THE RETURN-VOLUME REATIONSHIP FOR EMERGING MARKETS – ANALYSIS OF THE INTERNET TECHNOLOGY BUBBLE IN THE UNITED STATES

by

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Declaration

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I give consent to this copy of my thesis, when deposited in the University Library, being available for loan and photocopying.

Syed Akbar Zamin Ali

19th July, 2006.

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Thesis Summary

The Internet Technology (IT) bubble in the United States formed during 1998-99, and subsequently deflated during early 2000. This event provides an opportunity to examine the price-volume relationship for individual assets, as well as assets with similar characteristics, during a bubble period. This event is of interest for two reasons. First, IT firms, and the associated sector, is a relatively new equity sector and implies that investors may not be able to value firms similar to traditional, or old economy firms. Second, American Internet Technology (IT) firms are listed and traded in a market that is characterised by high levels of liquidity and transparency. IT firms are defined as those companies that derive more than 50% of their revenues from IT services. All IT firms in the United States are traded on the NASDAQ, although a proportion of all IT firms fulfils listing requirements for NYSE and AMEX. This thesis is a study of new technology assets in a mature market and has implications for traders, regulators and investors with regards to asset pricing.

This thesis addresses three questions with regards to the price-volume relationship for IT equities during the technology bubble. First, was there any change in the flows of information between various market participants during this event? Chapter 3 examines the types of information flows and changes during the various phase of the technology bubble that were observed. This chapter addresses the information flow issues using Variance Decomposition and Impulse Response methodology provided by Sims (1980). Analysis is conducted across Internet Technology firm characteristic-based portfolios in terms of liquidity, size and performance. Empirical analysis in this chapter reveals intertemporal differences in price adjustment process across various firm characteristics;

for instance, it takes a longer period for information adjustment during bubble deflation than during bubble formation by a day. Finally, this chapter also presents empirical evidence regarding specific aspects of firm characteristics-based portfolios, and finds that smaller, less liquid and past loser firms derived most of their price variability due to its own innovations during market upturn, but were led during market downturn.

The second question that this thesis contemplates is the existence, and level, of speculative trading behaviour with regards to the Internet sector during the bubble event. Chapter 4 provides empirical evidence to this question for groups of similar firms. This chapter uses Lloente, Michaely, Saar and Wang's (2002) rational expectation model based on two trading motives: trades to rebalance portfolios and trades to take advantage of private information including those that are speculative in nature. Their framework is used to test (i) the level of speculation in the dotcom sector before and after the crash (ii) changes in trading pattern after a significant economic event, and (iii) to verify the cross-sectional variation of the volume and return autocorrelation due to informational asymmetry. This chapter reveals interesting results on the rise and fall of the Internet equity market, in that (i) the level of speculation is weakly significant for the industry over the period formation and collapse of the bubble, though speculative trading decreased after the collapse (ii) trading patterns changed from predominantly speculative trading after the market peaked to more portfolio rebalancing after 11th September 2001, and (iii) information asymmetry is not inversely related to trading history or market capitalisation.

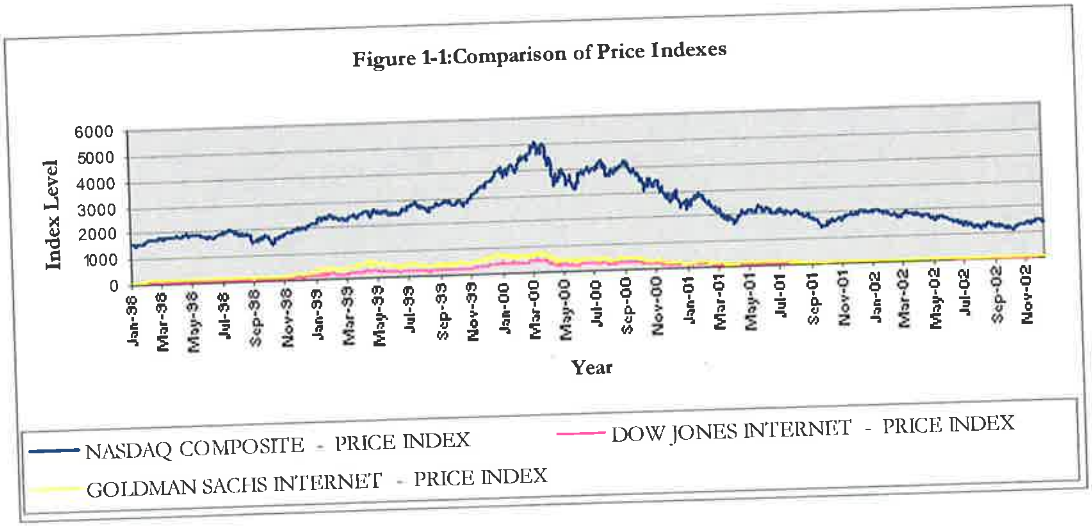
Finally, it is of interest if there is any predictability using trading information such as daily closing price and traded volume during the bubble formation stage. This portion of the study attempts to model linear and non-linear price volume dynamics during periods of lower and higher price variability. Understanding the linear and non-linear dynamics for a market, or subset of the market, during the creation of a bubble will help investors form better expectations regarding the underlying assets. Chapter 5 investigates the existence and stability of linear and non-linear stock price-volume relationship for US Internet stocks during periods of higher price volatility. Testing for linear causal price-volume relationship is conducted using a bivariate granger model, enhanced to account for conditional heteroskedasticity and long run cointegrative relationships. Results reveal intertemporal instability of relationship between the two market variables. This breakdown could possibly be explained due to fundamental changes in the informational content contained within prices and trading volume, and/or changes in trading behaviour. The results in this chapter show that while the causal relationship during lower price volatility period conform to prior studies, a breakdown in the relationship takes place during periods of higher price variability. Additionally, non-linear causality tests on the two variables, price and volume, also provide further support for changes in trading behaviour.

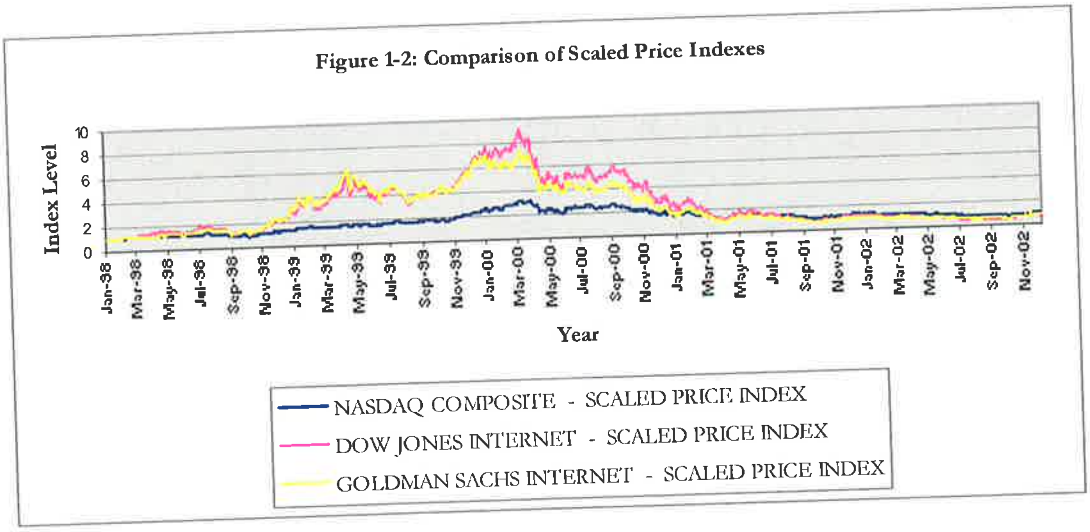
I provide an introduction to the thesis in Chapter 1, with details of the significance and objective of the research, while a review of literature is provided in Chapter 2. The last chapter, Chapter 6, provides concluding remarks regarding this study, implications for the industry participants, and direction for further research. This chapter also details limitation of my study.

Chapter 1: Introduction

1.1 The Event – Technology Bubble

During the late nineties, information technology firms experienced abnormal price increases, followed by rapid price decreases during 2000 - 2002 (see Figure 1-1 and 1-2 below)[1].





[1] Figure 1-1 is a plot of index levels to compare the performance of the NASDAQ Composite with two Internet indexes – The Dow Jones Internet Index(DJII) and The Goldman Sachs Internet Index (GSII). Readers should note that while The DJII reached its highest level on the 10th March 2000, the other two indexes peaked on the 13th March 2000.

The Internet sector witnessed strong growth in prices from 1998 to the first quarter of 2000 (most Internet indexes showed an increase of 600% in two years). This period also saw a dramatic increase in the number of initial public offerings (IPOs) for Internet and other technology stocks. Perhaps the most important aspect is that this emerging equity market is based in one of the largest and most efficient global capital markets. However, after reaching its highest level on the 10th March 2000, there was a dramatic fall in Internet equity prices. Almost a year and half later, on the morning of 11th September 2001, United States was attacked by terrorists which led to a four day market closure. In a period of declining consumer confidence the events of September 11th reinforced the despair amongst investors.

Internet equities provides the opportunity to examine the emergence of an industry with limited trading history and difficulties associated with conducting fundamental valuation of its assets due to uncertainty of future prospects. Most researchers agreed that the high price rises of IT firms during a short period of time indicated that the information technology industry underwent a speculative bubble state[2]. Researchers examined the characteristics of the industry, and the individuals and institutions associated with this industry, to explain reasons for such irrational market event.

Ofek and Richardson (2003) provide several explanation for the rise and fall in the dotcom industry, while there have been hosts of other work on the industry (see for example Perkins and Perkins (1999), Cooper et al (2000), Johansen and Sornette (2000), Demers and Lev (2000), Liu and Song (2001), Schultz and Zaman (2001)) who examined various aspects of the industry such as predictions of the eventual bursting of the bubble,

[2] For example see Perkins and Perkins (1999), Cooper et al (2000), Johansen and Sornette (2000), Demers and Lev (2000), Liu and Song (2001), Schultz and Zaman (2001) and Ofek and Richardson (2003).

the mania surrounding the industry, role of the analysts and conflict of interest, industry specific variables and comparisons with the 1929 crash etc. This literature is discussed further in Chapter 2, but the main issues were as follows:

i. Lack of history for the industry and difficulty in valuing New Economy assets.
ii. Role of Analysts and relationship with underwriters.
iii. Pessimistic insiders unable to exit the market due to contractual obligations
iv. Pessimistic investors unable to take advantage of their views due to uncertain investment horizon and capital requirements for margin calls.
v. Investors' demand for technology assets and mutual funds.

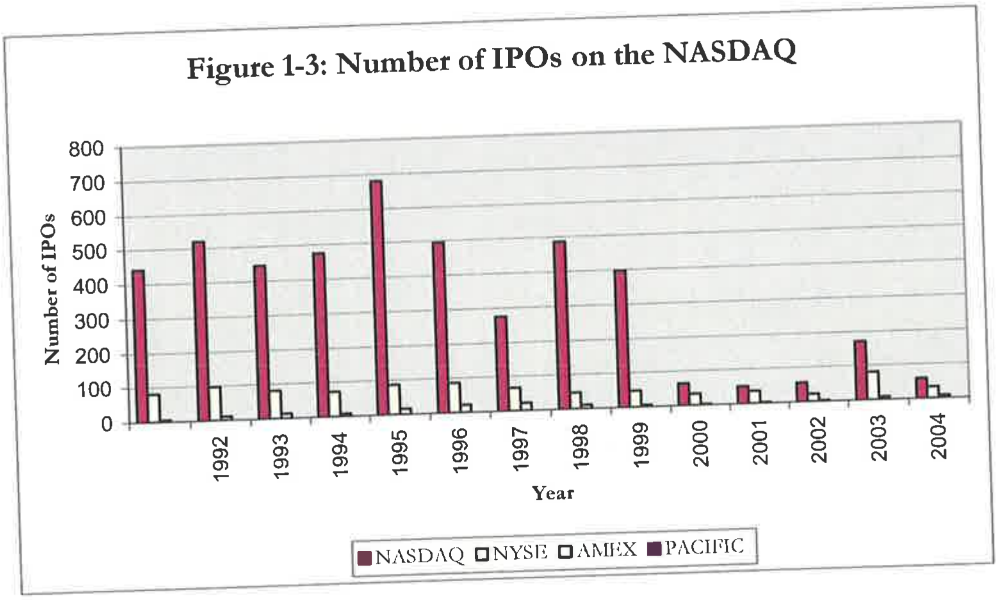
1.2 The Market - NASDAQ

Technology firms are primarily listed on the National Association of Securities Dealers Automated Quotation (NASDAQ), although a few large firms, such as Microsoft, Intel and Cisco are large enough to be listed on larger exchanges such as New York Stock Exchange (NYSE)[3]. The NASDAQ is a dealers market where multiple market participants are able to trade with each other through its ECN (Electronic Communication Network). Normal trading on the NASDAQ starts at 9:30am and closes at 4:00pm. Each dealer updates their bid and ask quotes for each security. The exchange then provides the inside quotes, obtained from the best bid and ask quotes amongst all the dealers for that security. The dealers also have to guarantee their quotes for up to

[3] Reasons for listing on other exchanges could be lower transaction costs. However, various researchers (see Cowan (1992) for a discussion of firms that choose to list on NYSE) have shown that only those firms choose to list on NYSE when perceived benefits are large.

1000 shares[4]. The NASDAQ also features a pre-opening session from 8:00am, where dealers are able to put up their quotes and observe others and perhaps revise their own. Although pre-opening quotes are non-binding, trading may take place on the inter-dealer electronic market. Like other large exchanges, the NASDAQ also offers after-hours trading, though after-hours trading volume on the NASDAQ is very small compared to that during normal trading hour volume.

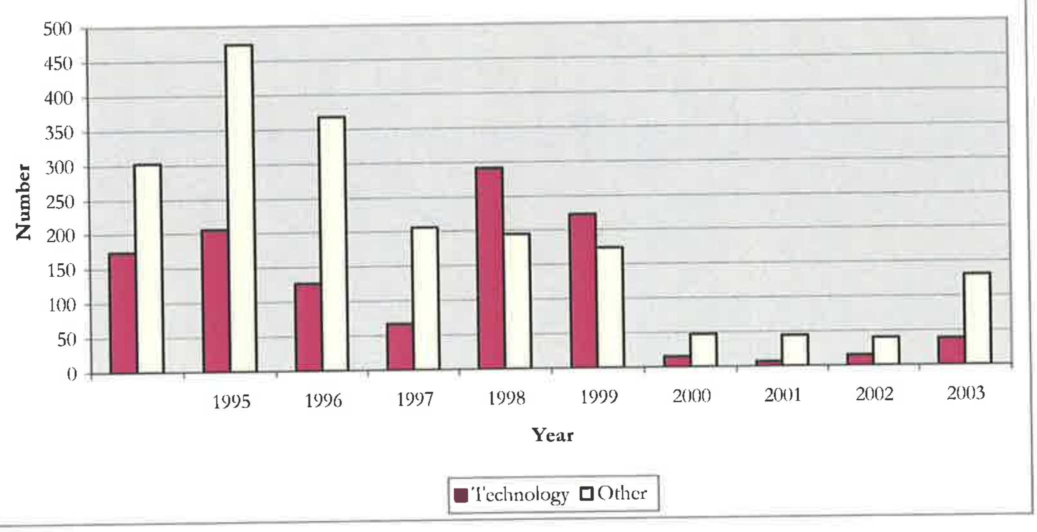
By April 2005, 3,200 firms were listed on the NASDAQ. These firms are categorised into 8 sectors: 10% Industrials, 21% Financials, 2% Telecom, 28% Information Technology, 19% Health Care, 2% materials, 15% Consumer and 3% Energy and Utilities (FactSet Research System, Inc.). It is interesting to note that the NASDAQ receives a large portion of the IPO market (83%) over the last 14 years compared with other exchanges[5]. The total number of IPOs on the NASDAQ compared with other exchanges is presented in Figure 1-3 below:



[4] Smaller stocks may have lower minimum of shares for which the quotes are guaranteed.

However, since 1995 almost 27% of all IPOs on the NASDAQ are from the Information Technology sector (see Figure 1-4 below). The Information Technology sector now represents 12.4% of all US listing and 18.9% by market capitalisation (FactSet Research System, Inc.).

Figure 1-4 - Technology vs. Non-Technology IPOs on NASDAQ



1.3 Research Objectives

This thesis addresses three areas of research with regards to price-volume relationship for Information Technology equities during the technology bubble. First, this research investigates if there was any change in the flows of information between various market participants during this event? The second question that this thesis contemplates is the existence, and level, of speculative trading behaviour with regards to Internet Technology sector during the bubble event. Finally, it is of interest to model the price-volume dynamics using trading information such as daily closing price and traded volume during the bubble formation stage. Additionally, the intertemporal stability of such a model during higher periods of volatility needs to be examined. Details and development of the research questions are detailed below.

1.3.1 The First Objective – Information Flows

The first objective explores several dimension of investors' behaviour. First, it investigates whether motivation to trade originates during normal trading hours or after the market closes. Although there has been past research in this area, analysis of information to trade during a speculative bubble is sparse. Analysis in Chapter 3 may provide additional insight into the sources of information used by market participants during the formation and the subsequent deflation of the technology bubble. This chapter also explores how knowledge of past trading volume contributes to the investment decision process, if daily trading levels form part of informational content to trade in future. For example, if investors are trend chasers, daily market data such as returns and trading volume should provide much of the information to base their trading decision for the following trading days. Alternatively, if fundamental information is of more value than past market data, and since corporate announcements are most often released after the trading day, then previous trading day's market data should be of no value. Since such trading behaviour might, to some extent, be size driven, market capitalisation of firms needs to be controlled during analysis. Information flows induce changes in price of an asset and can be approximated by changes in return or variability of returns[6]. Open to close volatility approximates variability of returns during normal trading hours, while close to open volatility is an approximation of information generated after hours[7]. Trading volume turnover describes the level of interest by market participants (Wang, 1998).

Second, if market participants are indeed affected by market data, it is of interest to observe if changes in firm valuation can be attributed to general market behaviour with regards to specific characteristics such as liquidity, returns and size. Cooper et al., (2000) have noted that firm value increased over the technology bubble in response to name changes, and their study implies that a large number of investors during the study period were not fundamental valuers, rather fad investors. This raises questions with regards to those attribute(s) of the firm that seems to lead the price discovery process in the industry. This study evaluates three commonly available market statistics, past returns, liquidity and size of a firm, in their significance over the formation and collapse of the technology bubble. The objective of this part of the study is to focus on these three firm characteristics across the information technology market and their dynamic behaviour over a speculative event. Also, analysis may reveal the magnitude of this relationship, which may be temporal and provide insight to the dynamic relationship between assets.

1.3.2 The Second Objective – Level of Speculation

The second objective of this study aims to estimate the level of speculative trading behaviour in Internet firms during the Technology bubble. Price bubbles are divergence

[6] Bollen and Inder (2002) provide a comparison of various volatility estimators and conclude that efficiency can be achieved by including as many observations as possible.
[7] An important assumption is that the opening prices reflect as close to equilibrium prices as possible. Cao et al (2000) show that the NASDAQ's pre-opening procedure help to achieve such prices.

in asset prices from their fundamental valuation on a prolonged basis that cannot be explained by rational behaviour by market participants. Rational trading behaviour should trade against such deviation and price bubbles should not exist.

Several theories describe such irrational investor behaviour. Prospect theory was one of the earliest theories and was presented by Kahneman and Tversky (1979). Prospect theory describes the risk-averse nature of investors and resulting trading behaviour. This theory also provides insight into irrational behaviour by speculators who would prefer to hold on to loss-making investments in the hope of a price rebound or mean reversion in prices. The theory also suggests that irrational trading behaviour may arise due to overconfidence of the investors. Investors may overestimate the future and enter into transactions (either buy or sell) that lead to losses. Misinterpretation of the information by investors or believing in obsolete, incorrect or non-existent information about the future will result in under-performance of an individual's portfolio before adjusting for transaction costs.

De Long, Sheifer, Summers and Waldmann (1990) note that, unlike previously postulated, irrational speculators may not only destabilise prices away from the fundamental, but also encourage rational speculators to move in the same direction. Irrational speculative traders are those who do not trade on the fundamental value of assets, but instead enter markets to realise profits from rising prices. These investors are in fact trend chasers[8]: they buy when prices go up and sell when prices decrease. This trading mechanism may also explain the lagged correlation in prices. An interesting outcome of this positive feedback behaviour also results in lowering of risk aversion due to increased wealth from rapid asset value increases as documented by Black (1988).

[8] Also called positive feedback or momentum investors in various literatures.

This reduced risk aversion, in turn, results in a further desire to acquire wealth and hence added speculative buying.

Rational speculators, on the other hand, are those who trade against the irrational speculators and bring prices back to the fundamental value, and thus dampen the effects of the irrational traders. However, this stabilising behaviour by rational speculators changes to take advantage of the escalating prices. This change in trading behaviour is irrational and displays feedback-trading behaviour that results in further destabilizing equilibrium prices. Changes in trading behaviour can be attributed to irrational extrapolative and speculative trades that will result in a larger profit in future. This rapid increase in price, due to the combination of the two types of speculative traders is documented by Delong et al. (1990), who model the behaviour to induce positive correlation in the short term but a mean reverting negative correlation in the long term.

The analysis and results in Chapter 4 point to the fact that trading in Internet stocks was predominantly speculative in nature and in firms that were larger in size and had longer trading history. This evidence could point on the one hand to the initial hype and exuberance in the Internet assets by market participants in the lead up to the crash and on the other hand to the winding down of the lockup contracts with the insiders of the firms as documented by Ofek and Richardson (2003). This chapter also provides stylised characteristics of return volume relationship for speculative bubbles in emerging markets.

1.3.3 The Third Objective – Stability of Linear and Non-Linear Return-Volume Dynamics.

The third research objective, presented in Chapter 5, is to provide evidence of change in both linear and non-linear price-volume relationships for Internet stocks during periods of high volatility. Establishing linear causal relationships using past prices and volume data can provide insight into the structure of the markets, since this relationship is based on the rate of information flows into the market and its dissemination amongst traders. Non-linear causal relationship between price and volume relationship can provide additional insight into market microstructure and trading behaviour of the market participants. The analysis presented in Chapter 5 contributes to existing body of knowledge in its observation of linear and non-linear price volume relationship for an emerging equity market as part of a developed capital market. Also this chapter is able to show that this relationship changes during periods of higher price volatility.

The primary hypothesis presented in this chapter is that the linear price volume relationship should have strong causality running from volume to price for assets in an emerging industry due to two reasons. First, in emerging industries, valuation of securities is more difficult due to lack of industry knowledge and its future by market participants. Second, due to its relatively recent emergence, assets in such an industry would also face lower liquidity compared to assets in more mature industries. The second hypothesis tested is the expectation that this linear price volume relationship is not stable during periods of high price volatility, or "non normal" market activity, since trading on specific assets in market may fall in and out of favour with the market participants. These expected linear relationships between price and volume are based on previous research.

Non-linear price volume relationship can provide additional insight into trading behaviour. Abhyankar (1998) points to the fact that nonlinearities maybe due to several reasons such as asymmetric trading cost structure, presence and actions of noise traders in the market and finally, due to market microstructure. The Internet technology market was faced with various short sales constraints as well as restrictions for pessimistic investors in using their expectations to their advantage. Also, an increasing number of retail investors contributing to the trading volume of Internet assets should result in nonlinearities in the relationship.

1.4 Data and Methodology

The data and methodology employed to address each of the above three research objectives is detailed in Chapters 3, 4 and 5. I will provide a brief overview of the description and sources of data, sample period chosen, and methodological issues and constraints faced. The primary objective of this research is to analyse daily price and trading volume for an assets class within an emerging market. I have chosen the Internet industry during the technology bubble of late 1999 and early 2000 as the event for my study, where the Internet index peaked on the 10^{th} March 2000[9]. However, the index level increased at an increasing rate from early 1998, while it continued to fall until the end of 2001 after the collapse of the bubble. This period also forms the sample period for the major portion of research work in this thesis. Data on adjusted[10] daily closing and opening prices, and trading volume, is obtained from DataStream and Yahoo.com.

[9] All Internet indexes did not reach their highest level on the same date due to differences in constituents and number of firms in the index (see comparison of indexes in Figure 1-1 and 1-2).
[10] Adjusted prices are adjusted for stock splits, IPOs, and right issues.

DataStream also provided the IPO dates and market capitalisation for each of the firms included in this study, as well as components[11], and values, for various indexes used in this study.

Since the objective of this study is to understand investors' trading behaviour for Internet assets, it is important to focus on the trading pattern of individual, or groups of assets, rather than the index. However, to gain the general trading patterns for such assets, this study does not analyse each and every asset within the Internet industry, rather, a representative group of assets, such as assets within a sector index. Companies included in indexes are the largest and most liquid assets in that sector, and represent the sentiments of the industry very closely. However, assets included in the index do not represent the industry perfectly, since indexes usually ignore smaller and less liquid assets, and thus create a size and liquidity bias in studies that use such a sample. Additionally, indexes change composition and current constituent list of firms included in the index may not reflect the past or future constituent list. This also implies that various indexes representing the same segment of the market do not track each other perfectly. Finally, the number of included firms may also increase (or decrease) over time.

This research uses several indexes[12] including DataStream Information Technology Index, Wall Street Research Network (WSRN) Index, CNN Internet Index, Street.com Internet index, Dow Internet Index and NASDAQ Internet Index. These indexes were used due to the research objectives and coverage of various sub-sectors provided by

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[11] Readers should note that components of indexes were obtained on a particular date. This research assumes that the index composition did not change over the sample period. Such methodology does induce biases in the analysis.

[12] DataStream Information Technology Index is used to answer the first research objective, Wall Street Research Network (WSRN) Index was used for the second research objective and the remaining indexes were used for the last research objective.

indexes[13]. Firms included in these indexes, at the time of each aspect of the study, were considered to be the full sample of firms that would be analysed. However, the actual sample used in the study was smaller as firms that did not fit the minimum requirement were removed from the original sample. The discarded firms had IPO dates prior to 1st of January 1998 and those with more than 5 consecutive non-trading days. However, the sample size and sample period varies for each study and is based upon the research objectives.

