CORE
Metadata, citation and similar papers at core.ac.uk
Provided by Brunel University Research Archive

Brunel UNIVERSITY WEST LONDON

Department of
Economics and Finance

Working Paper No. 10-01

Economics and Finance Working Paper Series

Ahmed A. Alzahrani and Andros Gregoriou

What Happens Around Earning Announcements? An Investigation of Information Asymmetry and Trading Activity in the Saudi Market

March 2010

http://www.brunel.ac.uk/about/acad/sss/depts/economics

What Happens Around Earning Announcements? An Investigation of Information Asymmetry and Trading Activity in the Saudi Market.

Ahmed A. Alzahrani*

Department of Economics and Finance, Brunel University

Andros Gregoriou

Norwich Business School, University of East Anglia

Abstract:

This paper 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. Abnormal price and volume reactions around earnings announcements suggest that these announcements produce highly informative contents. The magnitude of the cumulative abnormal returns around earnings announcement is induced by trading activity in the two weeks before the release date. We also show evidence of an increased adverse selection cost around earnings announcement, which is then gradually reduced in the post-announcement period, indicating that earnings announcements reduce uncertainty in the market. We also examine trading behaviour among small and large investors in the market through constructing order imbalance measures. In general, large investors are more sophisticated and show higher informed trading before earnings announcements whereas smaller investors show stronger reaction to news. Moreover, small investors show a buying pattern which is consistent with times-series based earnings surprise. They are net-buyers for good news and net-sellers for bad news portfolios.

* Corresponding author: zahraniaa@ipa.edu.sa

1 Introduction

Our paper is motivated by many factors: first, we 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. 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 no 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 on stock trading and return behaviour.

The paper is organized as following. Section discusses the literature review. Sections 3 & 4 illustrate the data and methodology used to implement the event study. Section 5 documents the event study restuls. Section 6 empirically examines the magnitude of abnormal returns and information asymmetry around earnings announcments. Finally, Section 7 summarizes and concludes.

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). In this study, 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 .The systematic increase in price returns around earnings announcements can be observed in periods either before or after earnings announcements .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).

Many researchers have confirmed the robustness of PEAD using different techniques and different data (e.g., Bernard and Thomas, 1989;Ball, 1992). Findings of research on the capital market 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. This impounding of information into prices and trading activities suggests the existence of privately informed traders and leakage of information

PEAD is typically explained by the magnitude of the earnings surprises or unexpected component of the earnings. The higher the surprise (the difference between anticipated earnings and actual earnings), the higher the drift found. 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, Walther, 1997; Berkman et al., 2009). 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 (Callen et al., 2005).

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.[1] Most of the theories explaining the volume-return relationship emphasise the dispersion of beliefs among investors. Earnings announcements provide an ideal environment to test the volume effect on returns, because they are regular, 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 responding differently (Karpoff, 1986; and Kim and Verrecchia, 1994).

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 (Barber and Odean, 2008).

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.

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. The increase in return volatility and trading volume around earnings announcements compared with non-announcement periods is well documented in the literature. However, the relationship property between volatility in the post-announcement period and the content or precision of the earnings announcement cannot be exactly defined.

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

Acker (2002) links volatility with the content of the earnings announcement. 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

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. Kim and Verrecchia(1991) suggest that since some investors are asymmetrically informed before the anticipated announcement, they may respond to it differently.

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. 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.

Chiang and Venkalesh (1986) and 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. Affleck-Graves et al. (2002) find that, on the day of the announcement, the adverse selection component of the spread increases. They also find that component increases even before the announcement day and suggest that spread is used as a proxy for both information asymmetry and market liquidity. 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 among investors.

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, wider bid-ask spread and more net buying by small traders. We also predict 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 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). [2]

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, 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.

[2] The sample firms represent around 95% of the total market value , only newly-found firms which haven't made operating earnings were excluded.

4 Methodology

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.[3] To compute abnormal return (AR) and cumulative abnormal return (CAR), we consider the following two return generating models (i.e., models for 'normal returns'):

A) Market-adjusted return model

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

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:

$$\mathbf{E(R_{it}) = \alpha_i + \beta_i\,(R_{mt})} \qquad \textbf{(2)}$$

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

[3] For reviews of the subject and event study econometrics, see MacKinlay (1997); Campbell et al. (1997); Binder(1998); and Kothari and Warner (2007).

