (2008) and Hirshleifer et al. (2008). However, we find that small investors are net-buyers for the good news and net-sellers for the bad news in the 3 days following earnings releases.

We investigate further the magnitude of the cumulative abnormal returns (CAR) and find it to be positively related to information asymmetry and trading activity in the pre-announcement period (15 trading days before earnings announcements). CAR is reduced by the size of the company: larger companies which have higher institutional ownership and better disclosure practices show a lower CAR around earnings announcement. Surprisingly, CAR seems to converse effect of the time-series earnings surprise, SUE. One explanation of this relationship is that time-series coefficients show downward bias in their estimating of the earnings forecasts, since the market shows an exceptionally high growth in EPS for the years 2002-2009. Hence, SUE does not accurately measure the earnings surprise in the SSM.

Finally, liquidity measured by the bid-ask spread is negatively associated with stock return volatility, stock price level and riyal trading volume. The time dummy variables which control for other spread components and test for information asymmetry indicate increasing spread around the date of earnings announcements which remains relatively high in the following 20 days. An earnings release as suggested by Kim and Verrecchia (1994) motivates informed judgement, creating information asymmetry between traders in the market which can lasts for some time after the announcement.

chapter 4 : **Bid-Ask Spread and Price Impact Asymmetry of Block Trades**

4.1 Introduction

This chapter examines the price impacts of buy and sell initiated block trades on the Saudi Stock Market (SSM) over the time period, 2005-2008. This is important for a number of reasons. First, to our knowledge this is one of the first studies to investigate the price impact of block trades in an emerging equity market. Emerging markets are of particular interest because a vast majority of mutual funds, investment banks and individuals are investing heavily in emerging markets to diversify risk. This is common given that institutional investment is not very well established in emerging equity markets. Second, the SSM is of particular interest because there have been a large number of structural changes affecting the microstructure of the equity market, as well as the role the exchange plays as a resource allocation mechanism. The major structural change was when the government established the Capital Market Authority (CMA) in 2004. The CMA is a centralised regulatory body that oversees the market regulation and activities of the SSM.

Our empirical findings reaffirm the previous literature by documenting a greater price impact of block purchases than block sales. However, unlike the previous literature we discover that the asymmetry persists even when we account for the bid-ask bias in block trades. Overall, our findings suggest that in an emerging market where institutional trading is relatively scarce, market microstructure cannot explain the asymmetry in the price impact of large trades.

The chapter is organized as following. Section 4.2 discusses the literature review. Section 4.3 illustrates the data and methodology used to implement the empirical analysis. Section 4.5 documents a price impact asymmetry between block purchases and sales on the Saudi Stock Market. The price asymmetry is investigated using different trade size categories. We also empirically examines whether the bid-ask spread can explain the asymmetry between block purchases and sales. Finally, Section 4.6 summarises and concludes.

4.2 Literature Review

In an efficient market ,prices are believed to change in response to the arrival of new fundamental information .On the other hand, in market microstructure research, market makers or traders update their beliefs about the true value of security prices in response to transaction data as well, hence trade itself conveys information to traders which is a key element of asymmetric information models . Large trades have the capacity to move prices directly through the trading itself, as well as indirectly, by influencing the trading decisions of other market participants who may observe the action of large trade initiators. In a less deep market, higher price impact reflects a major challenge to stock exchanges and policy makers. Large trades in the stock market are known as block trades.

It is commonly recognised that any trade volume higher than 10,000 shares is considered to be block trades. The proportion of equities traded in blocks has increased substantially in recent years. In 1994, block trades of 10,000 shares accounted for 55.5% of New York Stock Exchange (NYSE) share volume (Madhavan and Cheng, 1997); now it accounts for over 70%. In the LSE (London Stock Exchange) block trades (of 10,000 shares or more) accounted for mere 5% of total FTSE 100 trading volume in 1984 which reached over 50% in 2005.[26] Institutional trading, predominately made up of block trades, accounts for over 60% of total trading volume in the LSE (Stapledon, 1996).

Starting with Kraus and Stoll (1972) who noted “blocks are sold not bought” , prior empirical research has documented a permanent price impact asymmetry between buyer and seller initiated trades in many equity markets including the NYSE (Holthausen et al.,1987) ,DJIA, (Frino et al, 2003), LSE, (Gemmill, 1996 and Gregoriou, 2008) and the Australian stock exchange, (Aitken and Frino, 1996a) and for a study covering 37 international markets (Chiyachantana et al.,2004). The price impact asymmetry between block purchases and sales has been a “Puzzle” over the last three decades. Empirical work (see among others, Holthause et al., 1987, 1990; Keim and Madhavan, 1996; Gemmill, 1996, Frino et al, 2003 and Gregoriou, 2008) has suggested that stock prices react differently to buy and sell orders.[27] The price continuation following a block purchase and a price reversal following a block sale suggests that block sellers pay liquidity premium while block buyers do not (Aitken and Frino, 1996).

Scholes (1972) and Kraus and Stoll (1972) were the first to develop hypotheses on how stock prices react to block trades: the substitution hypothesis, short run liquidity costs, and the information hypothesis. The substitution effect draws attention to the lack of close substitute for a security which leads to a demand curve of a stock not to be perfectly elastic .Under the imperfect substitute hypothesis price effect is expected to be permanent. In the case of no perfect substitutes, prices tend to change permanently as the buyer or seller has to offer a

[26] The Financial Times, January 2006.
[27] Chan and Lakonishok (1993) call the price asymmetry of block trades a “key puzzle”.

higher discount to make the deal attractive for other traders to take the other side of the trade. Price pressure or short-run liquidity cost occurs because of the demand and supply friction at the time of the trade which may result in price effect that is most probably to be temporary and closely related to the depth of the market. The information effect depends on the identity of the traders and size of the transaction as a proxy for the information content of the trade. A permanent price change is expected to be associated with informed trading which subsequently lead to new equilibrium prices.

One established explanation of the asymmetry of the price impact of block trades is that there is more informed trading in purchases than in sales. Chan and Lakonishok (1993), Keim and Madhavan (1996) and Saar (2001) among others suggest that the block purchases are based on the arrival of new firm-specific information, whereas block sales are motivated by liquidity and portfolio composition. The decision to sell a block reflects the limited option a trader has among stocks in his/her portfolio, whereas the decision to buy a block indicates a fundamental interest in that particular stock among many stocks in the market.

4.3 Data and Econometric Methodology

We use high frequency data at one minute time intervals to evaluate the price impact of buyer and seller initiated block trades, in the SSM over the time period of January 2005 to September 2008. The data is taken from Mubasher, a vendor of quotes and transaction data in the SSM. It is a unique dataset because to our knowledge it is the only database that includes all listed companies (124 companies) in the SSM and the market index, Tadawul All Share Index (TASI) at the intraday level. The dataset contains all transactions which are time-stamped to the nearest minute and in some cases it aggregates all transactions occurred within the minute. Any inference about the data is applicable to the whole market as the dataset is free from any sample bias.[28]

It is a highly comprehensive dataset as it almost covers four-year intraday dataset, from Jan 2005 to September 2008, with over 16,076,414 records of all transactions and bid-ask quotes. Following the previous literature (see among others Madhavan and Cheng, 1997) we

[28] Two companies were delisted due to pending satisfaction of certain financial criteria, namely “Bisha” and “Anaam”. They were excluded from the data because no transaction data was available due to the suspension of trading.

define block trades in our study as any trade with over 10.000 shares, which is 4,221, 870 trades or 20.8% of all trades in our sample. Clearly, the sample size, when compared with those used in previous studies, is very large. For example, Frino et al. (2003) and Gregoriou (2008) used approximately 2,800,000 block trades, Chan and Lakonishok (1993) examined 1,215,387 transactions while Madhavan and Cheng (1997) and Gemmill (1996) analysed only 16,343 and 6,000 trades respectively.

Following the previous literature (see among others Madhavan and Cheng, 1997), block trade price effects are classified into three categories, the total price impact, temporary price impact and permanent price impact. We use a five trade "minutes" benchmark to compute the price effects.[29] The total price impact is calculated as the percentage return from five trades prior to the block trade to the block trade itself. The temporary price impact is calculated as the percentage return from the block trade to the fifth trade after the block trade. The permanent price impact represents the percentage return from five trades prior to the block trade to five trades after the block trade. All prices used in the computations are transaction prices. The following equations represent the three types of price effect used in this study:

$$\left(\boldsymbol{Total\ Impact} = \frac{\boldsymbol{Close - close_{-5}}}{\boldsymbol{close_{-5}}}\right) \tag{1}$$

$$\left(\boldsymbol{Temorary\ Impact} = \frac{\boldsymbol{close_{+5} - Close}}{\boldsymbol{close}}\right) \tag{2}$$

$$\left(\boldsymbol{Permanent\ Impact} = \frac{\boldsymbol{close_{+5} - close_{-5}}}{\boldsymbol{close_{-5}}}\right) \tag{3}$$

We use the trade classification algorithm established by Lee and Ready (1991) to identify the block purchases and sales. The idea underlying the Lee and Ready method is to infer the trade direction of the transaction using the "tick rule". The tick rule test compares trade price changes relative to previous trade prices. If the price change between trades is positive, then the transaction is coded as a buy-initiated trade. A negative price change yields a sell-initiated trade. We follow the Bonser-Neal et al. (1999) method to sign a trade when the change in the price is zero. We compare trade price P (t) with the trade price $\mathrm{P(t-2)}$ and if

[29] Given that we use intraday minute transactions data, we use the terms trades and minutes interchangeably.

the change in price is still zero, we repeat the process until we find a difference in prices. If the price change is still zero at $P(t - 5)$. Then this trade is unclassified and omitted. Using the “tick rule”, we classify 2,366,099 trades into buy trades and 1, 855,236 into sell trades with total sample number of 4,221,870 transactions. Consistent with prior research, we associate a trade indicator for each trade to indicate the nature of the trade: 1 (buy), −1 (sell), or 0 (undecided).

Table 4-1 reports descriptive statistics for our dataset. The dataset contains intraday one minute transaction data of all companies in the SSM making up the TASI index. Each one-minute interval includes the following fields for each trade: Ticker, Date, Time, Price, Ask, Bid, and Volume.[30] We analyse 4,221,870 transactions amounting to a value of S.R 8.7 trillion (equivalent to $ 2,32 trillions). The sample is very large comparing to previous studies and it covers all 124 listed companies. The average number of shares per trade is larger for purchases amounting to 29,130 shares whereas the average number of trades for sales is 28,204 shares. Moreover, the average quoted spread defined as the ask price minus the bid price, is slightly higher for purchases (S.R 0.3607) then for sales (S.R 0.3564). On the other hand, the relative spread defined as the ask price minus the bid price, divided by the midprice (the average of the bid and ask prices), indicates that the spread is larger in the sale trades than in the buy trades; however, the difference is negligible.

The average quoted and relative spreads for all trades are almost half of those found in block trades. Size of the trade can be seen as a proxy of the information content of the order. Easley and O’Hara (1987) indicate that informed traders prefer to trade a large amount at any given price, a finding that confirmed by many researchers. Consequently, informed trading is believed to have a higher effect on price impact and bid/ask spread.

[30] We follow (Engle and Russell, 1998, and Spierdijk, 2004) and treat multiple transactions at the same time as one single transaction with aggregated trade volume and average prices.

Table 4-1 : Summary Statistics of Block Purchases and Sales for the Saudi Stock Market.

	No of trades '05-'08	Avg No of shares	Avg Value Per trade	Avg Quoted Spread	Avg Relative Spread
All trades	16,076,414	9,528	58,000	0.19	0.0030
Block trades	4,221,870	29,130	1,880,473	0.3586	0.0063
Block Buys	2,366,099	30,046	1,932,452	0.3607	0.0062
Block Sells	1,855,236	28,204	1,827,466	0.3564	0.0064

Notes: Number of trades, average number of shares traded, average value per trade, average quoted spread where quoted spread is defined as the ask minus the bid price, and the average relative spread defined as the ask price minus the bid price, divided by the midprice (the average of the bid and ask prices). The exchange rate is approximately ($1=3.75 Saudi Riyal).

4.4 Results

In Table 4-2 we formally test whether the magnitude of the price impact of buyer and seller initiated block trades is significantly different. Our test entails a comparison of the means for the temporary, permanent, and total price impacts of block purchases and sales. The asymmetry between block purchases and sales reported in the previous literature is transparent when we observe the permanent and total price impact. Block buys have a permanent (total) price impact of 0.49% (0.51%), whereas block sales have a permanent (total) price impact of -0.38 %.(-0.43%). Tests of equality for all three measured price impacts demonstrate that block purchases have a significantly greater price impact than block sales. The price impact asymmetry gives strong support that the information content of block purchases is higher than block sales. This is because the. SSM has few institutional investors and a vast majority of the governmental mutual funds are not active in the market. The mutual funds primarily follow a buy-and-hold investment strategy, implying that the market has more purchases than block sales. The purchase of a large trade in the SSM is perceived as a fundamentally strategic decision, whereas the sale of a large trade is perceived as less strategic decision or liquidity- based decision.

The temporary price impact which is mainly a product of short-run liquidity costs suggests that following a block sale, a reversal in prices is predicted and that the magnitude of price reversal is higher in block sales than block purchases. The higher reversal in the price impact for block sales at 0.04%, suggests that sellers in the SSM pay a liquidity premium that is at least three times the liquidity premium paid by buyers at -0.013%. The best five quotes for the bid and ask prices are transparent in the SSM and trades seem to react to a large block sale before it is executed through discounting the price at -0.42%. Once the block sale has been executed, a price reversal of 0.04% on average is observed. On the other hand, block purchases are executed at a 0.5% premium with a smaller price reversal of -0.01%. Given that the price impact continuation is higher in the block purchases, the results suggest that block buys are more informative than block sells. Our results are consistent with the prior literature. See among others, Chan and Lakonishok (1993) and Keim and Madhavan (1995).

Table 4-2 : Transaction Price Effects of Block Trades in the Saudi Stock Market.

	Permanent effects	Total effects	Temporary effects
Panel A Buys(n= 2,366,099)			
Mean	**.004917**	**.0050667**	**-.000137**
SD	**.012490**	**.0097506**	**.0091441**
Panel B Sell(n=1,855,236)			
Mean	**-.003883**	**-.0042678**	**.0004012**
SD	**.01246**	**.0097611**	**.0095251**
Panel C Test of Equality			
Mean difference	**0.001034**	**0.000799**	**0.000264**
t-statistic*(two-sample mean comparison test)*	**585*****	**794*****	**-47*****

Notes: Transaction returns surrounding block trades of 10,000 shares or more executed on all companies listed on the Saudi Stock Market over the time period 2005-2008, broken down by buyer (Panel A) and seller (Panel B) initiated trades. Three measures of price impact are reported :(1) Permanent, defined as the algorithmic return of transaction prices from five trade before the block to five trades after;(2) Total, defined as the algorithmic return of transaction prices from five trade before the block to the block trade; and (3) Temporary, defined as the algorithmic return of transaction prices from the block to five trades after the block trade. Panel A reports the buy-block traders while Panel B reports sell-block trades along with mean and standards deviations. Panel C shows the tests of equality between the two samples by performing a two-sample mean comparison t test. Standard errors are reported in parentheses. *** Significant at the 1% level.

4.4.1 Price Asymmetry and trade size

Existing theoretical and empirical research suggests that informed traders submit larger orders than do liquidity traders. If that assumption holds true in the SSM, we expect to have an increasing function between price impact asymmetry and order size for both block purchases and sells. To examine how price effect might differ within different size groups , we divide block trades of buys and sells into different groups. Following Madhavan and Cheng (1997), we partition block trades into three categories of 10,000 to 20,000, 20,000 to 50,000 and greater than 50,000.

Table 4-3 : Permanent Price impact Asymmetry between BUY and Sell within different sizes of block trades

	G1 Share volume 10,000-20,000	**G2 Share volume 20,000-50,000**	**G3 Share volume >50,000**
***Panel A: Buys**(n=**2,366,099**)*	***G1(n=971091)***	***G2(n=852122)***	***G3(n=542886)***
Mean	.00331	.00467	.00781
SD	.01123	.01250	.01379
***Panel B: Sells** (n=**1,855,236**)*	***G1(n=560662)***	***G2(n=683068)***	***G3(n=382971)***
Mean	-.00339	-.00414	-.00440
SD	.01129	.01269	.01414
Panel C Test of Equality			
difference	-.00008	0.00053	0.00341
t-statistic*(two-sample mean comparison test)*	315***	349***	347***

Notes: Size of the trade is partitioned into three categories. Small blocks 10k-20k (G1), medium block size 20k-50k (G2) and finally large block trades of 50k and above (G3). Panel A reports mean permanent price impact for buyer initiated trade for the three size categories and Panel B reports the mean permanent price impact for seller initiated trades for all three size categories. Panel C lists the mean difference along with the t statistics for the two sample mean test. Standard errors are reported in parentheses. *** Significant at the 1% level.

Table 4-3 summarises the price impact of block purchases and sales broken by the trade size category. In smaller size category of (10k-20k), the price impact is higher in the seller initiated trades, however, the difference is negligible. On the other hand, price impact asymmetry (higher price effect for buy block trades) is observed in the other two categories (20k-50k) and (50k and above) with a different of 0.054 % and 0.34%, respectively. There appears to be a significant price asymmetry in the price impact between buyer and seller initiated blocks. However, the price asymmetry is an increasing function of size, asymmetry in the magnitude of the price effect reaches its highest in the large group category, 50k and above. Average permanent price impact per block sale does not vary substantially according to the block size category. Conversely, the average permanent price effect increases substantially in the buyer group, contributing to the price asymmetry. The permanent price impact for block purchases in the large block category is 0.78%, more than twice the average price effect for the small block purchases at 0.33%. Selling medium to small blocks has approximately similar effect on prices whereas buying large blocks conveys information to the market more than buying small to medium blocks. It could also mean that seller of block trades tend to split large orders into smaller to medium orders or they use more frequently "stealth trading" .However, the distribution of block sales into the three size categories is not substantially different from block purchases distribution suggesting that both buyers and sellers of block trades in the SSM follow similar trading strategies.

4.4.2 Price Impacts and the Bid-Ask Spread

There is an emerging literature (Frino et al, 2003 and Gregoriou, 2008) that attempts to explain the price impact asymmetry in block purchases and sales by the bid-ask bias in stock prices. This is because when using transaction prices to calculate the price impact of block trades a systematic error occurs. This is due to the fact transaction prices, implicitly, assume an equal probability of a trade to occur at the ask or at the bid price. If this is not true, block trade price effects will be systematically biased.

In order to mitigate this systematic error Frino et al. (2003) and Gregoriou (2008) have computed the price impact of block trades purged of bid-ask bias. This is done by using quote data to calculate price returns where bid prices are used to calculate price returns for the sell trades and ask prices for the buy trades. Frino et al (2003) and Gregoriou (2008) find that the asymmetric price impact of block purchases and sales is diminished in the DJIA and the LSE respectively, when price impacts are purged of bid-ask bias.

Therefore, following this line of literature, we empirically examine whether the price impact asymmetry between block purchases and sales in the Saudi Stock Market, can be explained by the bid-ask bias. Following Lease et al. (1991), Frino et al (2003) and Gregoriou (2008) we calculate the order flow ratio, to examine the propensity to trade at the quote. We document the frequency of trading for five classifications; 1) at the bid price indicating a block sell, 2) at ask price indicating a block buy, 3) at the midprice price indicating a matching order, 4) between the midprice and bid prices indicating selling pressure, 5) between midprice price and ask prices indicating buying pressure. The order flow ratio is calculated for the entire sample using the following formula:

$$\boldsymbol{order\ flow\ ratio = \frac{(Ask-close)}{(Ask-Bid)}} \qquad \textbf{(4)}$$

As the order flow ratio approaches 1, it is more likely the trade price is at the bid price, and when it reaches 0, the greater the likelihood that the trade is at the ask price .Table 4-4 evaluates the percentage of block trades occurring at the ask and bid prices in the Saudi Stock Market over the time period, 2005-2008. 40% of the block trades take place at the ask prices whereas 37% of trades occur at the bid prices. Moreover, the trades that happen between the midpoint and either the ask or bid prices have similar percentages, 9% and 7% respectively. Given that the number of block purchases are higher, and the distribution of the percentages of trading at the ask and bid price are similar, indicates a propensity to trade at the ask or between the midpoint and ask more frequently than at the bid price.

Table 4-4 : Block Prices Relative to the Ask and Bid Price in the Saudi Stock Market

Order Flow Ratio	**Order Flow < 0.5**	**Order Flow = 0**	**Order Flow 0.5 < 1**	**Order Flow = 1**	**Order Flow = 1**
Trade	Between Midpoint and the Ask	At Ask	Between Midpoint and the Bid	At Bid	At Midpoint
Distribution	**9%**	**40%**	**7%**	**37%**	**7%**

Notes: This table shows the distribution of block trade prices in the Saudi Stock Market over the time period 2005-2008. The distribution is determined by the order flow ratio broken into five categories: (1) At the Ask Price, (2) At the Bid Price, (3) At the midpoint (the average of the bid and ask price), (4) Between the midpoint and the ask price, (5) between the midpoint and the bid price.

In order to eliminate the bid-ask bias in block purchases and sales, we employ quotes data to calculate block price impacts instead of transaction prices. Ask (bid) prices are used to compute the price impact for block buys (sells). Mean returns purged of bid-ask bias are displayed in Table 4- 5. We witness that the asymmetry in block purchases and sales seen in Table 4-2, remains even when we account for the bid-ask bias in block trade transactions. However, the asymmetry is reduced in magnitude for all three price impact measures.

Table 4-5 : Quote Price Effects of Block Trades in the Saudi Stock Market

	Permanent effects	Total effects	Temporary effects
Panel A Buys(n=2,366,099)			
Mean	**.0090771**	**.0093398**	**.0051918**
SD	.0131882	0.011248	.0096929
Panel A Sell(n=1,855,236)			
Mean	**-.0091983**	**-.0096808**	**-.0051626**
SD	.0138164	.0120155	.0101444
Panel C Test of Equality			
difference	-0.0001212	-0.00034	.0000292
t-statistic*(two-sample mean comparison test)*	**1.4e+03*****	**1.7e+03*****	**1.3e+03*****

Notes: Mean Returns purged of bid-ask bias surrounding block trades of 10,000 shares or more executed on all companies listed on the Saudi Stock Market over the time period 2005-2008, broken down by buyer (Panel A) and seller (Panel B) initiated trades. Three measures of price impact are reported :(1) Permanent, defined as the algorithmic return of transaction prices from five trade before the block to five trades after;(2) Total, defined as the algorithmic return of transaction prices from five trade before the block to the block trade; and (3) Temporary, defined as the algorithmic return of transaction prices from the block to five trades after the block trade. Panel A reports the buy-block traders while Panel B presents sell-block trades along with mean and standards deviations. Panel C shows the tests of equality between the two samples by performing a two-sample mean comparison t test. Standard errors are reported in parentheses. *** Significant at the 1% level.

4.5 Summary

In this paper we empirically examine the price impact of block trades, in the Saudi Stock Market over the time period of 2005-2008. Using a unique dataset of intraday data consisting of 2.3 million block buys and 1.9 million block sales, we replicate the asymmetry between block purchases and sales documented in the previous literature. However, unlike prior research the price impact asymmetry persists even when we encapsulate the biases in block transactions through the existence of the bid-ask spread. Overall, our findings suggest that in an emerging market where institutional trading is relatively scarce, market microstructure cannot explain the asymmetry in the price impact of large trades.

Our results suggest that bid-ask spreads do not fully incorporate the information asymmetry present within block transactions in emerging equity markets. This implies that the electronic limit order book system may not be the optimal trading mechanism for emerging markets. This is because as mentioned by Benveniste et al (1992) and Snell and Tonks (2003) market makers are superior in resolving information asymmetry than the order book system. Our analysis reveals that emerging markets may require a dealership system to improve the quality of their equity markets. Given the extensive trading in emerging equity markets as a result of international diversification, the empirical findings in this paper cannot be ignored.

chapter 5 : **Liquidity and Price Impact of Block Trades**

5.1 Introduction

The focus of this study is to examine some market microstructure implications in the Saudi Stock Market (SSM). Market microstructure is the study of the process by which prices are formed in a market including the role of information and the interaction of different agents within different sets of rules. Market microstructure studies have been covering various aspects, e.g., liquidity, transaction cost, bid-ask spreads, trading mechanism, trade size, and block trades. While there have been several studies of the impact of large trades on more developed markets, there have been none for the SSM and the other similarly related markets.

The SSM has been undergoing remarkable changes during the last five years and it is believed to continue gradually changing the infrastructure of the market. Such rapidly changing market is an interesting story by itself; however this market lacks microstructure research coverage which can be explained by the inaccessibility of the required trade and tick data. Hence, this is the main motive to cover such a market.