The first research question revolves around information releases during daytime and after hours trading for the pre and post bubble period. This analysis was conducted using a reduced sample set of 53 firms from the DataStream Information Technology Index over a period of 4 years (from 2/1/1998 to 31/12/2001). DataStream Information Technology Index[14] reached its highest level on 27th March 2000[15], and this date was considered a break point to construct sub-samples for pre and post bubble analysis.

Information was proxied by price volatility, calculated using two consecutive observed prices using the Simple volatility estimator[16]. Price of an asset changes due to demand – supply imbalances. This equilibrium changes results in price changes due to new information that has entered the market, both private information and public[17]. Hence price variability using opening and closing prices from the same day is a proxy for daytime volatility, while price variability from closing price to next day's opening price is

[13] Yet another reason was the unavailability of DataStream during the first part of this thesis. For example the data used in the study presented in Chapter 6 uses data from Yahoo.com
[14] DataStream Information Technology Index has one of widest coverage of the Technology sector. At the time of conducting this research the index consisted of 167 firms. However, this index did not achieve its highest level on the same days as other Internet and Technology indexes.
[15] Since each index is not perfectly correlated, some indexes peaked prior to this date and others after this date.
[16] See Bollen and Inder, 2002 for details regarding biases with various volatility estimators.
[17] Demand-supply imbalances could also be due to rebalancing trade. However, the literature on behavioural finance and speculative bubbles show that during the bubble period most fund managers displayed herding behaviour.

a proxy for after hours volatility. Also the trading levels provide the level of disagreement regarding the information set held by various investors in the market, and should be important in determining the variability of prices.

Since liquidity, normal hour and after hour volatility may affect each other on a simultaneous basis[18], this aspect of my research utilises vector autoregression (VAR) and granger causality to identify if any of the three variable(s) were exogenous to the other variable(s). This analysis also considers the effect of shock to one variable on the other(s) using variance decomposition (VDC) and impulse response function (IRF). This aspect of the study attempts to distinguish such interactions by conducting analysis on extreme portfolios constructed based on firm characteristics such as liquidity, returns and market capitalisation. Further details regarding the analysis and the model are provided in Chapter 3.

If the results from the first part of this thesis are indicative of speculative trading behaviour within the Internet industry, it will then be important to verify the extent of such investor activity. Hence, the second research objective is to analyse the level of noise traders, or speculative interest, in the market and if the investor behaviour differed due to firm characteristics. Additionally, this aspect of the study also contemplates if an event such as 9/11 had any impact on the way investors behaved. The sample period is 2/1/1998 to 30/11/2002. Firms included in this aspect of research are taken from the Wall Street Research Network (WRSN) and 42 firms met the requirement for analysis due to listing and trading constraints applied as before. Daily adjusted closing prices and

[18] Details of economic justification of the interaction between turnover and price variability can be found in Chapter 3.

trading volume for all 42 firms and the NASDAQ composite index[19] is obtained from DataStream.

WRSN index peaked on the 10th of March 2000 and provides the breakpoint for pre and post bubble analysis and 11th September 2001 is the second break point to consider investors' trading behaviour before and after the terrorist event. A longer period of analysis was used to be able to conduct analysis on sub-periods without compromising the validity of results due to lack of data. This part of the study applies Lloente, Michaely, Saar and Wang's (2002) rational expectation model. Analysis is conducted on size-based and maturity-based portfolios to explore investor behaviour, and changes in this behaviour, due to information asymmetry. I employ multivariate regressions as the analysis tool, while further details regarding the model and hypothesis are provided in chapter 4.

After having established that investors traded irrationally within the Internet sector (detailed in chapter 3 and 4), it is of importance to model such behaviour using price-volume dynamics. However, during a speculative event, investors' dynamics change, and hence the model may change as well. Thus, the final aspect of this thesis evaluates the stability of linear and non-linear price-volume dynamics during the formation of a bubble process using adjusted daily closing price and trading volume information. Sample of firms are obtained from the CNN Internet Index, Street.com Internet index, Dow Internet Index and NASDAQ Internet Index. The sample of firms is reduced based on the listing and trading frequency criterion mentioned earlier. Due to constraints in

[19] NASDAQ composite index consisted of 4,785 firms in March 2000. NASDAQ 100 is the top 100 "blue chip" firms listed on the NASDAQ and accounts for about two thirds of NASDAQ composite market capitalisation.

accessing databases such as DataStream, data for this part of the study was obtained from Yahoo.com[20].

The sample period is from 30 days after each firm was listed on the exchange until 3/12/1999. The sample period is divided into lower and higher volatility period, with 13/03/2000 as the breakpoint determined visually to obtain the turning point and then confirming it through Chow structural breakpoint test[21]. Since volume and prices are simultaneously observed, they are considered in a simultaneous system. The concurrent relationship is established using short-term and long-term dynamics. Additionally, the model is adjusted for conditional heteroskedasticity with an asymmetric component. Further details are provided in chapter 5.

1.5 Contribution

The Internet industry has different characteristics to traditional or old economy firms, as described in the next chapter, and its emergence has implications to a vast segment of the population. These include board members, shareholders, employees, suppliers and customers, lenders and creditors, fund managers, underwriters and analysts, and regulators associated with the industry. Understanding the price-volume relationship for such an industry during its growth phase, which eventually manifested as a bubble, makes this study unique in nature. Most price-volume[22] literature focuses on traditional industries and a large concentration of literature provides analysis of this relationship in

[20] Data obtained from Yahoo.com is contaminated unlike that obtained from DataStream.
[21] It may be argued that such a breakpoint was an exercise in data mining. To this end I utilized a regime-switching algorithm to search for the turning point and obtained the same date.
[22] A review of theoretical and empirical work is present in Chapter 2.

the backdrop of developed markets. Some literature does look at this relationship for mature industries in emerging markets. However, this study differs in that it analyses the price-volume relationship of an emerging industry in one of the most developed markets. Secondly, previous literature has looked at the causes and factors that resulted in a speculative bubble[23]. Most research uses various forms of data that is not commonly available[24]. This study uses only daily market data, that is freely available, to explain various aspects of the technology bubble. Finally, this research lends support to other research that has shown the Internet sector having undergone a speculative bubble. However, this research also investigates firm characteristics in determining the level of speculative and irrational behaviour displayed by the investing community.

[23] A review of associated literature is presented in Chapter 2.
[24] Such data could either be costly to obtain and/or available to only a select group of researchers.

Chapter 2: Literature Review

Synopsis

This chapter addresses three streams of literature. First, a review of behavioural finance and its significance in the creation of speculative bubbles is presented. Behavioural finance provides an understanding of the rationale underlying the departure from conventional finance, and the reasons for such events. One of the main themes of behavioural finance is that for a certain prerequisite market conditions, coupled with human psychology, investors' expectations converge resulting in momentum and herding behaviour. Momentum behaviour is essentially feedback behaviour where rising prices feed into increased future expectations that then feed back into further price increases. Investors also look at the volume of shares transacted that increases their confidence with regards to liquidity and investors' disagreement. I next review past research on return-volume relationship. Finally I provide a review of the Internet bubble event, peculiarities of the Internet equity assets, and the market they are traded in. Some discussion also focuses on information origination in the Internet industry and its subsequent dissemination in the market.

2.1 Behavioural Finance

Traditional finance is limited in its capacity to explain financial phenomena where agents are not completely rational. Some of these phenomenon are the equity premium puzzle (see Hansen and Singleton(1983), Mehra and Prescott (1985), Campbell and Cochrane (1999)), the volatility puzzle (see Campbell (1999), the predictability puzzle (see Fama and French (1988)). Rationality has two implications. First, agents are able to receive and accept new information to update their belief system as per Bayes' law. Second, agents make normatively acceptable choices that are consistent with maximising Subjective Expected Utility (SEU) (see Barberis et al., 2002). Rational agents should therefore price assets to their fundamental levels and hence market efficiency is achieved. Fundamental prices are the present value of future cash flows discounted by a factor that is consistent with acceptable preference specifications (Barberis and Thaler (2002)). Hence, if prices of assets do move from fundamental value, mispricing occurs resulting in arbitrage opportunity. Rational agents would then take advantage of the mispricing and prices of assets move back to fundamental values (Friedman (1953)). However, when agents are not completely rational – where either belief system is not updated correctly, or that the choices made were incompatible with SEU, or both - inefficiencies in market place is observed in way of anomalies.

Behavioural finance is able to explain these deviations of prices from fundamental values using two aspects with regards to the agent and the market place – psychology and limits to arbitrage (Shleifer and Summer (1990)).

2.1.1 Limits to Arbitrage

Limits to arbitrage refer to various constrains faced by a rational agent to take advantage of mispricing. These constrains may be in the form of fundamental and noise trader risks as well as implementation costs. Fundamental risk refers to the risk of a mispriced asset moving further away from fundamental value. When an asset is mispriced, rational agents would recognise the deviation from fundamental prices and would try to take advantage of this mispricing preferably through a riskless arbitrage. This could be accomplished by taking a long (short) position in the mispriced asset and eliminating fundamental risk by taking a short (long) position in a substitute asset that has similar cash flows to that of the underlying mispriced asset. However, finding perfect substitute assets is difficult. It is also possible that the substitute asset is also mispriced. In such situations rational agent are unable to bring the mispriced asset back to its fundamental value.

Noise trader risk provides explanation for not only mispricing to exist but to worsen over short periods. De Long et al (1990b) suggest that noise traders, irrational agents, can affect prices in two ways. First, they could base their future expectations of certain assets on various psychological factors such over confidence, framing etc. rather than rational expectations and that the outcome of these factors are unpredictable. This would lead to further deviation of asset prices from their fundamental levels.

Second, they could influence the rational agents, who either manage noise traders' capital, or else are overwhelmed by the levels of noise trading in the market, to promote further mispricing. Shleifer and Vishny (1997) refer to this phenomenon as "a separation of brain and capital". Investors, who do not have sufficient investment and asset pricing knowledge, often utilise the skills of fund managers. Ironically, compensation of fund managers is tied to their performance. Fund managers' performance is based on their ability to search and take advantage of mispriced assets using principles of arbitrage.

However, arbitrage opportunity needs to have a finite (and certain) time horizon for two reasons. First, the investors may not be able to understand the level of mispricing and the strategies employed by the manager. If the level of mispricing worsens in the short run, the investments would make losses. The investor may then judge the managers' performance to have deteriorated, and may pull out their capital. This would require the fund manager to wind down their positions, which would then lead to further losses. Second, to take advantage of mispricing, arbitragers would take strategies involving short selling of mispriced asset (if the mispriced asset was over-priced). If the mispricing worsened in the short term, complete recall of borrowed assets may occur, leading to unwinding of positions. This would again lead to losses incurred by the arbitrageur. Thus the arbitrageur in future, may be cautious in trying to eliminate mispricing and inefficiencies may exist for long periods.

Finally, implementation costs include transaction costs[25] (Barberis et al. (2002)), as well as cost to research the existence and level of mispricing for a particular asset[26] (see Merton (1987)). Other costs of risks include rents charged for borrowing an asset to be shorted, or the inability to find an appropriate asset to be shorted. Shorting an asset can be costly, especially in the face of increased mispricing. As the level of mispricing increases, margin calls will lead to higher costs. This implies that arbitrageurs need a finite time horizon for the mispricing to be eliminated since capital is a scarce resource, and the reputation and

[25] Transaction costs include bid-ask spreads, commission costs, taxes, price impact etc.
[26] Research cost to find mispriced assets could be high. Shiller (1984) and Summers (1986) show that existence of noise traders and levels of mispricing may not be easy to detect.

following of the arbitrageur is at stake[27]. Hence arbitrageurs are faced with horizon risk. In the extreme case, mispricing takes a very long time to be eliminated such that arbitrageur's profits are eventually smaller than total transaction costs. Readers should note that this risk would overwhelm the arbitrageur even if he were not forced by the capital providers to close his position.

Additionally, to eliminate any mispricing, significant number of agents need to realise and attempt to take advantage of this opportunity. Hence, if a particular arbitrageur is not sure of the support he would get from other agents, he may not attempt to exploit such opportunities. Abreu and Brunnermeier (2002) refer to such risk as synchronisation risk. It is also interesting to note that markets don't see a large number of short interest on stocks. Dechow, Hutton, Muelbroek and Stone (2001) show that during 1976-83, only 2% of all stocks had short interest greater than 5%.

Having discussed the risks and costs involved in arbitrage activities, it is important to consider situations under which mispricing not only persists, but may also increase. First, if no substitute asset exists, arbitrage activity would be limited if the arbitrageur is of a risk averse nature and that fundamental risk is systematic[28]. Second, if substitute assets do exists, arbitrage activity may be limited if arbitrageurs have short investment horizon and noise trader risk is systematic in nature. Third, high implementation costs can impede the arbitrage process. Finally, De long et al (1990a) show that noise traders may in fact be joined by arbitrageurs to gain from the mispricing in the short run. This implies that arbitrageurs will trade in the same direction as the mispricing and provide support for increased mispricing. This strategy would result in gains for the arbitrageur.

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[27] If mispricing increases, the arbitrageur with the opposite position will accumulate losses and hence his clients will abandon him, forcing him to liquidate his position. This would lead to higher losses.
[28] Implementation costs and noise trader risk further impedes arbitrage activity.

2.1.2. Psychology

Agents act irrationally due to their beliefs and preferences[29]. It is important to understand how agents form beliefs and how they evaluate risky ventures as it impacts on the price of assets. Beliefs are formed due to various reasons, such as:

1. **Overconfidence** leads to individuals to be confident with regards to future outcomes (see Alpert and Raiffa, 1982 and Fischhoff et al., 1977). Overconfidence is partly due to self-attribution bias and hindsight bias. Self-attribution bias exists when people take credit for success and blame failure to others (Geravis and Odean, 2001). Hindsight bias exists when individuals feel that they have predictive ability ex post. Hence, they may then start believing that they can predict future outcome better than they are actually able to. Irrational agents may believe they are able to predict future market upturns and downturns and hence are able to time the markets.
2. **Optimism** implies that individuals overestimate future outcomes and their own capabilities (Weinstein, 1980). Irrational agents may believe in positive future outcomes even though fundamentals dictate otherwise.
3. **Representativeness** refers to the probability that a particular item belongs to a particular set if the item shows essential characteristics of the set (Kahneman and Tversky, 1974). This could lead to two biases – Base rate neglect and Sample size neglect. Irrational agents may judge market outcomes based upon their recent experience.
4. **Belief Perseverance** refers to individuals who hold on to prior belief system even though evidence contrary to what they believe exists. Irrational agents may hold on

[29] See Camerer (1995), Rabin (1998), Kahneman, Slovic and Tversky (1982), Kahneman and Tversky (2000) and Gilovich, Griffin and Kahneman (2002) for details.

to losing assets for too long if they believe that its price should be higher than what it currently is in the market. Alternatively, they may sell a winning asset too soon, if they believed that such an asset should not have increased to such levels.

5. **Anchoring** refers to individuals form future estimates based upon an initial starting value rather than future outcomes. Irrational agents may consider an asset to have performed well (or poorly) based on its initial purchase price rather than present value of future cash flows.
6. **Availability Biases** refers to judgements based on their most retrievable memory (Kahneman and Tversky, 1974). Irrational agents may feel that the stock market is extremely risky if the last stock market crash was their most vivid experience.

Preferences refer to the choice agents make between risky assets. Von Neumann and Morganstern's (1974) expected utility (EU) framework for such decision making process has weaknesses that are overcome by prospect theory. Prospect theory provides a justification for why individuals are risk averse over gains and risk seeking over losses (Kahneman and Tversky, 1979). The utility function is described as S-shaped and describes individuals as being focused on the gains and losses but not at their ending wealth. This phenomenon is also known as loss aversion. The second aspect of prospect theory is that individuals attach more significance to higher probabilities than lower probabilities. This is called the certainty effect. Additionally, prospect theory also explains why individuals make different choices based upon how the investment is presented. This is because individuals address such choices through mental accounting. An illustration of such decision making process is the investment decision. Portfolio theory suggests that investments should be considered with regards to their risk, return and covariance with other investments (Markowitz, 1959). However, individuals tend to divide their investments into portfolios with varying risk levels designed for specific objectives. High-risk investments are considered for upside potential (and spent on luxuries) while lower risk portfolios are designed for downside protection (such as retirement fund). However, such individuals ignore covariance between assets/portfolios resulting in sub-optimal asset allocation.

In reality probability of outcomes is not objectively known and can be handled by subjective expected utility (SEU) framework presented by Savage (1964). Although this model allows individuals to attach weights to the expectations of utility function, it does not allow individuals to express the level of confidence with regards to the outcomes. Experimental work suggests that individuals are ambiguity averse and prefer investments with certain outcomes than those with more ambiguity with regards to future outcomes (see Ellsberg, 1961).

2.1.3. Investor Behaviour

Theoretical literature on behavioural finance provides explanations for a wide range of market anomalies observed. This research focuses on investor trading behaviour and empirical evidence regarding such behaviour particularly their trading patterns.

2.1.3.1 Excessive Trading

Trading incurs costs, both implicit and explicit, and thus decreases returns. Additionally, trading implies disagreement on information, unless the motive to trade is due to liquidity or rebalancing requirements. However, much evidence points to the fact that individuals and institutions trade more than they should and this behaviour is irrational. Barber and

Odean (2000), amongst a host of others, show that frequency of trading is inversely related to after costs returns. Odean (1999) shows that returns are higher when investors sell compared with when they buy. As discussed previously, individuals are overconfident about the information they have and optimistic with regards to the future, and are thus on the demand side of the trade. Odean and Barber (2000) then show that, in general, men are more confident than women, and hence trade more often with net lower returns. Finally, overconfidence, in terms of access to information, has been shown to increase by online trading (Barber and Odean, 2002). As we move towards a more integrated information age, trading levels have increased, and returns have decreased.

2.1.3.2. Selling Decision

Aversion to loss (as described by Kahneman and Tversky, 1979) implies that individuals will not sell assets that have decreased in price. Shefrin and Statman (1985) refer to this phenomenon as disposition effect. Odean (1998) also confirms the existence of this effect. Further he provides evidence that although investors tend to sell past losers in December, perhaps to book tax losses, they sell past winners during the remaining months. This evidence also shows that the tax advantage gained during December is lost when losses and gains are aggregated for tax purposes. Genesove and Mayer (2001) show similar results from the housing market. In their study, investors' ask prices are higher than the price they paid for their asset, and during falling market, the ask prices are above similar value houses. Coval and Shumway (2000) show that traders of Treasury bond futures' risk taking activities during afternoon session is directly related the profits made by the middle of the day.

2.1.3.3. Buying Decision

Odean (1999) and Barber and Odean (2002) show that the buying decision is different from selling decision. Individual investors tend to buy stocks with equal probabilities given past performance, especially if past performance was either very good or very bad. Additionally, they show that individual investors' buying decision is biased to assets that have caught their attention. Attention effect exists since these investors only sell the assets that they own, but have a wider choice when buying an asset. Hence assets that have shown very high or low returns, those publicised in the media and those with high trading volume are more likely to be purchased.

2.1.3.4. Feedback Models

Feedback models describe non-rational trading behaviour. Non-rational trading behaviour has been witnessed in financial markets as early as 1630s. The first documentation of such behaviour was the Dutch tulip mania by Charles MacKay in 1841. Prices of tulip bulbs rose rapidly from 1636 till January 1637, and then collapsed by February of that year. It is important to note that the collapse of the tulip bubble did not coincide with any economic distress. However, Garber (1991) disagrees with Mackay in the reason for the collapse of the prices. In his analysis, Garber questions the reason for the rapid price increases before February 1937, and if prices decreased faster than expected. He explains that the reason for the rapid price increases was due to a diseased variety, called Semper Augustus, which grew in popularity amongst flower connoisseurs and thus traders. Garber also shows that the decline in prices after February of 1637 was in part due to increase in the production of the demanded asset. Finally Garber asserts that decline in prices was not excessive and that the crash accounted for only 16% of the price decline.

The efficient market hypothesis (EMH) asserts that if market participants are informationally rich, then asset prices should be at their fundamental levels. However, in the case of tulip mania, word-of-mouth increased the demand of the asset that resulted in the bubble. This feedback behaviour is also the catalyst for other bubbles that have been observed since. Feedback behaviour is based upon investors overcoming their rational doubts with regards to the price through word-of-mouth, media and by observing others attain financial success. Such behaviour also adheres to representative bias (discussed above). Feedback models can also be described as following the self-attribution principle (Daniel, Hirschleifer and Subramanyam, 1999). Here, individual investors believe that outcomes that conform to their expectations are due to their ability to predict and those events that don't are due to bad luck or sabotage.

Feedback models imply that asset prices will move in the same direction, and hence serial correlation of returns should be observed. Shiller (1990) models future asset price returns based upon past returns where the weights of past returns decrease exponentially. His model also incorporates shocks to the system in addition to feedback. The model suggests that other factors influence future returns in aggregate at a very slow decay rate, and thus serial correlation of returns may not eventuate. Jagdeesh and Titman (1993) do provide evidence of some return momentum over short term (6 months), strong momentum of returns over mid-term (1 year) and return reversal over longer term. De Bondr and Thaler (1985) confirm this long-term (3 years) reversal of stock performance.

If momentum effects exist, then rational agents should be able to take advantage of any mispricing as a result. However, I described earlier the constraints faced by rational agents (such as implementation costs, fundamental and noise trader risks) that limits such arbitrage. For example, De Long et al. (1990) show that instead of bringing the prices back to fundamental levels, rational agents, instead, help amplify the level of mispricing. Barberis and Shleifer (2002) on the other hand point to the fact that feedback traders base their future style-based investment decision on last period performance. The style with higher last period performance has a higher probability of receiving investment capital. They show that feedback traders are constrained by capital and hence have ability to invest in a single style. This concentration of feedback investors also results in amplified style cycles. Grinblatt, Titman and Wermers (1995) show that institutional investors engage in momentum strategies. Goetzman and Massa (1999) show that of the two types of investors, momentum investors and contrarian, smart money chooses contrarian strategy. They also show that individual investors did not switch between the two strategies. Bange (2000) provide empirical evidence that small individual investors engage in momentum trading. I next show that a feedback pattern is necessary for a speculative bubble.

2.1.4. Herding, Cascades and Bubbles

If past price increases affect investors' perception about the future, and demand for such assets increase, then a feedback chain is initiated. If past high returns increase investor enthusiasm about the future that then translates into higher demand, which further increases prices. This in turn results in higher returns for the investor. This momentum[30] results in herding behaviour and informational cascades, and speculative bubbles are thus created.

Herding[31] can amplify the destabilising effects of momentum trading as more investors flock to the same asset/industry. The reason for herding phenomena is a convergence of opinion and could be behavioural or rational in nature. Behavioural reasons include positive informational spillovers (Froot, Scharfstein and Stein, 1992) and fads (Shiller, 1984)[32]. Rational herding occurs when rational investors ignore their own private information and imitate those that they think have better quality of private information. This is also termed as informational cascade by Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992)[33]. When individuals are in an informational cascade, their actions do not provide a valuable signal to others, and hence create an informational blockage[34]. This blockage does not last forever due to various reasons, such as a new entrant into the market with divergent views. However, since the cascade model implies that aggregation of information is slow, informational blockage could last for long periods. It should be noted that loss of sensitivity to private signals might occur suddenly or gradually resulting in complete informational blockage. However, Smith and Sorenson (2000) show that with a gradual loss of sensitivity to private information may only result in partial blockage.

[30] It is important to note that rational momentum is due to portfolio insurance strategies, stop-loss orders, margin calls or tax-loss selling. These events usually cause a downward momentum, where prices decrease. Behavioural biases, during boom periods, usually cause positive momentum.
[31] For a review on this subject see Hirshleifer and Teoh (2003).
[32] It should be noted that rational momentum might also result in fads.
[33] Readers should refer to Bikhchandani et al. (2001) for a review of research relating to cascades.
[34] Readers should refer to Gale (1996) reviews social learning and herding models.

2.1.4.1. Asset Price Bubbles[35]

In 1999 Alan Greenspan, Chairman of The Federal Reserve, commented on the general rise in the market in late 1999, "We never know a bubble event until after the event". Chairman Greenspan was right, in that the definition of a bubble is not easy and market participants get to know about a bubble after the bubble collapses[36]. A review of literature regarding definition of speculative price bubbles is presented next.

"A bubble is an upward price movement over an extended range that then implodes" (Kindleberger, 1978). Kindleberger's definition was not very precise. Eatwell et al., 1987 defines a bubble as a sharp rise in price of asset(s), which generates expectations of future profits and hence attracting more buyers. His definition follows the momentum and herding literature in that buyers are interested in quick profits from the asset(s) rather than the earning capacity of the asset. However this definition lacks details with regards to unjustified price rises since the fundamental price of the asset(s) is not detailed.

Fundamental prices are the present value of the future cash flows from the asset. Garber (2000) uses the idea of measuring price changes against fundamental values. Rosser (2000) defines a bubble much more precisely, as "A speculative bubble exists when the price of something does not equal its market fundamentals for some period of time for reasons other than random shocks. [Fundamental] is usually argued to be a long-run equilibrium consistent with general equilibrium." Although his definition is more precise, there are still missing definitions regarding various aspects of a bubble. For example there is no clear definition of "long run" or "short period of time" and most importantly

[35] A review of fads and bubbles literature see Carmerer (1989),
[36] By the time the investors realise that the market is in a bubble state, most of the smart money has been taken off the table

"fundamentals". Fundamental is the present value of future cash flows. During a bubble state, either the expectation of cash flows is too high (low), and/or the discount rate used is too low (high).

The period of consideration is the second issue. Siegel (1995, 2002) has shown that during a bubble state, returns demanded from an asset by investors may not be in line with cash flows generated in the short term but are very close to the cash flows generate over a long term. He analysed "Nifty Fifty" rise in 1972, and pointed that the valuation of assets at the peak of the bull-run was very close to the present value of cash flows over several decades not a couple of years. He similarly points to similar analysis with regards to the 1929 bubble. Using a 130-year period (from 1871 to 2001), Siegel (2003) determined that one should use the next 30 years to evaluate the present value of assets to confirm if prices today are justified. His analysis shows that one third of the value of the asset is based on the price of that asset 30 years from today while the rest of the value is based upon the present value of dividends over the same period.