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, 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. 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:

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

Where V_{event} is the event period interval, $\bar{V}_{benchmark}$ is the mean value over the benchmark period intervals [-30,-11] and $\sqrt{Var(\bar{V}_{benchmark})}$ 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 similarly to those of Bushee et al. (2003) which can be written as follows:

$$\boldsymbol{VOL_{i,t} = \frac{P_{i,t}^{H} - P_{i,t}^{L}}{P_{i,t}^{L}}} \quad \textbf{(3)}$$

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 .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). 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 can be used to estimate the bid-ask spread.

They estimate the informational asymmetry component of the bid-ask spread, $\emptyset_{i,m} = 1 - \pi_{i,m}$ which is that part of the spread that 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, $\pi_{i,m}$ represents that part of the spread which is not due to information asymmetry. The spread estimation equation can be written as follows:

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

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 $RD_{i,t}$.[4]

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.[5] It is calculated as follows:

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

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. 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. 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

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

[5] 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.

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. Like Shanthikumar (2004), we define order imbalance as follows:

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

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).

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 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 T-test of average stock price response to earnings announcements around different event windows is shown as follows: $t - \text{statistics} = \frac{\text{CAAR}\ (t_1, t_2)}{\sqrt{(K+1)s_{\text{AAR}\ t}{}^2}}$.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 changing the expected return but is constant among firms and discounts matching the 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 1 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.

Abnormal Trading activity

we present average abnormal returns (AARs) along with three measures of 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 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.

Liquidity and information asymmetry

Table (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) 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 happens 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 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 volatility in control period.

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. 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, Venkatesh and Chiang, 1986; Krinsky and Lee, 1996).

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 (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: 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 around earnings announcments along with their t-statistics. All variables are averaged cross-sectionally for all days in the event window (-5, +10). All hypotheses were accepted or rejected according to the t-statistic, formulated as follows: $t = \frac{\text{Volatility}_{t}}{(\text{var}(\text{Volatility}_{T}))^{1/2}}$, $\frac{\text{ONI}_{t}}{(\text{var}(\text{ONI}_{T}))^{1/2}}$,, $\frac{\text{Spread}}{(\text{var}(\text{Spread}_{T}))^{1/2}}$.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. *, **, *** denote statistical significance at the 10%, 5%, 1% levels, respectively.

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 (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. 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 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.

6 Regression

We 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. We use Cumulative Abnormal Return (CAR) in the window (-1, +1) to capture the market reaction of the announcement. Then, We regress CAR on a set of variables which is expected to affect the magnitude of the stock return. For the pre-announcement explanatory variables, We 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. We 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 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:

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

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 $E(e_{i,t}) = e^i_{t-4} + \delta^i$, 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 1: 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*** **	**-0.00840** **
	(0.00538)	(0.00416)
ONI	**0.000215** **	**-0.000218*** **
	(0.000101)	(4.67e-05)
$\overline{\boldsymbol{Abvol}}$	**0.000328** **	**-0.000272** **
	(0.000128)	(0.000109)
SUE	**-0.000153***	**0.000134*** **
	(5.95e-05)	(4.26e-05)
size	**-0.00130*** **	**0.00126*** **
	(0.000403)	(0.000327)
Constant	**0.0402*** **	**-0.0394*** **
	(0.00907)	(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, with significant coefficients at 10% and 1% for the good and bad news, respectively. 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. 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.

Liquidity, Information asymmetry around earnings announcement

We first examine the change in liquidity (models 1 & 2 in table 6) around earnings announcements using an approach similar to that of Venkatesh and Chiang (1986) and Chan and Chunyan (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:

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

where:

BAS_{it} = Estimated 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 Chunyan (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 variable.

Table 2: 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 Chunyan (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.

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.

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 placements around earnings announcements is similar to those found 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.