We analyze two dimensions of liquidity in the SSM: price impact and bid/ask spread. First, we attempt to examine the determinants of the price impact of block trades in the SSM to understand how this market, and perhaps similar markets, responds to large trades in a microstructure framework. Second, we study the relationship between liquidity and other trading activities such as volatility, volume and firm size. In both dimensions, we focus on intraday patterns of liquidity and cross-sectional variation effects of trading activities .

The SSM is a pure order-driven market where most of the activities taken places are initiated by private investors not institutional investors. In fact more than ninety percent of trading is individually initiated trades. The presence of institutional investors is still new and hesitant. Moreover, foreign direct investment is restricted and does not entail full ownership of shares bought.

Since establishment of the capital Market Authority (CMA) in 2004, the SSM has experienced important structural reforms. However, the need for strong market architect is crucial for SSM and other markets in the region. The CMA is promoting stability and liquidity in the market through introducing sets of regulations that encourage institutional investment and reduce information asymmetry in the market.

In this study we focus on the trading process, more precisely, the impact of block trades and the effect of asymmetric information on market liquidity and asset prices .We extend the research of this area in market microstructure and provide out-of-sample evidence through examining new dataset that covers all listed companies in the SSM at the one minute intraday level. We aim to study micro-structural effects on price behaviour of securities listed in the market .we focus on the liquidity issue and resiliency of the market following a block trade.

5.2 Literature review

The National Bureau of Economic Research(NBER) has a market microstructure research group that, it describe itself as , "is devoted to theoretical, empirical, and experimental research on the economics of securities markets, including the role of information in the price discovery process, the definition, measurement, control, and determinants of liquidity and transactions costs, and their implications for the efficiency, welfare, and regulation of alternative trading mechanisms and market structures".[31]

O'Hara (1995) defines the term as "the study of the process and outcomes of exchanging assets under a specific set of rules. While much of economics abstracts from the mechanics of trading, microstructure theory focuses on how specific trading mechanisms affect the price formation process".

While much of the financial investment theories focus on the equilibrium prices or the mechanic of trading where supply and demand interact, market microstructure has focused on how these mechanics work to determine price formation. Or as Biais et al. (2005), put it "In perfect markets, Walrasian equilibrium prices reflect the competitive demand curves of all potential investors. While the determination of these fundamental equilibrium valuations is the focus of (most) asset pricing, market microstructure studies how, in the short term, transaction prices converge to (or deviate from) long-term equilibrium values.''[32] This deviation of transaction prices from their long term equilibrium prices is attributed to the existence of frictions in the markets such as handling costs and the asymmetric information in the market.

The price formation process is a central issue of market microstructure literature. More specifically, market microstructure analyses how the market structure and design affect the following characteristics of financial markets: (i) Liquidity, (ii) transaction and timing costs, (iii) price formation and price discovery, (iv) volatility, and (v) trading profits.

[31] http://www.nber.org/
[32] Simultaneous auction type where in a perfect market, each participant submit their net demand at every price level possible, then price is set to match all demand submitted with total supply

Does Market microstructure matter?

For decades, academics, practitioners, and regulators have been debating and contributing to this issue. They are all concerned with market microstructure as it could enhance the efficiency and pricing mechanism in a market. Most of the literatures of financial markets microstructure focus on stock returns behaviour, transaction cost, volatility and liquidity as the most popular studied variables.

Vast topics and practical issues are usually covered in the literature, e.g., If market microstructure matters, then what is the optimal structure for a stock market? Do prices reflect true values of assets traded and how that is related to the market design? How does information play important role into price formation? Can we prevent price manipulation? What type of transaction costs exist in each market? How trading rules effect the price formation and discovery? Academic answers to such questions position, perhaps, the branch of market microstructure as the closest branch of financial research to practice. It is one of the most engaging finance topics by practitioners from banks and stock exchanges.

Empirical research suggests that market structure has important effects on properties of asset prices. See for example, (Amihud and Mendelson ,1987; Amihud et al.,1990). Moreover, Madhavan(2000) and Biais et al.(2005) are some of the most recent extensive surveys of the literature.

It is agreed upon that no single market design will serve all exchanges well. Differences in organisations set up, nature of markets and participants necessitate the adaptation of different architectural approaches. In other words, different market structures handle different market situations.

The field of market microstructure has been growing rapidly in the past two decades. Much of that rise is attributed to the developments and changes in structures and technologies of many stock markets around the world. Emerging market growth has fuelled the subject of market microstructure too. Obviously, the availability of transactions and quotes data such as high frequency data and real time data combined with increasing computing power has spurred the literature and made it possible to enhance the field with more research data that can be exploited for new opportunities of empirical works.

Clearly, we don't attempt to answer all the previous microstructure questions. Nonetheless; the market microstructure research argues that the transaction process and the organisation of markets have effects on the securities' prices. And in light of that assumption, we will discuss briefly different types of market design according to who provide the liquidity and whether trading is continuous or not to position our topic well within the context of market microstructure.

Market architecture (trading process mechanism)

The fundamental design characteristic of a market is called market architecture. There are many basic market architectures employed around the world. However, the two most popular trading systems are the quote-driven market and order-driven market. The most noticeable distinguishing feature between these two markets designs are the presence or the absence of intermediaries. In a quote-driven market or a dealer market, designated intermediary agents who can be called a specialist, broker or dealer undertake the responsibility to sell when somebody wants to buy and to buy when somebody wants to sell**.** In this type of market, investors trade against the prices quoted by the market maker. Based on information in their book, the designated market makers will post the bid and ask offers that they are willing to trade for at that time. Individual orders are not seen by other traders and the market maker will have to fill in the order from his inventory or match it with another order. Market makers work to smooth trading through balancing demand and supply of liquidity. One drawback of this type of market is the lower level of transparency as the order book only known to the market maker.

Since 1990, many stock exchanges have introduced electronic limit order trading, either to replace, or to run in parallel with batch auctions or a quote system .Major US exchanges, i.e. NYSE, AMEX and NASDAQ and London Stock Exchange (LSE) are all using quote-driven trading mechanism to an extent with some of them have hybrid systems now. For example, NYSE is a hybrid system (quote-driven and order-driven) where the specialist is in charge of monitoring the order book.

Unlike quote-driven markets, pure order-driven markets operate without the intermediation of dedicated market makers.[33] Instead, investors submit their buy and sell orders specifying their price and quantity, thus creating the limit-order book which should be

[33] In many order-driven markets, market makers still exist but they are not the only main quote setters. Traders can equally set the quotes in the market by interaction with other traders through the limit order book.

seen, at least partially, by all traders. Buyers and sellers provide liquidity to the market by posting limit orders (orders to buy or sell at a given price) and demand liquidity by placing market orders (orders to buy or sell at the current price in the order book). The price discovery happens based on the chosen price determination mechanism (discussed below) but in general order execution is usually prioritised based on price and then time. The majority of the stock exchanges outside the US employ order-driven systems which use computerised order matching. To name just a few; Paris Bourse, the Tokyo Stock Exchange, and the Singapore Stock Exchange.

Price determination mechanism

Like any other product, share prices are determined by interaction of demand and supply, however this interaction or trading can take place continuously or at specific points/periods in time. Market participants submit their bid/ask orders which are stored in a record called the book order until they are executed, amended or cancelled. In the case of continuous trading which is referred to as continuous auction, orders are matched as they arrive and are executed at the price available on the counter side of the order book. The order book contains all submitted bid and ask orders which can be matched and executed instantly and on a continuous basis. A trade takes place whenever a new bid (ask) arrives with a limit price equal to or higher (lower) than the limit price of the best ask (bid)in the limit order book meaning a higher price have priority in the bid (buy) side and a lower price takes priority at the ask (sell)side. If two orders have the same limit price on one side, then the order entered first into the book has the priority of trading.

In theory, the limit order book should be seen to all participants in the market. However for practical issue, normally several best prices on each sides are shown with each price level accumulating multi-orders volume.

A trade also can takes place in continues auction through market order. The market order is non-priced order to buy(sell) with specific volume that is met at the best order on the other side, if volume is not satisfied completely then the market order is executed against next best order at the other side climbing up the book until it is completely executed.

The other type of trading mechanism is called call auction which allows trades to take place at specific points of time. In a call auction, limit orders are stored and accumulated in the book, and then matching takes place at a specific time at a single price. This single market clearing price is determined in a way that should maximise trading volume and results in the execution of bids (asks) with the same or higher (lower) limit prices. Call auction is usually employed at the opening of the trading day, at the close of the trading day, and after trading halts. On the other hand, most stock exchanges uses continuous auction throughout the trading day.

Market microstructure models

Two major groups of models dominate the market microstructure theory literature. The first is inventory-based models, which studies how the intermediary (dealer, specialist, or market maker) uses prices to balance supply and demand across time and taking in consideration the uncertainty about the order flow and its relationship to the market maker's inventory position.[34] The second group of models is information-based models, which views the trading process as a product of different participants possessing different information regarding the prices of securities. In other words, information is distributed asymmetrically among participants in the market.

Inventory based models have actually predated the information based models. As the name implies, Inventory based models focus on the problem of inventory management where the market maker uses the price to balance supply and demand across time but facing unbalanced risk related to uncertainty about the order flow. The dealer controls the inventory through changing his quotes of bid and asks prices to induce the imbalance of buy and sell orders.[35] The difference between the bid and ask that is set by the dealer represents the spread which is his profit on any trade. The changing of the spreads by the dealer reflects his inventory position, the flow of orders and other factors like market condition. Early and pioneering models focus on dealers' optimisation and how agents set prices in order flow uncertainty environment (see for example, Stoll ,1978; Amihud and Mendelson, 1980; O'Hara and Oldfield, 1986). Issues discussed on these models include the nature of the order flow in determining the asset trading prices, dealer's optimisation problem, and the bid-ask spread as a function of inventory level, dealer's risk aversion and transaction size and cost. One important implication of these models is that transaction costs along with inventory cost determine the bid-ask spread.

[34] We use the terms dealer and market maker interchangeably throughout the thesis .It refers to those economics agents who set the quotes for the bid and ask in the market.

[35] Bid-Ask spread are the difference in prices traders welling to sell and buy at. In the following pages, Bid-Ask spread is discussed in more depth.

Contrary to the Theory of Efficient Market that assumes all participants in the market are equally informed about the true value of the asset traded, information-based models assume that information is not equally distributed among all participants in the market. A consequence of asymmetric information is that trading itself conveys information.

Starting with Bagehot (1971), a new theory emerged to explain market prices and spreads that does not depend on transaction cost, but rather centred on the importance of information on price formation. Examples of important work that follow are(Kyle ,1985;Glosten and Milgrom ,1985; Easley and O'Hara ,1987; Stoll ,1989; Glosten and Harris ,1988). A central idea in the information based models is that asymmetry information cost is an important component of the bid-ask spread which was ignored in the inventory based models.

Empirical findings suggest that the bid-ask spread can be decomposed into two or three components. Glosten and Harris (1988), George et al. (1991), Kim and Ogden (1996) and Madhavan et al. (1997) use models that decompose spreads into a combined inventory and order processing cost components and an information asymmetry cost component. Stoll (1989) , and Huang and Stoll (1997), however, provide a three-way decomposition of the spread into three components that is order processing, inventory, and information asymmetry components.

The inventory holding component is to compensate the dealer from undesirable inventory level situation while the order-processing component is to compensate the market maker for handling the transactions. Finally, the adverse selection component is to compensate the market maker when dealing with potentially informed traders which is the focus of the information-based models.

The third component or cost arises because information-based models stipulate that some investors are better informed “informed traders’’ about a security true value than others “uninformed traders or liquidity traders” who trade for any other reason.[36] Company directors, mutual fund managers, large shareholders and other insiders having access to private information not available to the market at large all are considered to be “informed traders’’ who are also motivated by profit maximising goals. In this type of trading environment, the dealer on average losses to the informed trader and therefore should normally profit when dealing with the uninformed trader. However, as the dealer is presumably unable to distinguish

36 Investors, who trade to adjust the size or the contents of their portfolio, are called liquidity traders or uninformed traders. Uninformed trading should be reflected in non-price change in the long-run.

the informed traders from the uninformed ones, he offsets losses by making gains from uninformed traders. This gain is a portion of the spreads that is to compensate the dealer for risk taking when trading with potentially informed trader(for details on how market maker set the bid-ask spread in response to adverse selection problem , see for example, Kim and Verrecchia, 1994; Gregoriou et al.,2005). The information based model first evolved in a sequential trade framework addressing issues related to adjustment of prices to information based on updating belief and expectation that is implied by the trading process. See for example ;(Glosten and Milgrom ,1985; Easley and O'Hara ,1987). The sequential trade models allow the learning process of the market maker or uninformed trader to be examined .In other words, the market maker learns from his previous trades. O'Hara (1995) explains that these models explicitly detail how asymmetric information affects market behaviour by demonstrating how market parameters such as size of the market or the ratio of large trades affects the bid ask spread and prices. Hasbrouck (1991a) measures the information effects as the permanent price impact of a trade while inventory, order processing, and other frictions should have temporary impact on prices. A liquidity-motivated trading has a temporary price impact on the stock because the order-flow does not carry value-relevant information.

In contrast, informed-motivated trading has a permanent future effect on prices of stocks. Most of the recent research focus on the adverse-selection component (the variable cost) as it represents an important function that is related to trade size. On the other hand, order processing cost is largely fixed and does not vary significantly with the trade size.

Other extensions of information-based models, consider the strategic behaviour of segments, informed traders and uninformed traders, these extension models are called strategic trade models. Kyle (1985), Holden and Subrahmanyam (1992), are some of the most prominent papers that have been analysing the former segment of traders. In the informed strategic trade models, participants can choose their timing or size of the trade therefore making equilibrium prices differ from those in sequential trade models. The focus of strategic informed trade models is how informed traders exploit their information and maximise their profit in dealing with the market maker. The other sets of strategic trade models, the uninformed trader case, relax the restriction that uninformed traders are not permitted to act strategically (see for example, Foster and Viswanathan, 1990; Seppi, 1990). These models add the strategic element and behaviour of the uninformed trader to the interaction between the market maker and the informed trader creating new dimension which is the price effect and behaviour of those uninformed traders or "noise traders".[37]

Liquidity

Liquidity is one of the main issues in microstructure literature. The word liquidity is often used in loose and imprecise way because it can cover many aspects. However, a market is considered perfectly liquid if a participant can trade at the observed prices irrespective to the quantity, time and order type (buy or sell) desired. It is defined as the ability to buy or sell significant quantities of a security quickly, anonymously, and with little price impact.

Since the start of market microstructures studies, liquidity has been the focus of some researchers trying to understand the price formation process. Starting with Demsetz (1968) who concludes that trading volume and number of trades, volatility, firm size and prices are the main determinants of liquidity. Tinic (1972) finds a positive relation between trading activity and liquidity and a negative relation between trading activity and volatility. Subsequent papers usually use bid-ask spread and price impact as main proxies for transaction costs and liquidity. These papers study the topic in two different ways. First, in cross sectional analysis where they investigate whether higher bid-ask spreads and higher price impact would lead to higher returns in assets. In general, these papers find positive relationship between expected stock returns and alternative proxies for individual illiquidity levels such as bid-ask spreads, price impacts and probability of informed trading (e,g., Amihud and Mendelson,1986, Brennan and Subrahmanyan ,1996) .

Second group of papers study the time-series properties of aggregate liquidity measures and find existence of liquidity patterns and predictability in how liquidity might affect asset prices. Example of these papers include (Chordia et al.,2001; Hasbrouck and Seppi ,2001; Amihud , 2002).

It is generally accepted that asset prices are closely affected by liquidity risk and liquidity patterns. Many research papers have focused on the liquidity effect on assets prices, the main finding is that liquidity is negatively related to stock returns. For example, Amihud

[37] O'Hara in her book "Market Microstructure Theory" had reviewed the most prominent models of both inventory-based and information-based.

and Mendelson(1986) suggest that average liquidity is priced in the market while Pastor and Stambaugh (2003) find that security return sensitivity to market liquidity is a risk factor that is priced in the market. Amihud (2002), Bekaert et al., (2007) provide evidence that liquidity commoved with returns and can predict future returns.

In any stock exchange, liquidity can impact the price at which securities are traded, therefore, it is crucial to measure and model liquidity for the assets and the market in general. Various measures have been used for liquidity, e.g. Grossman and Miller (1988) indicate that market liquidity can be measured by investigating the ability of executing trades under the current quotes price and time wise. More commonly cited is Kyle's (1985) practical definition of liquidity. Kyle identifies three components of market liquidity; the bid-ask spread "tightness", the depth of the market for a particular stock, and resiliency. Tightness is defined as the cost of turning around a position over a short period of time. Generally, the narrower or the smaller the spread the more liquid is the market. Depth of the stock or the market in general is the volume needed to move the prices by a given amount. The larger volume needed to move the prices the higher liquid is the market. Resiliency is the speed with which prices return to equilibrium or current level following a large trade. The price effect of a trade in a resilient market is small and short-lived. Depth and breadth of the market are concepts that are closely related to each other. A deep market is a one that you find incremental quantity ready to for trade above and below current price level.

Amihud and Mendelson (1986) suggest that liquidity can be measured by the cost of immediate execution in a view that bid and ask price is the sum of the buying premium and the selling concession. Recent work has introduced different metrics of liquidity, such as the illiquidity measure of Amihud (2002) where he shows that expected market illiquidity increases expected return because essentially illiquidity ratio serves as a proxy for the price impact of trade. He has proposed a liquidity cost in the markets using daily dollar volume and stock returns where illiquidity is measured as the average ratio of the daily absolute return to the dollar trading volume on that day as follow:

$$ILLIQ_i(t) = \frac{1}{Days_i(t)} \sum_{d=1}^{Days(t)_i} \frac{|r_i(td)|}{V_i(td)}$$

Where $r_i(td)$ is the return of the i^{th} security on day d in t^{th} month, Vi(td) is the dollar volume of the i^{th} security on day d in t^{th} month, and $Days_i(t)$ is the total number of trade days of the i^{th} security in t^{th} month. The basic intuition of this ratio is that the higher ILLIQ indicate the less liquidity a stock is. Thus, a higher ILLIQ means that the price of a stock changes more in response to smaller volume.

Persaud (2003) identifies a different but rather insightful fourth measure for liquidity which he calls diversity .He argues that lack of diversity can lead to liquidity black holes. Diversity refers to the differences in beliefs among traders in their market view. Persaud states "a liquidity black hole is where price falls do not bring out buyers, but generate even more sellers." Contrary to the normal belief that when prices go down an increasing number of buyers will exist, this is a condition where liquidity dries up and falling prices incline more seller. One important factor of this condition is the homogeneity of investors and how it could create the liquidity black holes. A stock market crash where panic selling motivates more selling is a clear example of liquidity black holes.

Market liquidity is considered an important factor that is closely related to market efficiency and stability. Liquidity is an important determinant of market behaviour. A liquid market has more capacity to accommodate order flow, hence promoting efficiency of the market. Chordia et al. (2005) consider the market's capacity to accommodate order imbalances as an indicator of market efficiency.[38]

Market systems differ in their role of who provides liquidity. In a quote-driven system, the dealer is responsible for creating liquidity in the market. He stands by ready to buy and sell shares at anytime. Quantity of shares (volume) demanded or supplied is determined by the traders not the dealer creating inventory balance risk for him. Hence the dealer is given exclusive rights as compensation by an exchange over a share; therefore the dealer can post different prices for purchases and sales. The dealer buys at the bid price P_b and sells for higher ask price P_a and the spread is the difference between the bid and ask prices $P_b - P_a$, known as the bid-ask spread. The spread is the main source of profit for the dealer in return for providing the market liquidity. The dealer sets prices first then investors submit quantities.

In contrast, in the order-driven system, investors voluntarily provide the liquidity for the market through the limit orders and subsequently creating the spread in the order book. Prices and quantities are set by investors as the order-driven system operates without

[38] Conditions where buy (sell) orders outnumber sell (buy) orders for a security in the market, which might halt trading for that security.

intermediary.[39] All orders are entered into the order book and wait for execution which could follow call auction or continuous auction mechanism. Trade transactions and best price levels on both sides are visible to all traders in the market, and orders submitted but not executed yet can be amended or cancelled by a trader.

Trading rules and mechanisms varies in the way liquidity provision is handled. For example, some markets allow for “upstairs market” to facilitate the large trade transactions. Upstairs market is a network of dealers and brokers that facilitate negotiation of block trades between the buyers and sellers or dealers who syndicate among themselves to take the other side of the trade. This alternative trading mechanism is used for different reasons, one of which is the information problem naturally embedded in the large trades as they may signal information to other investors thus creating adverse selection problem. The block trader might be at price disadvantage when a large trade moves the price unfavourably if the order is submitted to the downstairs market.

Asset Pricing and Liquidity

Conventionally financial theory argues that risk is the principal determinant of differences in expected asset returns and that trading volume and transaction costs can be neglected in asset pricing models. This view is well documented in the classical asset pricing papers such as, Sharpe (1964) and Lintner (1965) as well as the subsequent enrichments of that framework provided by Merton (1973). The traditional view is also at the heart of the general equilibrium analyses of many subsequent papers.

However, within asset pricing framework, liquidity and transaction costs have been integrated recently in some theoretical studies, which established that transaction costs are an important determinant of excess returns. Jacoby et al. (2000) develop a liquidity adjusted CAPM, where systematic and liquidity risks are inseparable. They show that the true measure of systematic risk when considering liquidity costs is based on net (after bid-ask spread) returns. Lo et al. (2004) propose a dynamic equilibrium model of asset prices and trading volume when agents face fixed transaction costs. In their study, they show that even small transaction cost can provoke “no-trade” regions for each agent optimal trading policy. Liu (2004) confirms these findings in an environment where multiple risky assets are traded.

[39] A broker exists to facilitate the matching of buyers and sellers in an electronic order driven market.

In an empirical framework, Fisher (1994), Marquering and Verbeek (1999) and Gregoriou and Ioannidis (2007) combine transaction costs with asset pricing models. In Fisher study(1994) it was shown that transaction costs parameters are relatively and significantly different from zero in US equity market which imply that transaction costs can explain a component of the equity premium as investors want to be compensated for relatively high transactions costs. This was reaffirmed in Marquering and Verbeek (1999) and in an extended model Gregoriou and Ioannidis (2007) in UK equity market.

More recently, there has been an emerging literature on the impact of liquidity risk "liquidity premium" on asset pricing, such as the work of (Amihud , 2002; Pastor and Stambaugh ,2003; and Sadka ,2006). These papers look at the systematic component of liquidity as a source of priced risk. However this work is mainly emerging and is of empirical nature.

Bid-Ask spread

The spread represents the difference between the best demand prices (Bid prices) and the best supply prices (Ask Prices). The ask price should always exceeds the bid price, otherwise one could benefit by buying at the Ask and immediately selling at the Bid which could create clear arbitrage opportunity. In other words, the spread should be positive or the market is in locked situation.[40] The spread can be thought of as the cost or the price of immediacy in both buying and selling securities (Demsetz, 1968). The bid-ask spread is determined differently in the "quote driven" market and "order driven" market. In "quote driven" market, investors trade against the market maker who sets the spread. The specialist should stand ready at any time to buy from sellers and sell to buyers. The market maker sets the quotes on the stock to compensate him/her for the costs and risks associated with holding and trading the stocks. In "order driven" market, there are no market makers, hence liquidity is provided to the market by investors and the spread is determined subsequently by those investors (individuals or institutions). They submit their orders to an order book (Limit Order Book) which enter into computerised systems that match buy and sell orders and information regarding transactions is available to all investors. Bid-Ask spreads are determined according to liquidity preferences of investors.

[40] Temporary situation when spreads between Bid/Ask prices are identical which made trading to stop until prices are corrected by subsequent orders.

There are two main theories of the bid-ask spread, ‘asymmetric information’ and ‘inventory control’. In ‘asymmetric information’ model, dealers trade with informed traders and liquidity traders. Informed traders have private information and seek to utilise it. Therefore, bid and ask prices are set in order to compensate dealer for the adverse selection problem. In ‘inventory control’ model the trade-off between price changes while holding the stock and being unable to trade the stock is considered by the market maker. The bid-ask spread should compensate market makers for order processing costs, inventory costs and the risk of trading against the better-informed traders. Each component of the spread has been modelled and empirically examined, however, information asymmetry perhaps is the most related component to the bid-ask spread .

Numerous researchers have tried to decompose the bid-ask spread into its three components using different statistical modelling approaches. Huang and Stoll (1997) group the various statistical models into two categories. In the first group of models, the covariance-based models , inferences about the components of the bid-ask spread are made by the use of serial covariance properties of observed transaction prices to infer about the components of the bid-ask spread (Roll, 1984; Stoll, 1989 ; George et al., 1991).

The second group of models is the trade indicator regression models, was initially proposed by Glosten and Harris (1988). This class of models uses the direction of trade flows to estimate the bid-ask spread components (e.g., Huang and Stoll, 1994; Lin et al., 1995; Hasbrouck, 1991a; Madhavan et al., 1997).