Siegel (2003) also presents an operational definition of bubbles as "a period of rising (falling) prices in an asset market can be described as a *bubble* (or *negative bubble*) at time **t** it can be shown that the realised return of the asset over a given future time period, that time period defined by the *duration* of the asset, can be shown to be inconsistent, i.e. more than two standard deviations from the *expected* return, given the historical risk and return characteristics of that asset at time **t**." Duration is measured as the time weighted-average of all future expected cash flows. Readers should realise that it is only ex post that realised returns can be observed and existence of a bubble event can be justified. It is also interesting to note that a negative bubble is much more easily identified, since price today needs to be lower than future identifiable dividends. However, the reverse is not true.

Siegel (2003) compares the Internet bubble to the August 1929 bubble[37]. His analysis shows that according to his operational definition, the latter was not a bubble as it could be justified by future dividends and prices. However, the internet stock price levels in early 2000 requires that over the next 30-year period, Internet firms should provide a return of 17% year-on-year, a prospect that seems implausible, since such returns have not been witnessed over such a time frame.

2.2. Past Research on Price and Volume Relationship and Associated Results

This section is divided into three sub-sections; the second sub-section details past research on linear relationship between price and volume, while the third sub-section looks at non-linear relationships between the two variables.

2.2.1 Return predictability

Research on predictability of returns has been the focus since Capital Asset Pricing Model of Treynor (1961), Sharpe (1964), Lintner (1965) and Mossin (1966). Various firm factors have been presented as having additional powers of predicting returns, such as size (see Banz (1981), Reinganum (1990), Fama and French (1993, 1996)) and lagged

[37] In his paper, Siegel (2003) justifies the prices of August 1929 as being rational over a 30-year period.

returns (see Debondt and Thaler (1985 and 1987) for long term mean reversion, and Jagdesh and Titman (1993) for short term return continuation). However, volume of shares traded also contains information regarding future returns. Karpoff (1987) provides a review of the interaction between volume and returns and notes that volume is an important factor to consider. Llorente, Michaely, Saar and Wang (2000) consider volume to be a scaling factor for traders' level of interest based on either private information or portfolio rebalancing. Datar, Naik and Radcliffe (1998) suggest that low volume stocks induce risk premium and hence provide higher returns.

Chordia and Swaminathan's (2000) research shows the importance of trading volume in predicting future returns. They find that highly traded assets adjust to information flows at a faster rate and thus result in contributing to returns. Lee and Swaminathan (1998) provide an alternative hypothesis for medium term joint price and volume relationship they term as Expectation Life Cycle. Their model suggests that volume turnover is indicative of investors' interest in the asset. Low volume winners are at the bottom of the cycle, and as the stock generates more investor interest, turnover increases, until the stock becomes a high volume winner. Soon the stock increases above its fundamental value and falls out of favour with the investors. This leads to selling activity and a stock becomes a high volume loser. As the selling activity continues, there is less interest and hence a decrease in trading activity. The asset is now a low volume loser, until investors' interest in the stock picks up. According to Lee and Swaminathan's (1998) results, low volume winners take a longer period to become high volume winners compared to low volume losers.

2.2.2. Linear Granger Causality

Work on price-volume relationship started with seminal work by Clark (1973), Copeland (1976), Epps and Epps (1976). Theoretical literature on price volume relationship provides several reasons for the causality. The Mixture of Distribution Hypothesis provides the first reason to observe a price volume causal relationship. According to this model, trading volume shows the level of disagreement on the information on the underlying assets and the level of price revision. Hence, higher the level of disagreement on the correct valuation of the traded asset, greater will be the price difference and higher will be the volume. Clark (1973) used volume as a proxy for the speed of information flow to the traders that affect subsequent price and volume changes.

Price and volume relationship can also be explained by the sequential information arrival model (see Copeland, 1976), which proposes that new information flows from one trader to the next in a sequential manner. As the information flows from one trader to the next, a new equilibrium of price and volume is reached, until the news is dissipated to the whole market. At this time a final equilibrium is reached. However, this model proposes a bi-directional causal relationship between absolute price and trading volume.

A third reason is due to the existence of speculative traders in the market. De Long et al (1990) provide a model where noise traders induce temporary mispricing of the securities over the short run that is corrected, or should be, over a longer run, as markets tend towards fundamental valuation. This results in a causal relation that runs from volume to price. Also, a noise trading strategy based primarily on rising past prices, results in price causing volume (see DeLong, Sheifer, Summer and Waldmann (1990), Epps and Epps (1976)).

Finally, Lakonishok and Smidt (1989) also demonstrated how tax and non-tax reasons could induce a price volume causal relation, where the current volume is affected by past price changes. Specifically, institutional investors and large managed portfolios and funds require re-balancing after stock price changes, to restore portfolio diversification or to optimise tax positions.

Empirical evidence on linear price-volume relationships for equity and derivative markets has documented Granger causality in at least one direction. Karpoff (1987) has provided a survey on the early work conducted in theoretical and empirical aspects of the price-volume relationship. However, prior research work on US equity has been conducted on industries that have considerable history for a more precise valuation. Some research has also been conducted on futures and derivative markets [see Rutledge (1984), Tauchen and Pitts (1983), Rogalski (1978), Najand and Yung (1991), Besseminder and Seguin (1993) and Fung and Patterson (1999)]. Below is a summary of research conducted in three distinct areas, and the associated results:

i. Linear Price Volume Relationship in the US equity Markets
ii. Linear Price Volume Relationship in the US futures markets
iii. Linear Price Volume relationship in Emerging Markets

2.2.2.1 Price Volume Relationship in the US Equity Markets

Studies have revealed that the US equity market displays a uni-directional price-volume relationship where price changes lead volume changes. Smirlock and Starks (1988) look at price-volume relationships in an event study. Their findings show that the relationship gets stronger after the event. However, the direction of causality was mixed, though most results indicate uni-directional relationship. Hiemistra and Jones's (1994) work on the US market show uni-directional causality from returns to volume changes. Bhagat and Bhatia (1996) also demonstrate strong uni-directional causality of price change to volume.

2.2.2.2 Price Volume Relationship in the US Futures Markets

Fuhihara and Mougoue (1993) looked at three different petroleum futures markets and found evidence ranging from no causality (for the heating oil), unidirectional causality running from volume to price (for crude oil) and unidirectional causality running from returns to volume (for unleaded gasoline). McCarthy and Najand (1993), Malliaris and Urrutia (1998). Moosa and Silvapulle (2000) looked at crude oil futures markets and found consistent results in both, the overall and sub-sample periods, of volume causing price changes. This relationship is attributed to market inefficiencies but rejects the sequential information arrival hypothesis.

2.2.2.3 Price Volume relationship in Emerging Markets

Price-volume relationships have been tested for two separate emerging markets (Latin American and Asian markets) with mixed results. Moosa and Al-Loughani (1995) found uni-directional causality from volume to absolute price changes. However this relationship was reversed when considering price change per se to volume. Limited evidence of bi-directional causality between price per se and volume was also discovered. This behaviour was attributed to market and institutional differences. Also, some markets had options on the stocks while a few markets also allowed short sales.

Market size was yet another factor that lead to such price-volume behaviour, as documented by Moosa and Al-Loughani. Saatciouglu and Starks (1998) observed that in six Latin American markets volume changes led price changes in four of the six countries. They attribute this result to differences in information flow and market structure to that in the US. The Latin American markets had higher mean returns and higher volatility than the US markets. Silvapulle and Choi (2000) provide new evidence on price-volume relationships. They documented bi-directional causality, which implies low market efficiency in the small and restrictive Korean market.

2.2.3 Non-Linear Granger Causality

A mis-specified model will lead to spurious results. Hence, if the change in one variable is not completely offset by the other variable in question, linear causality testing will fail to detect such asymmetric relationships and in fact this relationship may even be termed as random. This outcome may be in part due to failure to model non-linear relationship between the variables. Savit (1988) notes that financial and commodity markets display nonlinearities due to the fact that adjustments of deviations from equilibrium values may not be proportionate. Abhyankar (1998) points to the fact that the nonlinearities maybe due to several reasons such as asymmetric trading cost structure, the presence and the actions of noise traders in the market[38] and due to the market microstructure. A small number of papers have looked at the non-linear causal relationship between price and volume and have consensus on the bi-directional relationship that is described below:

2.2.3.1 Foreign Exchange Market

Ma and Kanas (2000a) show unidirectional nonlinear causality from the French money to the FFr/DM exchange rate. They also show no existence of nonlinear causality from the

[38] See details on prospect theory presented above.

German money to the exchange rate, which lends support to the German Dominance Hypothesis. Ma and Kanas (2000b) also explored non-linear causality between two ERM exchange rates and fundamental variables and found unidirectional causal relationship from relative money supply to exchange rates but no causality between relative output and exchange rates. Their work lends support to literature on target zone arrangement. Asimakopolous et al (2000) conducted non-linear causality testing between four currency futures. They found significant unidirectional causality between returns, though the results became weak after accounting for volatility persistence.

2.2.3.2 Emerging Equity Markets

Silvapulle and Choi (1999) present Korean evidence on non-linear causality using the Korean Composite Stock Price Index over three sample periods. The Korean market index displays bi-directional causality in the overall sample and the period of low trading activities. The period of rapid growth shows unidirectional causality from volume to returns while the period of steady growth shows reverse unidirectional causality.

2.2.3.3 Developed Equity Markets

Hiemstra and Jones (1994) show bi-directional causality between price and traded volume data from the Dow Jones Index over two sample periods. Abhyankar (1998) provides evidence on bi-directional causality between FTSE 100 index futures and the cash market that persists after using volatility filtered series.

2.2.3.4 Commodity Markets

Fujihara and Mougoue (1997) looked at futures of heating oil, crude oil and unleaded gasoline traded at the NYMEX and obtained strong bi-directional non-linear causality between price and volume for each of them. Moosa and Silvapulle (2000) detected bi-directional non-linear causality on the price for WTI (West Texas Intermediate) crude oil futures and traded volume by using volatility-filtered series. They found reduced bi-directional non-linear causality after filtering the residuals through a GARCH process.

Although linear and non-linear price-volume causal relationship can reveal dynamics of the market, most studies, except Sillvapulle and Choi (2000), have considered market behaviour during "normal" conditions. Research in this chapter contributes to existing literature by considering non-normal market conditions, both in terms of trading behaviour and the assets being traded.

2.3 Factors and Causes of the Internet Bubble

This section describes the Internet bubble, the market place and causes for such a bubble.

2.3.1 Valuation Models

Internet firms were characterised by large price increases in the period of 1998-99, followed by large price decreases in the early 2000s. Various authors had noted its abnormally high pricing, before the actually bursting of the technology bubble[39]. However, Mauboussin and Hitler (1999) argued that four factors could explain such high valuation of Internet firms.

First, the business model for Internet firms is very different from traditional firms in that intellectual capital is the prime driver of business which requires less capital outflows than physical assets would have demanded. They also suggest that the unconventional nature of cash flows also needs to be recognised. Second, first-to-scale advantage resided with those firms that were able to establish a large user base compared with their competitors. Third, Internet firms should be viewed as a portfolio of real options, such as growth option and the flexibility to change business strategy. Option value increases with volatility of the underlying asset. Under this paradigm, volatility of cash flows for Internet firms would lead to increased value of the firm. Finally, Gorilla Game (see Moore et al., 1998) may be responsible for the high valuation. Investors invest in potential winners in the sector, sell those purchased assets that may not have been performing well, and investing the proceeds into those assets that show better prospects. This feedback behaviour helped increase the valuation of Internet firms as well. Noe and Parker (2000) provide a winner-take-all model that bases the valuation of Internet firms on various characteristics that are idiosyncratic to the industry (see also Perotti and Rossetto, 2000, Schultz and Zaman, 2000, Desmet et al., 2000 and Damodaran, 2000).

Market behaviour also contributed to the high valuations of the industry (see Perkins and Perkins, 1999 and Estrada and Blakely, 1999). First, investors did realise the potential of the industry in future. However, the valuation of assets was a proxy for the industry as

[39] These authors include Choi and Winston (1998), Siegel (1999), Perkins and Perkins (1999), Higson and Briginshaw (2000) and Shiller (2000).

whole, with a few firms that would survive and majority of them would fail. This meant that investors held diversified portfolios of the industry assets knowing that a large proportion of assets would be worthless, but a few that will survive would provide huge returns. This increased the demand for such assets and hence value of the industry increased. Fund managers, whose benchmarks included Internet assets, were compelled to include assets from the industry to ensure that they did not under perform their peers. It is of interest to note that most fund managers did recognise the overvaluation in the industry, but as behavioural finance suggests, that such fund managers had no choice but to become investors as well. Finally, irrational investors swamped the market with their enthusiasm. Momentum created by noise traders resulted in higher valuation and thus induced more investors. This feedback was critical for such a bubble to occur.

After the technology crash, a large volume of research analysed various factors that contributed to this event, including mispricing of these firms to various constraints in the market that prevented rational investors' behaviour. Inability to recognise the real options of entering this new industry, and future earnings capability were cited as the major issues to mispricing of the Internet firms (Schwartz and Moon, 2000a, 2000b, 2001). They test their models in valuing Amazon.com, Exodus Communications and eBay. Schwartz and Moon notice that valuations of Internet firms was sensitive to the parameters used and this resulted in the observed volatility of stock prices. Investors continually revised their opinions with regards to new information.

2.3.2 Financial and Non-Financial Valuation Factors

Factors that were relevant in pricing Internet firms included financial and non-financial characteristics. In terms of financial analysis, Internet firms differed from traditional assets in that earnings and market value found significant negative relationship (see Trueman (2000), Dermers and Lev (2000), Hand (2000) amongst others). These studies reveal several important aspects of the significance of this relationship, such as investors place less importance to the earnings per se but higher importance to high or low levels of profitability. Also investors place high importance to such expenditures as R&D, advertising & marketing, and product development. Interestingly Hand (2000) reports that net loss making firms show a direct relationship between levels of losses and market value. However, Bagnoli (2001) shows that investors respond to revenue surprises and not earning surprises for loss making Internet firms, while profitable firm values would change due earning surprises. Revenue changes have very little effect on stock prices of such firms.

Demers and Lev (2000) compare pre and post bubble value drivers and found investors initially attributed high expenses to firm value increases, but after the bubble burst, that relevance grew weak. However, they found that firms that had the ability to sustain cash-burn rate was viewed with optimism in both pre and post bubble time frame. Jorion and Talmor (2000) also analysed relevance of financial information and found insignificant negative relationship between net income and market value, though gross profit was positively related. Growth in profit and sales were positively and significantly related to market value, indicating that investors were optimistic about the future of firms that were able to operate and grow.

Research to find additional explanatory powers using non-financial information showed that website traffic, strategic alliances, affiliate programs, firm visibility, customer experience, and managerial actions were relevant in defining value for Internet firms (see Seiders and Riley (1999), Trueman et al. (2000), Hand (2000b), Demers and Lev (2000), Kozberg (20001)).

2.3.3. Irrational Market Behaviour

Did analyst and investors behave irrationally during the Internet bubble? Shiller (2002) answers in the affirmative to two questions with regards to bubble formation. First, whether feedback cycle is possible and second, if investment professionals do behave seemingly irrationally to cause speculative bubbles. I describe below various aspects of the market behaviour.

2.3.3.1 IPOs

Initial public offerings (IPO), on average, are underpriced since and the level of underpricing is negatively related to post IPO performance over the long term [40]. In hot markets, underpricing of issues and long run performance of the firm are related due to irrationality of the investors. Ritter (2001) showed that the average first day return from US IPO was 70.89% and 57.29% during 1999 and 2000 respectively, while during 1990-98 the underpricing ranged between 8.56% and 21.76%. Internet firms, on average, doubled on the first day after the IPO (see Ritter 2000, 2001). The level of underpricing was due to the uncertainty with regards to the industry, investor euphoria and deliberate

[40] See Ritter and Welch (2002) for a review.

actions by the issuers of shares by reducing supply in comparison to demand. Ducharme et al. (2001) documents the media hype surrounding IPOs as also being responsible for the underpricing. Additionally, they show that high quality underwriter were associated with the level of underpricing, indicative of collusion between the underwriters and large institutional clients.

2.3.3.2. Analyst and Investor Irrationality

Cooper et al. (2000) reveal that name changes to *dot.com* increased company value, regardless of the level of firm's association with the industry. They attribute this value change to investor mania. In Cooper et al. (2003) they show that following the crash of the bubble, investor reacted positively to name change, where *dot.com* was deleted from the name of the firm. This provides further evidence that investors react to cosmetic changes.

Analysts were questioned with regards to their optimistic earnings forecasts for Internet firms before the bubble burst, though their forecasts were more pessimistic after the crash (Liu and Song, 2001). They felt that such optimistic forecasts contributed to the bubble. Interestingly, they also show that affiliated (or embedded) analysts forecasts were more pessimistic compared to unaffiliated analysts. The larger the difference between actual and forecasted earnings results in better image for client firms in the market. This strategy also adheres to conflict of interest hypothesis and results in increasing demand for firm's ownership amongst investors.

Ofek and Richardson (2001) show that larger than usual proportion of irrational retail investors (noise traders) helped increase the volatility of Internet assets. They also demonstrate that pessimistic investors were constrained in taking advantage of their belief due to high costs since short selling of shares and margin calls required high capital. They also provide evidence of contractual obligation that prevented them to take advantage of their expectations with regards to the future.

2.3.5 The Exchange - NASDAQ

As mentioned in the Introduction, all Internet firms in the United States trade on the NASDAQ, which is an electronically connected dealers market. Normal trading on NASDAQ starts at 9:30am and closes at 4:00pm. The exchange provides the inside quotes, which are obtained from the best bid and ask quotes amongst all the dealers for that security at that point in time. The dealers also have to guarantee their quotes for up to 1000 shares[41]. Pre-opening session for the NASDAQ start from 8:00am, where dealers are able to put up their quotes and observe others and perhaps revise their own. Although pre-opening quotes are non-binding, trading may take place on the inter-dealer electronic market. Several authors have shown that the NASDAQ's pre-opening session contribute to most of the price adjustment to announcements made[42]. Hence opening prices on the NASDAQ reflect much larger price adjustments due to announcements made overnight than for firms listed on NYSE or AMEX. Cao et al. (2000) study confirms these studies and provides justification for the faster price adjustment on the NASDAQ, particularly the role played by the pre-opening session. For the purpose of this research, using daily opening and closing prices to calculate daytime and overnight volatility, removes biases associated with high volatility during the opening session.

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[41] Smaller stocks may have lower minimum of shares.

[42] Masulis and Shivakumar (1997) show that 80% of price adjustments to SEOs takes place during the pre-opening session. Greene and Watts (1996) show that firms listed on Nasdaq adjusts to earnings announcements much faster than NYSE.

Chapter 3: Information Transmission and Adjustment Process during the Technology Bubble

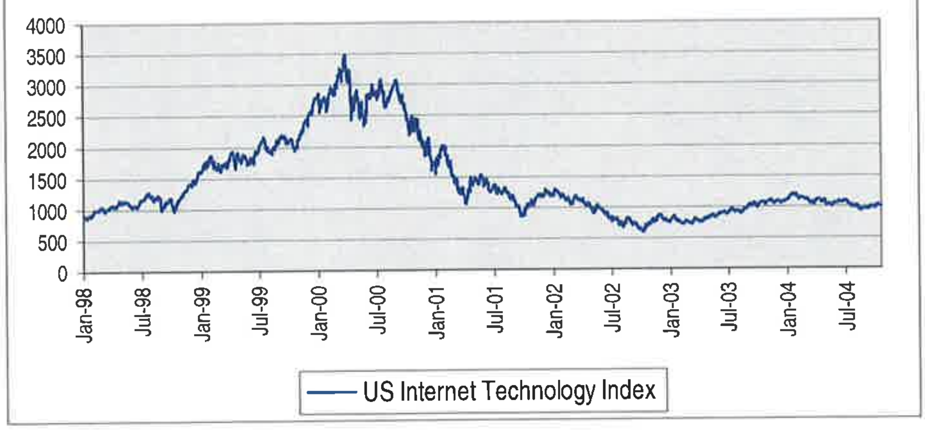
Synopsis

The Internet technology bubble formation during the late 1990s, and its subsequent deflation during the early 2000, provides an opportunity to examine the information transmission process. Additionally, this event provides the setting to examine asset price adjustment to this information across trading periods, and across different corporate dimensions. This chapter addresses these issues using Variance Decomposition (VDC) and Impulse Response (IRF) methodology provided by Sims (1980) across the Internet technology firms. Segments of the industry are analysed based on firm characteristics, such as liquidity, size and performance. Empirical analysis in this chapter reveals intertemporal differences in price adjustment process across various firm characteristics.

3.1. Introduction

Speculative conditions are characterised by prolonged deviations of asset prices from their intrinsic values. A market condition with prolonged up period followed by a prolonged down period is termed as a speculative bubble. Long periods of stock mispricing have a wide range of adverse effects ranging from investor wealth effects to systemic instability. During the late nineties, technology firms experienced abnormal price increases, followed by rapid price decreases during the early 2000s (see Figure 3-1 below).

Figure 3-1: US Internet Technology Index



Technology firms are primarily listed on the NASDAQ, as previously explained in chapter 1 and 2. Most of the trading on the NASDAQ takes place during normal trading hours, i.e. from 9:30am to 4:00pm, however after-hours trading volume on the NASDAQ is very small in comparison. This low level of after hours trading implies that investors most often choose to act upon their information during working hours. Information may be based upon fundamental valuation, such as information regarding the economy, industry or the specific firm. Alternatively, information could be technical in nature and may be based upon past market data.

Sources of fundamental information can be domestic or international. However, past research on global market integration has shown that the US economy dominates all other economies[43] and affects all other markets. Hence, timing of overseas news releases should not affect the domestic US investors significantly. At the domestic level, Corral et al (2004) show that technology firms choose to release announcements after normal trading hours. Hence, a large proportion of company-specific information, necessary for the price discovery process, is released after normal trading hours. Therefore, it is of interest to see if traders use previous day(s) trading information or fundamental information to price assets.

This chapter explores several dimension of investors' behaviour. As mentioned in Chapter 1, it investigates whether motivation to trade originates during normal trading hours or after the market closes. Second, if market participants are indeed affected by market data, it is of interest to observe if changes in firm valuation can be attributed to general market behaviour with regards to specific characteristics such as liquidity, returns and size. This study evaluates three commonly available market statistics, daily returns, volume of shares traded and size of a firm, in their significance over the formation and collapse of the technology bubble. The objective of this part of the study is to focus on these three firm characteristics across the information technology market and their dynamic behaviour over a speculative event. Also, analysis may reveal the magnitude of

[43] Various authors have shown that US market leads the other markets such as Mashih and Masih (1999, 2001, 2002), Eun and Shim (1989).

this relationship, which may be temporal and provide insight to the dynamic relationship between assets.

The chapter is organised into five sections. The introduction in Section 3.1 is followed by a brief discussion on price adjustment process and speculative bubbles. Detailed methodology and data to address research objectives has been discussed in Section 3.3. Section 3.4 provides discussion on the empirical results. The chapter ends with concluding remarks in Section 3.5.

3.2. Overview of Literature Addressed

Research in this chapter is based on three streams of literature and is described in detail in Chapter 2. First, past research on peculiarities of the Internet equity assets, and the market they are traded in, are considered. This stream of literature is presented in section 2.3, and shows that retail investors were employing feedback behaviour, that also encouraged institutional investors to join this herding behaviour. Research regarding the behaviour of investors during herding shows that investors' expectations converged, and investing community largely ignored fundamental information. This chapter also utilises theories and empirical evidence regarding volatility and volume relationships, which indicates how information is spread amongst market participants. Finally, causes of speculative trading behaviour are considered as a backdrop to investors' irrationality during this speculative event.

3.3. Methodology

Relationships between portfolios formed on average firm characteristics over a specific period may reveal further details with regards to flow of information within the market. Such a relationship could exist with larger assets and smaller assets, whereby changes in prices of larger assets may influence changes in prices of smaller assets in the market. To test for such short run relationships between 2 (or more) series, Engle and Granger (1987) have provided a Vector Autoregressive (VAR) specification of first differences of the two series, P_{1t} (ΔP_{1t} is p_{1t}) and P_{2t} (ΔP_{2t} is p_{2t}) for each series. The generic VAR model is expressed as follows:

$$p_{1,t} = \sum_{l=1}^{n} \alpha_{1,l} p_{1,t-l} + \sum_{l=1}^{n} \omega_{1,l} p_{2,t-l} + \upsilon_{p1,t} \qquad \text{Eq. 3-1a}$$

$$p_{2,t} = \sum_{l=1}^{n} \alpha_{2,l} p_{1,t-l} + \sum_{l=1}^{n} \omega_{2,l} p_{2,t-l} + \upsilon_{p2,t} \qquad \text{Eq. 3-1b}$$

Where

$\alpha_{1,l}$ and $\alpha_{2,l}$ are the lag coefficient terms of series p_1

and,

$\omega_{1,l}$ and $\omega_{2,l}$ are the lag coefficient terms of series p_2.

Testing for Granger causality/Block Exogeniety of each variable to another is conducted through the joint test of significance for $\omega_{1,l}$ and $\omega_{2,l}$. If $\omega_{1,l}$ for all l are jointly significant implies that a change in P_2 Granger causes changes in P_1, while joint significance of $\alpha_{2,l}$ for all l implies that a change in P_1 Granger causes changes in P_2. The appropriate lag length l is obtained by searching for the optimal Akaike (1974) Information criterion over various intervals up to 20 lags.

Such analysis may also reveal persistence in the contemporaneous variable that could provide further understanding of trading behaviour. For example significant $\alpha_{1,l}\,(\omega_{2,l})$ for some ls may show that past values of $p_1\,(p_2)$ may affect current values, or that either information takes more than one trading day to be incorporated in share prices.