References

1. ACKER, D., 2002. Implied standard deviations and post-earnings announcement volatility. Journal of Business Finance & Accounting, 29(3&4), 429-456.
2. AFFLECK-GRAVES, J., CALLAHAN, C.M. and CHIPALKATTI, N., 2002. Earnings predictability, information asymmetry and market liquidity. Journal of Accounting Research, 40(3), 561-583.
3. BAKER, M. and STEIN, J.C., 2004. Market liquidity as a sentiment indicator. Journal of Financial Markets, 7(3), 271-299.
4. BALL, R., 1992. The Earnings-Price Anomaly. Journal of Accounting and Economics, 15(2/3), 319–45.
5. BALSAM, S., BARTOV, E. and MARQUARDT, C., 2002. Accruals management, investor sophistication and equity valuation: Evidence from 10-Q filings. Journal of Accounting Research, 40(4), 987-1012.
6. BARBER, B.M. and ODEAN, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies, 21(2), 785-818.
7. BEAVER, W.H., 1968. The information content of annual earnings announcements. Journal of Accounting Research, 6(3), 67-92.
8. BERKMAN, H., DIMITROV, V., JAIN, P.C., KOCH, P.D. and TICE, S., 2009. Sell on the news: Differences of opinion, short-sales constraints and returns around earnings announcements. Journal of Financial Economics, 9(3), 376-399.
9. BERNARD, V.L. and THOMAS, J., 1989. Post-earnings-announcement drift: Delayed price response or risk premium. Journal of Accounting Research, 27(1), 1-48.
10. BONNER, S.E., WALTHER, B.R. and YOUNG, S.M., 2003. Sophistication-related differences in investors' models of the relative accuracy of analysts' forecast revisions. The Accounting Review, 78(3), 679-706.
11. BUSHEE, B.J., MATSUMOTO, D.A. and MILLER, G.S., 2003. Open versus closed conference calls: the determinants and effects of broadening access to disclosure. Journal of Accounting and Economics, 34(1-3), 149-180.
12. CALLEN, J.L., HOPE, O.K. and SEGAL, D., 2005. Domestic and foreign earnings, stock return variability and the impact of investor sophistication. Journal of Accounting Research, 43(3), 377-412.
13. CHIANG,M.H.,Wang.J.Y., 2007. Information Asymmetry and Investors behavior around earnings announcements. working paper edn. Vienna, Austria: European Financial Management Association.
14. CHORDIA, T., ROLL, R. and SUBRAHMANYAM, A., 2005. Evidence on the speed of convergence to market efficiency. Journal of Financial Economics, 76(2), 271-292.
15. COLLER, M. and YOHN, T.L., 1997. Management forecasts and information asymmetry: An examination of bid-ask spreads. Journal of Accounting Research, 35(2), 181-191.
16. DEMSETZ, H., 1968. The Cost of Transacting. The Quarterly Journal of Economics, 82(1), 33-53.
17. FRAZZINI, A. and LAMONT, O.A., 2007. The earnings announcement premium and trading volume. NBER working paper.
18. GALLO, G.M. and PACINI, B., 2000. The effects of trading activity on market volatility. The European Journal of Finance, 6(2), 163-175.
19. GEORGE, T.J., KAUL, G. and NIMALENDRAN, M., 1991. Estimation of the bid-ask spread and its components: A new approach. Review of Financial Studies, 4, 623-656.
20. GLOSTEN, L.R. and HARRIS, L., 1988. Estimating the components of the bid-ask spread. Journal of Financial Economics, 21(1), 123-142.
21. GREGORIOU, A., IOANNIDIS, C. and SKERRATT, L., 2005. Information Asymmetry and the Bid-Ask Spread: Evidence from the UK. Journal of Business Finance & Accounting, 32(9-10), 1801-1826.
22. GRINBLATT, M. and KELOHARJU, M., 2000. The investment behavior and performance of various investor types: a study of Finland's unique data set. Journal of Financial Economics, 55(1), 43-67.