Many studies suggest applying the information asymmetry component in explaining the bid-asking spread, e.g. (Glosten andMilgrom, 1985; Glosten and Harris, 1988). They suggest that information asymmetry alone is sufficient to induce the spread solely, since the market maker widens the spread in anticipation of any potentially informed trades. Information asymmetry is based on the adverse selection theory and suggests that changed in bid- ask spread merely reflects the changes in the level information asymmetry. In general, spread decomposition models successfully isolate the adverse selection or information related component of the spread, and analyses employing an estimated informed trading component should be more powerful than those employing total spreads (Heflin and Shaw, 2000).

In limit order markets, because investors are not obligated to trade or keep inventory, the spread decomposition models that consider only adverse selection and order processing costs produce more reliable results (Majois and De Winne , 2003) .The order processing component is largely fixed which represent a fee set by a market maker to stand ready to buy and sell. Furthermore, in electronic limit order market where computing have reduced substantially the cost of data and order processing, the asymmetric information component is the focus of the spread decomposition models.

Macrostructure studies have reported various intraday liquidity patterns of the bid-ask spread; the U-shaped, L-shaped, J-shaped along with other patterns (e.g., Wood et al., 1985; Brock and Kleidon,1992; Chan et al., 1995; Madhavan et al., 1997 ;McInish and Van Ness, 2002). Moreover, Al-Suhaibani and Kryzanowski (2000a) find the U-shaped behaviour of the bid-ask spread in the SSM even though it shows different structure and characteristics.

Most of these patterns indicate high spread at the beginning of the trading session then declining during the day, a behaviour that can be related to uncertainty. The similarity in liquidity patterns in different market system, suggests that market makers alone, in a quote-driven market, cannot be accounted totally to the widening of the spread at the open and close of the trading session.

Madhavan et al. (1997) in a study of sample of some NYSE listed companies, show that security prices change because of new arrival of public information, and because of the information revealed in the trading process itself. They report the U-shaped bid-ask spread with information asymmetry declines during the day, while transaction costs increase. Huang and Stoll (1997) finding supports the presence of a large order processing components and smaller adverse selection and inventory components. They also show that spread is affected by the trade size.

Existing market microstructure theories and models on the components of the bid-ask spreads are mainly developed within the framework of quote-driven dealer markets, specifically, using the NYSE data. However, many studies have shown that bid-ask spreads are not unique to quote-driven dealer markets.

Cohen et al. (1981) demonstrate that order-driven auction markets produce positive bid-ask spreads, and that the free entry and exit of informal market makers will sustain a viable securities market. Glosten (1994) also shows that information asymmetry costs generate positive bid-ask spreads in an order-driven trading system. Handa et al. (1998) study how the spread is determined in an order market environment and suggest that spread are a “natural property” of the order driven market. Spread exists because of the value participants place on trading with certainty. However, they emphasised that regulators should take in consideration that order driven market requires a reasonable balance between various types of participants. Other examples of order-driven market studies include ; Brockman and Chung (1999) who study the bid-ask spread components of (Hong Kong Stock Exchange) and Huang (2004) who focus on the bid-ask spread and its determinants in (Taiwan stock Market).

Spread as a measure of liquidity cost is defined in many different ways. Three types of bid-ask spreads are usually studied, quoted spread, effective spread and relative spread.

1- Quoted Spread is the difference between the ask price and bid price :

$$\textbf{Quoted spread}_{\mathbf{t}} = \textbf{ask price}_{\mathbf{t}} - \textbf{bid price}_{\mathbf{t}} \qquad \textbf{(1)}$$

The main intuition of this measure, is that when a trader buys at the ask price then sells at the bid price she will incur a transaction cost which is the difference between the two prices. This measure of the spread does not consider trades that take place inside the best bid-best ask quote and therefore is considered unreliable measure of liquidity cost. Many large trades take place outside the bid ask spread whereas the many small trades happen within the spread (see, e.g., Lee, 1993; Madhavan et al., 1997).

2- relative spread is calculated as :

$$\textbf{Relative spread}_{t} = \frac{(\boldsymbol{ask\ price_t} - \boldsymbol{bid\ price_t})}{\boldsymbol{mid\ price_t}} \qquad \textbf{(2)}$$

Relative spread method deflates the quoted spread by the share price which is the midpoint between bid and ask prices. It is very useful and gives meaning to the size of absolute spreads relative to the share price. In cases where the minimum price change unit is fixed (e.g., Saudi stock market), quoted spread at its lowest unit of change will be equal among many stocks and therefore will not show any statistical power in the analysis. In relative spread method, price variation will be reflected in relative spread variable which is more powerful in an analysis.

3- Effective spread is defined as the following:

$$\textbf{Effective spread}_{t} = \mathbf{2}(\textbf{trade price}_{t} - \textbf{mid price}_{t}) \qquad \textbf{(3)}$$

Here the midpoint price is just the average of bid and ask prices, where:

$$\boldsymbol{mid\ price_t} = \frac{(\boldsymbol{ask\ price_t} + \boldsymbol{bid\ price_t})}{\mathbf{2}} \qquad \textbf{(4)}$$

The effective spread avoids some drawback associated with using the quoted spread. The idea of the effective spread is that it measures how costly an investor is trading relative to the midpoint. It shows how trade price varies from true price approximated by the bid/ask mid price. This estimate is often used to proxy for the total price impact of trades and has been suggested by many (e.g., Lee, 1993; Huang and Stoll, 1996). If all trades take place at the prevailing bid and ask quotes, the effective spread is equal to the quoted spread. If some trades take place within the spread, the effective spread is smaller than the quoted spread (Bollen et al., 2004). This measure assumes that any trade above mid price is considered a buyer-initiated and any trade below mid price is seller-initiated. It measures how far a trade is relative to the midpoint to show price improvement and to reflect to true round trip of buy and sell trade the effective spread is multiplied by two.

Probability of Informed Trading (PIN)

Easley et al. (1996) develop an empirical technique called Probability of Informed Trading (PIN) to measure the degree of information asymmetry in the market. Subsequently, PIN has been firmly established in the literature as a measure of the extent of informed trading (see, e.g., Brown et al., 1999). The technique which is built on the sequential trade model, estimates the PIN directly from the trade process data. Originally this technique was used to investigate whether the change in spread is explained by the difference in information based trade in both less-frequent and more-frequent traded stocks. The PIN has been since employed in wide range of applications in market microstructure and other fields of empirical finance, e.g., the importance of trade size, the order flow in an electronic market and the order flow around corporate event announcements. The PIN microstructure model assumes that there are three types of agents in the market; informed trader, market maker and liquidity trader “noise trader” who trade for exogenous reasons. The market maker adjusts the spread according to his belief about the order flow arrival and information event occurrence. The arrival of liquidity traders’ orders of buy or sell is modelled as independent Poisson processes .Liquidity traders are equally to submit buy or sell order and the numbers of buy and sell trades are independent of one another. The informed trader arrival is conditioned on information event occurrence with some form of probability. If the information event is good news, the informed trader will buy and sell otherwise. It is crucial to classify trades to buys and sells and then to count the number of buyer- and seller-initiated trades per day and per stock to calculate the PIN. Using maximum likelihood ,four parameters are estimated in the model- the probability that an information event occurs on a given day , the probability that an information event is negative and the order arrival rates of informed and uninformed traders. The higher the probability of informed traded the higher the degree of information asymmetry is expected.

Easley et al. (1996) show that PIN is closely related to the spread which reflects the adverse selection cost of trading. It is important to mention that an estimation bias of PIN can arise from inaccurate classification of the trade; however, PIN as discussed has been used in varieties of studies and proved to provide insightful empirical inference about the information asymmetry in the market. Easley et al. (2002) use PIN in capturing the information asymmetry aspect of illiquidity and they indicate that PIN has a direct impact on expected stock returns, regardless of the stocks' illiquidity and return characteristics.

Price impact and Block Trades

In market microstructure research, market makers or traders update their beliefs about the true value of security prices in response to transaction data as well, hence trade itself convey information to traders which is a key element of asymmetric information models. Large trades have the capacity to move prices directly through the trading itself, as well as indirectly, by influencing the trading decisions of other market participants who may observe the action of large trade initiators.

The security's price change that is attributed to trade information is the price or market impact of a trade. The effect of trade size on securities' prices measures the market depth indirectly through measuring the price impact of large trades. However this depth is only analysed when the block trade happens. In a less deep market higher price impacts reflect a major challenge to stock exchanges and policy makers. Large trades in the stock market are known as block trades. How trading volume affect prices is an evolving topic especially large trade that concerns institutional investors and other types of investors. Information asymmetric models consider that trade size is correlated to the probability of holding private information by the trade initiator and suggest that the price impact of a trade is an increasing function of order size (Easley and O'Hara, 1987). Within adverse selection context, block trades might signal information to other traders in the market.[41] If a trader wants to buy a small volume immediately then he can submit a limit order at the ask price or alternatively he can submit a market order. The transaction takes a place through matching between the buyer's price and quantity and the seller's price and quantity at the ask price which is the cost of immediacy. Normally, in block trades case, the volume at the other side is not sufficient to satisfy the quantity completely unless the trader is welling to jump up to the next higher ask price. Consequently, to satisfy block trades investors face unwanted upward price impact in case of buying and unfavourable downward price impact in case of selling.

The price impact of block trades is of interest to various groups; researchers, regulators and practitioner. From researchers' point of view, understanding the interrelationship between trade, information and prices is the core business of market microstructure research and other related fields. Moreover, exchanges and regulators who are concerned with issues like liquidity, transparency, trading process and rules show great amount of interest in the price impact of block trade research. Understanding the relationship between trade size and price impact can help investors and practitioners, who are profit maximisation seeker, to formulate the best action to transact in a way that would minimise the affect of block trades on their investment performance, e.g., trading in the upstairs market or splitting large orders into smaller multi-orders that are traded anonymously in the downstairs market. Seppi (1990) suggests that upstairs markets are preferred to electronic downstairs markets by those traders who can credibly convey that their trades are uninformed. Block trades are used by uninformed agents for liquidity reason whereas informed agents split their large orders into smaller ones when trading for information reasons.

Madhavan and Cheng (1997) relate the choice to trades at the upstairs or downstairs market to the ability of the trader to credibly signal their motive for trading. A liquidity trader who can convincingly signal the liquidity motive behind his trade can trade large block at the upstairs market with less price impact. On the other hand, a trader who cannot signal his trade motive will trade anonymously in the downstairs market and face the consequence of a higher price impact.

The price effect of block trades has been extensively analysed in the literature with normally classifying the impact into permanent and temporary components. The permanent component is the price change that is due to the information content of the trade while the

[41] market impact studies that show the effect of trading activity on stock prices include but not limited to (Chan and Lakonishok,1995, Keim and Madhavan ,1995 ,Chakravarty ,2001, Chiyachantana et al., 2004,Chordia and Subrahmanyam ,2004).

temporary price impact is the transitory change in prices due to the market friction such as liquidity effect and imbalance between demand and supply.

Chan and Lakonishok (1993) summarise three potential explanations for price changes caused by large trades that were discussed in the literature: (I) short-run liquidity cost,(II) imperfect substitution, and (III) information effect(adverse selection problem).[42] Short-run liquidity cost occurs because of the demand and supply friction at the time of the trade which may result in a price effect that is most probably temporary. A large trader who wants to trade would pay a price concession for the immediacy. On the other hand, liquidity providers should be compensated for taking the other side of the deal with a price concession to their favour.

Large trades move prices also if there are no perfect substitutes for a particular stock. In the case of no perfect substitutes, prices tend to change permanently as the buyer or seller has to offer a higher discount to make the deal attractive. Large trades are believed to convey information about the prospects of a stock. Participants in the market learn new information about underpricing or overpricing of stocks from the decision of large traders to initiate buy or sell trades. The information effects depend on the identity of the traders and size of the transaction as a proxy for the information content of the trade. A permanent price change is expected to be associated with informed trading which subsequently lead to new equilibrium prices.

Different approaches are being used to measure the price impact of block trades. For example, event study methodology was used by (Kraus and Stoll, 1972; Holthausen et al.; 1987; Keim and Madhavan, 1996). Other researchers have used time series methodology, vector autoregressive VAR-model specifically, to test the relationship between trading volume and price movement (See, e.g., Hasbrouck, 1991a,1991b; Dufour and Engle, 2000). The VAR-model was used to test for the dynamic changes in the model and to test for time wait between trades. Chan and Lakonishok (1997), Domowitzet al. (2001), and Chiyachantana et al.(2004) study the stock price volatility and its relation to price impact , they find that when volatility as a measure of dispersion in beliefs increases it results in greater price concessions or price impact. Frino et al. (2007) measure the price impact of the block trade in the Australian stock exchange through cross-section regression method and added time of the day variable along with other variables to a theoretical model in an attempt to examine the price impact determinants.

[42] Scholes (1972) and Kraus and Stoll (1972) were the first to develop hypotheses on how stock prices react to block trades: the substitution hypothesis, the price-pressure hypothesis or short run liquidity costs, and the information hypothesis.

Most of the previous models used were linear in nature, however several papers have used and suggested non-linear models to test the price impact of block trades (See, e.g., Hasbrouck, 1991a, 1991b; Kempf and Korn ,1999).

The majority of the empirical studies concerning block trades have documented intriguing results supporting an asymmetric price impact, where absolute price responses for buys and sells are significantly different.[43] The obvious result, so far, is that buyer-initiated trades have a stronger price impact than seller-initiated trades. It indicates that block trades sellers pay liquidity premium while buyers do not as price continuation is usually associated with block trade purchases and price reversal is associated to block trade sales. One established explanation to this phenomenon attributes it to a higher informed trading in purchases than in sells. Chan and Lakonishok (1993), Keim and Madhavan (1996), and Saar (2001) among others provide institutional explanation to this asymmetry that is the buy side is assumed to act on information whereas the sell side trades for liquidity motives. Based on the previous analysis, sell block trades can be motivated by many reasons one of which is liquidity motive whereas the buy block trades are likely to convey firm-specific information. The decision to sell a stock reflects the limited option a trader has among stocks in his portfolio, whereas the decision to buy a stock indicates a fundamental interest in that particular stock among many stocks in the market. The difference of price effect between block purchases and sales has been confirmed in many other markets outside the US where it was first depicted and in different trading systems (see, e.g., Gimmil,1996 ; Gregeriou , 2008 , in the UK market ;Aitken and Frino, 1996a, in the Australian market; Chiyachantana et al.,2004 in study covering 37 international market) .

In attempting to include variables that affect the price impact, researchers usually choose size of the trade as a proxy of information asymmetry. Barclay and Warners (1993), and Dufour and Engle (2000) argue that, trading frequency would be a suitable explanatory variable that captures informed trading as informed traders prefer to use medium size orders but more frequent trading ,therefore the number of orders might provide superior information than the order size. Other variables beside the size of the trade itself and the direction of the trade(buy or sell) that have been considered in various studies as determinants of the price impact include; stock price volatility, market condition, bid-ask spreads, turnover, firm size and momentum return effects .

[43] Some studies that have found asymmetry of price impact include Kraus and Stoll (1972), Holthausen et al. (1987, 1990),Gemmill(1996), and Chan and Lakonishok (1993, 1995).

5.3 Saudi Stock Market (SSM).

At the heart of microstructure research, lies the assumption that structure of the market and its trading process design has an effect on equilibrium prices. In other words, market microstructure could play important role in making prices to deviate from their fundamental values. The rapid structural, technological and regulatory changes the SSM has been facing recently have brought interests to focus on the microstructure aspects of this market. The newly established Capital Market Authority, CMA has made dramatic reconstruction to the exchange in terms of regulations and structural changes to promote efficiency and liquidity. The number of companies that are traded in the market has nearly doubled in 5 years time and commercial banks are no longer the only entities authorised to provide brokerage service. Now around 80 brokerage houses have been granted licenses to operate in the market. [44] The list of changes goes on from establishing insider trading rules and imposing fines on companies who pass deadline of earnings announcements to changes of trading time and tick size. Clearly all these changes are microstructure related and motivate us to study how price formation are affected .Therefore , an attempt to explain some of SSM aspects in a micro-structural framework should give insight to all interested parties.

Al-Suhaibani and Kryzanowsky (2000a ,2000b) are the only studies that have attempted to examine the trading activities in a pure market microstructure context .[45] Al-Suhaibani and Kryzanowsky (2000a) find that although the SSM has distinct structure, its intraday liquidity patterns are similar to those found in other markets with different structures but the average relative inside spread is large compared to other markets which they related it to the tick size being relatively high. They also record that market width and depth is relatively low and finally the limit order has a short duration on average and has high probability of subsequent execution.

In a study covering the market index, five industries and fifteen listed companies, Alsubaie and Najand(2009) investigate volatility–volume relationship in the SSM. They show strong volatility persistence and indicate that the rate of information arrival can be significant source of the conditional heteroskedasticity at the firm level in SSM. They also suggest that price volatility is potentially forecastable with knowledge of trading volume.

[44] Thirty Five are already operating and provide intermediation by the beginning of 2009.
[45] Chapter one of this thesis covers characteristics and studies related to the SSM in details.

SSM is relatively newly established market, officially organised in 1985, and by far the biggest stock exchange in the Middle East region. According to the Arab Monetary Fund's annual report for the year ended December 2008, which provides statistics for 15 stock markets, the capitalization of the SSM represents 41% of the total market capitalization of these markets, while the value traded of the SSM represents 67% of the total stock value traded in all member markets. The market value of the stocks at the end of 2008 amounts to 246.5 billion dollars down from 518.984 billion dollars just one year back in 2007, which is more than 52 percent drop in value. The SSM is an interesting market to examine in the way that a few companies are publicly listed with government owning the majority of shares, yet it is very actively traded market . The average company size is 4.7 billion dollars, the highest in the region where the average of company size for 15 stock markets is around one billion dollars[46]. Many firms exhibit a low dispersion of shareholdings and the concentration of shares is relatively high the SSM, compared to other developed market. By the end of 2008, the free floating stocks that are available for trade represent 37% of total stock outstanding in the market (excluding major passive shareholders and government shares).

It is characterised as large active market with few number of companies. Trading in the market is only for common stock and no option market or short selling is allowed. The distinctive characteristics of a large market size and trading volume relative to the number of companies combined with different characteristics such as absence of institutional investors , undergoing development and small breadth of the market make it very unique environment to study the effect of these specific structural aspect on securities' returns and how the order size affect prices.

The SSM is a fully electronic pure Order – driven market where buyers and sellers provide liquidity through the limited order book. They provide liquidity by limit orders and demand liquidity through market orders. The SSM lacks the existence of major institutional players, who usually form the backbone of such market. A few government-owned pension and investment funds are the major shareholders of "blue Chip" companies; nonetheless, they are passive buy-and-hold investors. Foreign investors are forbidden from market participation directly but they can enter into equity swap agreement with local authorised brokerage companies where the foreign investors have right to economics benefits of the equity but do not enjoy voting rights or any other rights, the dealer retain the legal ownership of the shares.

[46] All figures are taken or calculated from the Capital Market Authority ,CMA.

As for the domestic mutual funds, their total value represent only insignificant portion of total market value of the stock market at 1.8 percent by the end of 2008. [47]

The Number of shares traded and number of transactions have grown remarkably in the period 2001-2008 averaging 142% and 174% ,respectively. The SSM has witnessed high growth in trading volume and in number transactions. However the average number of shares per transaction has sharply decline from 8,873 shares per trade in 2003 to just 1,144 shares per trade in 2008. This decline is partially ascribed to the remarkable increasing number of small investors who enter the market each year.

Investors who want to trade large block trades normally do so in the downstairs market or go through the unofficial “upstairs market” where the two parties are introduced to the deal through personal networks of the dealers and then the trade is recorded in the normal way. At other times, large investors meet directly without any dealer efforts, and then they go through a dealer to register the trade. The upstairs market trades in Saudi does not affect the index calculation , however, it implicitly has a price effect on the security traded as the quantity is recorded for the trading volume and the stock exchange announces it on its official website at the end of the day or the next day but not on regular basis. The criteria followed to announce or not is not fully understood, but we assume the more significant the block trade in terms of value and percentage of company ownership the more likely that this trade would be announced at some time. A report by the IMF (2006) regarded the SSM as buoyant market, with significant turnover and limited provision of investment information.[48] Recently, the stock exchange starts listing major shareholders (5%or more) in any company, and the lists is updated on a daily basis. Some active investors can infer about large trades through watching the changes to the major shareholders’ list.

In this study block trades are examined to see how they could affect prices. In principal prices should only be moved by the arrival of new fundamentals information and block trades information should not have effect on the prices, therefore, in our study we will examine market frictions such as liquidity measures, volatility and bid ask spreads.

[47] The number is calculated from the Capital Market Authority, CMA.
[48] A market in which prices have a tendency to rise easily with a considerable show of strength.

Trading rules

Since September, 2006, trading on the SSM consists of one trading session from11:00 AM to 03:30 PM and five trading days that is Saturday through Wednesday. The market has four states during the day, Market Open (Order Maintenance), Market Open (Trading), Market Pre-Close and Market Close.[49] The official stock exchange (Tadawul) in its website has a description of each state and how orders are maintained, entered and executed throughout the stages.

Trading on the SSM takes two different forms of trading mechanism , call auction is used to open trading in the market open state (maintenance and trading states) and then continuous auction is used throughout the day(trading state). Call auction is used during the first five minutes of a day's trading to determine an opening price which is an average that maximises trading volume. Orders entered during the pre-open periods are queued in the system until an opening price is determined which is recalculated every time an order in the pre-trade period is submitted and finally a trading price is set once per trading day at the opening. The following criteria are used to determine the opening price; share volume, minimum order imbalance and share price from the previous close. Once the allocation of volume at the opening price is complete, the market is now open for continuous trading where limit orders are submitted by buyers/sellers and transactions take place immediately upon the availability of counterparty order or instantly in the case of market order. During the continuous period, limit orders that do not immediately match with any another orders on the other side are queued in the system .Orders that are queued in the system follow price and FIFO time priority. Settlement time for transaction is t+0, that is the time of transfer of ownership is the time of transaction.

During continuous trading period, orders must be prices within the 10% higher or lower than the previous day closing price, this cap is set by TADAWUL (daily cap on price movement up or down) to control for large swings in prices during a day for all stocks listed. The only exception is for new IPO's where the stock is normally allowed to move freely for the first a few days of initial trading.

The trading mechanism followed in the SSM is very much similar to the theoretical model of electronic limit order book by Glosten (1994). The information of trades and status

[49] In the old system, there were two sessions per day (10: AM-12AM and 4:30PM-6:00PM) and six trading days per week from Saturday through Thursday where Thursday has morning session only. The Official Government weekend in Saudi is Thursday and Friday.

of the book are available immediately to the public through electronic screens either at the trading rooms at the dealers or through online access for subscribed users .Traders can also phone their brokers to inquire about prevailing quotes and prices, and to place orders. In particular, the limit order book is partially displayed to the public by most brokers where the five best ask/sell quotes and quantities are publically available with less than five minute time lag. However, the best quotes are displayed in aggregate format (a best quote shows only total quantity available at that quote). The status of the best quotes along with quantities is updated each time an order arrives, is cancelled or is executed. The last trade is shown to all participants containing price, quantity and time after it takes place and the last 20 trades are shown in TADAWUL official website at the end of the trading day.

Independent quotes and trades data providers who charge premium on their services can show more detailed real time quotes and have facility to allow users to watch the Order Book for bids and offers – particularly the 5 best quotes by price level and 10 by orders in real time. Independent data vendors also show trade by trade data at end of the trading day.

Investors who want to transact large block trades can choose to transact anonymously in the downstairs market through automatic routing and execution but probably face a higher price impact due to the trade size implication and adverse selection problem. As an alternative, negotiation and search is taken place between buyers and sellers through personal networks of investors and dealers thus creating informal "upstairs market".[50] Once a buyer and a seller agreed on price and volume they ask for the trade to be handled through the system. Price of such deal may not reflect current market/firm condition; therefore the trades in the upstairs market are not integrated into the price discovery mechanism of the trading system except when it is reported by Tadawul during the trading hours or sometimes at the end of the trading day. The price and volume are entered into the system as put-through to satisfy transparency and reporting requirements. However , upstairs trades prices are not considered in the computation of the market index nor the firm current prices because they affect the volume traded only but not the price even though there is an implicit price impact on the market due to the fact that these large trades are assumed to contain information that is not revealed publically . For the previous reasons, we only consider block trades that take place in the normal automated downstairs market. Any identified "upstairs" block trade is excluded from

[50] Sometimes Tadawul officially send messages to dealer in search for counterparties. Presumably, only liquidity trader would seek help from the stock exchange to facilitate the trade.

the study, but not all these upstairs blocks are effectively identified. Sometimes Tadawul do not announce every off-market block trade.[51]

Explicit direct transaction cost in the SSM is comparatively low at 0.12% of total value of the trades levied on each party of the trade(buyer and seller) or the minimum of (SR12=USD 3.2) for trades less than SR10,000. The minimum price variation unit, or tick size, for all shares used to be at 25 Hallalas (1 Saudi Riyal=100 Hallalas), regardless of the trading price of the share traded. The unified tick size has sever effect on the cost of trading and market liquidity because it limits the prices that traders can quote and thus restrict price competition especially for the low-priced shares. For example , if the share price is SR 10, the least change, up or down, in ask or bid price will be 25 Hallalas; that is, SR 10.25, or SR9.75, equivalent to 2.5% change in the share price while it is only 0.25% for a stock priced at S.R 100. Clearly that would create return bias because stocks with relatively low prices would show higher price impact and volatility in their returns. The stock exchange realising the problem has introduced a new scheme where Tick Size is measured based on the share price, at three new bands as shown bellow in the table.