Finally, the sign of the coefficients may also reveal whether there has been an over-reaction in the assets pricing or under-reaction. For example, if lagged coefficients of the dependent variable are significant and of the same sign, it could imply under-reaction, or that it takes more than one trading day to adjust to information. Alternating signs or insignificant coefficients for the lagged dependent variable may show that the series adjusts very quickly and past information does not help in contributing to future returns.

Evaluation of information during opening hours and after hours and the interaction with volume traded is conducted. For examining information transmission between trading hours and its adjustment process, a Wald test is performed on the three variables, open-to-close (OC) volatility, close-to-open (CO) volatility, and volume turnover. Firms are ranked in terms of average market value over the sample period, and each quintile is grouped in a value-weighted portfolio. Daily estimates of the three variables are organised in a panel format for each portfolio. The generic restricted and unrestricted regressions, with open-close volatility as a dependent variable, are conducted as follows:

$$\sigma_{OC,t} = \alpha_{OC} + \sum_{j=1}^{n} \beta_j \sigma_{OC,t-j} + \sum_{j=1}^{n} \gamma_j \sigma_{CO,t-j} + \sum_{j=1}^{n} \lambda_j \tau_{t-j} + \varepsilon_{OC,t} \qquad \text{Eq 3-2a.}$$

$$\sigma_{OC,t} = \alpha_{OC} + \sum_{j=1}^{n} \beta_j \sigma_{OC,t-j} + \sum_{j=1}^{n} \lambda_j \tau_{t-j} + \varepsilon_{OC,t} \qquad \text{Eq 3-3a.}$$

$$\sigma_{OC,t} = \alpha_{OC} + \sum_{j=1}^{n} \beta_j \sigma_{OC,t-j} + \sum_{j=1}^{n} \gamma_j \sigma_{CO,t-j} + \varepsilon_{OC,t} \qquad \text{Eq 3-4a.}$$

$$\sigma_{OC,t} = \alpha_{OC} + \sum_{j=1}^{n} \beta_j \sigma_{OC,t-j} + \varepsilon_{OC,t} \qquad \text{Eq 3-5a.}$$

Similarly, restricted and unrestricted regressions where close-open volatility is the dependent variable is:

$$\sigma_{CO,t} = \alpha_{CO} + \sum_{j=1}^{n} \beta_j \sigma_{OC,t-j} + \sum_{j=1}^{n} \gamma_j \sigma_{CO,t-j} + \sum_{j=1}^{n} \lambda_j \tau_{t-j} + \varepsilon_{CO,t} \quad \text{Eq 3-2b.}$$

$$\sigma_{CO,t} = \alpha_{CO} + \sum_{j=1}^{n} \gamma_j \sigma_{CO,t-j} + \sum_{j=1}^{n} \lambda_j \tau_{t-j} + \varepsilon_{CO,t} \quad \text{Eq 3-3b.}$$

$$\sigma_{CO,t} = \alpha_{CO} + \sum_{j=1}^{n} \beta_j \sigma_{OC,t-j} + \sum_{j=1}^{n} \gamma_j \sigma_{CO,t-j} + \varepsilon_{CO,t} \quad \text{Eq 3-4b.}$$

$$\sigma_{CO,t} = \alpha_{CO} + \sum_{j=1}^{n} \gamma_j \sigma_{CO,t-j} + \varepsilon_{CO,t} \quad \text{Eq 3-5b.}$$

and, volume turnover as a dependent variable is:

$$\tau_t = \alpha_\tau + \sum_{j=1}^{n} \beta_j \sigma_{OC,t-j} + \sum_{j=1}^{n} \gamma_j \sigma_{CO,t-j} + \sum_{j=1}^{n} \lambda_j \tau_{t-j} + \varepsilon_{\tau,t} \quad \text{Eq 3-2c.}$$

$$\tau_t = \alpha_\tau + \sum_{j=1}^{n} \gamma_j \sigma_{CO,t-j} + \sum_{j=1}^{n} \lambda_j \tau_{t-j} + \varepsilon_{\tau,t} \quad \text{Eq 3-3c.}$$

$$\tau_t = \alpha_\tau + \sum_{j=1}^{n} \beta_j \sigma_{OC,t-j} + \sum_{j=1}^{n} \lambda_j \tau_{t-j} + \varepsilon_{\tau,t} \quad \text{Eq 3-4c.}$$

$$\tau_t = \alpha_\tau + \sum_{j=1}^{n} \lambda_j \tau_{t-j} + \varepsilon_{\tau,t} \quad \text{Eq 3-5c.}$$

where:

$\sigma_{OC,t}$ is the open-close volatility for a certain quintile at time t. $\sigma_{OC,t}$ calculated as $\dfrac{\left|\ln(price_{close,t} - price_{open,t}\right|}{\sqrt{2\Pi}}$

$\sigma_{CO,t}$ is the close-open volatility for a certain quintile at time t. $\sigma_{CO,t}$ calculated as $\dfrac{\left|\ln(price_{open,t+1} - price_{close,t}\right|}{\sqrt{2\Pi}}$

τ_t is the volume turnover at time t.

j is the number of lag (in days) used.

A Wald test with one restriction is conducted by comparing the equation 3-2 (a, b or c) with either equation 3-3 or 3-4 (a, b, or c), while a Wald test with two restrictions involve comparing equation 3-2 (a, b, or c) with equation 3-5 (a, b, or c). For example, to determine whether past turnover and after hours volatility is exogenous to the next day's trading hour volatility, a Wald test on equations 3-2a and 3-5a and testing the restrictions γ_j and λ_j are jointly equal to 0. The null is asymptotic χ^2 distribution with degrees of freedom equal to the number of restrictions. Similar tests are conducted for the other two variables. Each variable should also be tested for exogeniety with only one set of restrictions, to better understand the causal relationships. If, after having established that past values of the two of the variables jointly affect the third variable, then empirical evidence is necessary to establish the role of each variable in its effect. Wald testing of equation 3-2 with either equation 3-3, or with equation 3-4, can be used again.

However, any lead-lag relationship observed between variables using Granger causality testing reveals only in-sample effects but is unable to provide the dynamic nature of relationship between these variables. Also, the magnitude and direction outside the sample period cannot be gauged. This relationship is further studied by observing the forecasted variance of each market and the effects from the other markets. Sims (1982) has shown that for a given systems of equations, its reaction to a random innovation can be observed for each variables by the impulse response function (IRF). Through this technology, one is able to observe the transitory as well as permanent effects on each variable in the system due to a random shock originating from one of the variables within the system. Graphically, one can observe the path of one of the variables due to a one standard deviation shock within the system.

Additionally, Sims (1982) has shown that if the forecasted error of each variable and for each time period can be attributed due to its own innovations and those due to the other variables in the system. This means that each variable's forecasted variance can be decomposed to provide understanding of its future direction through variance decomposition (VDC). For example, if the large capitalised assets had a larger influence on smaller assets, then the large sized firms' forecasted variance would primarily be due to its own innovations, but the variance of the smaller sized firms would show a much larger impact due to effects from the large firms' innovations. This can be shown graphically as well using the IRF to provide not just the magnitude but also the path of those innovations due to a shock of one standard deviation. Both VDC and IRF are derived from a moving average representation of the original VAR equation[44].

To establish in-sample and out-of-sample relationships, the samples of equities are grouped in terms of size (market value), returns (price changes) and liquidity (volume turnover). The extreme portfolios (HIGH and LOW portfolios) based on the three firm characteristics are then analysed for (i) Block Exogeniety (ii) Variance Decomposition and (iii) Impulse Response.

3.4. Data Description and Preliminary Results

Daily adjusted closing prices, traded volume and number of shares issued to the general public was obtained from the 2nd January 1998 until the 31st December 2001 for 53 companies trading on the NASDAQ[45]. All companies were chosen from the Information Technology industry and are also represented on DataStream Information Technology Index. Firms with infrequent trading and IPO dates post 1998 are removed from the sample, which left 53 firms in the sample. The sample period is divided into two sub samples: (i) Market Upturn period (2/1/1998 – 27/3/2000) and (ii) Market Downturn period (28/3/2000 – 31/12/2001). Descriptive statistics for each firm over the whole sample period and individual sample periods is provided in table 3-1 and 3-2. Table 3-1 shows average market value, volume turnover and returns for each firm over the whole

[44] For further details see Sims (1980, 1982).
[45] Adjusted daily opening and closing price and trading volume data are obtained from DataStream.

sample period as well as for the two sub-periods associated with rapid price increases in the general market and the subsequent collapse.

Table 3-1: Average market value (*MV*), daily turnover (*TO*) and returns (*RET*) for each firm during the overall period (*ALL*) period during market rise (*UP*) and market fall (*DOWN*) for each firm in the sample is provided. *MV* is calculated as the number of shares outstanding multiplied with the closing price of the share on day *t* and all figures are in $m. *RET* are calculate as the logarithmic mean ($\ln(P_t/P_{t-1})$). *TO* is calculated as the number of shares traded in a day divided by the total number of shares outstanding. The period *All* is 2/1/1998 to 31/12/2001. *UP* period is 2/1/1998 – 27/3/2000, and *DOWN* period is 28/3/2000 – 31/12/2001.

Name	MV_{ALL}	MV_{UP}	MV_{DOWN}	TO_{ALL}	TO_{UP}	TO_{DOWN}	RET_{ALL}	RET_{UP}	RET_{DOWN}
3COM	6460.76	12293.05	3518.53	0.0488	0.1090	0.0372	-0.0004	0.0011	-0.0036
ACTIVISION	868.02	280.19	1164.57	0.0584	0.0448	0.0796	0.0006	-0.0004	0.0017
ACXIOM	1721.10	1717.12	1723.11	0.0093	0.0085	0.0111	0.0001	0.0009	-0.0033
ADC TELECOM.	6159.43	5868.19	6306.36	0.0285	0.0556	0.0188	-0.0009	0.0017	-0.0056
ADOBE SYSTEMS	7944.61	4608.22	9627.73	0.0323	0.0598	0.0253	0.0009	0.0031	-0.0023
ADTRAN	1467.99	1280.39	1562.64	0.0210	0.0150	0.0179	0.0004	0.0015	-0.0034
ADVANCED FIBRE COMMS.	1849.42	1786.06	1881.39	0.0246	0.0293	0.0283	-0.0003	0.0018	-0.0046
ALTERA	8549.63	6779.39	9442.66	0.0432	0.0825	0.0293	0.0005	0.0029	-0.0029
AMER.POWER CONV.	3591.70	3784.37	3494.51	0.0106	0.0146	0.0112	0.0002	0.0021	-0.0031
ANDREW	1640.98	1563.68	1679.98	0.0123	0.0098	0.0113	-0.0005	0.0001	-0.0011
APPLE COMPUTERS	8321.70	7750.62	8609.80	0.0337	0.0620	0.0278	0.0009	0.0038	-0.0040
APPLIED MATS.	32619.73	24504.68	36713.54	0.0485	0.0839	0.0461	0.0005	0.0035	-0.0035
ATMEL	3478.43	2860.78	3790.03	0.0390	0.0738	0.0297	-0.0002	0.0031	-0.0039
AUTODESK	2039.11	1781.17	2169.24	0.0264	0.0391	0.0262	0.0005	0.0005	-0.0013
BEA SYSTEMS	6838.50	2801.98	8874.81	0.0380	0.0601	0.0303	0.0003	0.0043	-0.0045
CIENA	7385.73	5305.21	8435.29	0.0595	0.0885	0.0730	-0.0016	0.0017	-0.0055
CISCO SYSTEMS	180792.51	179145.58	181623.34	0.0186	0.0370	0.0099	0.0004	0.0038	-0.0050
CITRIX SYS.	4199.56	5034.54	3778.34	0.0450	0.0862	0.0329	0.0002	0.0037	-0.0043
COMPUWARE	5237.42	9764.00	2953.88	0.0134	0.0222	0.0126	-0.0007	0.0007	-0.0029
COMVERSE TECH.	5657.41	4848.03	6065.72	0.0275	0.0406	0.0261	0.0002	0.0037	-0.0044
DELL	81753.96	87504.47	78852.98	0.0263	0.0600	0.0122	0.0007	0.0030	-0.0030
ELECTRONIC ARTS	7280.17	3477.58	9198.46	0.0530	0.0703	0.0491	0.0010	0.0013	0.0003
INTEL	204690.53	204534.42	204769.28	0.0160	0.0300	0.0096	0.0001	0.0024	-0.0034
INTUIT	7579.47	5230.96	8764.23	0.0254	0.0446	0.0168	0.0007	0.0026	-0.0013
JDS UNIPHASE	17727.19	12420.36	20404.34	0.0629	0.1387	0.0316	-0.0002	0.0058	-0.0079
KLA TENCOR	7744.81	5263.34	8996.64	0.0484	0.0476	0.0385	0.0004	0.0026	-0.0028
LAM RESEARCH	2547.85	1836.45	2906.74	0.0472	0.0912	0.0349	0.0005	0.0029	-0.0031

Table 3-1 continued: Average market value (MV), daily turnover (TO) and returns (RET) for each firm during the overall period (ALL) period during market rise (UP) and market fall (DOWN).

Name	MV_{ALL}	MV_{UP}	MV_{DOWN}	TO_{ALL}	TO_{UP}	TO_{DOWN}	RET_{ALL}	RET_{UP}	RET_{DOWN}
LINEAR TECH.	11375.24	7958.91	13098.68	0.0269	0.0454	0.0144	0.0005	0.0022	-0.0014
MAXIM INTEGRATED PRDS.	12615.64	7627.04	15132.25	0.0204	0.0221	0.0152	0.0005	0.0025	-0.0019
MERCURY INTERACTIVE	3392.91	1778.57	4207.30	0.0448	0.0508	0.0408	0.0010	0.0049	-0.0046
MICROCHIP TECH.	3961.33	2142.05	4879.11	0.0328	0.0549	0.0257	0.0007	0.0021	-0.0014
MICROSOFT	328504.87	363563.73	310818.65	0.0145	0.0209	0.0154	0.0003	0.0021	-0.0018
NATIONAL INSTS.	1730.68	1222.31	1987.13	0.0065	0.0067	0.0066	0.0005	0.0016	-0.0018
NETWORK APPLIANCE	9121.68	7844.91	9765.78	0.0350	0.0572	0.0283	0.0010	0.0057	-0.0071
NOVELL	3632.52	6480.12	2195.98	0.0123	0.0149	0.0137	-0.0001	0.0024	-0.0059
NOVELLUS SYSTEMS	4475.95	2431.69	5507.22	0.0768	0.1259	0.0483	0.0005	0.0031	-0.0021
ORACLE	82606.83	58419.76	94808.53	0.0228	0.0491	0.0118	0.0006	0.0044	-0.0033
PEOPLESOFT	7133.44	6194.93	7606.90	0.0222	0.0194	0.0236	-0.0004	-0.0010	-0.0005
PMC-SIERRA	6245.26	4763.80	6992.62	0.0515	0.0669	0.0540	0.0001	0.0060	-0.0083
POLYCOM	1701.77	950.50	2080.76	0.0221	0.0288	0.0208	0.0012	0.0053	-0.0020
QLOGIC	3626.50	2215.70	4338.21	0.0903	0.1196	0.0592	0.0012	0.0066	-0.0056
QUALCOMM	35353.91	23152.18	41509.34	0.1381	0.3407	0.0441	0.0015	0.0056	-0.0032
SANDISK	2244.81	1380.42	2680.88	0.0703	0.0661	0.0609	0.0009	0.0046	-0.0073
SIEBEL SYS.	10755.89	6083.13	13113.17	0.0405	0.0613	0.0366	0.0003	0.0047	-0.0045
SUN MICROSYSTEMS	49328.11	51420.64	48272.49	0.0451	0.0991	0.0198	-0.0002	0.0041	-0.0049
SYMANTEC	4834.19	1718.96	6405.74	0.0699	0.0742	0.0880	0.0013	0.0021	-0.0019
SYNOPSYS	3440.37	3249.01	3536.91	0.0332	0.0278	0.0425	0.0000	0.0006	-0.0006
TECH DATA	1900.72	1710.14	1996.86	0.0149	0.0169	0.0145	0.0000	-0.0004	0.0005
TELLABS	11677.07	17642.89	8667.48	0.0194	0.0303	0.0152	-0.0006	0.0016	-0.0050
VERITAS SOFTWARE	16510.37	10617.13	19483.35	0.0368	0.0612	0.0273	0.0005	0.0055	-0.0059
XILINX	11332.07	7541.15	13244.48	0.0442	0.0808	0.0245	0.0006	0.0039	-0.0035
YAHOO	26791.61	32742.85	23789.37	0.1963	0.5126	0.0417	0.0012	0.0057	-0.0082
ZEBRA TECHS. 'A'	1510.28	864.54	1836.05	0.0210	0.0207	0.0240	0.0009	0.0010	-0.0009

Table 3-2 - Descriptive statistics of turnover (*TO*), daily returns (*RET*), open-to-close volatility ($\sigma_{OC,t}$) and close-to-open volatility ($\sigma_{CO,t}$) for each size-based (*MV*) quintile, over the whole sample (*ALL*) and the two sub-sample periods associated with Market upturn (*UP*) and Market downturn (*DOWN*). *RET* on day *t* are calculate as the logarithmic mean ($\ln(P_t/P_{t-1})$). *TO* is calculated as the number of shares traded in a day divided by the total number of shares outstanding. The period *All* is 2/1/1998 to 31/12/2001. *UP* period is 2/1/1998 – 27/3/2000, and *DOWN* period is 28/3/2000 – 31/12/2001.

	Turnover (*TO*)			Daily Return (*RET*)			Close-Open Volatility $\sigma_{CO,t}$			Open-Close Volatility $\sigma_{OC,t}$		
All Firms	*All*	*Up*	*Down*	*All*	*Up*	*Down*	*All*	*Up*	*Down*	*All*	*Up*	*Down*
Mean	0.0400	0.0662	0.0261	0.0004	0.0025	-0.0007	0.1594	0.1597	0.1592	0.1592	0.1592	0.1592
Median	0.0217	0.0368	0.0175	0.0000	0.0000	-0.0008	0.1593	0.1596	0.1592	0.1590	0.1590	0.1590
Maximum	4.8574	4.8574	0.9451	0.3720	0.3720	0.3655	0.2087	0.2071	0.2087	0.2354	0.2354	0.2253
Minimum	0.0000	0.0000	0.0006	-0.7391	-0.7391	-0.7312	0.0713	0.0713	0.0839	0.0887	0.0887	0.1094
First Quintile												
Mean	0.0217	0.0295	0.0213	0.0004	0.0014	0.0001	0.1592	0.1595	0.1591	0.1593	0.1592	0.1594
Median	0.0131	0.0151	0.0128	0.0000	0.0000	0.0000	0.1592	0.1592	0.1592	0.1592	0.1592	0.1592
Maximum	1.1464	1.2418	0.9451	0.2849	0.3720	0.2849	0.2002	0.2002	0.2001	0.2209	0.2096	0.2209
Minimum	0.0000	0.0000	0.0006	-0.7391	-0.4487	-0.5964	0.0713	0.1276	0.1030	0.1018	0.1018	0.1174
Second Quintile												
Mean	0.0424	0.0660	0.0263	0.0005	0.0027	-0.0007	0.1594	0.1598	0.1592	0.1591	0.1592	0.1591
Median	0.0260	0.0445	0.0162	0.0000	0.0000	-0.0009	0.1593	0.1596	0.1592	0.1590	0.1589	0.1590
Maximum	2.5811	2.5811	0.6262	0.3720	0.2967	0.3655	0.2087	0.1924	0.2087	0.2282	0.2282	0.2051
Minimum	0.0000	0.0000	0.0009	-0.6159	-0.7391	-0.6159	0.0948	0.0713	0.0948	0.1105	0.1155	0.1105
Third Quintile												
Mean	0.0433	0.0511	0.0338	0.0001	0.0022	-0.0010	0.1595	0.1598	0.1593	0.1591	0.1591	0.1591
Median	0.0304	0.0379	0.0223	-0.0002	0.0000	-0.0012	0.1594	0.1596	0.1592	0.1588	0.1587	0.1588
Maximum	1.3221	0.8292	0.9448	0.3468	0.3468	0.2821	0.1976	0.1976	0.1945	0.2289	0.2354	0.2236
Minimum	0.0000	0.0000	0.0014	-0.6826	-0.5968	-0.7312	0.0819	0.1103	0.0839	0.0887	0.0887	0.1094
Fourth Quintile												
Mean	0.0331	0.0670	0.0273	0.0005	0.0029	-0.0006	0.1593	0.1598	0.1592	0.1592	0.1591	0.1592
Median	0.0222	0.0460	0.0221	0.0000	0.0021	-0.0008	0.1593	0.1597	0.1592	0.1590	0.1589	0.1590
Maximum	1.5644	1.5644	0.4260	0.3430	0.3059	0.3430	0.1969	0.1904	0.1969	0.2354	0.2097	0.2160
Minimum	0.0018	0.0001	0.0018	-0.7312	-0.5493	-0.4458	0.0839	0.1031	0.1181	0.1174	0.1113	0.1204
Fifth Quintile												
Mean	0.0586	0.1220	0.0193	0.0005	0.0032	-0.0011	0.1594	0.1596	0.1593	0.1591	0.1593	0.1590
Median	0.0193	0.0441	0.0137	0.0000	0.0021	-0.0010	0.1594	0.1596	0.1592	0.1590	0.1592	0.1589
Maximum	4.8574	4.8574	0.2687	0.3270	0.3270	0.3122	0.2071	0.2071	0.1927	0.2253	0.1968	0.2253
Minimum	0.0000	0.0000	0.0010	-0.3109	-0.2557	-0.3109	0.1210	0.1300	0.1210	0.1298	0.1182	0.1336

The relationship between firm characteristics and sample periods is better understood through correlations presented in Table 3-3. Rank correlations were also calculated for the three periods of observations, while aggregate descriptive results over all sample periods and firm characteristics are reported in the last column of Table 3-3.

Table 3-3: Average and Rank correlation of firms based on Size (*MV*), Returns (*RET*) and Liquidity (*TO*) over the complete observation period (*ALL*) and the two sub-samples of Market Upturn (*UP*) and Market Downturn (*DOWN*). *MV* is calculated as the number of shares outstanding multiplied with the closing price of the share on day *t* and all figures are in \$m. *RET* are calculate as the logarithmic mean ($\ln(P_t/P_{t-1})$). *TO* is calculated as the number of shares traded in a day divided by the total number of shares outstanding. The period *All* is 2/1/1998 to 31/12/2001. *UP* period is 2/1/1998 – 27/3/2000, and *DOWN* period is 28/3/2000 – 31/12/2001.

	MV_{ALL}	MV_{UP}	MV_{DOWN}	TO_{ALL}	TO_{UP}	TO_{DOWN}	RET_{ALL}	RET_{UP}	AVERAGE
MV_{ALL}	1.00								24187.77
MV_{UP}	0.93	1.00							23315.89
MV_{DOWN}	0.98	0.85	1.00						24627.61
TO_{ALL}	0.15	0.03	0.22	1.00					0.040
TO_{UP}	0.38	0.29	0.42	0.90	1.00				0.068
TO_{DOWN}	-0.10	-0.20	-0.02	0.91	0.70	1.00			0.030
RET_{ALL}	0.06	-0.14	0.17	0.34	0.26	0.28	1.00		0.00035
RET_{UP}	0.43	0.32	0.51	0.49	0.60	0.30	0.42	1.00	0.00285
RET_{DOWN}	-0.29	-0.35	-0.26	-0.31	-0.43	-0.20	0.15	-0.66	-0.00343

During the market upturn and collapse the average size of the firm varies by only 5%. Correlations between firms on size show that market capitalisation ranking did not change over the rise and collapse of the bubble. Average turnover decreases by more than half during market downturn, perhaps indicating that during the market upturn there was much interest in Internet assets that eventually fell out of favour during the later period.

The ranking of firms based on turnover were correlated with a factor of 0.7 between the up and down period, though the correlation between turnover and size was very low (0.2 and –0.02 during rise and fall periods respectively). Larger firms were in favour during the Internet bubble formation period, but no relationship was discovered during the collapse period. Returns decreased by 3 times from 0.2% per day to more than –0.3% per day and were correlated with a factor of –0.66. Although returns were positively correlated with market capitalisation and turnover during the formation of the bubble, a slight negative relationship is observed during the downturn in Internet equities.

Table 3-2 provides descriptive statistics on daily turnover, return, open-to-close volatility and close-to-open volatility for the whole sample set, and each quintile. These statistics are for the whole sample period and the two sub sample periods, market upturn and market downturn. The first quintile consists of 10 smallest firms by market capitalisation, while the fifth quintile consists of the largest 10 firms. Only the third quintile, which contains the median sized companies from the sample, consists of 13 firms.

Returns distribution amongst firms and during the two sub samples provides interesting insight. For example, average returns do not increase (or decrease) monotonically over the quintiles during bubble formation (deflation) period, though a weak relationship between size and returns is revealed. The smallest sized firms, similar to firms of larger size, provide positive returns during market rises. However, the smallest sized assets provide the highest (and positive) returns during market collapse.

Turnover amongst quintiles show that during market rises, the largest and smallest capitalised firms had highest and lowest turnovers respectively during market rises, while the other three quintiles had similar turnover figures. During falling markets, although all quintiles display similar turnover, the decrease in turnover is highest for the largest firms (85%). This perhaps may imply that Internet firms had fallen out of favour, perhaps due to overvaluation, particularly the larger (and the better known) firms.

Open-to-close and close-to-open volatility show that there is no significant difference between quintiles or between the bubble formation or deflation period. Previous researchers show that most corporate announcements are made after trading hours and hence increased volatility should be observed after such announcements. However, descriptive statistics show that volatility during normal trading hours and after-hours is similar, and raises questions as to the factors that result in similar levels of volatility during the two periods, and if turnover plays a part in the information formation process.

Finally, firms are ranked on the basis of average market value, returns and turnover. Average returns of value-weighted portfolios composed of the top 10 firms (*High*) and bottom 10 firms (*Low*) are provided in Table 3-4.