23. HAKANSSON, N.H., 1977. Interim disclosure and public forecasts: An economic analysis and a framework for choice. Accounting Review, 52(2), 396-426.
24. HAND, J.R.M., 1990. A test of the extended functional fixation hypothesis. Accounting Review, 65, 740-763.
25. HANDA, P., SCHWARTZ, R. and TIWARI, A., 2003. Quote setting and price formation in an order driven market. Journal of Financial Markets, 6(4), 461-489.
26. HAYN, C., 1995. The information content of losses. Journal of Accounting and Economics, 20(2), 125-153.
27. HIRSHLEIFER, D., MYERS, J., MYERS, L.A. and TEOH, S.H., 2008. Do individual investors drive post-earnings announcement drift? working paper. Electronic copy available at: http://ssrn.com/abstract=1120495.
28. JARRELL, G.A. and POULSEN, A.B., 1989. The returns to acquiring firms in tender offers: Evidence from three decades. Financial Management, 18(3), 12-19.
29. KARPOFF, J.M., 1986. A theory of trading volume. Journal of Finance, 41, 1069-1087.
30. KIM, O. and VERRECCHIA, R.E., 1994. Market liquidity and volume around earnings announcements. Journal of Accounting and Economics, 17(1), 41-67.
31. KRINSKY, I. and LEE, J., 1996. Earnings announcements and the components of the bid-ask spread. Journal of Finance, 51, 1523-1535.
32. LAKHAL, F., 2008. Stock market liquidity and information asymmetry around voluntary earnings disclosures: New evidence from France. International Journal of Managerial Finance, 4(1), 60-75.
33. LEUZ, C. and VERRECCHIA, R.E., 2000. The economic consequences of increased disclosure. Journal of Accounting Research, 38 (Supplement), 91-124.
34. MUCKLOW, B. and READY, M.J., 1993. Spreads, depths and the impact of earnings information: An intraday analysis. Review of Financial Studies, 6(2), 345-374.
35. SHANTHIKUMAR, D.M., 2004. Small and large trades around earnings announcements: Does trading behavior explain post-earnings-announcement drift? Working paper, edn. University of Stanford.
36. VAN NESS, B.F., VAN NESS, R.A. and WARR, R.S., 2001. How well do adverse selection components measure adverse selection? Financial Management, 30(3), 77-98 .
37. VENKATESH, P.C. and CHIANG, R., 1986. Information asymmetry and the dealer's bid-ask spread: A case study of earnings and dividend announcements. Journal of Finance, 41, 1089-1102.
38. WALTHER, B.R., 1997. Investor sophistication and market earnings expectations. Journal of Accounting Research, 35(2), 157-179.
39. WELKER, M., 1995. Disclosure policy, information asymmetry and liquidity in equity markets. Contemporary Accounting Research, 11(2), 801-828.

Appendix

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)

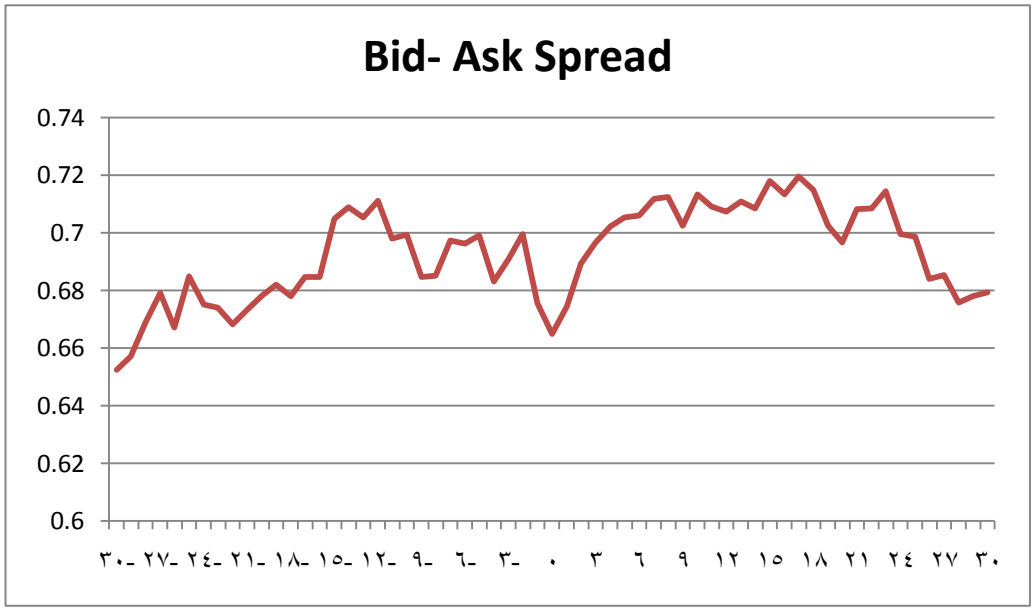

Figure 2 : Daily Overnight Indicator measured as: $ONI_t = \left| log \frac{Open_t}{Close_{t-1}} \right|$