Table 5-1: Old and New Tick size

BANDS	Tick Sizes
New system	
BAND 1 :Shares SR25.00 or Below	**SR 0.05**
BAND 2 :Shares SR25.10 to 50.00	**SR 0.10**
BAND 3 :Shares SR50.25 and above	**SR 0.25**
Old System	**Fixed (SR 0.25) for all stocks**

This table compares the new system for tick sizes that is adopted in Sep, 2008 with old unified tick system.
Source: TADAWUL, USD1=S.R3.75

[51] Al-Suhaibani and Kryzanowsky (2000a) consider large value trades to be qualified for an upstairs market usually has minimum value of SR500.000 that is equal to $133.333

5.4 Data Processing and Descriptive Analysis

We use high frequency data (one minute interval). The dataset is taken from Mubasher, a vendor of quotes and transaction data in the SSM .However historical prices had to be stored in a monthly basis because data vendors only provide at anytime one month historical data. It is a unique dataset in the way that it includes all listed companies (124 companies) in the SSM and the market Index, Tadawul All Share Index (TASI) at the intraday level. The dataset contains all transactions which are time-stamped to the nearest minute and in some cases it aggregates all transactions occurred within the minute. Any inference about the data is applicable to the whole market as the dataset is free from any sample bias. It is highly comprehensive dataset as it is almost four-year intraday dataset, from Jan 2005 to October 2008, with over 16,076,414 records of all transactions and bid-ask quotes. We define block trades as any trade with over 10,000 shares that is 4,221, 870 trades or 20.8% of all trades in our sample. Clearly, the sample size, when compared with those used in previous studies, is very large. Frino et al. (2003) used 2,796,561 block trades in their working papers. Chan and Lakonishok (1993) examine 1,215,387 transactions while Madhavan and Cheng(1997) analyse only 16,343 blocks.

Trade classification is used to estimate our model of price impact, the probability of informed trading, and effective spreads. For this purpose we use Lee and Ready (1991). The idea underlying the Lee and Ready (1991) method is to infer trade direction using the transaction price relative to the previous price "tick rule" or to the quote mid-point price "midpoint test". The tick rule test compares trade price changes relative to previous trade price. If the price change between trades is positive, then the transaction is coded as a buy-initiated trade. A negative price change yields a sell-initiated trade. We follow Bonser-Neal et al. (1999) for how to sign a trade when the change in the price is zero. We compare trade price P (t) with the trade price $P(t-2)$ and if the change in price is still zero, we repeat the process until we find a difference in prices or we stop at $P(t-5)$. If the price change is still zero at $P(t-5)$ then this trade is unclassified and omitted.

We conduct the midpoint test by comparing trade prices to quote midpoints prevailing at trade time calculating the midpoint between the bid and the ask quotes. In "LR" test, the prevailing midprice corresponding to a trade is used to decide whether a trade is a buy, a sell, or unclassified. If the transaction price is higher (lower) than the midprice, it is viewed as a buy (sell). Any trade price at the midpoint will be unclassified. Although there is a possibility of misclassification, we follow this procedure as it is standard and widely accepted in the literature.

Using “tick rule”, we classify 2,366,099 trades into buy trades and 1, 855,236 into sell trades with total sample number of 4,221,335 transactions. On the other hand, using “midpoint test” we classify 1,714,072 trades as buy trades and 1,646,728 trades as sell trades. The total number of the sample is 3,360,800 after data cleaning which is lower than the tick rule sample, because we exclude unclassified trades. Consistent with prior research, we associate trade indicator for each trade to indicate the nature of the trade: 1 (buy), −1 (sell), or 0 (undecided). Table (5-2) reports some descriptive information about our dataset. The dataset contains intraday one minute transaction data of all companies in the SSM making up the TASI index. Each one-minute interval includes: Ticker, Date, Time, Open, (Ask), (Bid), Close, and Volume.

Minute intervals in this study are treated as trades; however it sometimes happens that multiple trades take place at the same minute. We follow (Engle and Russell, 1998, and Spierdijk, 2004) and treat multiple transactions at the same time as one single transaction with aggregated trade volume and average prices.

Since the data do not provide, directly, information on the prevailing direct quotes of bid and ask prices, we cannot use the Lee and Ready (1991) midpoint rule to assess the trade sign effectively. We believe the “tick rule” should provide more accurate trade classification algorithm that fits the nature of the data .Lee and Ready (1991) state that “When only price data is available... the 'tick' test performs remarkably well”. However, for comparison purposes, we report both tests classifications and number of trades along with means of price impact in the following table.

Table 5-2 : Summary Statistics for Block Trades.

	No of trades	Avg No of shares	Price Impact%	Variance
Panel A: Trade sign classification using Tick Rule.				
All Trades	16,076,414	9,528	---	---
BlockTrade(26.2%)	4,221,870	29,130	0.067	0.01323
Buy (14.7%)	2,366,099	30,046	0.491	0.01125
Sell(11.5%)	1,855,236	28,204	-0.388	0.01247
Panel B: Trade sign classification using Midpoint Rule				
Buy (10.6%)	1,714,072	27,613	0.28777	0.01193
Sell (10.2%)	1,646,728	23,472	-0.1926	0.01176

Notes: This table reports the number of observations in the dataset with some descriptive statistics regarding the average of number of shares per trade, average value, average price impact and its variance. Panel A uses tick rule and Panel B used Midpoint test which shows less number of observations as we exclude unclassified trades that happen at the midpoint.

Table 5-2 provides some descriptive statistics about the number of trades for all transactions and for the buys and sells trades. Panel A lists main characteristics of block trades using the tick rule. Block trades amount to 26.2% of all trades which is not as high as the more developed markets where institutional investors play active role in the market. However, considering the lack of institutional investment in the SSM, block trades making up one quarter of all trade is very high percentage. Large "off-market" trades are sometimes included in the dataset which is hard to filter out as the reporting of these trades are not accurate and does not follow timely strict manner. However, these off-market large trades do not happen frequently and as robustness, we exclude the largest 1% trades from our analysis.

14.7% of all trades are considered buyer-initiated trades and 11.5% of all trades are classified into seller-initiated trades. The numbers of buy trades are higher than sell trades, and that seems to be the case for stocks with larger market capitalisation (Gemmill, 1996). The mean of price impact has different magnitude between the two categories, where the averages of price impacts are 0.5% and (-0.38%), respectively. The averages suggest an asymmetry of price impacts that have been found in many previous papers.

Panel B lists the number of block purchases and sales according to the “midpoint rule” after excluding the “unclassified” category. The mean price impact of block purchases is 0.29% and (-0.19%) for block sales. The price impact asymmetry is robust even when using different trade classification algorithm. Even though the price impact is higher for the buy trades, the number of purchases exceeds the number of the corresponding sales. One would assume since price impact is higher for purchases, hence trading cost is higher, we should expect higher numbers of sales than purchases. In contrast, many previous studies report higher number of sales, on a downtick, compared with purchases, on an uptick. One explanation to the higher number of purchases is that it is easier to sell large amount of stocks than to buy the same amount with minimal price impact. We can imply that number of trades is closely related to the price impact asymmetry in purchases and sales.

5.5 Methodology

In order to estimate the price impact of block trades, we classify the price effect of large transactions into three types which is a common practice in the literature.[52] Consistent with (Holthausen et al., 1990; and Gemmill, 1990; and Frino et al., 2007) we use five trades “minutes” benchmark to calculate price effects. The total price impact is calculated as the percentage return from five trades prior to the block trade to the block trade itself. The temporary price impact is calculated as the percentage return from the block trade to the fifth trade after the block trade. The permanent price impact represents the percentage return from five trades prior to the block trade to five trades after the block trade. Because quotes data are not directly available in the SSM, all prices used in the computations are transaction prices. The following equations represent the three types of price effect:

$$(\boldsymbol{TotImp} = \frac{\boldsymbol{Close - close_{-5}}}{\boldsymbol{close_{-5}}}), \tag{5}$$

$$(\boldsymbol{TemImp} = \frac{\boldsymbol{close_{+5} - Close}}{\boldsymbol{close}}), \tag{6}$$

$$(\boldsymbol{PerImp} = \frac{\boldsymbol{close_{+5} - close_{-5}}}{\boldsymbol{close_{-5}}}) \tag{7}$$

[52] Within the asymmetric information models, the permanent price impact of large trades is due to new information conveyed by the trade, while the temporary price impact is associated with liquidity shortages. For in depth analysis, refer to Holthausen et al., 1987, Glosten and Harris, 1988, Chan K. and Lakonishok, 1995, among many others).

Because the price impact and the bid-ask spread are both considered liquidity cost functions, the variables that drive the price impact of trading seem to be similar to the variables that determine the bid-ask spread. In order to employ comprehensive measures that capture trading activity and market liquidity, we use multi- measures for these activities in the right hand side of the equation as explanatory variables for the price impact.

We mainly follow Frino et al. (2007) model where the price impact of block trades is a function of a list of variables that are expected to be the determinants of the price effect. The Following regression is estimated:

$$\boldsymbol{Price\ Impac = \alpha + \beta_1 InSize + \beta_2 Volatility + \beta_3 InTurnover + \beta_4 Market\ Return + \beta_5 momentum + \beta_6 BAS + \varepsilon} \quad \textbf{(8)}$$

We list all variables used with a brief definition of each variable and how it is computed. The right hand side in our analysis include the following variables:

1- ln(size) is the natural logarithm of the number of shares traded(Volume) reported to the nearest minute. Size of the trade is used as a proxy of the information content of the order, an informed trader would only sell when he believes the stock is overpriced and buys when the stock is underpriced. We expect size to have a direct effect on price movement. See for example, Easley and O'Hara (1987).

2- Volatility is the standard deviation of trade to trade prices on the trading day prior to the block trade. We include the standard deviation of the transaction price as a measure of intraday volatility to capture variation in true prices of the stock. Volatility represents dispersion in beliefs among traders, hence it is an indirect measure of the adverse selection. An increase in volatility of a stock will increase its market risk, therefore, traders will demand higher compensation in the form of price concessions . We thus expect that more volatile stocks will have higher price impact (see Domowitz et al., 2001).

3 - ln (turnover) is the natural logarithm of total "Saudi Riyal" value of stocks traded divided by the value of shares outstanding on the trading day prior to the block trade, using the following ratio , turnover = value of shares traded/value of shares outstanding. Turnover is used as a measure of liquidity in the market. Many researchers use turnover as their sole measure for trading activity or market liquidity. For example, lakonishok and Lev (1987) and

Hu (1997) suggest that turnover is a good measure of liquidity. We anticipate that turnover will be negatively related to price impact of block trades.

4- BAS represents the bid-ask spread which is another measure of liquidity and either relative or effective spreads are used in the analysis. Relative spread is the proportional bid–ask spread immediately prior to the block order being released to the market, calculated in Equation (2). And the effective spread is the difference between transaction price and midpoint of the bid and asks prices multiplied by two to show the actual round-trip transaction cost for the buy and the sell. Relative spread is calculated for a round trip trade as shown in Equation (3). When liquidity is high, bid ask spread tend to be tight, thus we expect positive relationship to exist between bid-ask spread (BAS) and price impact.

5- Market Return represents the daily return on the Tadawul All Shares Index (TASI) which covers all listed companies in the market. We follow Aitken and Frino(1996a) and Bonser et al.(1999) where they use the market return on the day of the block trade. A positive relationship is expected to exist between market return and price impact.

6- Momentum is calculated as the lagged cumulative daily return to the stock on the five trading days prior to the block trade. Lagged returns measure if there is any momentum in the price performance of the stock. In other words, it indicates whether there is a buying or a selling trend for a particular stock. We follow Saar (2001) when he differentiates between the price impact for a stock when it is at the beginning of a price run-up or after long period of a price run-up. He suggests that past price performance, represented by cumulative lagged returns, affects the magnitude of price impact. Since there is some evidence of herding in the market, we expect a positive relationship between momentum and price impact.

7- Time dummy variables. These dummy variables were constructed to analyze if there are systematic intraday variations in the magnitude of the block trade price impact, a day is divided into three time intervals. Because the trading hours of SSM are 11:00 –15:30 ,we classify time as follows: First trading hour (11:00-12:00), midday trading (12:00-14:30) and last trading hour (14:30-15:30).

5.6 Regression Results and Analysis

Table 5-3 presents the estimated result of the parameters in regression for the entire sample, (4,221,870 block transactions). Because of the large sample size and the high t-statistics, almost all variables were found to be significant. Panel A reports the mean price effect of the independent variables using three types of price impact permanent, total and temporary. On average, the temporary effect is only (-0.11%) whereas the total effect is (-0.96%) for all block trades. The temporary impact as a measure for immediate demand effect shows that immediacy is not highly priced in the SSM which indicate a higher depth for the market .Hence, liquidity traders have very low level of price impacts on stocks, which is considered as non-informational price impact. All constants are negatively signed which could be a model specification problem .e.g., data points are serially correlated, However, the main variables that should measure trading activities are included in our model .

The permanent impact which represents the information content of the trade is roughly ten times higher than the temporary effect at (-1.08%). The SSM seems to be very sensitive to potentially informed trades. Panel B presents the regression results of the estimated coefficients for the explanatory variables. All coefficients are significantly different from zero at the 1% level. The size of the trade appears to have a direct positive effect on the price impact , the larger the volume the higher is the impact. Volatility, as expected, increases market risk for traders therefore higher volatility has greater price impact on stocks. Turnover has negative relationship to price impact, indicating that increased liquidity in the market reduces the price impact of the block trade. When liquidity is high, the spread tends to be narrow; however, we find that BAS has negative relationship with permanent price impact and positive relationship with temporary price impact. The wider spreads have temporary effect on prices. The market return has a positive effect on price impact, a higher market return indicate greater price impact. Finally, the momentum return which is the cumulative of the five days returns prior to the block trade shows significant negative relationship between the temporary and permanent price impacts and the previous return.

Our results thus provide some evidence that permanent price impact increases following larger trades, higher volatility and positive market returns. On the other hand, permanent price impact is decreased when the stock is actively traded, relative spreads is higher and when it has momentum trend in its returns.

Table 5-3: Determinants of Price Impact for Block Trades

VARIABLES	Permanent effects	Total effects	Temporary effects
Panel A: Price Effect			
Mean Return	**-0.0108*** **	**-0.00965*** **	**-0.00115*** **
Panel B: Regression Results			
Ln(size)	**0.00106*** **	**0.000957*** **	**9.89e-05*** **
	(7.32e-06)	(5.87e-06)	(5.36e-06)
Volatility	**0.000368*** **	**0.000439*** **	**-6.14e-05*** **
	(8.93e-06)	(7.16e-06)	(6.53e-06)
Ln(turnover)	**-0.000147*** **	**-0.000121*** **	**-2.93e-05*** **
	(3.36e-06)	(2.69e-06)	(2.46e-06)
Mktreturn	**0.0663*** **	**0.0370*** **	**0.0293*** **
	(0.000288)	(0.000231)	(0.000211)
Momentum	**-0.000264*** **	**-0.000346*** **	**7.13e-05*** **
	(3.15e-05)	(2.53e-05)	(2.31e-05)
BAS(relative)	**-0.0392*** **	**-0.0604*** **	**0.0276*** **
	(0.00110)	(0.000880)	(0.000803)
Observations(All)	**4,221,870**	**4,221,870**	**4,221,870**
R-squared	**0.018**	**0.013**	**0.005**

Notes: This table shows the regression results of the determinants of the price impact of block trades. The Price impact, dependent variable, is one of three types; permanent, total. We use the following model:

$\mathbf{Price\ Impact} = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\mathbf{InSize} + \boldsymbol{\beta_2}\mathbf{Volatility} + \boldsymbol{\beta_3}\mathbf{InTurnover} + \boldsymbol{\beta_4}\mathbf{Market\ Return} + \boldsymbol{\beta_5}\ \mathbf{Momentum} + \boldsymbol{\beta_6}\mathbf{BAS} + \boldsymbol{\varepsilon}.$ Size is the natural logarithm of the number of shares per trade, volatility is the standard deviation of trade to trade prices on the trading day before the block trade is taking place, turnover is the natural logarithm of the total stock turnover on the trading day prior to the block trade, BAS is the bid-ask spread (relative to the midpoint between bid and ask) at the time of the block trade. Market Return is TASI returns on the day of block trade. Finally Lagged Return is the five days cumulative returns of the stock preceding the block trade .Standard errors in parentheses.*** Significant at the 1% level.

Using Effective Spread

We run the same regression model replacing the relative spread with the effective spread to examine any differences as the effective spread reflects the actual round-trip cost for a trader relative to a midpoint price between the bid and ask prices.

Table 5-4: Determinant of the Price impact Using Effective Spread.

VARIABLES	Permanent effects	Total effects	Temporary effects
Ln(size)	**0.000997***** (7.14e-06)	**0.000871***** (5.73e-06)	**0.000125***** (5.22e-06)
Volatility	**0.000266***** (9.64e-06)	**0.000421***** (7.73e-06)	**-0.000155***** (7.05e-06)
Ln(turnover)	**-0.000138***** (3.37e-06)	**-0.000116***** (2.70e-06)	**-2.54e-05***** (2.46e-06)
Mktreturn	**0.0673***** (0.000287)	**0.0382***** (0.000230)	**0.0289***** (0.000210)
Momentum	**-0.000211***** (3.15e-05)	**-0.000264***** (2.52e-05)	**3.28e-05** (2.30e-05)
BAS(effective)	**0.000238***** (1.80e-05)	**-0.000280***** (1.45e-05)	**0.000597***** (1.32e-05)
Constant	**-0.0104***** (7.54e-05)	**-0.00902***** (6.04e-05)	**-0.00134***** (5.51e-05)
Observations	**4221870**	**4221870**	**4221870**
R-squared	0.018	0.012	0.005

Note: This table presents estimates of the price impact regression using effective Spread. All three types of price impacts have been reported here, permanent, total and temporary.
$\textbf{Price Impact} = \alpha + \beta_1\textbf{InSize} + \beta_2\textbf{Volatility} + \beta_3\textbf{InTurnover} + \beta_4\textbf{Market Return} + \beta_5\textbf{ Momentum} + \beta_6\textbf{BAS} + \varepsilon.$ .All variables have been defined in table (5-3). Only relative spread was replaced by effective spread "BAS" which is defined as two times the deviation of transaction prices from the midpoint prices at the time of the block trade. Standard errors in parentheses. *** Significant at the 1% level

Effective spread represents the true cost of trading because it measures how a stock was traded relative to the midpoint and whether this trade price in favour of the trader or not " price improvement". Effective spreads also measure the tendency of block trades to move the prices "price impact" as it uses actual execution prices.

The estimates of the parameters in the regression are presented in table 5-4 for the entire sample for all three types of price impact permanent, total and temporary. The estimates of the slope coefficients on the volume, volatility, turnover, market return, momentum returns and finally effective spreads in the regression are all significant, and their signs, for most variables, are consistent with prior empirical research. Size of the trade, volatility, BAS and market returns all have positively significant relationship with permanent price impact with market returns being the most important explanatory variable for price impact consistent with Frino et al. (2007). Turnover and momentum returns show negative coefficients indicating liquidity in the market mitigate the price impact and that a price run-up increases probability of price reversal. The effective spread (BAS), when used in the second regression instead of relative spread differs substantially from the relative spread in the table 5-3 in the sign and strength of the coefficient. Effective spread shows positive significant relationship between the spread and the price impact which is in line with the conjecture that a wider spread should cause higher price impact. It is expected that a higher transaction cost (effective spread) would trigger a higher price impact.

It is worthy to note that in contrast to the permanent price impact behaviour, the temporary price impact has a negative relationship with volatility and positive signed coefficient with BAS and momentum returns but not significant for the latter .

The price impact of buy and sell transactions will be investigated separately to explore the possibility of different magnitudes for their regression coefficients. The following section discusses the relationship between price impact and trade sign.

5.6.1 Price Impact and Trade sign

Table 5-5 investigates block transactions with regard to trade sign. buy block trades are presented in Panel A and sell block trades are in panel B .A permanent price asymmetry between buy and sell block trades can be seen in the table in term of magnitude but both have negatively signed intercepts which is expected in the sell subsample but not in the buy subsample. The negative constant could be a model specification problem or a mere reflection of the bearish market that the SSM has experienced from beginning of 2006 .Our data covers almost four years from 2005 to 2008. Later in this section, we will differentiate between block trades in a bullish or bearish market following Chiyachantana et al. (2004) where they show that market condition, being bearish or bullish has direct effect on price impact and its asymmetry between purchases and sales.

We start our analysis by examining block purchases transactions which have 2,366,099 observations. The constant mean return for the permanent price impact is (-1.43%) whereas (-0.37%) for the transitory effect. We mentioned earlier that the SSM seems to be more sensitive to informed trading, which has permanent effect on the price impact, than to liquidity trades which have transitory effect on stock prices. With regards to sell transactions in panel B, the mean permanent price impact is (-0.026%) while the temporary price impact is 0.23%.

The regression results of the estimated coefficients for the explanatory variables are all significantly different from zero at the 1% level. Size (trade volume) coefficients are significantly positive for the block purchases and significantly negative for the block sales. The size of the trade coefficients show, as the literature suggest, direct positive affect on the price impact, the larger the volume the greater the effect. Volume has both transitory and permanent effects on prices which mean volume convey information to the market and that other traders would change the perceived market value of a stock according to volume traded. The price impact is an increasing a function of the trade size.

Volatility as measured by the standard deviation of returns represents the market risk faced by the traders, therefore higher volatility has greater price impact on a stock and is expected to have a positive relationship with the price effect. Volatility shows positive coefficient for the buy block trades and negative for sell trades which confirm the greater price impact that is attributed to higher risk and dispersion of beliefs among traders. The volatility coefficients are consistent with prior research (e.g., Chan and Lakonishok, 1997; Chiyachantana et al., 2004; Frino et al., 2007)

Turnover has negative relationship to price impact for the buy blocks, indicating that increased liquidity in the market reduces the price impact of the block trade. Our results confirm prior market research that turnover as a measure of liquidity should have negative relationship with the price impact. The negative relationship between liquidity and price impact can in part be linked to a more general relationship between stock returns and liquidity. For example, Hu (1997) argues that turnover is a useful measure of liquidity and a negative relation between stock returns and turnover exists. Brennan and Subrahmanyam (1996) also find a negative relation between expected returns and liquidity. Conversely, the block sales has negative turnover coefficient, indicating that increased liquidity results in greater price impact. Large block sales combined with highly active traded stocks might convey negative information because they reflect a likely action of informed traders and induce more selling which increases the price effect of these large trades.

The market return has positive coefficients for both block purchases and sales, a higher market return indicate greater price impact for the block purchases and a lower price impact for block sales. Our market return coefficients are consistent with Frino et al. (2007) where they have positive coefficient for both subsamples, buy and sell, and the market coefficient is higher for block sales than purchases.

The momentum has negative (positive) coefficients with the price impact for the block purchases (sales), indicating a lower price impact following a price trend. Our result lends support to Saar (2001) who finds that recent large price run-up of a stock leads to a lower price impact for both block purchases and sales. A stock that has shown an increased momentum trend in its performance is expected to have a lower price impact for block trades, the price-run up effect. This relation between the price impact of trades and the history of price performance is similar to the one documented in Chiyachantana et al. (2004). They report that the institutional purchases of stocks with several days of price run-up induce smaller permanent price change.

Moreover, the momentum variable for the sell transaction shows a positive relationship with regard to the temporary price effect (negatively signed coefficient) and a negative relationship with the permanent price impact (positively signed coefficient). The reverse in the sign of the momentum indicate the price reversal of the block sales. Finally, we find that BAS has positively significant coefficient for buyer- initiated block trades and negatively significant coefficient for seller- initiated block trades. When spread is wider the price impact is greater for both buy and sell block trades. Our BAS coefficients are consistent with Aitken and Frino(1996b) and Gemmil(1996) and Frino et al.(2007)

Our results provide some evidence that permanent price impact for block purchases increases following larger trades, less liquidity, higher volatility and market returns. Permanent price impact is decreased when the stock is actively traded and when it has just established a weekly trend in its price momentum. In contrasts, the regression results suggest that permanent price impact for block sales increases when associated with larger trading volume, higher volatility and high turnover. The coefficients for market returns and momentum for the block sales suggest that price impact is decreased when there are higher market returns or when a stock has recently experienced a recent trend in its returns performance. It is worthy to mention that total price effect reports the highest adjusted-R among other price impacts in both buy and sell block trades. Total price impact is calculated from five minutes before the execution of the block price and it suggests the SSM is very quick into incorporating the block trade information into prices. Once a block order ,either sell or buy , is displayed on screen,the market reacts immediately with greater price impact followed by a price reversal once the block trade has been executed.