Table 3-4: Average returns on value-weighted portfolio based upon Market Value, Liquidity and Returns during the complete sample period (*ALL*) as well as the two sub periods of market rises (*UP*) and market falls (*DOWN*). Stocks are ranked according to Market value (*MV*), Liquidity (*TO*) and Returns (*RET*). The top 10 stocks are formed into a value-weighted portfolio *High*, while the bottom 10 stocks are formed into a value-weighted portfolio *Low*. The period *All* is 2/1/1998 to 31/12/2001. *UP* period is 2/1/1998 – 27/3/2000, and *DOWN* period is 28/3/2000 – 31/12/2001.

	ALL		*UP*		*DOWN*	
Firm Characteristics	***High***	***Low***	***High***	***Low***	***High***	***Low***
***MV* based portfolio**	0.0003	0.0007	0.0028	0.0018	-0.0034	-0.0011
***TO* based portfolio**	0.0006	0.0003	0.0036	0.0018	-0.0035	-0.0036
***RET* based portfolio**	0.0014	-0.0005	0.0058	0.0006	-0.0002	-0.0062

Highly capitalised firms showed much larger swings in returns, compared to smaller firms, over the observation period, as confirmed by table 3-3 correlations between size of the firm and returns (0.32 during period *UP* and –0.26 during *DOWN* period). In other words, *High* portfolio shows that returns during bubble formation were much larger followed by much larger negative returns during the deflation period, compared to *Low* portfolio. Turnover based *High* and *Low* portfolios behaved interestingly, in that during market downturn both portfolios showed similar magnitude (and signed) returns, while during market upturn, high turnover firms showed much higher (twice) returns compared to the more illiquid firms. As mentioned earlier, correlation between the average performance and turnover for firms, during market upturn, was 0.6 and that larger firms had 4 times the turnover as small firms. It shows, on a descriptive level, that investors' interest in large firms was rewarded with high returns.

3.5. Results and Discussion

Tests on Block Exogeniety, variance decomposition and impulse response are conducted on various firm-characteristic based portfolios and over various time periods. The results from these tests and a discussion on the results obtain is presented below:

3.5.1. Results of Information Transmission between Trading and Non-Trading Period.

Results of testing two variable block exogeniety testing of daytime trading volatility, after-hours trading volatility and turnover are provided in Table 3-5, while Table 3-6, contains results from testing of each independent variable. Except for open-to-close volatility, both trading volume and after-hours volatility are influenced by past trading information over most sample periods and size portfolios.

Table 3-5 - Turnover (*TO*), open-to-close volatility ($\sigma_{OC,t}$) and close-to-open volatility ($\sigma_{CO,t}$) are tested for block exogeniety using Wald's χ^2 test for restrictions on two variables. Wald's test statistics with the associated level of significance is shown for each dependent variable, with the other two variables as the independent variables. Quintiles are formed on the basis of size (MV) of the firms over each period. The period *All* is 2/1/1998 to 31/12/2001. *UP* period is 2/1/1998 – 27/3/2000, and *DOWN* period is 28/3/2000 – 31/12/2001.

	Close-Open Volatility $\sigma_{CO,t}$	Open-Close Volatility $\sigma_{OC,t}$	Turnover (*TO*)
All Firms - *ALL*	7.39***	1.04	8.40***
All Firms - *UP*	4.27***	1.49	6.80***
All Firms - *DOWN*	2.35***	1.14	4.98***
First Quintile - *ALL*	5.13***	1.33	7.70***
First Quintile - *UP*	4.40***	1.92***	2.76***
First Quintile - *DOWN*	1.95***	0.96	5.69***
Second Quintile - *ALL*	4.62***	0.84	3.94***
Second Quintile - *UP*	2.07**	1.04**	2.55**
Second Quintile - *DOWN*	3.78***	0.68	2.54***
Third Quintile - *ALL*	3.95***	0.72	3.52***
Third Quintile - *UP*	1.04**	0.84	4.04***
Third Quintile - *DOWN*	1.55	1.29	2.01**
Fourth Quintile - *ALL*	3.05***	0.93	7.87***
Fourth Quintile - *UP*	1.83**	1.90**	4.83***
Fourth Quintile - *DOWN*	0.95	2.58***	3.90***
Fifth Quintile - *ALL*	4.85***	1.63*	3.68***
Fifth Quintile - *UP*	1.33	1.14	2.45***
Fifth Quintile - *DOWN*	2.55***	1.30	3.27***

Level of significance is specified as * (10%), ** (5%), *** (1%)

3.5.1.1. Open-Close (Normal Trading hour) Volatility

Daytime volatility is affected by a combination of after-trading hour volatility and/or past volatility during market rises (*UP*) and for size-quintiles 1, 2 and 4. However, during market downturns (*DOWN*) daytime volatility (except for the 4th quintile firms) does not seem to be influenced by past overnight volatility and/or turnover. This could be due to several reasons. First, as investigated by several authors, firms tend to release firm specific announcements after-hours and market participants are able to realise their overnight information the following day and hence no persistence should be observed[46]. Hence only overnight volatility should be of importance. Second, market participants view prior day(s) trading behaviour and may tend to chase a certain trend. This would imply that there would be a slow decay of past information, and past trading volume, and volatilities, should play an important part in determining next day's volatility.

A review of Table 3-6 below reveals how each dependent variable (given in the first row of the table) is individually affected by the independent variables (given in the second row of the table). Block exogeniety tests on trading hour (open-close) volatility reveal inconsistent and statistically weak influences due to trading volume and close-to-open volatility, and no generalities could be suggested or hypothesis tested.

[46] Authors such as Corral et al (2004), Cao et al (2000), Maulis and Shivakumar (1997) show that overnight firm announcement shocks do not tend to persist for very long after the pre-opening session on the NASDAQ.

Table 3-6 - Turnover (*TO*), open-to-close volatility ($\sigma_{OC,t}$) and close-to-open volatility ($\sigma_{CO,t}$) are tested for block exogeniety using Wald's χ^2 test for restrictions on one variable. Wald's test statistics with the associated level of significance is shown for each dependent variable, with the other two variables as the independent variables. The period *All* is 2/1/1998 to 31/12/2001. *UP* period is 2/1/1998 – 27/3/2000, and *DOWN* period is 28/3/2000 – 31/12/2001.

Dependent variable	Close-Open Volatility $\sigma_{CO,t}$		Open-Close Volatility $\sigma_{OC,t}$		Turnover (*TO*)	
Independent variables	$\sigma_{OC,t}$	***TO***	$\sigma_{CO,t}$	***TO***	$\sigma_{CO,t}$	$\sigma_{OC,t}$
All Firms - *ALL*	3.08***	13.23***	0.51	1.57	0.75	17.01***
All Firms - *UP*	1.52	8.03***	2.14*	1.03	5.01***	11.10***
All Firms- D*OWN*	1.96*	2.15*	1.17	1.32	0.44	8.63***
First Quintile – *ALL*	5.15***	6.95***	0.67	1.88*	1.04	14.74***
First Quintile - *UP*	1.78	8.22***	1.68	2.28**	0.63	5.01***
First Quintile - *DOWN*	3.21***	0.89	0.16	1.76	0.23	10.86***
Second Quintile – *ALL*	1.63	8.23***	0.83	0.85	0.32	7.46***
Second Quintile - *UP*	1.9*	2.9**	1.89*	0.38	1.44	4.34***
Second Quintile- *DOWN*	1.50	5.67***	0.36	1.08	0.66	4.53***
Third Quintile - *ALL*	2.80***	5.83***	1.11	0.29	1.08	6.23***
Third Quintile - *UP*	0.88	2.23**	1.37	0.23	3.09***	5.51***
Third Quintile - *DOWN*	1.11	1.47	1.83*	0.95	0.12	3.72***
Fourth Quintile - *ALL*	1.63	4.40***	0.41	1.40	1.33	14.07***
Fourth Quintile - *UP*	1.25	1.94*	2.55**	1.59	2.64**	7.69***
Fourth Quintile- *DOWN*	0.77	1.02	2.05*	3.12***	0.69	6.80***
Fifth Quintile - *ALL*	3.42***	6.74***	0.68	2.52**	0.21	7.06***
Fifth Quintile - *UP*	1.10	2.17**	0.74	1.39	2.22**	3.10***
Fifth Quintile - *DOWN*	2.87***	1.50	1.50	1.18	0.96	5.35***

Level of significance is specified as * (10%), ** (5%), *** (1%)

3.5.1.2. Turnover (Liquidity)

Turnover seems to be affected by exogenous factors within each sample period and for each size quintile. This should not be of any surprise, since trading needs to take place for information to be incorporated in current prices, unless market participants simultaneously agree upon the information. Information may be firm specific in nature, such as corporate announcements, or market data, such as trading volume, market (and sectors) returns etc. The influence of daytime volatility seems to affect trading volume in each and every quintile and time period, which is also the time when almost no corporate information is released. Hence this trading may be due to several reasons including previous day's price changes (Table 3-6 show that this may not be the case), some exogenous macro-economic news that may need to be reflected in share prices, liquidity or noise traders etc. Most macroeconomic news is released during the daytime.

However, past close-to-open volatility seems to have very little influence on smaller firms (quintile 1 and 2) but the influence seems pronounced for larger assets during market upturn (quintile 3, 4, and 5). There could be several reasons for this phenomenon, including the fact that more corporate announcements were made after trading hours in recent times, so that market has a longer time to absorb new information. Also, it may be the case that during periods of rapid price increases, investors, both retail and institutional, use past price changes to base their future trading strategy. Griffin et. al. (2003) show that not only did institutional investors have a very high level of ownership of internet stocks, but also the institutional investors entered the buy side of transactions a day after the market rose. Their research shows that it was indeed the institutional investors that contributed greatly to the bubble formation.

3.5.1.3. Close-Open (After Hours) Volatility

Unlike daytime volatility, overnight volatility seems to be significantly affected by exogenous factors during most periods and for most size quintiles, as shown in Table 3-5. Table 3-6 identifies the variables that influence after-hours price variability, and shows that past daytime volatility only affected the largest and the smallest size portfolio during market falls. However, previous day(s) trading history seems to affect nighttime volatility during the bubble formation period but not during the bubble collapse. These results imply that investors knowledgebase during market upturn was primarily sourced from past trading levels.

3.5.2. Results on information transmission between firm characteristics-based portfolios.

Value-weighted return series are constructed for Internet firms based upon returns and liquidity, over three sample periods. Interaction between portfolios is then analysed by Sims (1980) vector autoregressive analysis. The results are provided in Table 3-7, and show that high returns-based portfolio led low returns-based portfolios. These results imply that while loser firms lagged the winning firms during the overall sample period in both market conditions, market rises and fall revealed very different results. Significant bi-directional causality between the extreme return-based portfolios over the period of market rise was identified, but during market downturn, winners and losers did not display any causal relationship. This should be of interest, as these results may imply that investors were using information derived from winner (loser) assets to form opinion with regards to loser (winder) assets during the bubble formation period. This also shows that investors grew confident about the prospect of the industry, and their optimism feed into the prospect of the assets in the industry.

Table 3-7: Block Erogeneity Wald Test of *High* and *Low* portfolios based on Returns (*RET*) and Liquidity (*TO*) over the complete sample period (*ALL*) and sub sample periods of market upturn (*UP*) and subsequent downturn (*DOWN*). Stocks are ranked according to *TO* and *RET*. The top 10 stocks are formed into a value-weighted portfolio *High*, while the bottom 10 stocks are formed into a value-weighted portfolio *Low*. The period *All* is 2/1/1998 to 31/12/2001. *UP* period is 2/1/1998 – 27/3/2000, and *DOWN* period is 28/3/2000 – 31/12/2001.

	RET	*TO*
ALL		
High	2.594604	8.845959***
Low	4.479085*	0.263304
UP		
High	8.558989***	5.933288**
Low	14.3741***	1.458047
DOWN		
High	2.912233	6.295515***
Low	1.984546	2.270994

Level of significance is specified as * (10%), ** (5%), *** (1%)

Liquidity-based portfolios displayed unidirectional Granger causality, where returns from *Low* portfolio significantly affected *High* portfolio returns, over each time period. This could provide evidence that investors derive their information regarding assets with higher investor interest based upon information originating from low turnover assets. Assets with lower turnover also have lower investor interest as these assets may be at their peak (or bottom) of their performance (see Lee and Swaminathan, 1998).

3.5.3. Variance Decomposition and Impulse Response between firm characteristics-based portfolios.

Lead-lag relationship is further analysed by decomposing each portfolios' variance in terms of effects due to its own innovations and due to that of the other portfolio, and the results are presented in Table 3-8 below.

High portfolios based on size, liquidity and returns explained almost 100% of their variances due to innovations from within itself. However, *Low* portfolios were able to explain their forecasted variance to varying degrees, which provide insight to the differences in portfolio characteristics. For example, during the bubble formation period, *Low* size and return-based portfolios explained almost three fourths of its forecasted variance due to its own disturbances, while liquidity based portfolios were able to explain 62% of the variance due to its own innovations. However, during market downturn, the effect on its forecasted variance due to its own disturbances dropped to almost half. In other words, during market upturn, changes in the value of small firms or those with low liquidity or returns were mostly due to firm specific information rather than influences from large, highly liquid or those with good performance.

Table 3-8: Variance Decomposition of High and Low portfolios based on Market value (*MV*), Returns (*RET*) and Liquidity (*TO*) for the complete sample period (*ALL*) and the two sub periods of Market upturn (*UP*) and market downturn (*DOWN*). Stocks are ranked according to *MV*, *TO* and *RET*. The top 10 stocks are formed into a value-weighted portfolio *High*, while the bottom 10 stocks are formed into a value-weighted portfolio *Low*. The period *All* is 2/1/1998 - 31/12/2001. *UP* period is 2/1/1998 – 27/3/2000, and *DOWN* period is 28/3/2000 – 31/12/2001.

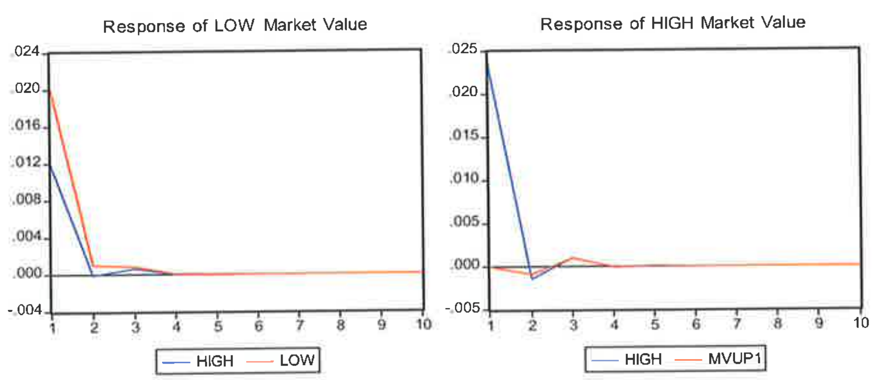
Variance Decomposition of *MV*-based Portfolios:						
	ALL		*UP*		*DOWN*	
Days	*High*	*Low*	*High*	*Low*	*High*	*Low*
1	100.00	56.35	100.00	74.05	100.00	43.12
2	99.68	56.21	99.85	74.10	99.64	43.49
5	99.60	56.09	99.69	74.08	99.41	43.13
10	99.60	56.09	99.69	74.08	99.41	43.13
Variance Decomposition of *RET*-based Portfolios:						
	ALL		*UP*		*DOWN*	
Days	*High*	*Low*	*High*	*Low*	*High*	*Low*
1	100.00	40.75	100.00	72.27	100.00	37.07
2	99.84	40.84	97.55	72.46	100.00	37.25
5	99.73	40.80	97.44	72.41	99.46	38.00
10	99.73	40.80	97.44	72.41	99.44	38.03
Variance Decomposition of *TO*-based Portfolios:						
	ALL		*UP*		*DOWN*	
Days	*High*	*Low*	*High*	*Low*	*High*	*Low*
1	100.00	47.10	100.00	62.38	100.00	31.91
2	100.00	46.89	99.86	61.91	99.94	32.26
5	99.99	46.80	99.73	62.09	99.46	33.69
10	99.99	46.80	99.73	62.09	99.44	33.76

Figures 3-2, 3-3 and 3-4 provide a graphical representation of the effect of one standard deviation shock from a Low (High) portfolio on itself and on the High (Low) portfolio. Low and High portfolios are based on market value (Figure 3-2), returns (Figure 3-3) and liquidity (Figure 3-4). Panel A shows the impulse response during market upturns, while Panel B shows the IRF during market downturns.

The plots show that information adjustment process takes, on average 4 days, during market upturn, though during market downturn, information adjustment takes 6-7 days. The results are consistent for portfolios constructed any of the three firm characteristics.

Figure 3-2: Impulse Response for Sized based Portfolios.

Panel A: Impulse Response during Market Upturn.



Panel B: Impulse Response during Market Downturn.

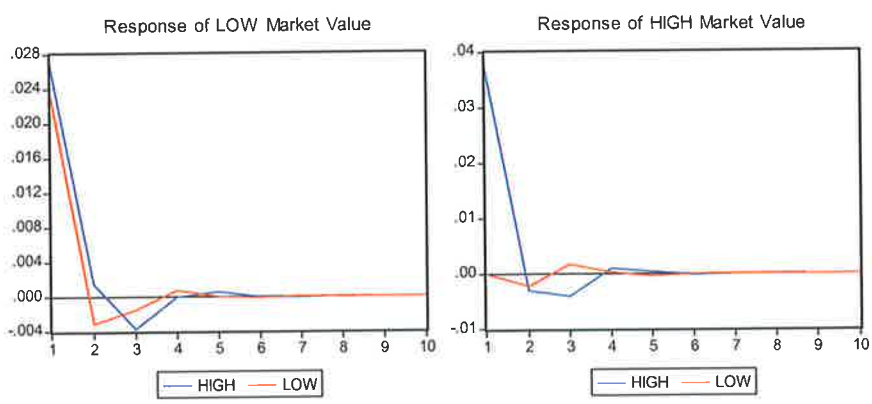
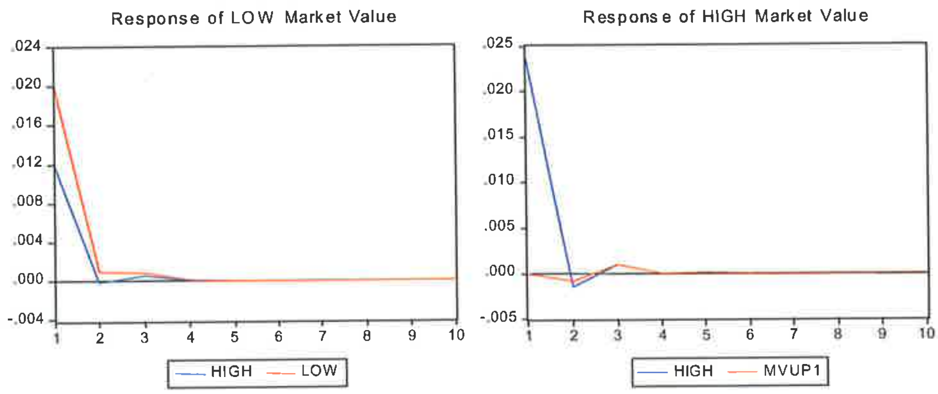


Figure 3-3: Impulse Response for Returns based Portfolios.

Panel A: Impulse Response during Market Upturn.



Panel B: Impulse Response during Market Downturn.

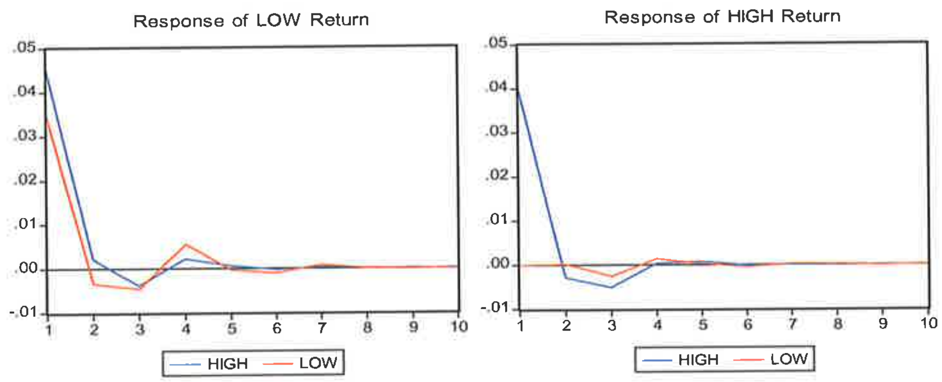
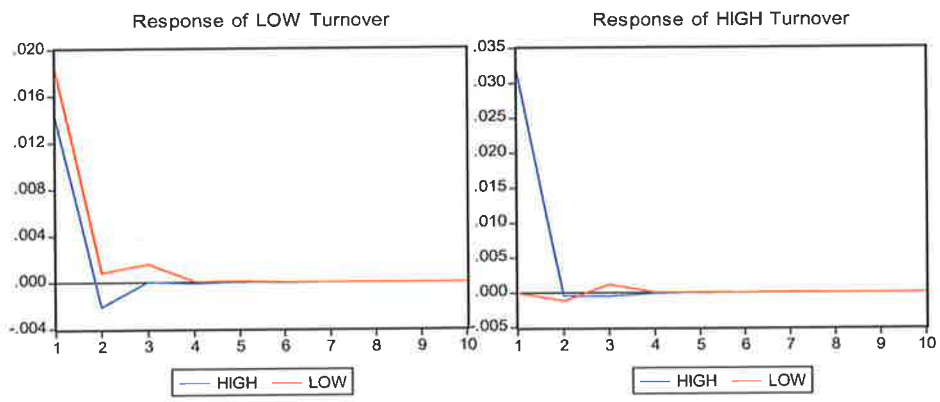
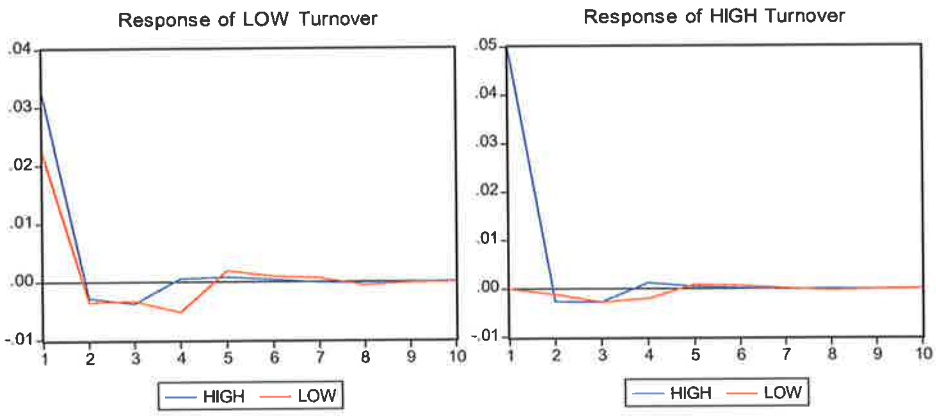


Figure 3-4: Impulse Response for Liquidity based Portfolios.

Panel A: Impulse Response during Market Upturn.



Panel B: Impulse Response during Market Downturn.



3.6. Conclusion

This chapter analysed information transmission and adjustment process of information technology stocks listed on the NASDAQ during the period termed as the Internet Technology Bubble. The basic purpose of this investigation is to see whether information transmission process differs between regular trading hours and after hours, as well as, other market information. Much research has been devoted to price discovery and information spillovers, and to how investors use various firm characteristics to derive their trading strategy. This study shows that investors' value trading volume only in a rising market. Additionally, daily volatility is equally divided amongst daytime and after-hours volatility. It is important to note that the source of variation in prices is due to different reasons. After-hours volatility was motivated primarily due to historical trading volume, while no consistent exogenous factors for daytime volatility was revealed in the first part of the study.

The second part of this chapter focused on how various firm-specific characteristics due to trades, such as returns, size and liquidity influenced investors' behaviour. Research in this chapter finds that portfolios based on assets that had the largest size, highest returns and those that were most liquid were not affected by innovations from other assets within the same market. Interestingly, the smaller, less liquid and those that provided lower returns behaved very differently. Market rise and its eventual collapse revealed that investor behaviour was focused on trend chasing during rising prices followed by interest in larger assets during market downturn and is indicative of flight to quality during trouble times.

Chapter 4: Level of Speculation within the Internet Stock Market

Synopsis

On 10th March 2000 the NASDAQ Composite Index stood at its highest level of 5048.62 (an increase of approximately 200% over the previous two years). This date also coincided with the Dow Jones Internet Index recording its highest level of 506.84, an increase of approximately 600% over the same period. Lloente, Michaely, Saar and Wang (2002) proposed framework is used to test (i) the level of speculation in the dotcom sector before and after the crash, (ii) changes in trading pattern after a significant economic event, and (iii) to verify the cross-sectional variation of the volume and return autocorrelation due to informational asymmetry.

This chapter adds to the existing literature by looking at the dynamic relationship between volume and returns autocorrelation. This relationship is analysed in the context of an emerging sector within a mature capital market.

4.1 Introduction

Ofek and Richardson (2001) provide a explanation of the rise and fall in the dotcom industry, while there have been hosts of other work on the industry (see for example Perkins and Perkins (1999), Cooper et al (2000), Johansen and Sornette (2000), Demers and Lev (2000), Liu and Song (2001), Schultz and Zaman (2001)) who examine various aspects of the industry such as predictions of the eventual bursting of the bubble, the mania surrounding the industry, role of the analysts and conflict of interest, industry specific variables and comparisons with the 1929 crash etc. The "irrational exuberance" by investors in the Internet market has generated extensive interest, as it not only affected the wealth of a large percentage of investors (both retail and institutional) but also provides researchers the opportunity to examine continual deviations in fundamental pricing in a well-developed and mature capital market.

This chapter attempts to estimate the level of speculative trading behaviour in the Internet firms listed on the NASDAQ, and provides some empirical evidence to the ideas by Ofek and Richardson (2001). The model used in this research is provided in the next section. The results in the chapter point to the fact that trading in Internet stocks was predominantly speculative in nature and in firms that were larger in size and had longer trading history. This evidence could point on the one hand to the initial hype and exuberance in the Internet assets by market participants in the lead up to the crash and on the other hand to the winding down of the lockup contracts with the insiders of the firms as documented by Ofek and Richardson (2001). This chapter also provides stylised characteristics of return volume relationship for speculative bubbles in emerging markets.