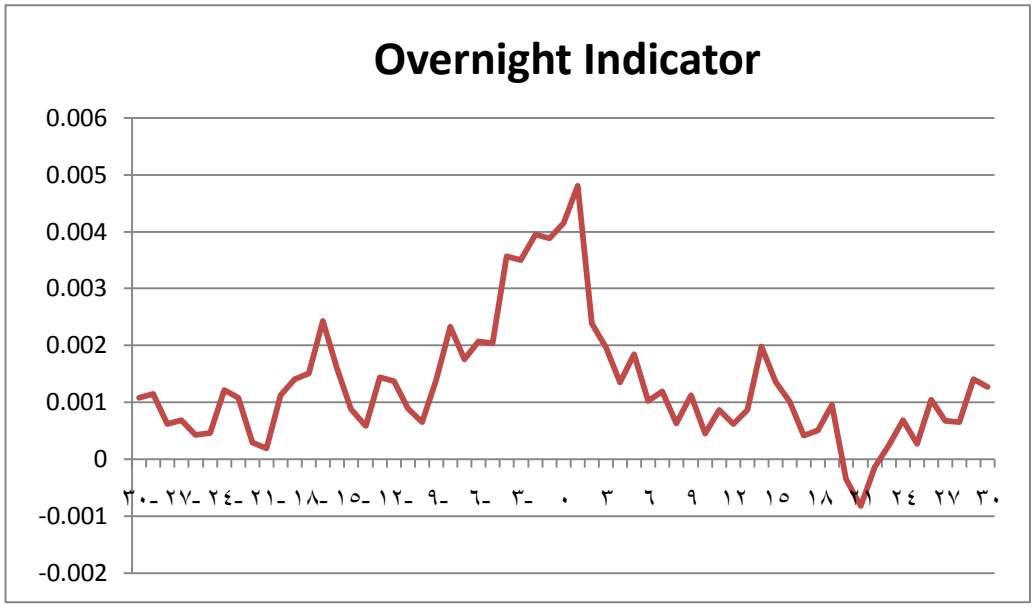

Figure 3: Cross –section Average Volatility measured: $VOL_{i,t} = \frac{P_{i,t}^{H} - P_{i,t}^{L}}{P_{i,t}^{L}}$

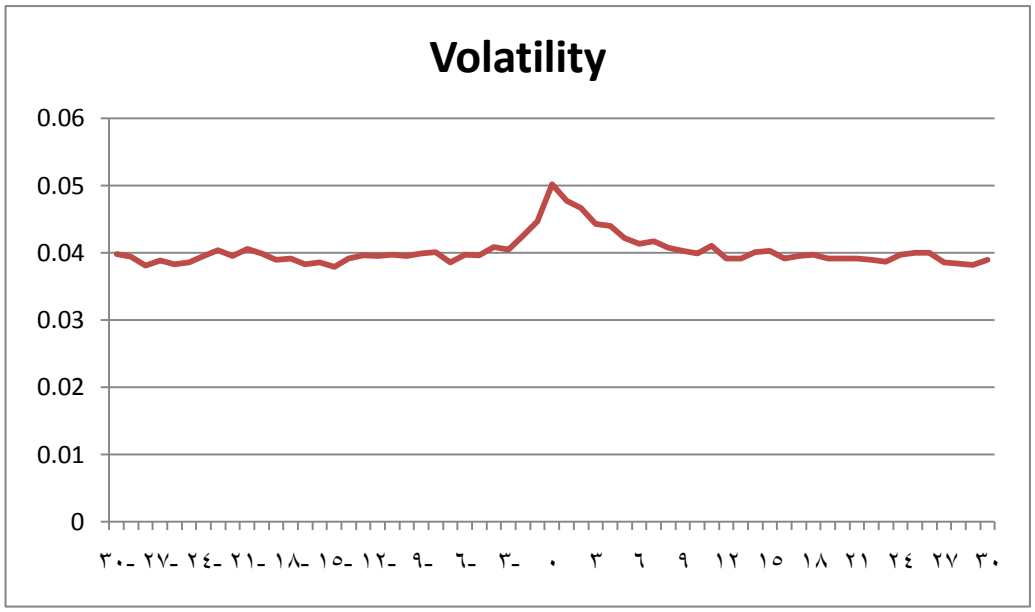

Figure 4: Daily average Turnover (number of stocks divided by the number of outstanding shares).