Table 5-5 : Price Impact Estimates and Trade Sign (buy and sell block trades)

	Panel A: Buy			Panel B: Sell		
	Permanent effects	**Total effects**	**Temporary effects**	**Permanent effects**	**Total effects**	**Temporary effects**
Ln(size)	**0.00152***** (8.79e-06)	**0.00114***** (6.54e-06)	**0.000382***** (6.69e-06)	**-0.0009 ***** (1.10e-05)	**0.000145***** (8.10e-06)	**-0.000246***** (8.63e-06)
Volatility	**0.00157***** (1.16e-05)	**0.00141***** (8.62e-06)	**0.000169***** (8.82e-06)	**-0.000568***** (1.28e-05)	**-0.000172***** (9.48e-06)	**-0.000389***** (1.01e-05)
Ln(turnover)	**-0.000311***** (1.04e-05)	**-0.000366***** (7.70e-06)	**4.91e-05***** (7.88e-06)	**-0.000362***** (1.12e-05)	**-7.54e-05***** (8.29e-06)	**-0.000294***** (8.83e-06)
Mktreturn	**0.0361***** (0.000364)	**0.0106***** (0.000271)	**0.0252***** (0.000277)	**0.0750***** (0.000406)	**0.0368***** (0.000301)	**0.0385***** (0.000320)
Momentum	**-0.000514***** (4.13e-05)	**-0.00114***** (3.07e-05)	**0.000606***** (3.15e-05)	**0.00053***** (4.27e-05)	**0.000483***** (3.16e-05)	**-0.000459***** (3.37e-05)
BAS(relative)	**0.247***** (0.00139)	**0.361***** (0.00103)	**-0.109***** (0.00106)	**-0.327***** (0.00154)	**-0.507***** (0.00114)	**0.188***** (0.00122)
Constant	**-0.0143***** (8.96e-05)	**-0.0104***** (6.66e-05)	**-0.00378***** (6.82e-05)	**-0.000206*** (0.000111)	**-0.00251***** (8.23e-05)	**0.00237***** (8.77e-05)
Observations	**2366099**	**2366099**	**2366099**	**1855236**	**1855236**	**1855236**
R-squared	0.045	0.089	0.009	0.054	0.117	0.020

Notes: The table presents estimated parameters separately for the buys and sells subsamples. We use tick test for trade classification. Buyer initiated trades (2,366,099 observations) are reported in panel A and seller initiated trades (1,855,236 observations) are reported in panel B. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5-6 : Price Impact Estimates and Trade Sign using Effective Spread

	Panel A: Buy			Panel B: Sell		
	Permanent effects	Total effects	Temporary effects	Permanent effects	Total effects	Temporary effects
Ln(size)	**0.00175*** **	**0.00149*** **	**0.000262*** **	**-0.000542*** **	**-0.000541*** **	**1.08e-06**
	(8.57e-06)	(6.38e-06)	(6.54e-06)	(1.07e-05)	(8.08e-06)	(8.43e-06)
Volatility	**0.000873*** **	**0.000536*** **	**0.000340*** **	**-0.000255*** **	**0.000421*** **	**-0.000679*** **
	(1.25e-05)	(9.28e-06)	(9.52e-06)	(1.38e-05)	(1.04e-05)	(1.08e-05)
Ln(turnover)	**-0.000276*** **	**-0.000329*** **	**4.80e-05*** **	**-0.000385*** **	**-0.000122*** **	**-0.000270*** **
	(1.03e-05)	(7.70e-06)	(7.90e-06)	(1.13e-05)	(8.48e-06)	(8.85e-06)
Mktreturn	**0.0324*** **	**0.00503*** **	**0.0270*** **	**0.0814*** **	**0.0465*** **	**0.0351*** **
	(0.000363)	(0.000270)	(0.000277)	(0.000407)	(0.000306)	(0.000319)
Momentum	**-0.000860*** **	**-0.00164*** **	**0.000759*** **	**0.000483*** **	**0.00118*** **	**-0.000713*** **
	(4.12e-05)	(3.07e-05)	(3.15e-05)	(4.29e-05)	(3.23e-05)	(3.37e-05)
BAS(effective)	**0.00472*** **	**0.00620*** **	**-0.00142*** **	**-0.00353*** **	**-0.00594*** **	**0.00251*** **
	(2.38e-05)	(1.77e-05)	(1.82e-05)	(2.43e-05)	(1.83e-05)	(1.90e-05)
Constant	**-0.0159*** **	**-0.0130*** **	**-0.00293*** **	**0.00324*** **	**0.00277*** **	**0.000448*** **
	(8.85e-05)	(6.59e-05)	(6.76e-05)	(0.000110)	(8.30e-05)	(8.67e-05)
Observations	**2366099**	**2366099**	**2366099**	**1855236**	**1855236**	**1855236**
R-squared	0.048	0.089	0.008	0.042	0.076	0.017

Estimates of the price impact regression using Effective spread. We use the same previous model but with effective spread. All variables have been defined in table 5-3. The effective spread “BAS”, is defined as two times the deviation of transaction prices from the midpoint prices at the time of the block trade. The sample is classified into buy blocks and sell blocks according to tick rule. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Price Impact and Trade sign using effective Spread

Table 5-6 reports the same OLS regression model using effective spread instead of relative spread. Effective spreads is a measure of the tendency of block trades to move the prices "price impact" as it uses actual execution prices. The estimated coefficients using effective spread do not change significantly from the previous model using relative spread. The main difference is that the constants coefficients are significantly positive for the block sales and significantly negative for block purchases. Both relative and effective spread has positive relationship with permanent price impact for both subsamples of buys and sells. Nonetheless, the temporary effect has an opposite relationship with the bid-ask spreads, relative and effective spreads. When liquidity is low BAS tends to be wider and a higher, therefore, BAS should lead to a greater price impact. But in the case of temporary effect which measures the transitory and liquidity related effects of a block trade, the relation is negative. BAS reports negatively significant coefficient for the block purchases and positively significant coefficient for the block sales. The less liquid a stock is, the lower the temporary price impact. A result that seems to be odd, liquidity providers should impose liquidity premium on large orders, however it seem the transitory effect shows puzzling relationship with regard to liquidity function in the market. BAS and Turnover are two proxies for liquidity in the market, both indicate that the higher liquidity a stock shows, the higher the transitory price effect. One strong candidate explanation of this relationship between liquidity and temporary price impact is that the SSM overreact to block trades once an order is entered the book, that is reflected in the higher total impact. A price reversal is expected once the block order has been executed, that can be seen from the opposite signed coefficients for the temporary price impact. Uninformed traders can misinterpret large trades and assume they always contain valuable information.

An informed trader or even a sophisticated one can benefit from such overreaction behaviour in prices and gain abnormal returns. Moreover, the temporary price impact is closely related to the bid-ask bounce in prices, the bounce back in prices after block trades is observed in both buy and sell trades, however the magnitude of the price reversal is higher for the sell trades (liquidity premium).

5.6.2 Time of the day effect

Many empirical research papers have reported that spreads show U pattern throughout the day. Spread, as a measure of liquidity, tends to be wider and depth tends to be lower toward the beginning and ending of the day. Since price impact is another type of liquidity cost, we expect that any block trade occurs at the beginning or ending of the trading day will have higher price impact. To investigate whether there are any systematic intraday variations in the magnitude of the block trade price impact, a trading day is divided into three time intervals first hour, midday, and last trading hours. The details of SSM trading hours and how the trading day is divided into three intervals are discussed in the methodology section.

Table 5-7 : Price Impact and Time of the Day Effect.

	All	Buy	Sell
Ln(size)	**0.000988*** **	**0.00175*** **	**-0.000539*** **
	(7.12e-06)	(8.56e-06)	(1.07e-05)
Volatility	**0.000321*** **	**0.000914*** **	**-0.000260*** **
	(9.85e-06)	(1.25e-05)	(1.39e-05)
Ln(turnover)	**-0.000338*** **	**-0.000229*** **	**-0.000363*** **
	(8.22e-06)	(1.05e-05)	(1.15e-05)
Mktreturn	**0.0672*** **	**0.0324*** **	**0.0814*** **
	(0.000287)	(0.000362)	(0.000407)
Momentum	**-0.000250*** **	**-0.000913*** **	**0.000476*** **
	(3.14e-05)	(4.12e-05)	(4.29e-05)
BAS(effective)	**0.000218*** **	**0.00463*** **	**-0.00351*** **
	(1.81e-05)	(2.39e-05)	(2.44e-05)
TimeDum1	**0.000364*** **	**0.000504*** **	**0.000273*** **
	(1.73e-05)	(2.15e-05)	(2.51e-05)
TimeDum2	**0.000168*** **	**-0.000243*** **	**0.000694*** **
	(1.50e-05)	(1.86e-05)	(2.18e-05)
Constant	**-0.0100*** **	**-0.0159*** **	**0.00277*** **
	(7.44e-05)	(8.98e-05)	(0.000112)
Observations	**4221870**	**2366099**	**1855236**
R-squared	0.018	0.049	0.042

Notes: This table lists the estimated coefficients for the cross-section price impact model for the entire sample and for the subsamples, buys and sells. Model used:

$$\mathbf{Price\ Impact} = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\mathbf{InSize} + \boldsymbol{\beta_2}\mathbf{Volatility} + \boldsymbol{\beta_3}\mathbf{InTurnover} + \boldsymbol{\beta_4}\mathbf{Market\ Return} + \boldsymbol{\beta_5}\ \mathbf{Momentum} + \boldsymbol{\beta_6}\mathbf{BAS} + \boldsymbol{\beta_7}\mathbf{t_1} + \boldsymbol{\beta_8}\mathbf{t_2} + \boldsymbol{\beta_9}\mathbf{t_3} + \boldsymbol{\varepsilon}.$$

All variables have been defined in the previous analysis.TimeDum1 is a dummy variable that assigns the value of 1 for all block trades that took place in the first trading hour, otherwise 0.Timedum2 is dummy variable taking the value of 1 for all bock trades happened during mid trading day, otherwise 0.Timedum3 is the reference group, which is dummy variable for all block trades recorded during the last trading hour and all other trades take the value of 0. *** p<0.01, ** p<0.05, * p<0.1.

The time of the day is divided into three groups, each group is assigned a dummy variable that takes the value of 1 if the trade takes place in that time, otherwise it takes the value of zero.TimeDum1 and TimeDum2 represent the first trading hours and midday trading hours, respectively. The last trading hours (TimeDum3) is the reference group for our dummy variables analysis, therefore it is omitted from the regression. The coefficients of the other two dummy variables represent the difference in price impact behaviour between the reference group and the other two dummy variables.

The price impact in the buyer initiated trades tends to decrease as the trading hours pass by. The highest impact is found in the first trading hours where the coefficient is positively significant. Trading during the day has the lowest price impact among all three categories. Block trades executed in the first trading hours experience the greatest price impact. We can infer that informed trading is highest at the beginning of the day and as trading continue the information asymmetry decreases or incorporated in the prices. The closest pattern that could resemble the SSM price impact behaviour around the day is the reverse J-shape, similar to McInish and Wood (1992) who find identical pattern in bid/ask spreads and the time of the day dummy variables coefficients. Our time of the day results coincide with Frino et al. (2007) who find price impact is the largest for block trades executed in the first hour. Moreover, the intraday spread pattern that found by Al-Suhaibani and Kryzanowski (2000a) in the SSM is similar to our finding of the price impact for the buy block trades. They show that spreads are at their highest at the open and narrow over the trading day.

The seller initiated block trades show similar pattern to the one found in buyer group but closely similar to J shapes in general, price impact is lower at beginning of the day and is at its highest toward the end of the day.

5.6.3 Price impact and trade size

Existing theoretical and empirical research suggests, that informed traders submit larger orders than do liquidity traders. If that assumption holds true in the SSM, we expect to have an increasing function between price impact and order size for both block purchases and sells. To examine how trading activities within different size groups might affect price behaviour, we divide block trades of buys and sells into different groups according to trading volume. Following Madhavan and Cheng (1997), we partition block trades into three size categories of (10K -20K), (20K – 50K) and greater than 50K. The SSM is mainly driven by individual investors; larger trades are mostly initiated by some wealthy business families and investors but rarely by some governmental funds which are not active in the market. Buy and sell block trades are reported in two different tables.

Table 5-8: Price Impact and Block Size (Purchases)

	G(1)	G(2)	G(3)
VARIABLES	10,000-20,000	20,000-50,000	>50,000
% of total	**41%**	**36%**	**23%**
Ln(size)	**0.00112*** **	**0.00156*** **	**0.00220*** **
	(4.98e-05)	(4.64e-05)	(2.72e-05)
Volatility	**0.000767*** **	**0.000827*** **	**0.000602*** **
	(1.63e-05)	(2.07e-05)	(3.31e-05)
Ln(turnover)	**-2.60e-05*** **	**3.69e-05*** **	**0.000539*** **
	(6.17e-06)	(7.45e-06)	(1.10e-05)
Mktreturn	**0.0270*** **	**0.0319*** **	**0.0434*** **
	(0.000506)	(0.000602)	(0.000895)
Momentum	**-0.00110*** **	**-0.00127*** **	**-0.000895*** **
	(5.94e-05)	(6.77e-05)	(9.88e-05)
BAS(effective)	**0.00352*** **	**0.00477*** **	**0.00584*** **
	(3.67e-05)	(4.06e-05)	(4.95e-05)
TimeDum1	**0.000576*** **	**0.000776*** **	**0.00130*** **
	(3.17e-05)	(3.72e-05)	(5.22e-05)
TimeDum2	**-4.84e-05* **	**-0.000159*** **	**-0.000211*** **
	(2.62e-05)	(3.13e-05)	(4.40e-05)
Constant	**-0.00966*** **	**-0.0143*** **	**-0.0203*** **
	(0.000477)	(0.000480)	(0.000319)
Observations	**971,091**	**851,890**	**542,886**
R-squared	0.023	0.033	0.056

Notes: this table lists the estimated coefficients for the cross-section price impact model for the block trades purchases

$$\textbf{Price Impact} = \alpha + \beta_1 \textbf{InSize} + \beta_2 \textbf{Volatility} + \beta_3 \textbf{InTurnover} + \beta_4 \textbf{Market Return} + \beta_5 \textbf{ Momentum} + \beta_6 \textbf{BAS} + \beta_7 t_1 + \beta_8 t_2 + \varepsilon.$$

The Model is run separately for each size category. Block trades are partitioned into three groups. 10k-20k, 20k-50k, and above 50K. The 10k-20k category has the highest number of observations amounting to 41% following by 20k-50k of 36% and finally over 50k category which has 23% of total observations. Standard errors in parentheses. . *** p<0.01, ** p<0.05, * p<0.1.

Table 5-8 presents the price impact coefficients across different block size categories. All explanatory variables, except TimeDum2, show significant coefficients at the 1% level. Price impact is an increasing function of a trade size, the larger the trade size the greater is the price impact. The size coefficient for group 3 is as twice as the size coefficient of group 1, suggesting that informed traders prefer larger order size which induces higher price impact. This finding is consistent with the literature. [53]

Volatility has roughly identical positive coefficients, confirming volatility effect that is stable over different size categories. Turnover as a proxy for liquidity shows significantly negative coefficient in the first group (10k-20k), increased liquidity reduces the price impact of block trades. However, the coefficients signs for the other two groups are positive suggesting positive relationship between liquidity available to the market and the price impact. For the higher volume groups, liquidity increases the price impact of block purchases. Larger block trades change the market value perception about the stocks traded, regardless of the liquidity available in the market. The facts that Insider trading is not transparent in the SSM and the absence of analyst forecasts both have created a higher weights on trading volume as a mean by which traders interpret as a strong indication of informed trading.

Market return as found previously has a positive relationship with price impact and again the coefficient for the higher volume group is twice as much as the lower volume group. The difference in market return coefficients among different size categories, can confirm the hypothesis that larger trades tend to be more informative than smaller trades. Block trade purchasers might have some expectation about the market wide movement and time their buying accordingly. The negative momentum coefficient shows that block trade purchases are information incentive not just following a trend of a price increase. Block trades in the higher volume category act according to fundamental information rather than positive feedback trading.

The effective spread (BAS) shows positive increasing function between BAS, price impact and size. Higher transaction cost represented by the effective spread encourages larger price impact in an increasing behaviour relative to trade size. The positive continuation of price impact following block trade purchases works as a compensation for the higher costs these block trades face. Finally, the time dummies do not show intraday variations in their patterns among different size groups. Block purchases at the beginning of the day have the greatest price impact.

[53] See for example, Huang and Stoll (1997) and Glosten and Harris(1988).

Table 5-9 : Price Impact and Block Size (Sales)

VARIABLES	G(1) 10,000-20,000	G(2) 20,000-50,000	G(3) >50,000
% of total	**42%**	**37%**	**21%**
Ln(size)	**-0.000958***** (5.76e-05)	**-0.000800***** (5.42e-05)	**-2.22e-06** (3.73e-05)
Volatility	**-0.000233***** (1.80e-05)	**-0.000180***** (2.31e-05)	**6.32e-05*** (3.84e-05)
Ln(turnover)	**-0.000311***** (7.05e-06)	**-0.000353***** (8.61e-06)	**-0.000292***** (1.33e-05)
Mktreturn	**0.0703***** (0.000568)	**0.0851***** (0.000678)	**0.105***** (0.00104)
Momentum	**0.000745***** (5.99e-05)	**0.000849***** (7.26e-05)	**0.000236**** (0.000106)
BAS(effective)	**-0.00278***** (3.58e-05)	**-0.00397***** (4.19e-05)	**-0.00406***** (5.35e-05)
TimeDum1	**-0.000464***** (3.65e-05)	**-9.31e-05**** (4.33e-05)	**0.000586***** (6.41e-05)
TimeDum2	**0.000368***** (3.05e-05)	**0.000655***** (3.64e-05)	**0.00101***** (5.40e-05)
Constant	**0.00611***** (0.000551)	**0.00456***** (0.000561)	**-0.00437***** (0.000432)
Observations	**789197**	**683068**	**382807**
R-squared	0.037	0.047	0.047

Notes: this table presents the estimated coefficients for the cross-section price impact model for the block trades sales. The Model is run separately for each size category. Block trades are partitioned into three groups: 10k-20k, 20k-50k and above 50K. The 10k-20k category has the highest number of observation amounting to 42% followed by 20k-50k of 37% and finally over 50k category which has 21% of total observations. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5-9 lists the regression coefficients for different size groups for the block sales. Size has positively significant relationship with the permanent price impact for the first two size groups. However, the largest size group (over 50k) does not show a statistically significant coefficient. The coefficients for the size variable suggest that small to medium block trades are more informative than larger block trades. They indicate informed traders might split orders into small and medium orders and that is why size of the trade appears significant at the small and medium categories but not in the large blocks category. Volatility also exhibits intriguing coefficient behaviour, the largest size group has a positive coefficient that is significant at the 10% level. It is assumed that when a stock shows higher volatility on the trading day we would expect greater price impact for the risk level that is taken, which we experience in the first two size categories . Nonetheless, the largest group shows a negative relationship between volatility and price impact. The liquidity (turnover) has a positive relationship with price impact, negative signed coefficients that are significant at the 1% level for all block size categories. The market return coefficient , which is larger in the sell blocks than the buy blocks, suggests that general market movements play an important role in influencing price impact. Higher market returns seem to contribute to the price impact asymmetry between the buy and sell as they increase the permanent price effect for the buys and decrease the permanent price effect for the sells.

The behaviours of liquidity, size and momentum in the SSM for the block sales among different size groups, suggest that block sales are less information driven than block purchases. Uninformed investors seem to engage in momentum trading for the block sales which can be implied from the positive relationship between momentum trend and price impact. Moreover, the effect of momentum may be due to return autocorrelation property. The SSM has two characters that might induce returns autocorrelation, which is the prohibition of the short selling and the 10% daily cap on price movements. Short selling can mitigate the momentum or herding effect .Moreover, limit on prices might create additional "artificial" autocorrelation in stock returns. The intraday time dummy variation supports our finding that small to medium size categories, 10k-20k and 20k-50k, are more informed than the largest group size. Informed trading is highest at the beginning of the day then information slowly is incorporated into prices, until informed trading reaches its lowest point and stay low for the rest of the day. The inverse J-shaped pattern found is similar to the results of Nyholm(2002) who documents an inverse J-shaped informed trading pattern throughout the day . This informed trading pattern holds true for the first two categories but not for the last category, over 50k, where the price impact and supposedly the informed trading is at its highest toward the end of the day.

5.6.4 Price impact and market condition (year-by-year analysis)

Chiyachantana et al. (2004), link the price impact asymmetry to the market condition. They study two separate periods to test whether price impact of institutional trades vary significantly in bullish and bearish markets. Likewise, we run separate tests for each year to show any variance in the price impact behaviour according to the market condition .We run the cross-section model of price impact on each year of our sample separately, aiming to capture any micro-structural changes or development in the market. The period 2005-2008 experienced tremendous changes in the market in terms of regulation, development and trading rules. Moreover, years 2005 and 2007 were extremely bullish market where the index grew by more than 100 per cent and 40 per cent, respectively. Years 2006 and 2008 experienced a bearish market where they declined by 52.5 per cent and 57 per cents, respectively.

Table 5-10: Price Impact and Market Condition (Block Purchases)

Mkt Performance	2005 104%	2006 (-52%)	2007 40%	2008 (-57%)
Ln(size)	**0.00190******	**0.00213******	**0.00178******	**0.000735******
	(1.28e-05)	(2.00e-05)	(1.55e-05)	(1.81e-05)
Volatility	**0.000427******	**0.000489******	**0.00139******	**0.00187******
	(2.17e-05)	(2.02e-05)	(3.42e-05)	(5.01e-05)
Ln(turnover)	**-0.00345******	**-0.000100******	**0.000155******	**0.000284******
	(7.71e-06)	(1.07e-05)	(7.61e-06)	(1.14e-05)
Mktreturn	**0.0156******	**0.0398******	**0.0203******	**0.0309******
	(0.000865)	(0.000596)	(0.000809)	(0.000825)
Momentum	**-0.000178******	**-0.00177******	**-0.00263******	**-0.00151******
	(4.40e-05)	(9.93e-05)	(0.000113)	(0.000158)
BAS(effective)	**0.00562******	**0.00425******	**0.00552******	**0.00341******
	(5.09e-05)	(3.86e-05)	(6.08e-05)	(5.87e-05)
TimeDum1	**0.000977******	**0.000625******	**0.000257******	**0.000952******
	(3.59e-05)	(4.94e-05)	(3.75e-05)	(5.11e-05)
TimeDum2	**0.000385******	**-0.000164******	**-0.000791******	**8.35e-05*****
	(2.99e-05)	(4.08e-05)	(3.14e-05)	(4.22e-05)
Constant	**-0.0184******	**-0.0193******	**-0.0160******	**-0.00538******
	(0.000138)	(0.000213)	(0.000164)	(0.000197)
Observations	**610080**	**766174**	**658692**	**331150**
R-squared	0.068	0.044	0.052	0.035

Notes: this table presents the estimated coefficients for the cross-section price impact model for the block trades purchases. Model used:

$$\textbf{Price Impact} = \alpha + \beta_1 \textbf{InSize} + \beta_2 \textbf{Volatility} + \beta_3 \textbf{InTurnover} + \beta_4 \textbf{Market Return} + \beta_5 \textbf{ Momentum} + \beta_6 \textbf{BAS} + \beta_7 t_1 + \beta_8 t_2 + \varepsilon.$$

The Model is run separately for each year in the sample. The Bull market years ,2005 and 2007 show higher adjusted R-squared than the bear market years 2006 and 2008 . Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5-10 shows that all coefficients are significant at the 1% level.[54] Volume and volatility of the stock bought in bulk remain positively related to price impact across all years. The liquidity, measured in turnover, shows negative relationship with price impact for first two years, then the sign of the coefficient shift to a positive. The more traded stocks have higher price impact for the years 2007 and 2008. This positive relationship between liquidity and price impact is different from prior studies where it is found that liquidity reduces price impact. One of the reasons behind this unexpected coefficient signs is that the SSM lacks the presence of designated market makers who help to reduce volatility because of their obligation to provide liquidity to the market to insure continuous trading and smooth price changes from

[54] Except for the Timedum2 with respect to price impact of year 2008 where it shows significance level of 5%.

trade to trade. When a stock is highly traded, it attracts more attention and sends a signal to the market that this particular stock may possess new fundamental information that should affect the value of the stock being traded.