4.2 LMSW Model and the Internet Equity Market

Llorente, Michaely, Saar and Wang (2000)[47], hereon referred to as LMSW, describe an economy with two types of assets: a riskless asset (bond) in an unlimited supply that provide the investors with a constant non-negative return *r* and a risky asset (stock) in limited supply that provides the investor with a dividend D_{t+1} at the end of the period. D_{t+1} is composed of two components F_t and G_t as follows:

$$D_{t+1} = F_t + G_t \qquad \text{Eq 4-1}$$

F_t is the portion of the dividend that is forecasted by all investors at time *t*, while G_t is the private information regarding the stock payoff at the end of the period and is only known to a subset of the investors in the economy.

LMSW's model is based on an economy with two types of investors: the first type of investor has only public information regarding the stock's future payoff F_t, while the second type of investor has not only public information F_t but can also observe G_t based upon private information and thus the second type of investor has a richer information set. Both type of investors start with a certain endowment based upon a proportion of stocks and the remaining amount in non-traded assets. Based upon the information available to the investor, trade takes place to maximise expected utility over the next period with the following:

$$E\,[\,-\,e^{-\lambda W t+1} \mid \Phi_t^i\,] \qquad \text{Eq 4-2}$$

Where

λ the risk aversion parameter is set to 1
i is the i[th] class of investors; either informed or uninformed.
Φ_t^i is the information set present with the i[th] investor at time *t* regarding future stock payoffs.

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47 Readers can refer to the original paper by LMSW for more details on the model and the proof of the equilibrium stock price equation.

It is assumed in the model that all shocks to economy are normally distributed with zero mean, constant variance such that the shocks are uncorrelated. However contemporaneous stock payoff and endowment are correlated which provides investors an incentive to trade. As the expectation of future payoffs from the risky asset changes, investors will trade to maintain optimal portfolio holding in line with their risk preferences. This risk allocation trading process is also termed as a hedging trade. However, investors that perceive to have private information will trade to obtain maximum benefit from future payoff from the risky asset and will enter into speculative positions.

The return volume dynamics of stocks is based upon three sources. First, new information on future payoffs comes into the market, and changes investors' expectations on future payoffs. Information, by definition is random and independent, though the model assumes that market participants receive the information simultaneously and the stock prices change to incorporate this new information completely. This price change does not motivate any trading activity, as all participants agree on the future payoffs. Importantly, returns in the two periods are uncorrelated.

Trades generated due speculative positions and portfolio rebalancing leads to serially correlated returns, and are the other two sources of the return volume dynamics. Speculative trades are based upon investors' private information held today, and are designed to provide investors with higher returns in the next period when that private information is fully revealed to the market. This implies a positive correlation in returns as market incorporate the information into prices. Trades due to portfolio rebalancing, or hedging, is not information based, and occurs when a trader may increase (or decrease) his stock holding by buying (or selling) a portion of his stock holding. This will be accomplished by increasing (or decreasing) the stock price to induce the opposite side of the trade. Price changes without information is not in equilibrium, and must reverse in the next period, resulting in a negative correlation of returns. Both types of trade result in i) correlated returns and ii) a portion of stock holding that changes ownership.

LMSW proposition 2 shows that the next period expected return from the stock is given by:

$$E\left[r_{t+1} \mid v_t, r_t \right] \approx \alpha_1 r_t + \alpha_2 v_t^2 r_t \qquad \text{Eq 4-3}$$

Where

r_t is the dollar return in time t

α_1 and α_2 are constants

v_t is normalized volume at time t

This return volume dynamics can be observed from the coefficient of α_2. If the trades are only speculative in nature α_2 should be positive, since returns are positive correlated. The level of speculation will be measured by the scaling factor v_t. However, if the trades are primarily to rebalance portfolio (hedging), α_2 will be negative, and the scaled by v_t. Thus the level of private information will be directly related to the value of α_2.

LMSW test this model using stocks from the NYSE and AMEX. This chapter tests this model on Internet stocks listed on the NASDAQ over the period of dramatic rise and fall of the Internet equity market. Internet equities provides the opportunity to with the emergence of a new market with a limited trading history and difficulties associated with conducting fundamental valuation of assets in such a market due to uncertainty of future prospects. In addition, this market had witnessed strong growth in 1998 to the first quarter of 2000 (an increase in major Internet index of 600% in two years) as well as a dramatic increase in IPOs of Internet stocks. Perhaps the most important aspect is that this emerging equity market is based in one of the largest and most efficient global capital markets. However, after reaching its highest level on the 10th March 2000, there was a dramatic fall in Internet equity prices. Almost a year and half later, on the morning of 11th September 2001, United States was attacked by terrorists which led to a four day market closure. In a period of declining consumer confidence the events of September 11th reinforced the despair. This chapter provides insight into investor behaviour during the US Internet equity market bubble.

Test of the influence of information asymmetry on dynamic return volume relationship for the Internet equities is based on the regression:

$$r_{i,t+1} = C0 + C1 * r_{i,t} + C2 * r_{i,t} * v_{i,t} + \varepsilon_{i,t+1} \qquad \text{Eq 4-4}$$

for each stock selected over various periods. However, the above regression does not provide information regarding the level of speculation on a firm specific level. To extract idiosyncratic component of the return-volume relationship, residual from market index model for both return and volume are used. Following Lo and Wang's (2000) justification of using the market index model for volume, the residuals are used in equation 4-4.

Various proxies for information asymmetry exist including market capitalisation, length of operation since initial public offering, bid-ask spreads and ownership of shares. This chapter uses market capitalisation and length of operations since IPO to examine the cross sectional variation in the coefficient C2 over all the sample periods. Following LMSW (2002) methodology, average market capitalisation is ordered in an ascending order and individual companies are ranked on an ordinal scale from 1 to 41 over each sample period[48]. Similar procedure is used to obtain the ordinal ranking for length of operations since IPO.

4.3 Data and Descriptive Statistics

The sample consists of stocks represented on Wall Street Research Network (WSRN) Index that trade on the NASDAQ. Daily closing prices, trading volume, shares outstanding, IPO dates, the NASDAQ composite Index and the Dow Jones Internet Index values were obtained from Datastream. The sample period starts from the first trading day of 1998 to the last trading day in November of 2002, and consists of 1235 trading observations. This period consists of two sub-periods of analysis: (i) formation of the Internet price bubble (2nd January 1998 to 10th March 2000), and (ii) collapse of the Internet price bubble (13th March 2000 to 29th November 2002). The collapse of the bubble is divided into two further sub-samples: (i) pre-September 11th tragedy, and (ii) post-September 11th, 2001.

WSRN is a comprehensive Internet Index that categorises firms into sub-indices according to various business and services structure. However, all firms included in the index are not chosen for analysis, as they may lack trading history or may be relatively illiquid over the period of analysis. Hence shares that do not have trading history prior to 2nd January 1998 or had 5 or more non-trading days over the sample period, were excluded. The final sample consisted of 42 firms.

[48] A rank of 1 implies the lowest average market capitalisation for that sample period, and 41 the highest.

Figure 4-1 Comparison of NASDAQ Composite Index and Dow Jones Internet Index – Values and Returns

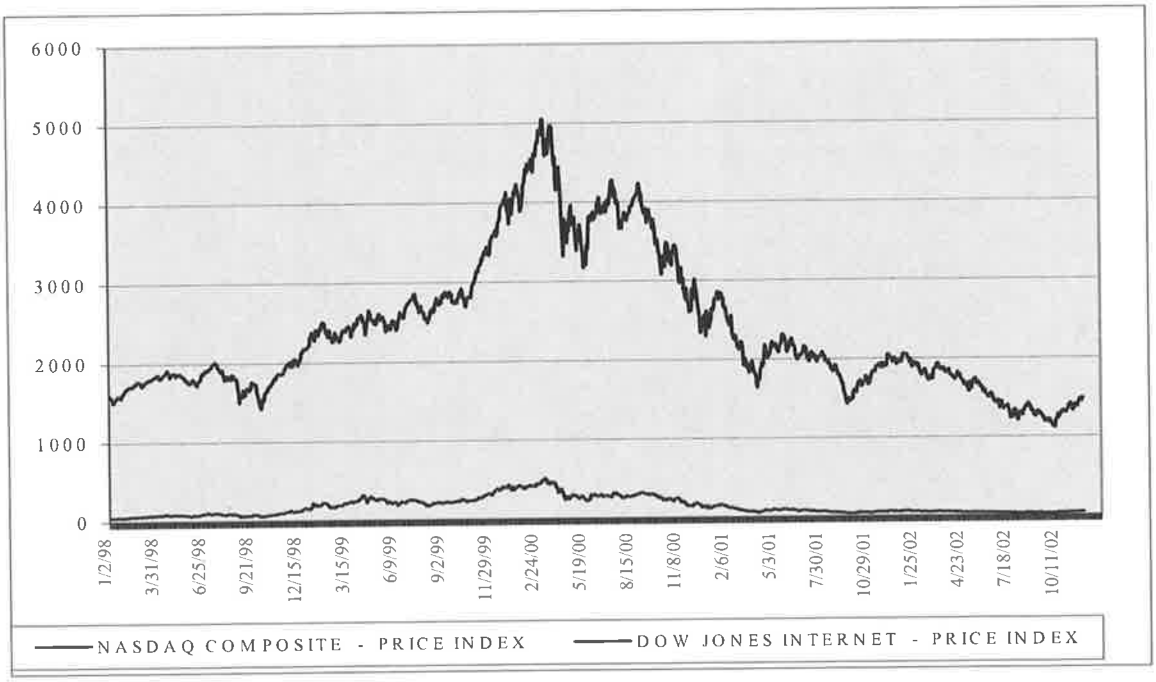

Figure 4-1 shows a comparison between the NASDAQ Composite Index and the Dow Jones Internet Index. To estimate equation 4-4 log returns[49] and log trading volume[50] is used. Average market capitalisation[51] is calculated over the period of analysis. Table 4-1 provides summary statistics for the three variables over the five sample periods.

49 $r_{i,t} = \ln(\text{closing price}_{i,t} + \text{dividend}_{i,t}) - \ln(\text{closing price}_{i,t-1})$

50 $v_{i,t} = \ln(\text{trading volume}_{i,t}) - \ln(\text{trading volume}_{i,t-1})$

51 market capitalization = daily closing price x number of shares outstanding.

Table 4-1 Descriptive Statistics

	MARKET VALUE				RETURNS				NORMALISED VOLUME			
	ALL	PRE98	98	99	ALL	PRE98	98	99	ALL	PRE98	98	99
SAMPLE 1: 1/1/1998 - 29/11/2002												
Mean	10652.77	15583.97	3826.58	2017.81	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	7351.53	10696.20	2791.74	1266.63	0.00	0.00	0.00	-0.01	-0.03	-0.03	-0.03	-0.04
Maximum	36399.30	51810.84	15211.30	8938.12	0.42	0.36	0.56	0.44	3.33	3.20	3.53	4.05
Minimum	1859.86	2946.33	236.15	346.42	-0.48	-0.39	-0.69	-0.47	-2.79	-2.69	-2.82	-3.66
Std. Dev.	8283.50	12017.17	3114.38	1747.66	0.07	0.06	0.08	0.08	0.63	0.64	0.65	0.67
SAMPLE 2: 1/1/1998 - 10/3/00												
Mean	9180.62	13251.23	3318.11	2792.53	0.00	0.00	0.01	0.01	0.00	0.00	-0.01	-0.01
Median	7679.14	11185.70	2739.08	1818.40	0.00	0.00	0.00	0.00	-0.04	-0.03	-0.04	-0.06
Maximum	31963.09	45870.95	12301.82	8938.12	0.32	0.30	0.36	0.38	3.04	2.92	3.18	3.89
Minimum	2133.74	3281.26	356.01	739.36	-0.29	-0.31	-0.27	-0.34	-2.29	-2.24	-2.29	-2.94
Std. Dev.	6989.03	10041.98	2657.91	1984.29	0.06	0.06	0.07	0.08	0.66	0.65	0.68	0.72
SAMPLE 3: 13/3/2000 - 11/9/2001												
Mean	16794.94	24887.71	5620.10	2533.31	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00
Median	16926.72	25673.52	4671.79	2087.80	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-0.03	-0.02
Maximum	34755.17	49502.64	14661.83	7886.86	0.31	0.28	0.35	0.36	2.22	2.10	2.45	2.54
Minimum	5307.87	8039.71	1496.85	619.69	-0.35	-0.28	-0.47	-0.42	-1.83	-1.84	-1.79	-2.14
Std. Dev.	8213.63	11856.87	3243.24	1597.20	0.07	0.07	0.08	0.08	0.56	0.56	0.59	0.61
SAMPLE 4: 17/9/2001 - 29/11/2002												
Mean	5765.48	8278.74	2492.96	693.34	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	5635.91	8135.60	2358.94	663.03	0.00	0.00	0.00	0.00	-0.03	-0.04	-0.03	-0.04
Maximum	9172.27	13085.05	4104.77	1186.86	0.32	0.29	0.42	0.30	2.52	2.53	2.69	2.24
Minimum	3001.78	4290.61	1339.23	349.89	-0.33	-0.25	-0.52	-0.31	-2.13	-2.14	-2.14	-2.16
Std. Dev.	1520.37	2150.33	710.82	214.18	0.07	0.06	0.08	0.07	0.66	0.67	0.66	0.69
SAMPLE 5: 13/3/2000 - 29/11/2002												
Mean	11868.72	17469.30	4223.65	1711.65	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00
Median	8104.31	11847.44	3081.82	1032.86	-0.01	0.00	-0.01	-0.01	-0.03	-0.03	-0.03	-0.03
Maximum	34769.08	49472.69	14764.36	7886.86	0.38	0.33	0.50	0.36	2.70	2.68	2.87	2.65
Minimum	2865.58	4270.49	938.96	346.42	-0.44	-0.32	-0.69	-0.44	-2.25	-2.23	-2.27	-2.43
Std. Dev.	8422.80	12311.05	3070.97	1514.65	0.07	0.07	0.08	0.08	0.61	0.61	0.63	0.65

As noted by Ofek and Richardson (2001), Internet firms had comparable capitalisation to non-internet firms while the trading volume was several times higher dispelling the lack of liquidity in the Internet stock market. Average capitalisation for the Internet firms was \$10.652billion over the four-year period. This contrasts with an average capitalisation of \$16.794 billion after the market peaked till the events of September 11th. Interestingly, average market capitalisation post September 11th dropped dramatically to \$5.765 billion, almost a third of the value in the previous period.

4.4. Results and Discussion

The influence of combined market and firm specific factors on the return volume relationship are discussed, followed by the effects of only firm specific factors on this relationship. Finally the length of operation as an alternate proxy for information asymmetry is used to observe the combined factors and only firm specific influence on the return volume relationship.

4.4.1 Effects of Systematic and Unsystematic Factors on Return Volume Dynamics

Table 4-2a presents the summary results for all the stocks over the whole sample period. The results in Panel A do not suggest either dominance of speculative trading or hedging on a statistically significant basis. Interestingly, the low and high market capitalisation has, on average, a positive C2 coefficient while the medium group has a negative average C2 coefficient, suggesting that more speculative trading has taken place for the high and small cap firms. Cross-sectional analysis results from Panel B show a non-significant positive relationship between C2 and capitalisation ranking, and suggests that trading was speculative for larger stocks than for smaller stocks.

Table 4-2a Information Asymmetry Results – Overall Sample

This table summarises the influence of information asymmetry on the volume and return relationship. Average Market Capitalisation over the whole sample is used to proxy information asymmetry. The sample period is from 1/1/1998 to 29/11/2002. The relationship is measured from the regression:

$$r_{i,t+1} = C0_i + C1_i * r_{i,t} + C2_i * v_{i,t} * r_{i,t} + error_{i,t+1}$$

Where:

$r_{i,t}$ is the daily return for stock i at time t

$v_{i,t}$ is the daily volume for stocks i at time t

Panel A reports the information asymmetry effect on each group (Low market cap, Medium Market cap, and High market cap). Average capitalisation for each group is provided (in million $). The number of negative coefficients and the number of statistically significant parameters at the 10% level are noted.

Panel B provides a cross-sectional analysis of information asymmetry over the whole sample, with the following regression:

$$C2i = \alpha_i + \beta_i * ORDCAP_i + \zeta_i$$

Where

$ORDCAP_i$ is the ordinal representation of each stock by market capitalisation.

Panel A

	C0 < 0	C1 < 0	C2 < 0	|tC0| > 1.64	|tC1| > 1.64	|tC2| > 1.64	Av. Cap
Low	-1.22E-03	0.030017	0.002969				436.4283
n=13	9	4	6	0	3	1	
%	69.230769	30.769231	46.153846	0	23.076923	7.6923077	
Medium	-4.34E-04	-0.00399	-3.32E-03				2373.214
n=15	8	4	8	0	5	4	
%	53.333333	26.666667	53.333333	0	33.333333	26.666667	
High	3.30E-04	0.002048	0.00571				30964.2
n=13	4	8	7	0	2	2	
%	30.769231	61.538462	53.846154	0	15.384615	15.384615	

Panel B

Variable	α	β
C2	-0.00574	0.000346
t-Statistic	-0.31643	0.460459

The period of dramatic market rise results, summarised in table 4-2b, shows all three groups (low, medium and high market capitalisation) has an average negative C2 coefficient indicative of predominantly portfolio rebalancing trades during the market increase. It should be noted that larger negative coefficient is associated with the large group, while the medium group has the lowest negative mean C2 coefficient. This is confirmed with the cross sectional result in panel b though the results are not statistically significant.

Table 4-2b Information Asymmetry proxied by Market Capitalisation – Bubble Formation period results

This table summarises the influence of information asymmetry on the volume and return relationship. Average Market Capitalisation over the bubble formation is used to proxy information asymmetry. The sample period is from 1/1/1998 to 10/3/2000. The relationship is measured from the regression:

$$r_{i,t+1} = C0_i + C1_i * r_{i,t} + C2_i * v_{i,t} * r_{i,t} + error_{i,t+1}$$

where:

$r_{i,t}$ is the daily return for stock i at time t

$v_{i,t}$ is the daily volume for stocks i at time t

Panel A reports the information asymmetry effect on each group (Low market cap, Medium Market cap, and High market cap). Average capitalisation for each group is provided (in million $). The number of negative coefficients and the number of statistically significant parameters at the 10% level are noted.

Panel B provides a cross-sectional analysis of information asymmetry over the bubble formation period, with the following regression:

$$C2i = \alpha_i + \beta_i * ORDCAP_i + \zeta_i$$

Where

$ORDCAP_i$ is the ordinal representation of each stock by market capitalisation.

Panel A

	C0 < 0	C1 < 0	C2 < 0	$\lvert t_{C0} \rvert > 1.64$	$\lvert t_{C1} \rvert > 1.64$	$\lvert t_{C2} \rvert > 1.64$	Av. Cap
Low n=13	2.51E-03 1 7.69	0.05431 1 7.69	-0.00402 9 69.23	1 7.69	3 23.08	2 15.39	478.8006
Medium n=15	4.60E-03 0 0	0.049148 4 26.67	-2.63E-02 7 46.67	7 46.67	2 13.33	3 20	2309.001
High n=13	5.53E-03 0 0	0.018495 5 38.46	-0.00822 6 46.15	10 76.92	4 30.77	4 30.7	26162.01

Panel B

Variable	α	β
C2	-0.0042	-0.00044
t-Statistic	-0.14909	-0.38001

Market downturn sample periods are summarised in Table 4-2c, 4-2d, and 4-2e. Table 4-2c shows the pre September 11th episode results and post September 11th results are provided in Table 4-2d. Table 4-2e summarises the overall downturn period results. Pre-September 11th results, from Table 4-2c, indicates that larger stocks are associated with higher private information trading, while both the low and medium market cap stocks are dominated by hedging trades. Post September 11th period results from Table 4-2d show a reversal of results from the earlier period with larger stocks associated with hedging trades and small and medium cap stocks associated with speculative trades, also shown by cross sectional results that are more significant. The overall downturn period, a combination of pre and post September 11th, indicates that speculative trading is dominant in large firms and this effect decreases monotonically over firm size.

Information Asymmetry Results – Summary

The following tables summarises the influence of information asymmetry on the volume and return relationship. Average Market Capitalisation is used to proxy information asymmetry. The relationship is measured from the regression:

$$r_{i,t+1} = C0_i + C1_i * r_{i,t} + C2_i * v_{i,t} * r_{i,t} + error_{i,t+1}$$

Where:

$r_{i,t}$ is the daily return for stock i at time t

$v_{i,t}$ is the daily volume for stocks i at time t

Panel A reports the information asymmetry effect on each group (Low market cap, Medium Market cap, and High market cap). Average capitalisation for each group is provided (in million $). The number of negative coefficients and the number of statistically significant parameters at the 10% level are noted.

Panel B provides a cross-sectional analysis of information asymmetry, with the following regression:

$$C2i = \alpha_i + \beta_i * ORDCAP_i + \zeta_i$$

Where

$ORDCAP_i$ is the ordinal representation of each stock by market capitalisation.

Table 4-2c Information Asymmetry Results – Initial Bubble collapse period

The sample period is from 13/3/2000 to 11/9/2001.

Panel A

	C0 < 0	C1 < 0	C2 < 0	$\lvert t_{C0}\rvert > 1.64$	$\lvert t_{C1}\rvert > 1.64$	$\lvert t_{C2}\rvert > 1.64$	Av. Cap
Low	-6.87E-03	0.044423	-0.01564				430.5869
n=13	13	3	7	6	4	0	
%	100	23.08	53.85	46.15	30.77	0	
Medium	-6.74E-03	0.014242	-2.80E-02				3294.01
n=15	15	6	10	8	2	2	
%	100	40	66.67	53.33	13.33	13.33	
High	-5.26E-03	-0.01765	0.007578				49626.73
n=13	13	8	5	5	3	1	
%	100	61.54	38.46	38.46	23.08	7.69	

Panel B

Variable	α	β
C2	-0.0332	0.000968
t-Statistic	-1.42065	0.998675

Table 4-2d Information Asymmetry Results – Post-September 11th, 2001
The sample period is from 17/9/2001 to 29/11/2002.

Panel A

	C0 < 0	C1 < 0	C2 < 0	|tC0| > 1.64	|tC1| > 1.64	|tC2| > 1.64	Av. Cap
Low	-7.15E-04	-0.02416	0.007047				159.5616
n=13	6	9	5	0	3	2	
	46.15	69.23	38.46	0	23.08	15.39	
Medium	-6.66E-04	-0.04141	4.40E-02				856.3655
n=15	10	10	4	0	2	2	
	66.67	66.67	26.67	0	13.33	13.33	
High	-3.21E-04	-0.01868	-0.02336				17424.31
n=13	7	7	9	0	0	3	
	53.85	53.85	69.23	0	0	23.08	

Panel B

Variable	α	β
C2	0.052778	-0.00199
t-Statistic	1.751103	-1.59353

Table 4-2e Information Asymmetry Results – Bubble Collapse Period
The sample period is from 13/3/2000 to 29/11/2002.

Panel A

	C0 < 0	C1 < 0	C2 < 0	|tC0| > 1.64	|tC1| > 1.64	|tC2| > 1.64	Av. Cap
Low	-4.43E-03	0.015901	-0.0069				361.5948
n=13	13	7	7	6	4	1	
%	100	53.85	53.85	46.15	30.77	7.69	
Medium	-3.64E-03	-0.01838	4.99E-03				2300.187
n=15	14	7	10	3	2	3	
%	93.33	46.67	66.67	20	13.33	20	
High	-3.39E-03	-0.01871	0.011473				35082.17
n=13	13	6	6	3	1	2	
%	100	46.15	46.15	23.08	7.69	15.39	

Panel B

Variable	α	β
C2	-0.01309	0.000779
t-Statistic	-0.64643	0.927684

The above results are interesting as they contrast the findings by LMSW (2002) for stocks listed on AMEX and NYSE. The results show that small firm effect did not exist, except during the post September 11th period.

4.4.2 Effects of Firm Specific Factors on Return Volume Dynamics

Table 4-3a to 4-3e summarises the influence of firm specific factors on return volume dynamics, once market effects were removed. The results are much and C2 coefficient is highest for large stocks and decreases as market capitalisation decreases over the sample of stocks. Table 3a shows that speculative behaviour is twice for highly capitalised firms compared to smaller firms in the overall sample period, and panel B confirms this result, though the results are not significant at the 10% level.

Table 4-3 Firm Specific Information Asymmetry Results

The following tables below summarises the influence of information asymmetry on the volume and return relationship. Average Market Capitalisation is used to proxy information asymmetry. The relationship is measured from the regression:

$$r_{i,t+1} = C0_i + C1_i * r_{i,t} + C2_i * v_{i,t} * r_{i,t} + error_{i,t+1}$$

Where:

$r_{i,t}$ is the daily return for stock i at time t

$v_{i,t}$ is the daily volume for stocks i at time t

Panel A reports the information asymmetry effect on each group (Low market cap, Medium Market cap, and High market cap). Average capitalisation for each group is provided (in million \$). The number of negative coefficients and the number of statistically significant parameters at the 10% level are noted.

Panel B provides a cross-sectional analysis of information asymmetry, with the following regression:

$$C2i = \alpha_i + \beta_i * ORDCAP_i + \zeta_i$$

Where

$ORDCAP_i$ is the ordinal representation of each stock by market capitalisation.

Table 4-3a Firm Specific Information Asymmetry Results – Overall Sample

The sample period is from 1/1/1998 to 29/11/2002.

Panel A

	C0 < 0	C1 < 0	C2 < 0	$\|t_{C0}\| > 1.64$	$\|t_{C1}\| > 1.64$	$\|t_{C2}\| > 1.64$	Av. Cap
Low	-1.10E-04	-0.01307	0.017669				436.4283
n=13	9	8	3	0	1	4	
%	69.23	61.54	23.08	0	7.69	30.73	
Medium	9.18E-05	-0.05778	1.79E-02				2373.214
n=15	7	11	6	0	5	5	
%	46.67	73.33	40	0	33.33	33.33	
High	-1.19E-04	-0.04119	0.039179				30964.2
n=13	9	10	4	0	1	3	
%	69.23	76.92	30.77	0	7.69	23.08	

Panel B

Variable	α	β
C2	0.00792	0.000794
t-Statistic	0.410883	0.992715

Table 4-3b Firm Specific Information Asymmetry Results – Bubble Formation period
The sample period is from 1/1/1998 to 10/3/2000.