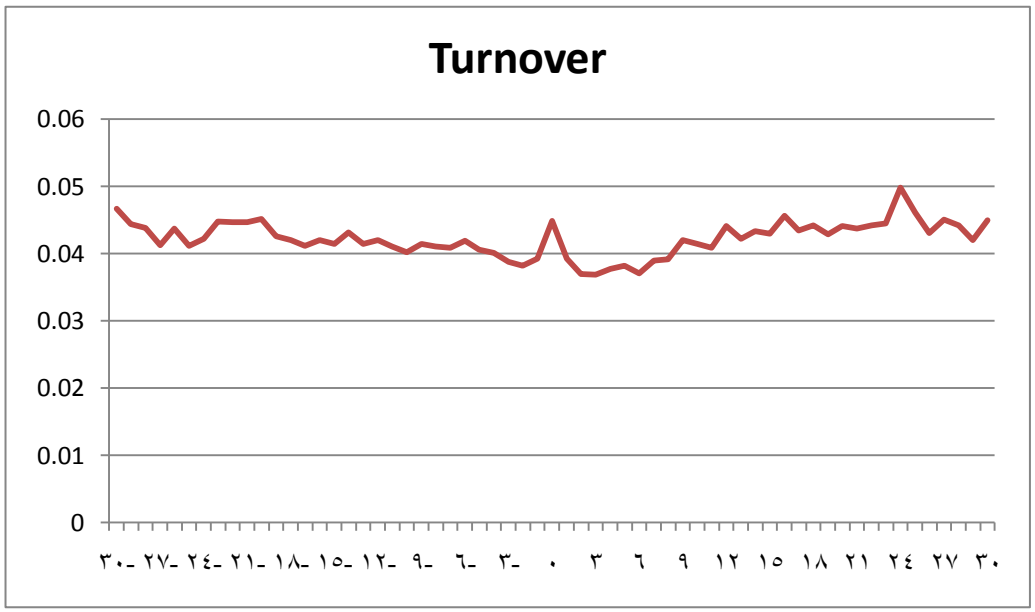

Figure 5: Average Number of trades per day

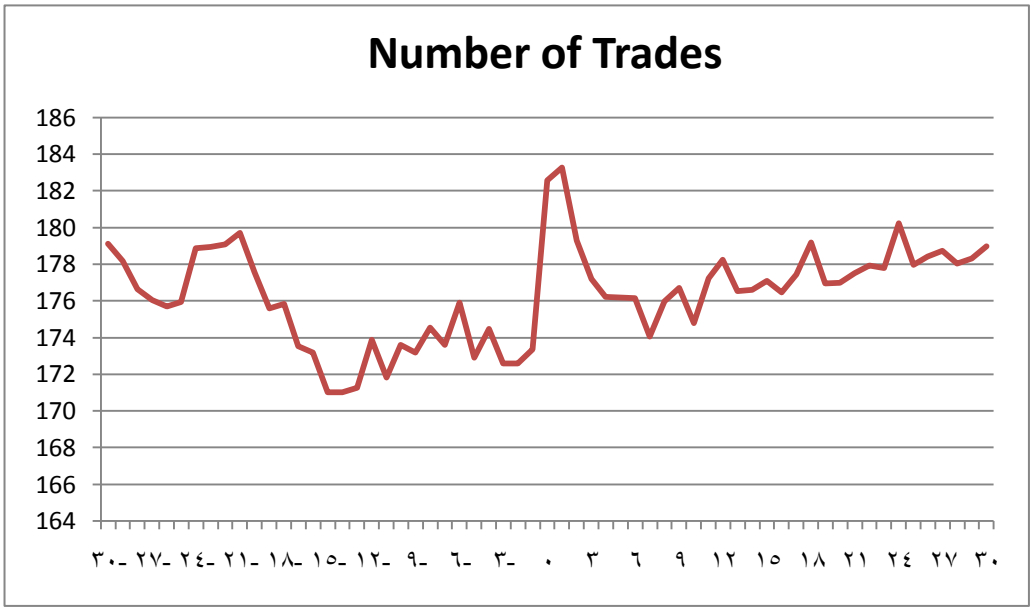

Figure 6: Average Abnormal Returns for all earnings announcements (2,437) before data cleaning