The market return is the only explanatory variable that shows clearly a distinguished relationship between price impact and market return according to the market condition. Price impact of buy block trades tends to be higher in bull market years than in bear market years, twice as much. Our market returns result is similar to Chiyachantana et al. (2004) who show that price effects , in general, of buys block trades in a bull market tend to be larger than those of buys in bear market. The liquidity available to traders and whether block trades are transacted on the same side of the market or against are all factors that affect the magnitude of the price impact. The other variables momentum, BAS and time dummies do not vary significantly according to market condition and show similar coefficients to previous models, momentum remains negatively related to the price effect. The consistent coefficients signs and levels over the years in different market conditions, suggest that block purchases are more of information incentive trades. The following table shows the same test conducted for the sales block trades.

Table 5-11 : Price Impact and Market Condition (Block Sales)

	2005	2006	2007	2008
Mkt Performance	**104%**	**(-52%)**	**40%**	**(-57%)**
Ln(size)	**2.16e-05**	**-0.000511*** **	**-0.00143*** **	**-0.000617*** **
	(1.35e-05)	(2.43e-05)	(2.20e-05)	(2.46e-05)
Volatility	**2.98e-05**	**4.23e-05***	**2.17e-05**	**-0.000352*** **
	(2.16e-05)	(2.25e-05)	(4.02e-05)	(5.75e-05)
Ln(turnover)	**-0.000152*** **	**-0.000345*** **	**-0.000432*** **	**-0.000407*** **
	(7.39e-06)	(1.19e-05)	(9.65e-06)	(1.41e-05)
Mktreturn	**0.0672*** **	**0.0879*** **	**0.0785*** **	**0.0647*** **
	(0.000819)	(0.000663)	(0.00102)	(0.00100)
Momentum	**-0.000114*** **	**0.00151*** **	**7.39e-05**	**0.00301*** **
	(3.95e-05)	(0.000109)	(0.000136)	(0.000173)
BAS(effective)	**-0.00361*** **	**-0.00344*** **	**-0.00529*** **	**-0.000573*** **
	(4.84e-05)	(3.88e-05)	(6.73e-05)	(6.24e-05)
TimeDum1	**-0.000216*** **	**0.000515*** **	**-0.000455*** **	**-0.000577*** **
	(3.47e-05)	(5.61e-05)	(4.93e-05)	(6.57e-05)
TimeDum2	**9.65e-05*** **	**0.00102*** **	**0.000508*** **	**0.000755*** **
	(2.85e-05)	(4.67e-05)	(4.15e-05)	(5.53e-05)
Constant	**-0.00216*** **	**0.000603****	**0.0106*** **	**0.00186*** **
	(0.000144)	(0.000257)	(0.000232)	(0.000265)
Observations	**566876**	**640521**	**436269**	**211563**
R-squared	0.026	0.045	0.051	0.032

Notes: this table presents the estimated coefficients for the cross-section price impact model for the sale block trades. Model used:

$$\textbf{Price Impact} = \alpha + \beta_1 \textbf{InSize} + \beta_2 \textbf{Volatility} + \beta_3 \textbf{InTurnover} + \beta_4 \textbf{Market Return} + \beta_5 \textbf{ Momentum} + \beta_6 \textbf{BAS} + \beta_7 t_1 + \beta_8 t_2 + \varepsilon.$$

The Model is run separately for each year in the sample. The years 2005 and 2007 are considered Bull market whereas the years 2006 and 2008 are bear market. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5-11 shows the regression coefficients for different years in the sample for the seller initiated block trades. The volume shows positive relationship with price impact (negative sign) for all years except year ’05 which is not statistically significant. The volume of the block sales in a strongly growing market (more than 100% growth) does not appear to have any effect on the price impact. In other words, liquidity providers do not discount heavily block sales in a bullish market because, naturally, liquidity available to sell orders is higher in bullish markets, a notion mentioned first by Chiyachantana et al. (2004).

Volatility does not show any significant coefficients for the years 2005 and 2007 where the market were bullish. It seems that traders in the SSM are less concerned with volatility and size of the trade in a bullish market. Expectations about growth in the market ignore the effect of trade size on prices or even how volatile a stock is. The momentum in price trend seems to have even greater price impact in the year '05 which is a bullish market year.[55] The declining market years of 2006 and 2008 report an inverse relationship between price impact and momentum. The higher the momentum the lower the price impact of block trades.BAS which is another measure of liquidity besides turnover in our study shows positive relationship (negative coefficients) between price impact and BAS regardless of market condition. When liquidity available in the market is lower, bid ask spreads tend to widen and price effect of block sales increased.

5.6.5 Information Asymmetry and Bid-Ask Spreads

The bid ask spread has long been of interests to traders, regulators and researchers. Many spread decomposition models have been designed and implemented to infer about the components of the spread. Two-way models combine order processing and inventory costs into one component and the information asymmetry into another. On the other hands, three-way models decompose the spread into order processing, inventory cost and information asymmetry component. The information asymmetry component is the cost reflected in the bid ask spread when there are informed traders. One prominent group of spread decomposition models is the trade indicator models which are spread decomposition models that are derived solely by the direction of the trade. Spread decomposition models have been able to isolate the adverse selection component of the spread to an extent which leads to more powerful analysis using the informed trading component instead of the total spread (Heflin and Shaw, 2000). Van Ness et al. (2001) have examined and compared the performance of several structural models that are commonly used for spread decomposition in the finance literature. They conclude that no single model appears to perform better than the others.

We attempt to apply the spread decomposition method of Huang and Stoll (1997) to estimate the information asymmetry component of the spread and then use that estimated component of the spread to measure how the informed trading cost might affect the price impact in our model. We are more interested to see how the information asymmetry component of the spread might affect the price impact of block trades, since these block trades have higher probability of being informed trades. We obtain Huang and Stoll (1997) estimate of the adverse selection component by estimating the following firm-specific regression using OLS:

[55] Year 2005 experiences the highest growth in all market aspects, even in the number of first time subscribers who naturally follow herding process due to lack of expertise.

$$\Delta \boldsymbol{price}_{i.t} = \boldsymbol{\beta}_{1,i}\boldsymbol{Q}_{i,t} + \boldsymbol{\beta}_{2,i}\boldsymbol{Q}_{i,t-1} + \boldsymbol{\beta}_{3,i}\boldsymbol{Q}_{A,t-1} + \boldsymbol{e}_{t} \qquad \textbf{(9)}$$

Where Δ denotes a change in prices (returns) from a previous trade and $Q_{i,t}$ equals 1(-1) if the trade at time t was a buy (sell). We use tick test rule as explained earlier to sign trades.[56] Trades at a price greater than the price at $t-1$ are assigned $Q_{i,t} = 1$, and trades at a price less than price at $t-1$ are assigned $Q_{i,t} = -1$. For trades that do not have a price change between current trade price and previous trade price, we compare to previous trade until we stop at $\mathrm{t}-5$. If the price change is still zero at $\mathrm{t}-5$ then this trade is unclassified and omitted. $Q_{A,t-1}$ is the sign of the trade at time $t-1$ .The third term $Q_{A,t-1}$ is the lag of an aggregate buy/sell indicator that should capture market wide pressure on liquidity and prices, it takes the value of 1 if the sum of $Q_{i,t-1}$ across all stocks is positive, otherwise it takes the value of -1. Following Heflin and Shaw (2000), when they indicate that the estimate of β_1 is one-half the estimated effective spread, and suggest the adverse selection component equals $2(\beta_{2,i} + \beta_{1,i})$. This estimated component, well replace bid ask spread (BAS) as the fitted spreads to see how this new variable might pick the information asymmetry and how it would interact in our model. In Huang and Stoll (1997) model, effective spread is estimated to reflect the true transaction cost for an average sized trade.

[56] Heflin and Show (2000) use both tick test and midpoint test and report more than 0.98 correlation between the two estimates.

Table 5-12: Block Purchases Price Impact coefficients using Estimated Bid-Ask Spread Component.

VARIABLES	Permanent effects	Total effects	Temporary effects
Ln(size)	**0.00175***** (8.57e-06)	**0.00149***** (6.38e-06)	**0.000262***** (6.54e-06)
Volatility	**0.000873***** (1.25e-05)	**0.000536***** (9.28e-06)	**0.000340***** (9.52e-06)
Ln(turnover)	**-0.000276***** (1.03e-05)	**-0.000329***** (7.70e-06)	**4.80e-05***** (7.90e-06)
Mktreturn	**0.0324***** (0.000363)	**0.00503***** (0.000270)	**0.0270***** (0.000277)
Momentum	**-0.000860***** (4.12e-05)	**-0.00164***** (3.07e-05)	**0.000759***** (3.15e-05)
BAS(Estimated)	**0.488***** (0.00246)	**0.640***** (0.00183)	**-0.146***** (0.00188)
Constant	**-0.0159***** (8.85e-05)	**-0.0130***** (6.59e-05)	**-0.00293***** (6.76e-05)
R-squared	**0.048**	**0.089**	**0.008**

This table presents estimates of the price impact using estimated Huang and Stoll (1997) adverse selection component of the spread as the realised effective spread to reflect the true measure of execution costs. All three types of price impacts have been reported here, permanent, total and temporary.
$\mathbf{Price\ Impact} = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\mathbf{InSize} + \boldsymbol{\beta_2}\mathbf{Volatility} + \boldsymbol{\beta_3}\mathbf{InTurnover} + \boldsymbol{\beta_4}\mathbf{Market\ Return} + \boldsymbol{\beta_5}\ \mathbf{Momentum} + \boldsymbol{\beta_6}\mathbf{BAS(Estimated)} + \boldsymbol{\varepsilon}$. 2,366,099 block purchases are included in the regression analysis. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The coefficients results are similar to previous relationships that we have already discussed where all variables show significant coefficients at the 1%. The estimated BAS shows large positive coefficients for the three price impacts. The total price effect which is calculated as the cumulative price returns from five trades "minutes" before the block trade to the block trade price shows the highest coefficients among all price effects suggesting that price discovery is very quick in the SSM. Best five quotes for the bid and ask are shown to all traders in market. Once a block trade arrives to the order book, it conveys the arrival of new information to the market, subsequently, traders update quotes and prices. On average, new information explain 64% of the price increase of block purchases at the execution. Once the block purchase is executed, the price drops by 14% (temporary effect) resulting in a permanent price impact of 49%. Since the identity of the trader is anonymous in the SSM, traders put stronger weight on the order size. Once a large order appears on the screen, the market perception about the true values of the assets being trades changes quickly. However, price impact diminishes on average of -14% five minutes after the block trade.

Table 5-13: Block Sales Price Impact coefficients using Estimated Bid-Ask Spread Component.

VARIABLES	Permanent effects	Total effects	Temporary effects
Ln(size)	**-0.000542***** (1.07e-05)	**-0.000541***** (8.08e-06)	**1.08e-06** (8.43e-06)
Volatility	**-0.000255***** (1.38e-05)	**0.000421***** (1.04e-05)	**-0.000679***** (1.08e-05)
Ln(turnover)	**-0.000385***** (1.13e-05)	**-0.000122***** (8.48e-06)	**-0.000270***** (8.85e-06)
Mktreturn	**0.0814***** (0.000407)	**0.0465***** (0.000306)	**0.0351***** (0.000319)
Momentum	**0.000483***** (4.29e-05)	**0.00118***** (3.23e-05)	**-0.000713***** (3.37e-05)
BAS(estimated)	**-0.364***** (0.00251)	**-0.614***** (0.00189)	**0.260***** (0.00197)
Constant	**0.00324***** (0.000110)	**0.00277***** (8.30e-05)	**0.000448***** (8.67e-05)
Observations	**1855236**	**1855236**	**1855236**
R-squared	0.042	0.076	0.017

Notes: this table reports the regression coefficients for the seller initiated block trades. Three types of Price effect are listed permanent, total and temporary. Effective spread was estimated using Huang and Stoll (1997) model to capture the information asymmetry component of the spread .
$Price\ Impact = \alpha + \beta_1 InSize + \beta_2 Volatility + \beta_3 InTurnover + \beta_4 Market\ Return + \beta_5\ Momentum + \beta_6 \mathrm{BAS(Estimated)} + \varepsilon.$ 1,855,236 block sales are included in the regression analysis. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The seller initiated blocks exhibit similar price behaviour with regard to trading activities as reported earlier. Temporary price impact has a positive coefficient with size of the trade, however, not significant. Size of the buy block trade moves the prices (all types of price effects) on average three times the size effects of block sales. A volume- price effect asymmetry is observed in the SSM. The estimated spreads (BAS) which is a reflection of the price asymmetry effect have similar pattern to the information asymmetry effect for the block purchases. Information asymmetry is responsible for 61% of price decrease that a block sale experiences at the time of execution.

A price reversal usually follows block sale execution of about 26% resulting in a permanent price effect of around 36%. Again, information asymmetry explains the price impact asymmetry between buy and sell block trades. Block sales are more affected by liquidity constraints, and block sellers usually pay higher liquidity premium than block buyers.

Table 5-14 : Information Asymmetry and Size, Volatility and Time of the Day

Independent Variables	Buy InfoBAS	Sell InfoBAS
Ln(size)	**0.000251*** **	**0.000206*** **
	(2.24e-06)	(3.12e-06)
volatility	**0.00195*** **	**0.00213*** **
	(2.73e-06)	(3.38e-06)
TimeDum1	**0.000766*** **	**0.000824*** **
	(5.55e-06)	(7.16e-06)
TimeDum2	**0.000137*** **	**0.000126*** **
	(4.87e-06)	(6.31e-06)
Constant	**-0.00181*** **	**-0.00133*** **
	(2.36e-05)	(3.26e-05)
Observations	**2,366,099**	**1,855,236**
R-squared	**0.180**	**0.178**

Notes: this table presents Cross-sectional OLS regression of the asymmetric information component of the spread as a function of size and volatility. Time of the day adverse section is examined through time dummies .T1=first trading hour, t2= midday trading hours, and t3=last trading hour (reference group). The sample is split into two subsamples buy and sell block trades using the following model : $\boldsymbol{InfBAS = \alpha + \beta_1 InSize + \beta_2 Volatility + \beta_3 \mathrm{t}_1 + \beta_4 t_2 + \varepsilon}$.

InfoBAS is the asymmetric information component of the bid ask spread estimated using Haung and Stoll (1997) model. Standard errors are reported in parentheses. *** p<0.01.

All variables have significant coefficients at the 1% level. Similar to Huang and Stoll (1997) who found trade size increase effective spread for NYSE stocks, we find that the adverse selection component of the spread is a function of the trade size. Volatility shows positive relationship with information asymmetry of the spread; the more volatile stocks imply higher information asymmetry and higher execution costs. Time dummies are constructed for the first trading hour t1, midday trading t2 and final hour t3 (reference group). Intraday time pattern shows diurnal behaviour where information asymmetry is at its highest at the beginning of the day, after the open as we exclude open transactions from the analysis. Information asymmetry decreases as prices impound information until it reaches its lowest for the final hour which show negative sign (constant) for block buys and sells, at (-0.18%)and (-0.13%), respectively.

5.6.6 Liquidity determinants and cross-sectional variation

The bid-ask spread is an indicator of the cost of trading and is a measure of market illiquidity. A central issue in the market microstructure research is the determinants of bid ask spread and its variation across securities or time. Prior research has made substantial contribution toward understanding the determinants and components of the bid/ask spread. A line of research that focuses empirically on which variables or trading activity measures can determine bid-ask spread and also capture variation in spread cross-sectionally include but not limited to Demsetz (1968), Tinic (1972), Stoll (1978b), Jegadeesh and Subrahmanyam (1993) and Heflin and Shaw (2000). The results of these variables differ , but some of the main findings are that spread is a function of price level, volatility ,firms size ,volume and the number of market makers. For example, Stoll (1978b) and Jegadeesh and Subrahmanyam (1993) find that spread is correlated negatively with the price level, volume and the number of market makers, and positively associated with volatility. Heflin and Shaw (2000) find that spread is positively related to volatility and ownership concentration while negatively correlated to share prices, trade size and firm size.

Intuitively, higher volume reduces inventory cost for the market maker which would be reflected in the bid-ask spread. Moreover, the volatility variable seems always to have a positive relationship with the spread because of the uncertainty and adverse selection problems that are usually associated with higher volatile stock. All previously mentioned studies have the intention to capture which trading activities affect the spread, however, they were conducted in a market maker environment where the market maker is mainly responsible for setting the bid and ask quotes. The hypothesis that trading activity is indeed an important cause of liquidity is confirmed in limit older markets as well, including some of the recent theoretical work on limit order market (see, e.g., Foucault, et al., 2005; and Rosu, 2009).

The SSM is a purely order –driven market where the bid and ask prices are set by the demand and supply of traders in the market. We anticipate that trading activities will have similar effect that found in quote-driven market but some deviations are expected too. For example, the volume of the trade variable might reflect an adverse selection problem in an order-driven market rather than an inventory cost as in a specialist market, hence we expect some variables in the SSM to capture different aspects of the trading activities and will have different effects than those found in the literature . We focus on the determinants of bid-ask spread across different trading activities attributes and across time of the day to examine any variation or irregularities in the market using multivariate regression analysis. We attempt to examine cross-sectionally the relationship between bid/ask spread and trading activities similar to prior established work of Demsetz (1968), and Heflin and Shaw (2000). We also analyse intraday patterns in bid-ask spreads through dividing the trading day into three times intervals and use dummy variables for each interval. Contrary to the quote-driven market where market makers set the quotes, the interaction between market orders that demand liquidity and limit orders that supply liquidity determines the liquidity in an order driven market. As mentioned earlier in this thesis, there are various dimensions of liquidity that were discussed in the literature. For example, Harris (1990) defines four dimensions of liquidity: width, depth, immediacy and resiliency. We measure how trading activities affect the bid-ask spread which is the width measure of liquidity. However, other dimensions of liquidity are examined as well. To examine the relationship between market liquidity and trading activities we estimate various forms of the following OLS cross-section regression that is similar in principal to Heflin and Shaw (2000) Model where they measure the relationship between liquidity and ownership structure. Our model is similar also to Harris (1994) who uses the market value of shares outstanding as a proxy for adverse selection and also uses the standard deviation of returns as a direct measure of volatility.

For the determinants of liquidity, we include well documented variables from the literature ; size of the trade, volatility of returns, size of the company, number of trades per day, sign of the trade (buy or sell) , and dummy variables for time of the day.

$$\begin{aligned} \boldsymbol{Liquidity} = {} & \boldsymbol{\alpha} + \boldsymbol{\beta_1}(\boldsymbol{volume}) + \boldsymbol{\beta_2}(\boldsymbol{volatility}) + \boldsymbol{\beta_3}(\boldsymbol{size}) + \boldsymbol{\beta_4}(\boldsymbol{No\ of\ trades}) \\ & + \boldsymbol{\beta_5}\,(\boldsymbol{trade\ sign}) + \boldsymbol{\beta_6}(\mathbf{t_1}) + \boldsymbol{\beta_7}(\boldsymbol{t_2}) + \boldsymbol{\beta_8}(\boldsymbol{t_3}) + \boldsymbol{\varepsilon} \end{aligned} \tag{10}$$

Where liquidity is either quoted spread (QBAS), relative spread (RBAS) or effective spread (EBAS). Volume is the natural logarithm of the number of shares per trade. Volatility is the standards deviation of returns computed from beginning of the day midpoint to the last trade prior to the current trade. Size is natural logarithm of the market value of common equity for each firm. Number of trades is the cumulative number of trades per day for each stock matched with the date of the trade. Trade sign is a dummy variable representing the direction of the trade using Lee and Ready (1991) “tick rule” classification technique, we assign value of 1 for buyer-initiated trades and value of 0 for seller-initiated trades. We include three dummy variables for the time of the day where the trading day is divided into three time intervals, first trading hour (t_1) , midday trading(t_2) and last trading hour(t_3). All variables are computed from the intraday data of block trades, we include only trades with volume larger than 10,000 shares.

Easley and O'Hara (1987) indicate that informed traders prefer to trade a large amount at any given price, a finding that confirmed by many researchers.[57] If this finding holds true, the adverse selection component of the spread should increase with trade size, subsequently, bid-ask spread should be higher. We expect trade size to have a positive signed coefficient with regard to bid-ask spread. Volatility is directly measured as the standard deviation of price returns. Volatility as a measure of risk is expected to widen the bid-ask spread, therefore we expect to have a positive coefficient with liquidity. The natural logarithm of the market value of shares outstanding serves as an inverse proxy for adverse selection costs. The larger the firm, the larger the government and other funds ownership which could indicated a greater degree of public information. Therefore, larger firms are believed to show less information asymmetry among investors and smaller adverse selection cost. We expect firm size to have a negative coefficient with the bid/ask spread.

The number of trades is a measure of trading frequency; the higher trading frequency the stock is the lower the spread and which induce lower transaction cost and higher liquidity in the market. The sign of coefficient for the number of the trades is expected to have negative relationship with regards to bid-ask spread. Trade sign is a dummy variable that takes the value of 1 if the trades are classified as buy and 0 for sell trades. We attempt to examine if a trade sign has any effect on liquidity in the market. Prior research has establish a price asymmetry between buy and sell block trades indicating that buy trades have permanent price impact on stocks while sell trades have somehow lower price impact that tends be transitory. In other words, sellers of block trades pay a liquidity premium. In fact the natural asymmetry between liquidity buyers and liquidity sellers lead to the asymmetry in price impact. If sale trades contain less information and are more motivated by liquidity then we would expect that purchase trades to have higher bid-ask spreads because of the higher probability of informed trading. Our results indicate that purchases have much greater effects on bid-ask spread than sales which can be explained by the fact that they are less likely to be driven by liquidity. our result is in favour of the literature explanation of this asymmetry, that is in purchases traders have to make actual investment decision whereas in sales the decision can be induced by a number of factors such as liquidity requirements or diversification needs.

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[57] Look for example, (Kyle, 1985; and subrahmanyam, 1991).

Finally, the time dummy variables are included in the regression to examine any intraday patterns of liquidity. The microstructure literature has detected and reported various patterns of liquidity .One of the most famous pattern is the U-shaped bid-ask spread where the spread is at its highest at the opening and closing of the trading day (McInish and Wood, 1992).[58] Similarly, AlSuhaibani and Kryzanowski (2000a) document the U-shaped pattern of liquidity in the SSM even though the market shows different structure and characteristics. Most of these patterns indicate high spread at the beginning of the trading session then declining during the day, a behaviour that can be related to uncertainty. The similarity in liquidity patterns in different market system, suggests that market maker alone, in a quote-driven market, cannot be accounted totally to the widening of the spread at the open and close of the trading session. Accordingly, we expect bid-ask spread to be at its highest at the opening and narrows as the trading hours continue and prices incorporate new information.

58 Some other well documented patterns include inverse U-shaped ,J-shaped, inverse J-shaped along with other patterns (e.g., Wood et al.,1985, Chan et al., 1995, Madhavan et al., 1997, McInish and Ness, 2002).