Panel A

	C0 < 0	**C1 < 0**	**C2 < 0**	**$\lvert t_{C0} \rvert$ > 1.64**	**$\lvert t_{C1} \rvert$ > 1.64**	**$\lvert t_{C2} \rvert$ > 1.64**	**Av. Cap**
Low	1.11E-03	0.03159	0.016479				478.8006
n=13	3	1	8	0	1	3	
%	23.08	7.69	61.54	0	7.69	23.08	
Medium	1.62E-03	0.01892	-9.21E-03				2309.001
n=15	2	8	7	2	2	3	
%	13.33	53.33	46.67	13.33	13.33	20	
High	1.86E-03	-0.00322	0.002095				26162.01
n=13	2	6	7	1	4	4	
%	15.39	46.15	53.85	7.69	30.77	30.77	

Panel B

Variable	α	β
C2	0.010092	-0.00036
t-Statistic	0.351185	-0.30251

Table 4-3c Firm Specific Information Asymmetry Results – Initial Bubble collapse period
The sample period is from 13/3/2000 to 11/9/2001. The relationship is measured from the regression:

Panel A

	C0 < 0	**C1 < 0**	**C2 < 0**	**$\lvert t_{C0} \rvert$ > 1.64**	**$\lvert t_{C1} \rvert$ > 1.64**	**$\lvert t_{C2} \rvert$ > 1.64**	**Av. Cap**
Low	-3.43E-03	-0.03472	0.02395				430.5869
n=13	11	8	2	2	2	1	
	84.62	61.54	15.39	15.39	15.39	7.69	
Medium	-2.56E-03	-0.08573	2.86E-02				3294.01
n=15	13	12	4	2	9	3	
	86.67	80	26.67	13. 33	60	20	
High	-1.28E-03	-0.07299	0.06376				49626.73
n=13	11	11	5	1	5	2	
	84.625	84.62	38.46	7.69	38.46	15.39	

Panel B

Variable	α	β
C2	0.017458	0.000982
t-Statistic	0.610838	0.828481

Table 4-3d Firm Specific Information Asymmetry Results – Post-September 11th, 2001
The sample period is from 17/9/2001 to 29/11/2002.

Panel A

	C0 < 0	C1 < 0	C2 < 0	$\lvert t_{C0}\rvert$ > 1.64	$\lvert t_{C1}\rvert$ > 1.64	$\lvert t_{C2}\rvert$ > 1.64	Av. Cap
Low n=13	1.30E-03 5 38.46	-0.3444 8 61.54	-0.00344 6 46.15	0 0	4 30.77	4 30.77	159.5616
Medium n=15	2.20E-04 10 66.67	-0.08792 13 86.67	6.68E-02 4 26.67	1 6.67	4 26.67	4 26.67	856.3655
High n=13	-4.06E-04 8 61.53	-0.101 11 84.62	0.09256 5 38.46	0 0	5 38.46	5 38.46	17424.31

Panel B

Variable	α	β
C2	-0.00337	0.002671
t-Statistic	-0.0852	1.625182

Table 4-3e Information Asymmetry Results – Bubble Collapse Period
The sample period is from 13/3/2000 to 29/11/2002. capitalisation.

Panel A

	C0 < 0	C1 < 0	C2 < 0	$\lvert t_{C0}\rvert$ > 1.64	$\lvert t_{C1}\rvert$ > 1.64	$\lvert t_{C2}\rvert$ > 1.64	Av. Cap
Low n=13	-1.42E-03 11 84.62	-0.04918 11 84.62	0.020764 2 15.39	0 0	6 46.15	1 7.69	361.5948
Medium n=15	-1.03E-03 11 73.33	-0.08271 11 73.33	2.70E-02 4 26.67	0 0	8 53.33	5 33.33	2300.187
High n=13	-1.10E-03 12 92.31	-0.08274 12 92.31	0.100906 2 15.39	0 0	8 61.54	5 38.46	35082.17

Panel B

Variable	α	β
C2	-0.00322	0.002461
t-Statistic	-0.14761	2.715537

Results in Panel A of Table 4-3b for the period associated with the formation of the Internet bubble show that trading in small caps is 8 times more speculative than larger stocks. Such trading behaviour is confirmed by a review of the cross section analysis in Panel B, where a negative relationship is revealed between market capitalisation and C2 coefficient. Results for the period following a market downturn are provided in Panel A of Table 4-3c and shows predominantly speculative trading across all firm sizes. Cross sectional analysis in Panel B confirm this result. Post September 11th market activity in smaller firms is dominated by portfolio rebalancing, while trading in larger firms is on the basis of private information. Combined results in Panel B of Table 4-3e for the two sub periods show a statistically significant at 10% level of speculative trading in larger stocks, and contradicts LMSW's (2002) results from AMEX and NYSE.

The effect of firm specific information asymmetry on return volume relationship contrasts those of the combined market and firm factors, in that, trading in Internet equity was dominated by speculative behaviour during the rise and fall of the market.

4.4.3 Alternative Definition for Information Asymmetry

If valuation of Internet firms was constrained due to the relative short history for the industry, is there a difference in investors' trading behaviour on the basis of operational history?

Table 4-4 Cross Sectional Results for Informational Asymmetry

This table provides the cross sectional results for the influence of information asymmetry on the volume and return autocorrelation relationship over the five sub samples. Time since Initial Public Offering is used as a proxy for information asymmetry. Panel A provides the results for the five periods used and Panel B provides the results for firm specific relationship over the same sample periods. The cross sectional analysis is estimated with the following regression:

$$C2i = \alpha_i + \beta_i * ORDLEN_i + \zeta_i$$

Where

$ORDLEN_i$ is the ordinal representation of time since IPO for each stock.

Panel A

Sample	Variable	Coefficient	t-Statistic
All 1/1/1998 – 29/11/2002	α β	-0.01781 0.000921	-0.99934 1.245963
Bubble Formation 1/1/1998 – 10/3/2000	α β	-0.02521 0.000557	-0.89655 0.477342
Initial Collapse 13/3/2000 – 11/9/2001	α β	-0.00359 -0.00044	-0.1522 -0.45096
Post September 11th 17/9/2001 – 29/11/2002	α β	-0.01641 0.001302	-0.53455 1.022408
Post Bubble Collapse 13/3/2000 – 29/11/2002	α β	-0.00601 0.000442	-0.29465 0.522534

Panel B

Sample	Variable	Coefficient	t-Statistic
All 1/1/1998 – 29/11/2002	α β	0.00792 0.000794	0.410883 0.992715
Bubble Formation 1/1/1998 – 10/3/2000	α β	0.01387 -0.00054	0.48337 -0.45409
Initial Collapse 13/3/2000 – 11/9/2001	α β	0.009487 0.001362	0.33466 1.158046
Post September 11th 17/9/2001 – 29/11/2002	α β	-0.00051 0.002534	-0.01271 1.536852
Post Bubble Collapse 13/3/2000 – 29/11/2002	α β	-0.0003 0.002322	-0.01351 2.535528

The results in Table 4-4 provide only the cross sectional analysis for the effect of combined market and firm factors on the return volume relationship in Panel A and only firm factor influence in Panel B. Positive β coefficients in Panel A show that firms with longer trading history do not have lower information asymmetry, except during the initial period of the market downturn. In fact, trading based on private information increases with the length of trading history, though none of the results are statistically significant at the 10% level. After removing the market effects, the results are statistically significant at the 10% level after a downturn in market conditions. Panel B reports that during the bubble formation period length of trading history reduced information asymmetry.

However, during the other sample periods, the level of investors' speculative trading behaviour was related to the maturity of the firm.

4.5. Conclusion

This chapter examined the influence of information asymmetry on return volume dynamics for the Internet equity market for firms listed on the NASDAQ. Two different proxies for information asymmetry are used: market capitalisation and length of trading history of a firm. The return volume relationship is examined in the framework of LMSW (2002) that focuses on return autocorrelation and associated trading volume. The simple model suggests that public information produces white noise in returns and does not have accompanying high trading volume due to lack of disagreement on the information content. However, trading due to either portfolio rebalancing or private information generate considerable high volumes. The difference lies in the return autocorrelation between the two types of trading behaviour. Hedging trades, or portfolio rebalancing, induce negative autocorrelation in returns while returns due to trades based on private information tend to continue and hence produce positively autocorrelated returns.

This chapter contributes to the existing literature in several ways. First, LMSW use firms listed on the NYSE and AMEX, and this chapter extends their model to apply to stocks listed on the NASDAQ, specifically firms that generate a significant portion of their revenues from the Internet related business. Second, this study investigates the return volume dynamics in the formation and collapse of a price bubble in a developed capital market.

The results of this study contradict that observed by LMSW (2002) for the US market where information asymmetry has a negative relationship on speculative trading behaviour. Trading in Internet equity is found to be predominantly speculative in firms with high market capitalisation and with a longer trading history. These results are similar to those by Grishchenko, Litov and Mei (2002) for the Russian and other emerging markets, except that they attribute the level of speculative trading behaviour to poor corporate governance and a legal environment that may not protect minority shareholder rights. These conditions do not exist in the US, and the level of speculation may instead be attributed to momentum behaviour by retail investors, an issue that needs to be investigated further.

Chapter 5: Breakdown of Linear and Non-Linear Price-Volume Relationship Within the Internet Equity Market

Synopsis

This chapter investigates the existence and stability of linear and non-linear stock price-volume relationship for US Internet stocks during periods of higher price volatility. Daily closing prices and trading volume on 46 Internet stocks traded on the NASDAQ are used, over different sub-samples ranging from 1993 to 1999, to provide empirical evidence in this regards. Testing for a linear causal price-volume relationship is conducted using a bivariate granger model, enhanced to account for conditional heteroskedasticity and long run cointegrative relationships. Results reveal intertemporal instability of relationship between the two market variables. This breakdown could possibly be explained due to fundamental changes in the informational content contained within prices and trading volume, and/or changes in trading behavior. The results in this chapter show that while the causal relationship during lower price volatility period conform to prior studies, a breakdown in the relationship takes place during periods of higher price variability. Additionally, non-linear causality tests on the two variables, price and volume, also provide further support for changes in trading behavior.

5.1. Introduction

The objective of this chapter is to provide evidence of change in both linear and non-linear price-volume relationships for Internet stocks during periods of high volatility. Establishing linear causal relationships using past prices and volume data can provide insight into the structure of the markets, since this relationship is based on the rate of information flows into the market and its dissemination amongst traders. Nonlinear causal relationship between price and volume can provide additional insight into market microstructure and trading behaviour of the market participants. The analysis in this chapter contributes to the existing body of knowledge in its observation of linear and non-linear price volume relationship for an emerging equity market as part of a developed capital market. Also this chapter is able to show that this relationship changes during periods of higher price volatility.

The next section details past research conducted and non-linear relationship between price and volume.

5.2. Overview of Literature

Detailed discussion on the theory and evidence with regards to linear and non-linear price-volume relationship is described in Chapter 2. A brief overview is presented here below.

As presented in Chapter 2, theoretical literature on price volume relationship provides several reasons for the causality. The Mixture of Distribution Hypothesis implies that trading volume shows the level of disagreement on the information regarding the underlying assets and the level of price revision. Hence, the higher the level of disagreement on the correct valuation of the traded asset, the greater will be the price difference and will result in higher volume of assets traded. Sequential information arrival (SIA) model proposes that new information flows from one trader to the next in a sequential manner. As the information flows from one trader to the next, a new equilibrium of price and volume is reached, until the news is dissipated to the whole market. At this time a final equilibrium is reached. However, this model proposes a bi-directional causal relationship between absolute price and trading volume. De Long et al (1990) provides a model where noise traders induce temporary mispricing of the securities over the short run that is corrected, or should be, over a longer run, as markets tend towards fundamental valuation. This results in a causal relation that runs from volume to price. Lakonishok and Smidt (1989) also demonstrated how tax and non-tax reasons could induce a price volume causal relation, where the current volume is affected by past price changes.

Empirical evidence on linear price-volume relationships for equity and derivative markets has documented Granger causality in at least one direction. Karpoff (1987) has provided a survey on the early work conducted in theoretical and empirical aspects of the price-volume relationship. However, prior research work on US equity has been conducted on industries that have considerable history for a more precise valuation. Some research has also been conducted on futures and derivative markets [see Rutledge (1984), Tauchen and Pitts (1983), Rogalski (1978), Najand and Yung (1991), Besseminder and Seguin

(1993) and Fung and Patterson (1999)]. A summary of research conducted in the following three distinct areas, and the associated results are presented in Chapter 2:

1. Linear Price Volume Relationship in the US equity Markets
2. Linear Price Volume Relationship in the US futures markets
3. Linear Price Volume relationship in Emerging Markets

A mis-specified model will lead to spurious results. Hence, if the change in one variable is not completely offset by the other variable in question, linear causality testing will fail to detect such asymmetric relationships and in fact this relationship may even be termed as random. This outcome may be in part due to failure to model nonlinear relationship between the variables. Nonlinearities could exist due to the fact that adjustments of deviations from equilibrium values may not be proportionate (Savit, 1988) due to asymmetric trading cost structure, the presence and the actions of noise traders in the market and due to the market microstructure (Abhyankar, 1998). A small number of research has looked at the non-linear causal relationship between price and volume and have consensus on the bi-directional relationship that is described in Chapter 2.

Although linear and non-linear price-volume causal relationship can reveal dynamics of the market, most studies, except Sillvapulle and Choi (2000), have considered market behaviour during "normal" conditions. Research in this chapter contributes to existing literature by considering non-normal market conditions, both in terms of trading behaviour and the assets being traded.

5.3. Development of Hypothesis

Research on price and volume relationship for NASDAQ-traded Internet companies since their IPO date until December 1999, requires analysis of the market in terms of the traders and the assets they trade. The following discussion details both aspects:

De Long, Sheifer, Summers and Waldmann (1990) note that positive feedback investors may induce rational speculators to move in the same direction. Irrational speculative traders are trend chasers: they buy when prices go up and sell when prices decrease. This trading mechanism may also explain the lagged correlation in prices. Prospect theory (Kahneman and Tversky, 1979) describes individuals maximising an S-shaped value function, and shows the risk averse nature of individuals. The phenomena of maximising the S-shaped value function leads to nonlinearities of trading behaviour where changes in trading volume when prices decrease are not symmetric to that when prices rise. Overconfidence by investors and overestimation of their belief of the future may also lead them to transact (either buy or sell). If investors do not interpret the information correctly or believe they have information about the future when the information may either be obsolete, incorrect or non-existent, it would result in under-performance of the individual's portfolio before adjusting for transaction costs. Once again such behaviour by irrational agents would introduce nonlinearities in the price and volume relationship.

However, it is important to mention that the analysis presented in this chapter is not to establish if asset pricing is influenced by behavioural aspects, but rather to establish the existence of linear and nonlinear price volume relationships, the direction of causality and its intertemporal relationship stability during volatile market conditions.

Internet equities is a new market segment with limited trading history and difficulties associated with conducting fundamental valuation of assets in such a market due to uncertainty of future prospects. In addition, this market has witnessed strong growth in 1998-99 (an increase in major Internet index of 500%) as well as a dramatic increase in IPOs of Internet stocks[52]. Perhaps the most important aspect is that this emerging equity market is based in one of the largest and most efficient global capital markets, though it lacks the liquidity that is seen for stocks listed on the NYSE[53]. Therefore investor behaviour in the US Internet equity market is of interest, as the trading strategies used may be considered speculative to an extent.

5.4. Data and Methodology

The data consists of daily closing prices and traded volume[54] of all the NASDAQ-traded Internet stocks listed on the major Internet indices[55] that have an IPO date earlier than 1st January 1998. The data series start from 30 trading days after the day these stocks were listed on the exchange[56] and are adjusted for stock splits. The choice of stocks from major Internet indices was taken since indices are developed to represent the characteristics of a market, but may be biased towards a particular aspect of a market[57]. The selection of stocks from more than one Internet Index should not only remove this selection bias, but also give a more accurate representation of the Internet market.

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[52] The sample size is limited due to recent emergence of this sector
[53] Several authors have noted that the trading volume reported on the NASDAQ are inflated by an order of 2.
[54] The data was obtained from Yahoo.com
[55] These indices include CNN Internet Index, Street.com Internet index, Dow Internet Index and NASDAQ Internet Index.
[56] It has been noted that the IPO of a stock follows an initial period of abnormally high volatility.
[57] The index may have different definitions for market representation.

Testing the two primary hypotheses lies in observing each stock's price-volume relationship and the change of this relationship under specific market conditions. The choice of sub samples will then be determined on the basis of the hypothesis under review. It is also important to note that while research in this chapter focuses on information flow into the market and trading behaviour of the market participants, it does not evaluate the fundamental valuation of the assets. The work in this chapter focuses on changing market conditions (changes in market volatility is used as a proxy) and presents an opportunity to study changes in trading behaviours and patterns.

Comparisons of the causal price-volume relationship of the assets under review and that with existing research on US equity stocks, each stock is tested over its entire time series. One should note that for US equities, past research concluded predominantly uni-directional causality from price to volume.

The Internet stock market due to its recent emergence, uncertain future prospects, smaller size and lower liquidity than stocks that are traded on the NYSE (and AMEX), should display a relationship that runs from trading volume to price. Hiemstra and Jones have noted that prices have a causal effect on volume though this relationship has been opposite for the smaller markets such as Korea (Sillvapulle and Choi (2000)) and for four of the six latin American markets (Saatcioglu and Starks (1998)) where volume changes lead price changes. Thus the first hypothesis states that the Internet equities should not display the relationships observed for the more developed and liquid stocks listed on the NYSE (and AMEX) and should display both linear and nonlinear causal relationship predominantly from trading volume to price per se. Trading volume leading price may be attributed to either lower liquidity and/or speculative participants active in the Internet market.

The second hypothesis, which is also an extension of the first hypothesis, is that price volume causal relationships should change from a low price volatility period to an initial high price volatility period in the same direction. Based on DeLong et al. (1990) argument, as markets start following a trend, extrapolative speculators jump on the bandwagon, to increase their wealth. This also induces the rational speculator to follow the actions of the feedback investors[58], and thus drive prices further away from fundamental values and increases the volatility in the market. However, as stock prices start to move away from fundamental valuation, informed traders would be moving out of the market. This profit taking might prompt a herd like behaviour causing the uninformed traders to follow. Observing the price-volume relationship during periods of higher price volatility can test this hypothesis.

To test the first part of the hypothesis, Granger causality from price to volume should not be consistent amongst all the stocks. In fact some stocks should display changes in causal direction. This change in causality could be due to new information regarding revised expectations on company's future, and changes in market's trading behaviour. Since this chapter's research is only interested in information flow and resulting trading activity based upon the market and not individual stocks, it is necessary that tests on common time periods for all stocks should be conducted.

The second aspect of the hypothesis, where uninformed market participants start to follow the informed traders would translate to a higher number of stocks displaying causality running from price to volume. Comparison of causal relationships during low

[58] The rational speculator acts in such a manner even though he knows that he is not trading on prices close to the fundamental value.

market volatility and higher market volatility can provide evidence to test this aspect of the second hypothesis.

If a large number of speculators are present in the Internet market, then stocks that IPO during higher market trading period should display similar price volume behaviour, as observed for Internet stocks that have had longer trading history. Frankel and Froot (1988) find that participants expect similar price changes for similar securities over a short horizon. They also show that over a longer horizon the prices should mean revert. If uninformed traders dominate market trading during higher volatility periods, due to their lack of information should have no preference on asset they choose to invest in, and hence the causality relationship should be similar to stocks that have a longer history. To test this, data for 8 firms that had IPO dates after the 1st August 1997, or just at the onset of market volatility, are used. Their relationship in the earlier and later period of higher market activity is observed, and compared to the other 38 stocks during the same period.

A third aspect of speculative trading is based on the leverage effect of the shares due to markets trading conditions. It has been observed that equities display asymmetries in volatility depending on the market upturns and downturns. Good news in the market is translated into lower volatility, while bad news is followed with higher volatility. As equity prices increase, the value of equity increases and this represents lowered financial leverage and hence lower risk for the equity. This asymmetric equity price volatility due to market movements should also be present for Internet equities though to a lesser extent. Although fundamental valuation for Internet equities is difficult, asset risk should decrease with increased prices. However, as participants in the market observe rising prices, feedback trading would encourage trading in the direction of market movements.

Further, as equity prices increase beyond the fundamental value (or what maybe considered fundamental value by informed traders), the risk of traders may increase as well. This implies that the asymmetry in volatility is not only for good news versus bad news but also when market participants feel that assets may be overvalued. Asymmetry in leverage between various market conditions is tested by observing changes in the leverage effect during low market volatility period (this period is termed LowVol) and higher market volatility periods[59] (this period is termed HighVol).

In this research four sample periods are used to test various hypotheses in terms of establishing the existence of causality, its direction and changes over various market conditions. Since the hypothesis involves observing the price-volume relationship for the market since inception, as well as to see the relationship change when prices increase rapidly in this market, the time series is divided into sub samples that are employed to observe intertemporal stability. The sub-samples are defined as *All*, *Common*, *LowVol* and *HighVol*. *All*[60] covers the period from 30 days after the IPO date of each stock till the 3rd December 1999 for each asset, and shows individual characteristics of each stock selected in this research. *Common* is the common sample period for all stocks[61], from 1st August 1997 to 3rd December 1999 and helps determine how stocks that make up the Internet technology sector[62] behave over the same time period. Analysis over this period will display common market trends. Time period *Common* is composed of two sub-samples *LowVol* and *HighVol*. *LowVol* is the initial period of *Common* and shows the common behaviour of the market, during periods of low volatility, while *HighVol* is the

[59] These periods will be defined in the next section.
[60] Note that the period *All* for each asset will be of varying length of time.
[61] Except for 8 firms with IPO dates after 1st August 1997.
[62] These stocks cover the Internet technology sector by capitalisation.

remaining sample period of *Common*, and shows market[63] behaviour during periods of high price increases in the Internet market. The sub-samples are obtained through graphical observation of the NASDAQ price series and confirmed using Chow tests on the NASDAQ index. The same break points are also observed using the Internet indices.

Since the time series for both price and volume are log normally distributed, the natural logarithm of the data is used. It can be shown, through preliminary descriptive statistics, that the series are leptokurtic in nature, which may be due to volatility persistence in financial time series. Q-test results show that the price and volume time series are not stationary at level up to 20 lags. This non-stationarity in the two variables is observed in most financial time series. However, the first difference of the series appears stationary. Both the series are differenced using logarithmic differences[64].

Test for short run relationships between two series is conducted using a Vector Autoregression (VAR) specification (Engle and Granger (1987)) of the first difference of prices, P_t (ΔP_t is p_t) and volume V_t (ΔV_t is v_t) for each stock while Dum_t is the holiday dummy[65]. The generic VAR model is expressed as follows:

$$p_t = \sum_{l=1}^{n} \alpha_l p_{t-l} + \sum_{l=1}^{n} \omega_l v_{t-l} + Dum_t + U_{p,t} \qquad \text{Eq. 5-1a}$$

$$v_t = \sum_{l=1}^{n} \gamma_l p_{t-l} + \sum_{l=1}^{n} \chi_l v_{t-l} + Dum_t + U_{v,t} \qquad \text{Eq. 5-1b}$$

Where α_l and γ_l are the lag coefficient terms of price and ω_l and χ_l are the lag coefficient terms of volume.

Testing for Granger causality of one variable to another is conducted through the joint test of significance for ω and γ. If ω is significant it reveals that the changes in volume

[63] It is important to note that analysis is conducted over each stock, rather than the market index.
[64] Each series is differenced as $\ln(X_t/X_{t-1})$
[65] If the previous day were a non-trading day, this variable would be assigned a value 1, and 0 otherwise.

causes changes in price, while a significant γ shows that changes in price Granger causes changes in volume. The appropriate lag length l is obtained by searching for the optimal Akaike (1974) Information criterion over various intervals up to 20 lags. The results indicate that a lag of 5 for both series provides the optimal AIC.

Hence, equations 1a and 1b look as follows:

$$p_t = \sum_{l=1}^{5} \alpha_l \, p_{t-l} + \sum_{l=1}^{5} \omega_l \, v_{t-l} + Dum_t + U_{P,t} \qquad \text{Eq. 5-2a}$$

$$v_t = \sum_{l=1}^{5} \gamma_l \, p_{t-l} + \sum_{l=1}^{5} \chi_l \, v_{t-l} + Dum_t + U_{V,t} \qquad \text{Eq. 5-2b}$$

The joint test of significance for ω_1 – ω_5 and γ_1 – γ_5 provides evidence of existence and the direction.

However, it has been noted that when two series show Granger causality they also have a long run equilibrium relationship. The two series would be integrated to form a cointegrating equation:

$$p_t = \beta v_t$$

where p_t is the price time series and v_t is the volume time series and β is the coefficient of cointegration.

The vector error correction is then given as:

$$P_t = \mu_1 (p_{t-1} - \beta v_{t-1}) + \varepsilon_{1,t} \qquad \text{Eq. 5-3a}$$

$$V_t = \mu_2 (p_{t-1} - \beta v_{t-1}) + \varepsilon_{2,t} \qquad \text{Eq. 5-3b}$$

Where V_t, P_t, v_t, p_t and β are defined as earlier, while μ_1 and μ_2 are the speed of adjustment to the long run equilibrium relationship for each variable.