Table 5-15 : Liquidity Determinants in the SSM

VARIABLES	(1) QBAS	(2) RBAS	(3) EBAS
Volume	**0.0682*** **	**0.00155*** **	**0.0385*** **
	(0.000222)	(3.28e-06)	(0.000199)
Volatility	**0.321*** **	**0.00124*** **	**0.219*** **
	(0.000250)	(3.68e-06)	(0.000223)
Size	**-0.00501*** **	**-0.000357*** **	**0.00118*** **
	(0.000116)	(1.72e-06)	(0.000104)
No of Trades	**-0.00121*** **	**-2.81e-06*** **	**-0.00115*** **
	(4.66e-06)	(6.88e-08)	(4.17e-06)
Trade sign	**0.0269*** **	**0.000251*** **	**0.0148*** **
	(0.000350)	(5.16e-06)	(0.000313)
TimeDummy1	**0.0202*** **	**0.000462*** **	**0.0153*** **
	(0.000645)	(9.52e-06)	(0.000577)
TimeDummy2	**-0.0325*** **	**-0.000478*** **	**-0.0341*** **
	(0.000489)	(7.22e-06)	(0.000438)
Constant	**-0.277*** **	**-0.00282*** **	**-0.221*** **
	(0.00333)	(4.92e-05)	(0.00298)
Observations	4221872	4221872	4221872
R-squared	**0.291**	**0.085**	**0.192**

Notes: this table presents Cross-sectional OLS regression coefficients of the liquidity determinants in the SSM.

$$\mathbf{Liquidity} = \boldsymbol{\alpha} + \boldsymbol{\beta_1}(\mathbf{volume}) + \boldsymbol{\beta_2}(\mathbf{volatility}) + \boldsymbol{\beta_3}(\mathbf{size}) + \boldsymbol{\beta_4}(\mathbf{No\ of\ trades}) + \boldsymbol{\beta_5}\ (\mathbf{trade\ sign}) + \boldsymbol{\beta_6}(\mathbf{t_1}) + \boldsymbol{\beta_7}(\mathbf{t_2}) + \boldsymbol{\beta_8}(\mathbf{t_3}) + \boldsymbol{\varepsilon}$$

Volume is the natural logarithm of the number of shares per trade, volatility is the standards deviation of returns computed from beginning of the day midpoint to the last trade prior to the current trade, size is natural logarithm of the market value of common equity for each firm. Number of Trades is the cumulative number of trades per day for each stock matched with the date of the trade. Trade sign is a dummy variable taking value of 1 for buy trades and 0 for sell trades. Time of the day variation of liquidity patterns is examined through time dummies, t1=first trading hour, t2= midday trading hours, and t3=last trading hour. Sample is split into two subsamples buy and sell block trades .Three measures have been used to proxy for liquidity that is quoted spread (QBAS), 2) relative Spread (RBAS) and 3) effective Spread (EBAS).spreads are calculated as the following:

1)$\mathbf{QBAS} = \mathbf{ask\ price}_{\mathbf{t}} - \mathbf{bid\ price}_{\mathbf{t}}$,
2)$\mathbf{RBAS} = \frac{(\mathbf{ask\ price_t} - \mathbf{bid\ price_t})}{\mathbf{mid\ price_t}}$, and
3)$\mathbf{EBAS} = \mathbf{2}(\mathbf{trade\ price}_{\mathbf{t}} - \mathbf{mid\ price}_{\mathbf{t}})$.
Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

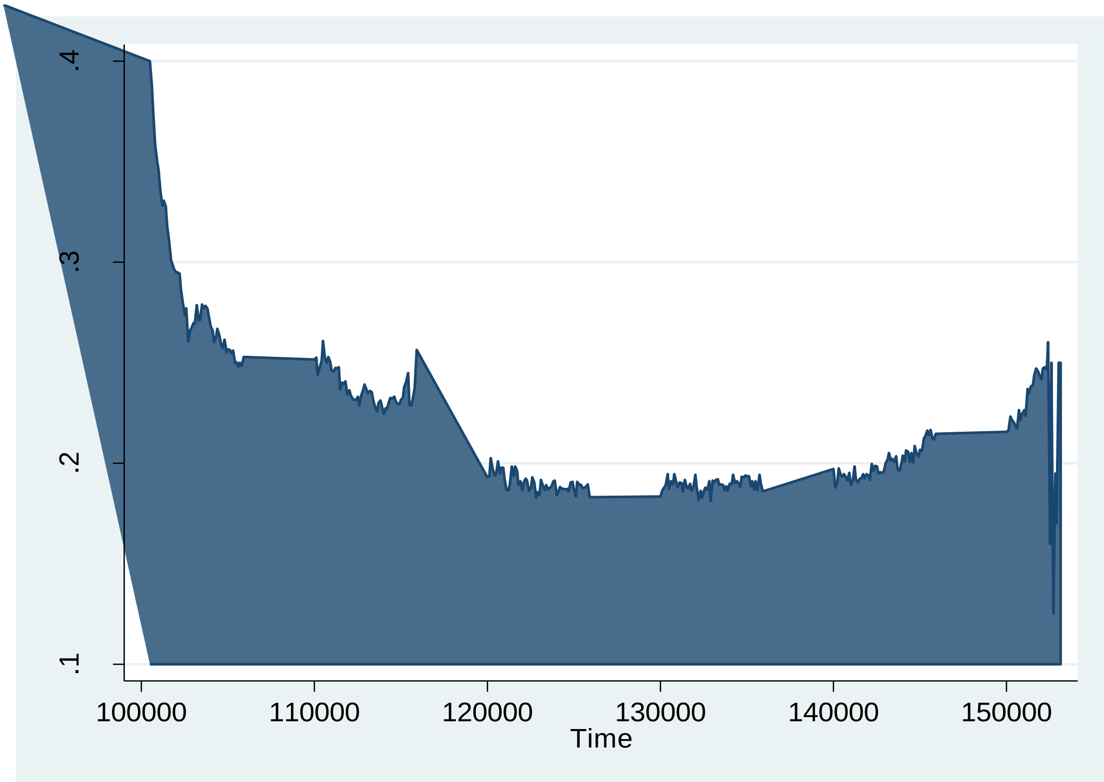
The quoted spread and effective spread report higher R-squared at 27 and 22 percent, respectively. The relative spread report a lower R-squared at 8 percent only. Someone has to be careful when including the relative spread as a measure of liquidity. Bollen et al (2004) when reviewing Tinic and West (1974) work on the bid-ask determinants, states “For the relative spread regression to be correctly specified, all of the explanatory variables must be deflated by share price”. All explanatory variables report significant coefficients at the 1% level for all forms of the models. Volume show positive relationship with the spreads indicating that informed traders tend to transact large volume, confirming to Easley and O’Hara (1987) model of informed trading. Volatility has significant positive effect, in fact its coefficients are the highest among all variables at 0.32 and 0.22 for the quoted and effective spread. Volatility augments spread in the SSM, a relationship that is very well documents in the literature. Size of the company has a negative relationship with the quoted bid-ask spread as expected with coefficient that is (-0.005). The larger the firm the more well known and lower the possibility of adverse selection cost that is reflected in the spread. Our firm size relationship coincides with Heflin and Shaw (2000) who report a firm size coefficient of (-0.008).Smaller firms in the SSM tend to be the target of both informed and speculative trading due to smaller number of shares and higher ability to control price movement of stocks regardless of fundamental values, therefore, smaller firms’ stocks tend to show higher volatility and adverse selection costs.

However, the effective spread shows a positive coefficient with the size of the company, the larger the firm the higher the effective transaction cost .Effective spread shows how a round-trip trade price was placed relative to the midpoint price(price improvement) and the tendency for larger orders to move the price (price impact) . Naturally, larger orders are associated with larger company size, the positive relationship between firm size and effective spread maybe due to the price impact of larger orders. Moreover, larger companies in the SSM exhibit higher stock prices, hence higher effective spread is also expected.

Number of trades which is a measure of the trading frequency appears to have a negative relationship with all types of spreads, confirming to prior research (Kim and Ogden,1996; Heflin and and Shaw ,2000; Giouvris and Philppatos, 2008) who also found significant negative relationship between number of trades per day and the components of the bid-ask spread. Number of trades can be explained as a way of reducing information asymmetry in the market. If a stock is relatively traded frequently, traders relate frequency of the trade as a high liquid stock, therefore the spread tightens between the bid and the ask prices. The trade sign dummy variable, 1 for buy trades and 0 for sell trades, indicates that on average buyer-initiated trades increase the spread more than seller-intuited trades with coefficients of 2.7% and 1.5% for the quoted and effective spread, respectively. A relationship that is confirmed by our previous analysis of the higher price impact for block purchases than block sales and is also supported by the numerous literature findings of price impact asymmetry between buy and sell block trades. Finally, the time dummies suggest that liquidity cost is at its highest at the beginning of the trading day then decreases throughout the trading day before it bounces again toward the end of the trading day forming an inverse J-shaped bid-ask spread pattern similar to McInish and Wood (1992)[59] . The time dummies coefficients for all types of spreads quoted, relative and effective report similar patterns of a positive coefficients for time dummy1 at 0.2, 0.0004, and 0.015 ,respectively, then followed be negative signs reported in the same order for timedummy2 at (-0.03),(-0.0005) and(-0.034). Our time of the day results are consistent with Frino et al.(2007) who find liquidity cost or price impact is the largest for of block trades executed at the first hour. Moreover, our intraday spread pattern is somehow similar to Al-Suhaibani and Kryzanowski (2000a, 2000b) who find that spreads are at their highest at the open and narrow over the trading day in the SSM. An obvious explanation for this pattern is that adverse selection is highest at the beginning of the day and as trading continues the information asymmetry decrease or incorporated in the prices. Graph (1) shows the average bid- ask spread pattern throughout the trading hours.

[59] Some other studies who document the reversed J-shaped document the reversed-J shape pattern of spreads and U-shape pattern of volume include (Wood et al., 1985, Foster and Viswanathan ,1990, and Jain and Joh ,1988)

Figure 5-1 : Intraday Variation Pattern of the Spread



Notes: The graph shows the intraday pattern for the effective bid/ask spread in the SSM averaged across all observation by the minute as the following:
$\mathbf{EBAS_t = \frac{1}{N}\sum_{t=1}^{270} 2(trade\ price_{\ t} - \ mid\ price_{\ t})}$. Spread is at its highest at the beginning of the trading hours then decreases throughout the trading day before it bounces again toward the end of the trading day forming an inverse J-shaped pattern similar to McInish and Wood (1992) and closely confirming Al-Suhaibani and Kryzanowski (2000a,2000b) for the Saudi market.

5.7 Summary

This chapter tests the price impact determinants for block trades in the SSM. The price impact asymmetry between buyer- and seller-initiated block trades indicates that separate regression should be run according to the trade sign. We test the price impact with relative to trade sign, trade size, market condition and time of the day. We use various forms of price impacts and spreads in our tests of the effects of the block trades. We also measure liquidity and information asymmetry determinants and behaviour.

Our results suggest that informed traders in the SSM tend to trade large volume; the tendency is higher for the block purchases. The number of trades for each trade size group indicates that both buyers and sellers of block trades in the SSM follow similar trading strategies when it comes to splitting orders or “stealth trading”.

Price discovery is very quick in the SSM, the largest portion of the price reaction takes place in the five minutes prior to a block trade execution. On average, the price effect of block trades is small and short-lived. Our finding suggest that resiliency is high in the SSM, price effect is at its highest at the execution , then five trades “minutes” after the block trade has been executed a prices reversal is expected .However the price reversal is higher for block sales. On average, informed trading explains 64% of the price increase of block purchases at the execution. Once the block purchase is executed, the price drops by 14% (temporary effect) with 49% of the permanent price impact that is estimated to be related to information asymmetry. For block sales, informed trading explain 61% of the price decrease which reverts by 26 % five minutes after the exaction leaving 35% permanent price impact.

In spite of the unique structure of the SSM; price impact, volatility and spread show similar intraday patterns that were found in previous literature. For example, information asymmetry is at its highest in the beginning of the day (after the open) then shows diurnal pattern through the day. The price impact demonstrates an inverse J-shaped intraday pattern.

Finally, Informed or sophisticated traders can gain abnormal profits in the SSM through “free riding”, a trader can benefit from the overreaction before the block trade execution and price reversal after the block trade.

Conclusions

This dissertation brings up further evidence on the effect of different market characteristics on stock return behaviour and liquidity in the market. The research provides empirical evidence on issues such as the efficiency of the market, information asymmetry and price impact and the liquidity of block trades. Two main lines of finance research dominate the thesis. First, literature in the context of capital market research was used to investigate the informativeness of quarterly earnings announcements and to examine other aspects of the market around earnings announcements (i.e., liquidity, information asymmetry, volume, volatility and investors' placement strategy). Event study methodology was the main research tool used to infer the market reaction to corporate events through computing and investigating cumulative abnormal returns (CAR) for both types of news, good and bad. Second, a market microstructure framework was employed to investigate block trades in the SSM. I compute different types of price impact to examine the cost of trading large volumes in a market where institutional investment is not yet well established. Variations in the magnitude of the price impact and liquidity of block traders were examined through various cross-section models. In this section, I also analyse intraday liquidity patterns using time dummy variables.

The research is divided into an introductory chapter and four essays. The first part (Chapters 2 & 3) examines stock returns behaviour and trading activity around earnings announcements. The second part (Chapters 4 & 5) examines price impact asymmetry and the price/liquidity effects of block trades in the market microstructure context. Each essay addresses some aspects of market microstructure and stock returns behaviour in order to aid researchers, investors and regulators to understand a market which lacks research coverage.

Chapter One shows the importance of the study and why the SSM is a very interesting experimental environment to test. Growth, development and market characteristics are discussed in this chapter to give the reader an understanding of the way in which the market evolved. The chapter briefly reviewed the few previous studies covering this market and then identified the research gap which aroused my curiosity and gave me the motivation to embark upon this study.

The first of the four essays is titled "How Markets React to Earnings Announcements in the Absence of Analysts and Institutions" and is organised in two parts. In part one, I document the functionality of the SSM and compare it with those of developed markets. The objective of this part is to describe the differences of the SSM and show how these differences might affect its behaviour. In part 2, I use standard event study to measure price reaction to earnings announcements, where I find post-earnings announcement drift (PEAD). I further analyse the market reaction using different measures of abnormal returns and earnings surprise. I also conduct sector-level analysis to examine whether government ownership and company size can affect the magnitude of the price drift.

The first essay goes on to analyse the price reaction to earnings announcements on the Saudi market. The analysis is conducted on two levels, market-level and sector-level. Various short event windows and portfolios around the release day are constructed to test the price reaction, which is measured using cumulative abnormal return (CAR) and buy-and-hold abnormal return (BHAR). 1667 quarterly earnings announcements for the period 2001-2007 are included in this chapter. It provides evidence on the post-earnings announcement drift (PEAD) in an environment which lacks both institutional investment and analysts' forecasts.

The results pose a challenge to the efficiency of the SSM. The SSM seems to underreact to positive news for the first five days and then produces a positive reaction which tends to be stronger for the following weeks, indicating the existence of a post-earnings announcement drift. In contrast, the SSM overreacts to negative news in the first five days and then reverses its direction and reports an upward post-earnings announcement drift. Our results suggest that the market is slow to adjust to new information when there is good news and reacts irrationally to bad news. The results are robust using different earnings surprises, EAR, and time-series earning expectation models. The absence of analysts' forecasts and an individually dominated market are the main explanation of this underreaction to positive news and overreaction to negative news. It is confirmed by higher PEAD in sectors containing smaller firms and where there is lower government and institutional ownership.

The second of the four essays has the title "Information Asymmetry, Trading Activity and Investor Behaviour around Quarterly Earnings Announcements". Covering 2,437 earnings announcements, it analyses the variation in stock returns, trading activity, volatility, information asymmetry and liquidity caused by earnings announcements for the period 2002-2009. It also investigates traders' placement strategy around earnings announcements distinguishing between small and large investors. The magnitude of the abnormal returns, liquidity and information asymmetry around earnings releases were also investigated, using a cross-section regression analysis.

Overall, this essay shows a higher level of private information acquisition in the pre-announcement period and persistent information asymmetry in the post-announcement period which can be attributed to the difference in investors' ability to interpret news. I observe a rise in trading activity and volatility around earnings announcements, with a higher information asymmetry which gradually reduces in the 20 days following the announcement date. The persistence of volatility and information asymmetry in the post announcement period can be explained by the heterogeneity in investors' ability to process the information in public announcements. Moreover, large investors show higher informed trading even before the announcement, whereas small investors show stronger reaction to news. The abnormal returns were found to be positively associated with pre-announcement trading activity and negatively related to firm size and time-series earning surprise measures. Finally, most of the rise in bid-ask spread around earnings announcements is attributed to the increase of the information asymmetry component, which is induced by uncertainty and the difficulty in interpreting news.

The third essay (Chapter 4) takes the title "Bid-Ask Spread and the Price Impact Asymmetry of Block Trades". In this paper, I empirically examine the price impact of block trades in the SSM over the time period 2005-2008. Using a unique dataset of intraday data consisting of 2.3 million block buys and 1.9 million block sales, I replicate the asymmetry between block purchases and sales documented in the previous literature. However, unlike prior research, the price impact asymmetry persists even when I encapsulate the biases in block transactions through the existence of the bid-ask spread. Overall, the findings suggest that, in an emerging market where institutional trading is relatively scarce, market microstructure cannot explain the asymmetry in the price impact of large trades. In addition, my results are consistent with Benveniste et al (1992) and Snell and Tonks (2003) in finding that market makers are superior in resolving information asymmetry than the order book system.

The final essay of the four (Chapter 5) explores the determinants of the price impact and liquidity of block trades in the market and is entitled "Liquidity and the Price Impact of Block Trades". Permanent, temporary and total price impacts were empirically investigated with regard to trade size category, market condition and time of day effects. Bid-ask spread as a measure of liquidity was decomposed, using the model of Huang and Stoll (1997) to infer the information asymmetry patterns in the market.

The results suggest that informed traders in the SSM tend to trade large volumes; the tendency is higher for block purchases. Price discovery is very quick in the SSM: the largest portion of the price reaction takes place in the five minutes prior to a block trade execution. On average, the price effect of block trades is small and short-lived. Our findings suggest that resiliency is high in the SSM. Once a block trade is executed, a reversal in price is expected: however, block sales price reversal is stronger than block purchases. Finally, informed or sophisticated traders can gain abnormal profit in the SSM through "free riding", whereby a trader can benefit from the overreaction before the block trade and price reversal after the block trade.

The four essays and their conclusions outline several possible directions for future research. The abnormal returns could be further investigated in relation to more firm-specific balance sheet variables. The effect of major government and family ownership on information asymmetry in the market is also a research gap which should be filled.

The intraday data which has been constructed expands the horizon for future research using high frequency data, for example, to investigate the probability of informed trading (PIN) or illiquidity measures in the market and their relationship with stock returns. A comparison between block and non-block trading data is another possible direction for future research.

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Appendices:

Appendix for chapter two

Table 1: This table shows some financial indicators for the Saudi market from the official starting date of 1985 until the end of 2007. This table presents the number of shares traded, value of traded shares, market capitalisation, number of transactions and finally the performance of the value weighted index (TASI).

SHARE MARKET INDICATORS					
End of Period	**Number of Shares Traded** (in Millions)	**Value of Shares Traded** (in Million RLs)*	**Market Value of Shares** (in Billion RLs)*	**Number of Transactions**	**General Index (TASI)** (1985 = 1000)
1985	4	760	67	7,842	690.88
1986	5	831	63	10,833	646.03
1987	12	1,686	73	23,267	780.64
1988	15	2,037	86	41,960	892.00
1989	15	3,364	107	110,030	1,086.83
1990	17	4,403	97	85,298	979.80
1991	31	8,527	181	90,559	1,765.24
1992	35	13,699	206	272,075	1,888.65
1993	60	17,360	198	319,582	1,793.30
1994	152	24,871	145	357,180	1,282.90
1995	117	23,227	153	291,742	1,367.60
1996	138	25,397	172	283,759	1,531.00
1997	312	62,060	223	460,056	1,957.80
1998	293	51,510	160	376,617	1,413.10
1999	528	56,578	229	438,226	2,028.53
2000	555	65,292	255	498,135	2,258.29
2001	691	83,602	275	605,035	2,430.11
2002	1,736	133,787	281	1,033,669	2,518.08
2003	5,566	596,510	590	3,763,403	4,437.58
2004	10,298	1,773,858	1,149	13,319,523	8,206.23
2005	12,281	4,138,695	2,438	46,607,951	16,712.64
2006	54,440	5,261,851	1,226	96,095,920	7,933.29
2007	57,829	2,557,712	1,946	65,665,500	11,175.96

*In April, 2006 there was a stock split of 5:1 for all listed companies. One U.S. Dollar = 3.75 Saudi Riyals.

Portfolios performances using Buy-And-Hold-Abnormal Returns (BHAR)

	A: Positive Returns Portfolio (807 firms)				B: Negative Returns Portfolio(860)			
Days Relative to Announcements	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
-19	1.000898	0.025357	0.903814	1.110847	0.999296	0.029223	0.888497	1.109487
-18	1.001412	0.037365	0.815995	1.199031	0.998886	0.042923	0.806938	1.21137
-17	1.000357	0.045971	0.774438	1.295063	0.997682	0.052058	0.755683	1.286136
-16	0.998555	0.054228	0.735207	1.423741	0.995959	0.062109	0.733062	1.325484
-15	0.998284	0.063585	0.678895	1.556179	0.994856	0.072021	0.700037	1.376166
-14	0.998295	0.065534	0.663424	1.462034	0.995901	0.081547	0.621324	1.529084
-13	0.998108	0.069942	0.651648	1.432922	0.995055	0.091324	0.551941	1.594877
-12	0.998594	0.079625	0.618159	1.496977	0.996259	0.093158	0.506798	1.571607
-11	0.999919	0.086063	0.612375	1.591271	0.997238	0.095179	0.455777	1.589985
-10	0.999091	0.091298	0.595867	1.649344	1.000391	0.099489	0.409071	1.737172
-9	1.000599	0.096411	0.543786	1.812392	0.999392	0.099038	0.391976	1.756416
-8	1.001619	0.105753	0.543852	1.985488	1.000758	0.10132	0.346955	1.922213
-7	1.001825	0.109403	0.544645	1.861447	1.003945	0.108396	0.385326	2.069583
-6	1.001694	0.107486	0.504028	1.893764	1.006976	0.118164	0.347663	2.275723
-5	1.000873	0.107891	0.435922	2.020956	1.008087	0.123227	0.336911	2.49426
-4	1.000046	0.109804	0.472022	2.083402	1.005445	0.129322	0.369504	2.766792
-3	0.999722	0.114385	0.508569	2.062791	1.002271	0.140052	0.408137	3.271579
-2	0.999715	0.118808	0.559484	2.055104	1.000307	0.145768	0.414833	3.14297
-1	0.997929	0.121794	0.541062	2.050935	0.999724	0.144586	0.426658	2.713395
0	1.016106	0.128034	0.574702	2.018904	0.978503	0.141681	0.401651	2.672179
1	1.012575	0.128232	0.62705	1.84583	0.973499	0.139774	0.385101	2.331718
2	1.012922	0.135426	0.603887	1.971668	0.970087	0.139394	0.338798	2.192669
3	1.010865	0.13525	0.522933	1.98742	0.968516	0.142325	0.311995	2.142502
4	1.010149	0.139025	0.517072	2.171148	0.966778	0.146304	0.280136	1.905663
5	1.010549	0.140967	0.45136	2.186009	0.966503	0.148487	0.264737	1.7394
6	1.008125	0.143206	0.426254	2.199382	0.967531	0.149323	0.251492	1.703966
7	1.009918	0.149336	0.417487	2.22583	0.968848	0.148538	0.256207	1.677225
8	1.011187	0.155422	0.416742	2.335332	0.969542	0.152304	0.237516	1.780678
9	1.013308	0.160139	0.432371	2.42973	0.971767	0.155059	0.22525	1.708647
10	1.013737	0.164648	0.421921	2.390192	0.974055	0.157813	0.231118	1.874709
11	1.015014	0.172046	0.373715	2.657103	0.976058	0.163162	0.243197	1.908682
12	1.017887	0.1803	0.378924	2.945493	0.978288	0.167359	0.223537	2.056151
13	1.019457	0.183884	0.409594	2.970548	0.979533	0.174715	0.198696	2.202779
14	1.02019	0.186055	0.412	3.133574	0.982468	0.184433	0.214846	2.489044
15	1.020468	0.185525	0.396524	2.86904	0.983796	0.192192	0.234015	2.724611
16	1.022678	0.18917	0.426693	2.820727	0.985411	0.194358	0.255891	2.857608
17	1.025454	0.195653	0.424702	2.859558	0.988059	0.195892	0.288852	2.632676
18	1.026759	0.201033	0.416078	2.767392	0.989235	0.204222	0.258868	2.830196
19	1.028142	0.204122	0.428324	2.791848	0.991287	0.214506	0.263708	3.119548
20	1.036704	0.21044	0.437621	2.729794	0.983635	0.221863	0.241556	3.421855

Table 2: The table shows the performance of a virtual investor's portfolio which is equally weighted and comprises 89 companies in the SSM .Portfolio performance is calculated using (BHAR) which are calculated as follows: $\mathrm{BHAR}_{i,t} = \prod_{t=0}^{T}[1 + \mathrm{R}_{i,t}] - \prod_{t=0}^{T}[1 + \mathrm{MR}_{t}]$.

The daily mean wealth index in Table (2) shows a constructed wealth index which is averaged across firms. We use the Buy-And-Hold-Abnormal Returns method (BHAR) to trace the value of One Saudi Riyal, 1.S.R, invested (in equally weighted portfolios) in all securities 20 days before the announcement day and held until 20 days after the announcement day, after removing market wide effect from the returns. Two portfolios were constructed according to their earnings announcement returns (EAR) in the event window (0, +1). Positive EARs were reported in Panel A and negative EARs in Panel B. One unit invested in the positive (negative) EAR portfolios would increase (decrease) by 3% (-1.06%) in excess of the market returns for the period (-20, +20). The biggest change in the wealth index formation for either the positive or negative EAR portfolios took place on the announcement day itself, T=0, where positive (negative) EAR portfolios increased (decreased) by 1.81% (-2.12%). This finding suggests that earning announcements are informative to the market. Moreover, if the information leakage is high in the market and on a large scale, the price reaction would take place in the pre-announcement period with even higher wealth change in any single day than that on the announcement day. Earnings announcement releases provide decision-relevant information to the SSM participant, at least in the short run.

Table 3 lists all firms included in the sample with names, symbol and number of announcements for each company.

No	Name	Symbol	Ann No	No	Name	Symbol	Ann No
1	RIBL	1010	25	46	3010	YSCC	27
2	BJAZ	1020	25	47	3020	SCC	26
3	SAIB	1030	27	48	3030	QACCO	26
4	SHB	1040	25	49	3040	SPCC	26
5	BSFR	1050	27	50	3050	YCC	24
6	SABB	1060	27	51	3060	E.P.C.C.O	26
7	ARNB	1080	26	52	3080	TCC	26
8	SAMBA	1090	27	53	3090	TACCO	25
9	Al Rajhi	1120	27	54	4010	SHARCO	22
10	ALBILAD	1140	7	55	4020	SRECO	26
11	SABIC	2010	25	56	4030	NSCSA	27

12	SAFCO	2020	27	57	4040	SAPTCO	26
13	SARCO	2030	18	58	4050	SASCO	25
14	Saudi Ceramics	2040	24	59	4061	Anaam	19
15	Savola Group	2050	27	60	4070	TAPRCO	16
16	NIC	2060	25	61	4080	Aseer	19
17	SPIMACO	2070	25	62	4090	TAIBA	21
18	GASCO	2080	23	63	4100	MCDC	17
19	NGC	2090	20	64	4110	Mubbard	24
20	githaiah	2100	25	65	4130	ALbaha	12
21	SCC	2110	21	66	4140	SIECO	24
22	SAIC	2120	22	67	4150	ARDCO	25
23	SIDC	2130	20	68	4160	Thimar	16
24	ADC	2140	25	69	4170	TECO	9
25	Zoujaj	2150	21	70	4180	Fitaihi	18
26	Amiantit	2160	25	71	4190	Jarir	16
27	Alujain	2170	26	72	4200	Aldrees	7
28	FIPCO	2180	16	73	4210	SRMG	7
29	SISCO	2190	19	74	4220	Emaar E	4
30	APC	2200	15	75	4230	Red Sea	4
31	Nama	2210	23	76	4240	ALhokair	4
32	Maadaniyah	2220	24	77	5110	Electric.	22
33	SCC	2230	20	78	6010	NADEC	25
34	Zamil Indust	2240	22	79	6020	GACO	15
35	SIIG	2250	15	80	6030	HADCO	19
36	Petrochemical	2260	12	81	6040	TADCO	23
37	SADAFCO	2270	10	82	6050	SFICO	10
38	Almarai	2280	9	83	6060	SHARQIYA	22

39	YANSAB	2290	4	84	6070	ALjouf	13
40	SPM	2300	6	85	6080	Bishaco	11
41	SIPCHEM	2310	4	86	6090	JAZADCO	17
42	AL-BABTAIN	2320	4	87	7010	STC	18
43	appc	2330	4	88	7020	Etihad	11
44	AlAbdullatif	2340	4	89	8010	NCCI	12
45	SVCP	2360	2				

Table 4 list New IPOS in the SSM. A careful look would reveal the strategy of the CMA to include relatively small and family companies as well. For example, the number of the companies listed in early years used to be very limited and large in size whereas in recent years, listed companies are larger in number and smaller in average size.

New IPO's Listing							
Year		**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
No of IPO's		1	-	2	5	10	26
Value of Issues(Million S.R)		200،10	-	300،1	715،7	446،10	18,036
Market Capitalisation	**Million S.R**	51,000	-	263،43	84,764	39,769	215،209
	% of total market	%15	-	%4	%3	%3	%11
Source: Bakheet Financial Group							

Appendix for chapter 3

The following graphs depict the daily cross-section average of all observations for the event window (-30,+30) for 2179 earnings announcements.

Figure 1: Daily estimated Average Bid-Ask Spread using the model of George et al. (1991)

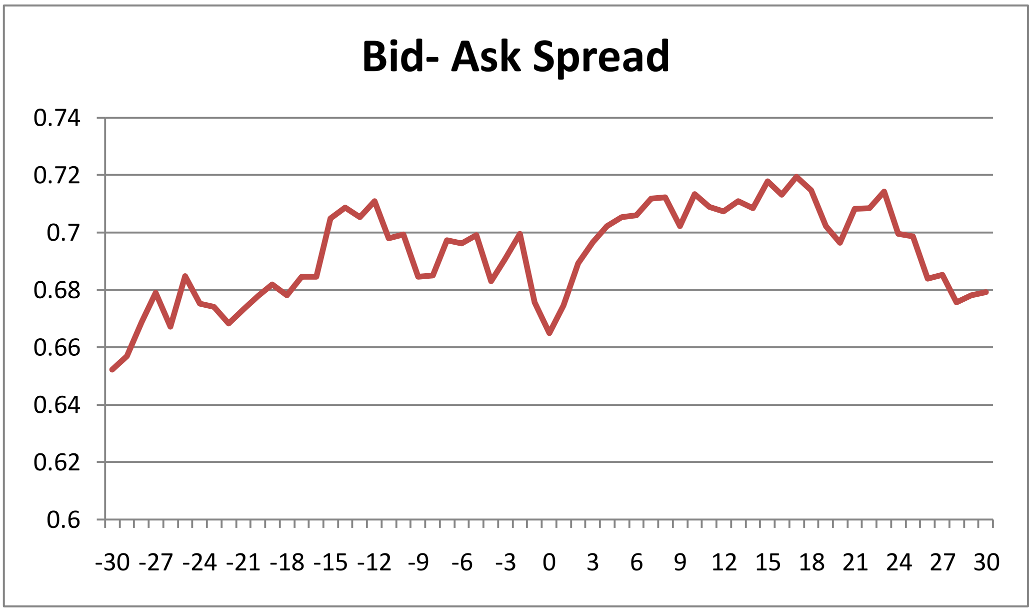


Figure 2 : Daily Overnight Indicator measured as: $ONI_t = \left| \log \frac{Open_t}{Close_{t-1}} \right|$

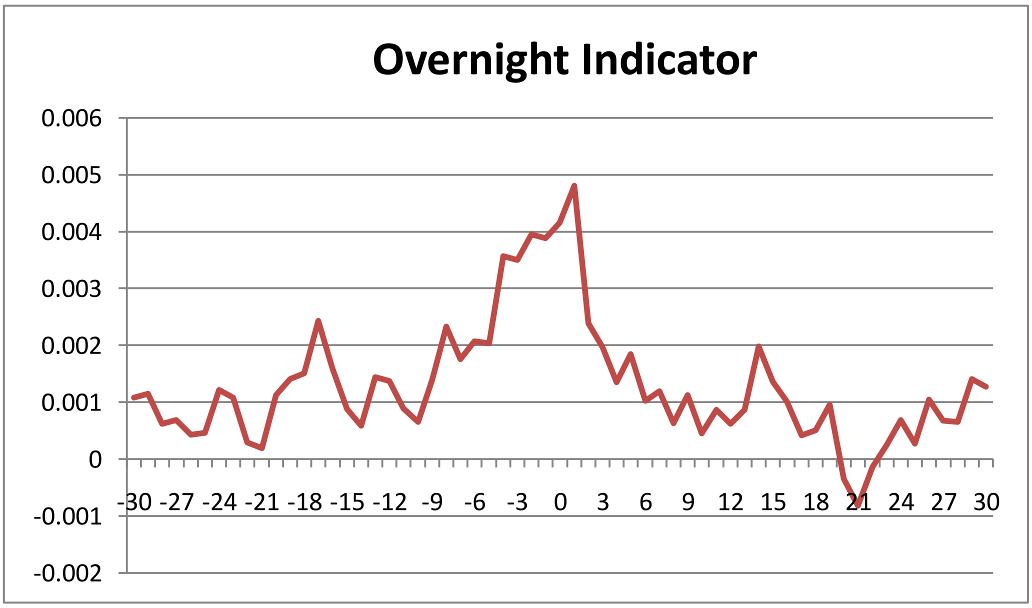


Figure 3: Cross –section Average Volatility measured: $VOL_{i,t} = \frac{P^H_{i,t} - P^L_{i,t}}{P^L_{i,t}}$

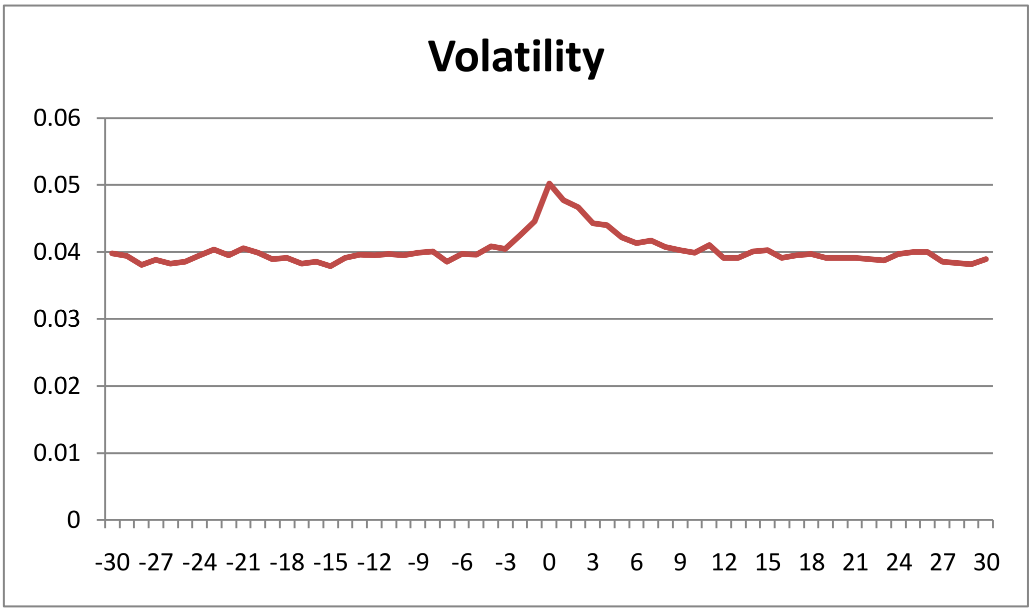


Figure 4: Daily average Turnover (number of stocks divided by the number of outstanding shares).

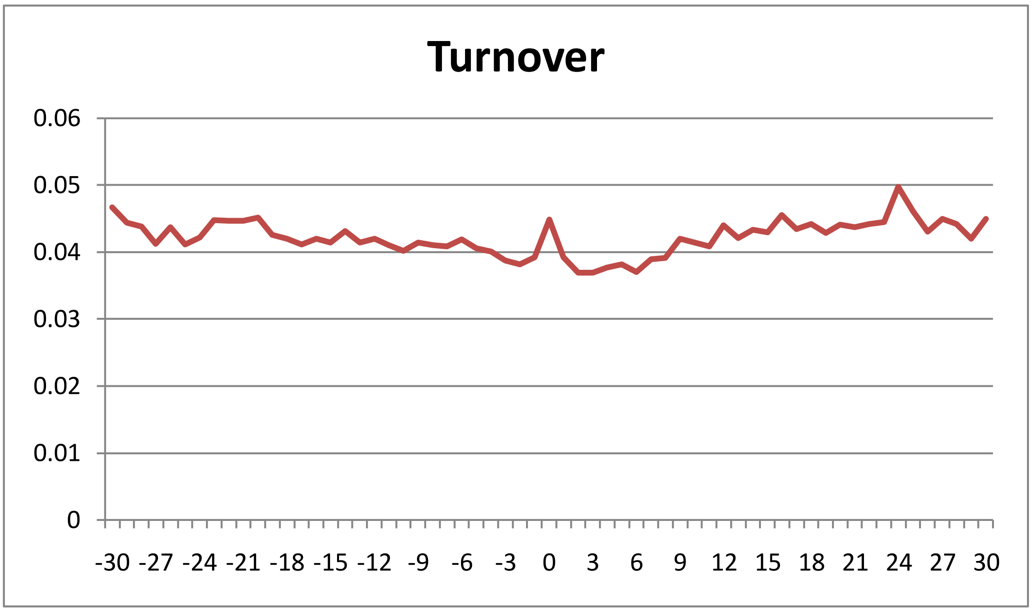


Figure 5: Average Number of trades per day

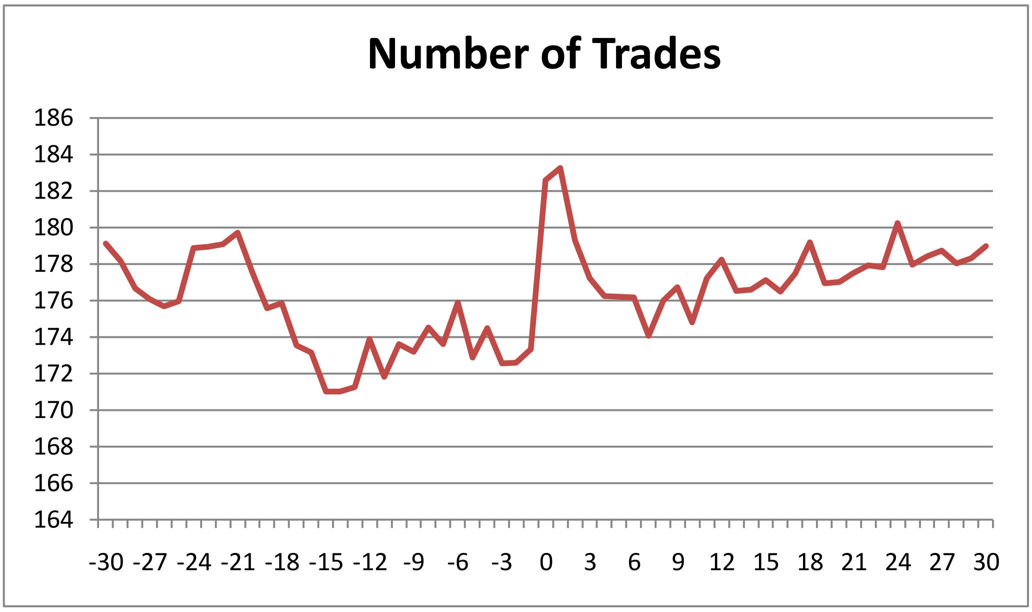
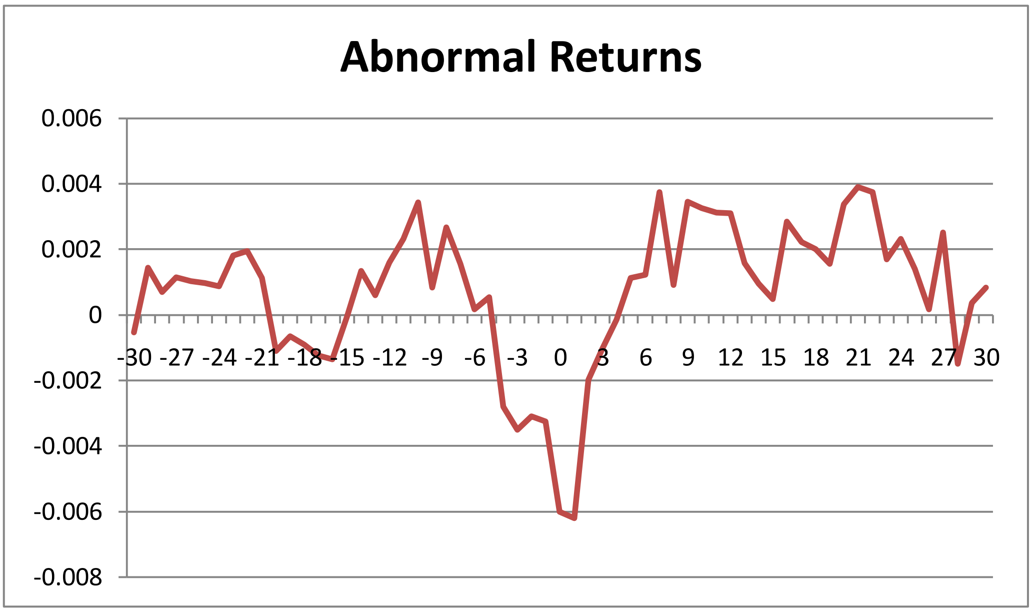


Figure 6: Average Abnormal Returns for all earnings announcements (2,437) before data cleaning



Appendix for chapters 4 & 5 :

Table 5 list main variables that have been used in the regression model along with brief description for the price impact regression and for the liquidity function regression:

Variable	Description
PerImpct	Permanent Price Effect
TotImpct	Total Price Effect
TemImpct	Temporary Price Effect
Lnsize	The natural logarithm of the number of shares trades(volume)
Volatility	Standard deviation of trade to trade returns on the trading day prior to the block trade.
Intrurnover	The natural logarithm of total dollar value of on market stock turnover on the trading day prior to the block trade.
Mktreturn	The market index (TASI)return on the day of the block trade
Momentum	The cumulative daily return to the stock on the five trading days prior to the block trade.
BAS1	Relative Spreads
BAS2	Quoted Spreads
BAS3	Effective Spreads
T1	Dummy variable taking the value of 1 for trades in the first hour, otherwise 0
T2	Dummy variable taking the value of 1 for trades in the Mid-day trading, otherwise 0
T3	Dummy variable taking the value of 1 for trades in last hour of the trading day ,otherwise 0
Infobas	Information asymmetry component of the spread estimated using Huang and Stoll (1997) model
size	Natural logarithm of the Market value of common shares
Number of trades	Number of trades per day per firm
Trade sign	Dummy variable taking the value of (1) for buy trades and (0) for sell trades

Table 6: report estimated coefficient of a trade indicator model for the price change in block trades, using Huang and Stoll (1997) three way model:

$$\Delta \mathbf{price}_{i,t} = \boldsymbol{\beta}_{1,i}\mathbf{Q}_{i,t} + \boldsymbol{\beta}_{2,i}\mathbf{Q}_{i,t-1} + \boldsymbol{\beta}_{3,i}\mathbf{Q}_{A,t-1} + \mathbf{e}_t$$

Effective spread is estimated from this model as two times the first two coefficients, $2(\beta_{2,i} + \beta_{1,i})$ which is the relationship between price change and trade sign for a particular trade and the previous trade.

VARIABLES	impact
buysell	**0.00295*****
	(5.78e-06)
Lag(buys ell)	**0.00189*****
	(5.78e-06)
MktDirection	**0.00163*****
	(1.44e-05)
Constant	**-0.00148*****
	(1.32e-05)
Observations	**4221746**
R-squared	**0.114**

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The trade indicator model is used to infer about the components of the bid-ask spread, we are more interested to find the information asymmetry component. The estimated signs of the adverse selection cost component are positive for all stocks and are statistically significant at the 1% level. Prices are adjusted in reaction to net buyer-seller initiated order flow. We report here aggregate coefficients for all-stock model to show general inference about the information asymmetry in the market. The market direction variable which is aggregate cumulative sell–buy indicator shows also a positively significant coefficient indicating market pressure increase the price change

Table 7 shows time of the day variation patterns of the open to close prices. Intraday open to close indicator is a measure of price volatility , spread and information asymmetry. Open to close shows diurnal patterns where the gap is at its highest in the first trading hour then open to close decline and then increase by the end of the trading hours.

VARIABLES	**opncls**
t1	**0.0105*****
	(0.000427)
t2	**-0.0128*****
	(0.000379)
Constant	**0.162*****
	(0.000320)
Observations	**4221870**
R-squared	**0.001**

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 8: trading Hours in the SSM, old and new trading hours are reported here. Trading hours are broken into three categories to study the time of the day effect on prices and trading activity.

Trading Hour	session	Time 1	Time2	Time3
Old system two session 01/01/2005- 3/10/2006	1(10:00-12:00) 2(16:30-18:30)	10:00-11:00	11:00-17:30	17:30-18:30
New System 28/10/2006	One session	11:00-12:00	12:00-14:30	14:30-15:30

New system for trading Hours from 28/10/2006-currenet

- Time $_1$ = taking the value of one if the block trade occurs in the first trading hour, that is 11:00-12:00 in the new system.
- Time $_2$ = taking the value of one if the block trade occurs during the trading day, midday, which is 12:00-14:30 in the new system.
- Time$_3$ = taking the value of one if the bock trade occurs during the last trading hour, which is (14:30-15:30) in the new system .
-

Old trading hours from 01/01/2005 to 03/10/2006

- Time $_1$ = taking the value of one if the block trade occurs in the first trading hour, that is from 10:00-11:00.
- Time $_2$ = taking the value of one if the block trade during the trading day ,midday, that is from 11:00-17:30 of which four hours and thirty minutes are afternoon break.
- Time$_3$= takes the value of one if the block trade occurs during the last trading hours, which is 17:30-18:30.

Table 9:Order Flow ration distribution reported here for each company(ticker) for the entire sample ,124 companies.

ticker	orderflow=0	between midpoint and ask	orderflow=1	between midpoint and bid	orderflow=.5
1010	4341	168	4172	113	47
1020	9898	849	9753	768	161
1030	2276	49	2373	57	10
1040	650	22	584	37	6
1050	1188	37	1092	25	3

1060	877	21	719	20	1
1080	1337	35	1331	28	8
1090	4313	303	4454	271	41
1120	18976	6482	17274	6088	1486
1140	12100	4324	15502	5506	3253
1150	3463	76	10160	82	365
1210	855	80	1005	117	439
1310	1327	101	1733	122	773
2001	225	126	836	128	187
2010	34761	12752	32387	12504	3913
2020	12048	2584	11527	2313	434
2030	1258	624	780	471	48
2040	6693	1607	5970	1370	1346
2050	22453	6457	21134	6136	2125
2060	24718	5434	24071	5000	769
2070	16223	3121	15346	2735	2709
2080	17041	3844	16179	3337	2707
2090	3205	722	2907	598	379
2100	25231	5311	22863	4716	8516
2110	24125	5059	22004	4603	3085
2120	17958	3845	16862	3601	1511
2130	28135	6346	25505	5534	5396
2140	28480	5453	26623	4910	5579
2150	12856	2713	12141	2376	985
2160	15973	2047	14812	1962	1784
2170	28338	8422	24896	7637	4694
2180	9761	3783	8857	3287	2404
2190	33424	10167	30313	8935	1122
2200	8526	1179	8069	1032	866
2210	35738	7685	32387	7115	2263
2220	17279	3937	16438	3576	1869
2230	25576	5070	24122	4566	3990
2240	4346	803	3774	666	371
2250	25505	6886	24654	6461	539
2260	12726	2845	12586	2654	1108
2270	11522	1640	11449	1552	3080
2280	6010	2258	6287	2507	1442
2290	11169	1045	16920	1197	3892
2300	5417	1512	5364	1629	686
2310	9284	1151	13086	1204	649
2320	4855	809	4925	873	2379
2330	8327	81	8810	101	1553
2340	8315	891	7357	836	1179
2350	14473	62	17897	68	1376
2360	1924	392	1795	337	800
2370	1428	411	1418	431	161
2380	6710	113	7935	126	1293
3010	4160	1463	3925	1192	86
					207

3020	5803	1094	5590	914	573
3030	4575	868	4165	748	216
3040	1137	156	823	99	43
3050	2906	422	2857	346	101
3060	2403	341	2143	292	73
3080	2188	181	1983	130	48
3090	11833	3385	11257	3069	355
4001	409	6	571	9	120
4010	17904	2094	16392	1813	3833
4020	16231	3274	15614	2960	1719
4030	31019	4813	29132	4577	1967
4040	35435	8294	32229	7762	4697
4050	23900	2094	21934	1960	5992
4061	3842	1327	3170	1177	1160
4070	20076	4146	18759	3769	3511
4080	16707	4298	16017	3823	937
4090	27378	8785	24543	8462	782
4100	18000	2967	16768	2626	4231
4110	24694	4981	22266	4391	7393
4130	23652	7784	20603	7025	1841
4140	11974	2136	11812	1939	1156
4150	33772	6722	29760	5992	6875
4160	20638	4935	18555	4392	6758
4170	17438	3089	15932	2710	5775
4180	27791	6327	25350	5575	1049
4190	835	162	685	145	44
4200	12058	2937	11349	2988	1956
4210	3165	447	3690	533	1122
4220	11597	52	22574	56	2156
4230	5191	669	5849	877	2424
4240	6971	1492	7413	1572	1288
4250	4693	18	6087	16	646
4260	442	96	463	132	133
4270	411	1	420	4	36
4280	3235	9	3375	11	47
4290	403	137	411	173	52
4300	2979	36	3058	41	490
5110	47846	4443	44937	4404	3717
6001	685	14	788	16	102
6010	19337	5197	17838	5037	1485
6020	35230	7438	31217	6739	8120
6030	32289	5550	28706	5053	8787
6040	18771	3297	17196	2984	5157
6050	12930	3562	11698	3157	5408
6060	17651	4059	16370	3463	5227
6070	25239	4047	22640	3606	6874
6090	28223	3496	26297	3196	4950
7010	21969	6049	21096	5751	2411
					208

7020	9829	4103	11670	4629	1765
7030	7649	154	13758	181	624
8010	5998	1210	6203	1195	256
8020	3194	618	3145	691	943
8030	5448	160	4695	154	1508
8040	825	308	641	360	240
8050	2133	576	1971	678	835
8060	2129	130	2038	142	670
8070	2205	169	1959	160	760
8080	1015	446	954	420	317
8090	1893	118	1635	128	571
8100	831	279	785	256	297
8110	1111	272	1123	295	363
8120	1510	64	1404	61	429
8130	267	128	287	155	51
8140	1528	290	1502	317	595
8150	1563	390	1496	499	601
8160	588	19	559	28	130
8170	779	4	626	7	92
8180	780	6	594	6	139
8190	456	13	364	6	34
8200	628	0	884	6	41
8210	682	6	672	6	75
subtotal	1414693	290387	1366710	270404	221041
%	0.397024895	0.081495327	0.383558761	0.07588722	0.062033798
	total	**3,563,235**			