The existence of cointegration is checked using the Johansen's cointegration test (1991, 1995). If the existence of the two series to have a long run equilibrium relationship were verified, it would be important to include the cointegrating equation in the VAR. The VAR equations in the presence of error correcting equation is as follows:

$$p_t = \mu_1 (p_{t-1} - \beta v_{t-1}) + \sum_{l=1}^{5} \alpha_l\, p_{t-l} + \sum_{l=1}^{5} \omega_l\, v_{t-l} + Dum_t + U_{P,t} \qquad \text{Eq. 6-4a}$$

$$v_t = \mu_2 (p_{t-1} - \beta v_{t-1}) + \sum_{l=1}^{5} \gamma_l\, p_{t-l} + \sum_{l=1}^{5} \chi_l\, v_{t-l} + Dum_t + U_{V,t} \qquad \text{Eq. 6-4b}$$

Where μ_1 and μ_2 are the coefficients of the VEC for price and volume respectively. Non-inclusion of the VEC in the VAR will lead to spurious results in testing of Granger causality amongst variables. However Happapis, Pittis and Prodromidis (1999) show that in the event of omitting of an important variable strongly affect the inferences on causality and cointegration results.

The existence of conditional volatility in financial time series needs to be accounted in the VAR equation to remove any spurious results from the causality testing procedures. An ARCH LM testing procedure was used to confirm the existence of conditional volatility in residuals. This test is run as an auxiliary regression for up to 20 lags on the squared residuals. On detection of conditional volatility, an EGARCH (1,1) formulation is used with a conditional variance specified with an exponential component to provide us with a leverage effect. The Exponential GARCH (1,1) model is able to provide evidence of whether the increases and decreases in the market resulted in asymmetric shocks to volatility in both variables (Nelson 1991). The EGARCH (1,1) model is given as:

$$p_t = \mu_1 (p_{t-1} - \beta v_{t-1} - \delta) + \sum_{l=1}^{5} \alpha_l\, p_{t-l} + \sum_{l=1}^{5} \omega_l\, v_{t-l} + Dum_t + U_{P,t} \qquad \text{Eq. 6-5a}$$

And the conditional variance of P_t is given as:

$$Log(\sigma^2_{p,t}) = \tau + \eta \log(\sigma_{p,t-1}) + \upsilon\, abs[\,(U_{p,t-1} / \sigma_{p,t-1}) - \sqrt{2/\pi}\,] + \theta\, [U_{p,t-1} / \sigma_{p,t-1}] \qquad \text{Eq. 6-6a}$$

Where:

$\sigma_{p,t}$ is the conditional variance estimate at time t based on past conditional volatility,

τ is the mean variance, θ is the leverage effect and υ is the asymmetry of this effect.

If θ is non-negative it implies that there is a leverage effect present in the change of the price equation.

Similarly for the change in volume equation we have:

$$v_t = \mu_2 (p_{t-1} - \beta v_{t-1} - \delta) + \sum_{l=1}^{5} \gamma_l p_{t-l} + \sum_{l=1}^{5} \chi_l v_{t-l} + Dum_t + U_{V,t} \qquad \text{Eq. 5-5b}$$

And the conditional variance of Vt is given as:

$$\text{Log}(\sigma^2_{v,t}) = \tau + \eta \log(\sigma_{v,t-1}) + \upsilon \text{ abs}[\,(U_{v,t-1} / \sigma_{v,t-1}) - \sqrt{2/\pi}\,] + \theta\, [U_{v,t-1} / \sigma_{v,t-1}] \quad \text{Eq. 5-6b}$$

The existence of Non-Linear Causality between the price and volume time series is possible as described in the previous section, and the traditional Linear Granger causality testing method is neither designed for nor does it detect nonlinearities. Back and Brock (1992) presented a nonparametric statistical method for uncovering Non-Linear Causality between two time series, which was later modified by Hiemstra and Jones (1994). The modified Back and Brock method can detect weak temporal dependence between two series, and is used to provide evidence of nonlinear causality between them.

Consider two strictly stationary and weakly dependent time series $\{W_t\}$ and $\{V_t\}$. Denote the m-length lead vector of W_t as W_t^m and the L_w - length and L_v - length lag vectors of W_t and V_t as W_{t-Lw}^{Lw} and V_{t-Lv}^{Lv} respectively. Hence:

$$W_t^m = (W_t, W_{t+1}, \ldots, W_{t+m-1} \quad m = 1, 2, \ldots, t = 1, 2, \ldots$$
$$W_{t-Lw}^{Lw} = (W_{t-Lw}, W_{t-Lw+1}, \ldots, W_{t-1} \quad Lw = 1, 2, \ldots, \quad t = Lw+1, Lw+2, \ldots$$
$$V_{t-Lv}^{Lv} = (V_{t-Lv}, V_{t-Lv+1}, \ldots, V_{t-1} \quad Lv = 1, 2, \ldots, \quad t = Lv+1, Lv+2, \ldots$$

For a given value of m, Lv and Lw $\geq$ 1 and for e>0, $\{V_t\}$ does not granger cause $\{W_t\}$ if:

$$\Pr\{\, || W_t^m - W_s^m || < e \mid\; || W_{t-Lw}^{Lw} - W_{s-Lw}^{Lw} || < e, || V_{t-Lw}^{Lv} - V_{s-Lv}^{Lv} || < e\} =$$
$$\Pr\{\, || W_t^m - W_s^m || < e \mid\; || W_{t-Lw}^{Lw} - W_{s-Lw}^{Lw} || < e\} \qquad \text{Eq. 5-7}$$

Where Pr {.} is the probability and ||.|| is the maximum norm.

The LHS of equation 5-7 is a conditional probability that two arbitrary length *m* lead vectors of $\{W_t\}$ are within a distance of *e* from each other given that the corresponding lag vectors of each Lw lag vector of $\{W_t\}$ and Lv lag vector of $\{V_t\}$ are within a distance *e* of each other. The RHS is a conditional probability that two arbitrary length *m* lead vectors of $\{W_t\}$ are within a distance of *e* from each other given that the corresponding lag vectors of Lw lag vector of $\{W_t\}$ are within a distance *e* of each other. Under the null hypothesis $\{V_t\}$ does not nonlinearly Granger cause $\{W_t\}$. That is, if the lag vector of $\{V_t\}$ has no significant impact on the conditional probability in the LHS, then it does not nonlinearly Granger cause $\{W_t\}$. The conditional probabilities in the above equation can be represented by joint probabilities as follows:

LHS of the equation can be expressed as $\dfrac{C1\,(m + LW, Lv, e)}{C2\,(Lw, Ly, e)}$ and LHS is expressed as $\dfrac{C3\,(m + Lw, e)}{C4\,(Lw, e)}$ for given values of m, Lw, Lv $\geq$ 1 and e > 0.

Where C_1 (m + LW, Lv, e), C_2 (Lw, Ly, e), C_3 (m + Lw, e) and C_4 (Lw, e) are correlation integral estimators of the joint probability described above and it can be shown that[66] the statistic:

$$\sqrt{n}\left\{\frac{C1\,(m + LW, Lv, e)}{C2\,(Lw, Ly, e)} - \frac{C3\,(m + Lw, e)}{C4\,(Lw, e)}\right\} \sim N(0, \sigma^2\,(m\,, Lw, Lv, e)).$$

Hiemstra and Jones (1994) show that the estimator is robust to nuisance parameters when applied to the residuals of a VAR model. This methodology is also shown to have good finite sample size and power properties for a variety of linear and nonlinear Granger causal relationships.

[66] The details and calculations can be seen in Hiemstra and Jones (1994).

The aim of these causality-testing procedures is to describe the market conditions overall and during periods of rapid price changes. To this end, each stock is analysed on the overall sample period[67], and also during sub-samples[68] which were obtained earlier.

5.5. Results and Discussion

This section discusses the preliminary descriptive results, followed by results from linear and non-linear granger causality tests.

The sample for this study consists of 46 firms. 38 of these have IPO dates earlier than the 1st August 1997. The remaining 8 stocks have IPO dates at least 30 days earlier than 1st January 1998[69]. The samples and sub-samples are defined as follows:

Overall: is the overall sample. The time series start 30 trading days after the stock IPOs till the 3rd of December 1999. This sample set provides an opportunity to study the characteristics of each stock.

Common: is the common sample for all the stocks and is composed of two sub-samples *LowVol* and *HighVol*. The sample *Common* provides an opportunity to study each stock during periods of low volatility in the market (*LowVol*) and period of high price increases in the Internet market (*HighVol*).

[67] The overall sample size may be different for each stock, as it starts from the day the stock was listed till 3rd December 1999.
[68] The subsamples are of uniform size for all stocks.
[69] These 8 stocks are USWB, RNWK, SPLN, TCMS, NSOL, CNCX, ATHM, QWST.

LowVol: This sample time series is the period of low volatility in the market and 38 stocks with this sample period will provide us the opportunity to study the characteristics and price-volume relationship during this period. Eight firms with late IPO dates are of shorter and unequal time series. However, these 8 firms also undergo the same testing procedure.

HighVol: This sample time series is common for all 46 stocks during high price increases in the Internet market.

5.5.1. Descriptive Statistics

Descriptive statistics are provided for the stocks over the whole sample and for the sub sample periods in Table A-1, while summary of the descriptive statistics is provided in Table 5-1 A survey of the mean price change of the stocks in various sample periods shows that almost 70% of the stocks (32 of 46 stocks) had a higher mean price change during *HighVol* over *LowVol*, indicating stock prices increased more rapidly (higher daily returns) in *HighVol* (the period of higher market volatility). A rapid increase in stock prices may imply that the market participants are revising their future expectation of the stock very quickly and/or are using short-term trading strategies.

Volume change, instead, provides the market with the level of disagreement among traders on the correct valuation of the asset. A high volume change shows higher level of disagreement. More than half the stocks (24 of 46 stocks) showed that volume change decreased from *LowVol* to *HighVol*. 17 of the 22 stocks that showed that mean volume change increased from *LowVol* to *HighVol* also showed price increases during the same period.

A more significant finding of the descriptive statistics is that the standard deviation of price for all stocks showed an increase from *LowVol* to *HighVol*, while all but five firms showed decreased volume volatility from *LowVol* to *HighVol*. The first result is consistent with the fact that the breakpoints were chosen correctly and that *HighVol* does indeed show higher price volatility. The second result could imply either more homogenous expectations by the market and/or extrapolative behaviour (as can be seen by the first results where more than half the stocks showed decreased changes in volume) and hence decreased volatility as well. Below is a list of firms used and their ticker symbols.

ADBE	ADOBE SYSTEMS INC	EPAY	BOTTOMLINE TECH.DEL.	TFSM	24/7 MEDIA
AMTD	AMERITRADE HLDG CP	GNET	GNET.com	TMCS	TICKETMASTER CL.B
AMZN	AMAZON.COM INC	HLTH	WEBMD	TSG	SABRE HLDGS CORP
AOL	America Online	INKT	INKTOMI	USWB	US Web
ATHM	@Home	INSP	INFOSPACE	VERT	VERTICALNET
AXNT	Accent Optical Technologies	ISSX	INET.SCTY.SYS.	VIGN	VIGNETTE
BEAS	BEA SYSTEMS	INTU	INTUIT INC	VOCL	VOCALTEC
BRCM	BROADCOM 'A'	ITWO	I2 TECHNOLOGIES	VRSN	VERISIGN
BVSN	BROADVISION INC	LCOS	Lycos Inc.	YHOO	YAHOO INC
CHKP	CHECK POINT SOFTWARE	MACR	Macromedia Inc.		
CKFR	CHECKFREE CORP	MERQ	Mercury Interactive Corp.		
CIEN	CIENA	NTBK	NETBANK		
CLKS	CLICK2LEARN	NSOL	NUCLEAR SOLUTIONS		
CMGI	CMGI INC	NTAP	NETWORK APPLIANCE		
CNCX	Crochet Network Coaster Exchange	OMKT	Open Market		
CNET	CNET NETWORKS INC	OTEX	Open Text		
COMS	3COM CP	PAIR	Pair Networks		
CS	Computer Systems Inc.	QCOM	QUALCOMM INC		
CSCO	Cisco Systems	QWST	QWST Communications		
CTXS	CITRIX SYSTEMS	RNWK	Real Netwoks		
CYCH	CyberCash, Inc.	RSAS	RSA SECURITY INC		
CYLK	CYLINK	SAPE	Sapient		
DCLK	DOUBLECLICK	SFA	SCIENTIFIC ATLANTA		
DRIV	DIGITAL RIVER	SONE	S1 CORPORATION		
EBAY	Ebay	SPLN	SPORTSLINE.COM		
EGRP	E Group	SPYG	SpyGlass Inc.		
ELCO	ELCOM INTL.	SUNW	SUN MICROSYS INC		
ELNK	EARTHLINK INC	SYMC	Symantec		
ENTU	ENTRUST	TERN	TERAYON COMM.SYS.		

Table 5-1: Summary of Descriptive Statistics

The table below provides a summary of descriptive statistics for the sample of firms over each sample period. The sample periods are described as:
Overall: is the overall sample. The time series start 30 trading days after the stock IPOs till the 3rd of December 1999.
Common: is the common sample for all the stocks and is composed of two sub-samples *LowVol* and *HighVol.*
LowVol: Period of low volatility in the market. 8 late IPO stocks are of shorter unequal time series.
HighVol: This sample time series is common for all 46 stocks during high price increases in the Internet market.
Returns are calculated as the log difference of the closing price on a daily basis.
ΔVolume is calculated as the log difference of the daily trading volume.
Firms are also categorised as: *All* – consists of all firms in the sample; *Pre98* – consists of firms with IPO dates pre-98; *98* – consists of firms that had IPO dates during 1999; and *99* – consists of firms with IPO dates during 1999.

	Price				**Δvolume (Returns)**				**Volume**				**ΔVolume**			
	ALL	**PRE98**	**98**	**99**	**ALL**	**PRE98**	**98**	**99**	**ALL**	**PRE98**	**98**	**99**	**ALL**	**PRE98**	**98**	**99**
Overall																
Mean	35.95	27.46	40.29	83.15	-0.0006	-0.0003	-0.0007	-0.0025	6104.4	8388.3	2142.2	2191.6	-0.0012	-0.0001	-0.0029	-0.0025
Std. Dev.	37.66	26.57	41.29	109.48	0.0696	0.0639	0.0786	0.0782	4295.8	5482.1	2064.6	2119.8	0.6248	0.6200	0.6530	0.6728
Skewness	1.32	1.34	1.26	1.65	0.1233	0.2591	-0.1731	0.4578	5.3	5.4	5.5	3.9	0.3345	0.3340	0.4087	0.3181
Kurtosis	4.66	4.69	4.62	5.26	13.9326	8.7253	25.4259	6.9353	67.9	74.1	65.3	41.2	7.1287	6.7797	6.4856	9.7957
Common																
Mean	31.58	26.59	34.55	50.81	-0.0039	-0.0036	-0.0040	-0.0061	6321.7	8610.0	2192.5	2317.5	-0.0014	-0.0015	-0.0014	-0.0001
Std. Dev.	32.57	24.51	36.37	79.12	0.0719	0.0663	0.0813	0.0779	3762.8	4662.1	1925.2	2272.9	0.5973	0.5900	0.6251	0.6487
Skewness	1.39	1.30	1.50	1.98	-0.0047	0.2680	-0.5499	0.2908	4.6	4.1	5.6	4.0	0.2852	0.2813	0.3801	0.2711
Kurtosis	5.20	4.82	5.62	7.35	12.5177	7.3111	23.9300	5.6287	46.4	37.4	65.8	40.4	4.5479	4.3171	4.5484	3.9728
Low Vol																
Mean	48.09	39.97	51.56	87.70	-0.0065	-0.0061	-0.0070	-0.0092	6127.1	8115.3	2248.2	2833.3	-0.0010	-0.0015	-0.0002	-0.0013
Std. Dev.	34.72	24.93	40.13	90.80	0.0739	0.0681	0.0829	0.0823	3689.0	4602.1	1752.4	2526.2	0.5553	0.5414	0.5897	0.6142
Skewness	0.83	0.73	0.95	1.28	0.0170	0.1944	-0.3506	0.2650	4.1	3.8	4.6	4.0	0.3040	0.2839	0.4031	0.3022
Kurtosis	3.70	3.46	4.01	4.74	7.4656	6.1554	10.5610	5.2052	36.5	31.2	46.7	41.3	4.2670	3.9677	4.3928	4.3024
High Vol																
Mean	11.17	10.09	13.47	5.08	-0.0007	-0.0007	-0.0004	-0.0023	6562.1	9222.0	2123.6	1678.2	-0.0018	-0.0017	-0.0030	0.0014
Std. Dev.	3.91	3.47	4.48	2.82	0.0676	0.0631	0.0761	0.0713	3476.8	4331.4	1810.7	1700.7	0.6415	0.6399	0.6636	0.6869
Skewness	0.38	0.29	0.52	0.35	0.0189	0.3403	-0.6156	0.3757	4.0	3.8	4.7	3.6	0.2489	0.2480	0.3606	0.2173
Kurtosis	2.28	2.15	2.58	2.10	11.0056	6.8209	20.1818	5.4017	34.6	32.5	42.1	23.4	4.5616	4.3790	4.4598	3.5209

A review of the Jarque-Bera test on the stocks during sub-samples shows that all but 5 stocks are not normally distributed in prices, while 30 stocks show non-normality in terms of volume distribution. Also all stocks display excess kurtosis for both price and volume in all sub-samples. This may indicate the presence of conditional volatility in the time series and does indicate that conditional volatility needs to be investigated and if present needs to be accounted for.

Dicky Fuller testing procedure is employed to test for unit roots. Although not reported here, it was noted that the overall sample and the sub-samples for each stock (i.e. *All, Common, LowVol, HighVol*) were not stationary on levels. However, the first difference of both variables resulted in a stationary series. This shows that the time series for both price and volume may be integrated at I(1) and may have a long run cointegrative relationship that needs to be accounted for.

5.5.2. Stationarity and Cointegrative Nature of Price and Volume Series.

The cointegrative nature of the price and volume series over the whole data set and the sub-sample periods is provided in Table 5-2. Evidence of change in the cointegrative results from lower price volatility periods to higher price volatility periods is also shown in the same table. These results imply, to some extent, the breakdown of a long run causality relationship between price and volume, during periods of high activity.

Table 5-2: Cointegration and ARCH effect

The following table provides summarised results for Johansen's cointegrating test (1991, 1995) and ARCH LM for each firm. The evidence of cointegration between the two series is given as (Y) else (N) for each sample period.

The sample periods are described as:
Overall: is the overall sample. The time series start 30 trading days after the stock IPOs till the 3rd of December 1999.
Common: is the common sample for all the stocks and is composed of two sub-samples *LowVol* and *HighVol*.
LowVol: Period of low volatility in the market. 8 late IPO stocks are of shorter unequal time series.
HighVol: This sample time series is common for all 46 stocks during high price increases in the Internet market.

The price and volume series would be integrated to form a cointegrating equation:
$p_t = \beta v_t$
where p_t is the price time series and v_t is the volume time series and β is the coefficient of cointegration.

The vector error correction is then given as:
$P_t = \mu_1 (p_{t-1} - \beta v_{t-1}) + \varepsilon_{1,t}$ Eq. 5-3a
$V_t = \mu_2 (p_{t-1} - \beta v_{t-1}) + \varepsilon_{2,t}$ Eq. 5-3b
Where V_t, P_t, v_t, p_t and β are defined as earlier, while μ_1 and μ_2 are the speed of adjustment to the long run equilibrium relationship for each variable.
The existence of cointegration is checked using the Johansen's cointegration test (1991, 1995).
ARCH LM testing procedure was used to confirm the existence of conditional volatility in residuals.

	C O I N T E G R A T I O N					ARCH			
Stock	*Obs.*	*All*	*Common*	*LowVol*	*HighVol*	*All*	*Common*	*LowVol*	*HighVol*
ADBE	2508	Y	Y	Y	Y	Y	Y	N	Y
AMTD	694	Y	Y	N	Y	Y	Y	Y	Y
AMZN	643	Y	Y	Y	N	Y	Y	Y	Y
AOL	1948	Y	Y	Y	N	Y	Y	Y	Y
ATHM	604	Y	Y	Y	Y	Y	Y	Y	Y
AXNT	911	N	N	Y	Y	Y	Y	N	N
BVSN	869	Y	Y	Y	Y	Y	Y	Y	Y
CHKP	865	Y	Y	Y	Y	Y	Y	Y	Y
CKFR	1055	Y	Y	Y	Y	Y	Y	Y	Y
CMGI	1423	Y	Y	Y	N	Y	Y	Y	Y
CNCX	589	Y	Y	Y	N	Y	Y	Y	Y
CNET	859	Y	Y	Y	Y	Y	Y	Y	Y
COMS	2508	Y	N	N	Y	Y	Y	Y	Y
CS	2508	N	N	Y	Y	Y	Y	Y	Y
CTXS	1005	Y	Y	Y	Y	Y	Y	Y	Y
CYCH	958	Y	N	N	N	Y	Y	Y	Y
EGRP	831	Y	N	N	Y	Y	Y	Y	Y
ELNK	722	Y	N	Y	N	Y	Y	Y	Y
GNET	649	Y	Y	Y	N	Y	Y	Y	Y
HRBC	1081	N	Y	Y	Y	Y	Y	Y	N
INTU	1649	Y	Y	Y	N	Y	Y	Y	Y
LCOS	927	Y	Y	N	N	Y	Y	Y	Y
MACR	1509	Y	Y	Y	Y	Y	Y	N	Y
MERQ	1528	Y	Y	N	Y	Y	Y	Y	Y
MSPG	938	Y	Y	Y	Y	Y	Y	Y	Y

COINTEGRATION						ARCH			
Stock	*Obs.*	*All*	*Common*	*LowVol*	*HighVol*	*All*	*Common*	*LowVol*	*HighVol*
NETA	1795	Y	Y	N	Y	Y	Y	Y	Y
NN	2450	Y	N	Y	Y	Y	Y	Y	Y
NSOL	550	Y	Y	Y	Y	Y	Y	N	Y
NTAP	1016	Y	Y	Y	Y	Y	Y	Y	Y
OMKT	890	Y	N	Y	Y	Y	Y	Y	Y
PAIR	1571	Y	Y	Y	Y	Y	Y	Y	Y
PSIX	1160	Y	N	Y	Y	Y	Y	Y	Y
QCOM	2013	Y	N	N	Y	Y	Y	Y	Y
QWST	616	N	N	N	N	Y	Y	Y	N
RNWK	510	N	N	Y	Y	Y	Y	Y	Y
RSAS	1255	Y	N	N	N	Y	Y	Y	Y
SE	944	N	N	Y	Y	Y	Y	Y	Y
SFA	2508	Y	Y	N	Y	Y	N	Y	Y
SONE	890	Y	Y	Y	Y	Y	Y	Y	Y
SPLN	515	N	N	Y	Y	N	N	Y	Y
SPYG	1120	Y	Y	Y	Y	Y	Y	Y	N
SUNW	2508	Y	Y	N	Y	Y	Y	Y	Y
TCMS	526	N	N	Y	N	Y	Y	Y	Y
TSG	793	Y	Y	Y	N	Y	Y	Y	Y
USWB	501	Y	Y	Y	Y	Y	Y	Y	Y
YHOO	919	Y	Y	Y	Y	Y	Y	Y	Y

The residuals from Vector Autoregression and Vector Error Correction are checked for conditional heteroskedasticity. The existence of persistent volatility is noted for most stocks and in almost all sample and sub-sample periods, a result that is consistent with past finding for financial time series. To account for this persistence in volatility, an Exponential Generalized Autoregressive Conditional heteroskedastic (EGARCH(1,1)) implementation (Hiemstra and Jones (1994) and Moosa and Silvapulle (2000)) is applied in the VAR or VEC model, if evidence of persistence of conditional heteroskedasticity or long-run relationships are found.

Further, volatility filtered residuals from a VAR (or a VEC if the two series were cointegrated) are used to test for non-linear granger causal relationships between the two variables. The results from the modified Back and Brock (1992) nonparametric test for nonlinear causality were performed with Lw = Lv upto 8 lags, e=1.0 (however values of

0.5 and 1.5 were also used and provided the same results) and m=1. The results are summarised by noting the significance of rejection of the null hypothesis for each lag length[70].

5.5.3. Linear and Nonlinear Causal Relationship between Returns Per Se and Volume

Table 5-3 presents the Linear Granger causality test results for each sample period. While table 5-5 presents the results for non-linear causality tests. Table 5-4 shows the leverage effect for the shares for each sub-sample. The direction of causality for the 46 Internet equities is compared with previously observed results for US equity.

Table 5-3: χ^2 test results for Returns and Volume Granger Causality relationship.
The table below provides results from the Granger Causality testing for each firm over each sample period. The sample periods are described as:
Overall: is the overall sample. The time series start 30 trading days after the stock IPOs till the 3rd of December 1999.
Common: is the common sample for all the stocks and is composed of two sub-samples *LowVol* and *HighVol*.
LowVol: Period of low volatility in the market. 8 late IPO stocks are of shorter unequal time series.
HighVol: This sample time series is common for all 46 stocks during high price increases in the Internet market.
Returns are calculated as the log difference of the closing price on a daily basis.
ΔVolume is calculated as the log difference of the daily trading volume.

Significance level from the test is provided as superscript for each firm.

Stock	*obs*	*All*		*Common*		*LowVol*		*High Vol*	
		Return	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**
ADBE	2508	1028.83[a]	13.17[b]	208.75[a]	6.17	0.85	1.12	80.85[a]	14.95[b]
AMTD	694	383.16[a]	10.13[c]	361.93[a]	8.05	131.92[a]	7.06	191.04[a]	3.35
AMZN	643	215.73[a]	5.71	204.53[a]	5.64	97.94[a]	3.20	123.06[a]	11.66[b]
AOL	1948	460.10[a]	12.36[b]	114.70[a]	1.95	69.71[a]	5.68	45.03[a]	0.63
ATHM	604	242.76[a]	7.41	242.76[a]	7.41	174.57[a]	2.89	83.62[a]	9.97[c]

[70] Each result is summarised by providing a significance level for the lowest lag to the highest lag. E.g. only an "a" implies a significant at 1% for all lag length. A "b, c/0, 0" implies the test statistics for the shorter lag length is significant at 5% level, and grows weaker for longer lag lengths.

Stock	*obs*	*All*		*Common*		*LowVol*		*High Vol*	
		Return	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**
AXNT	911	291.81[a]	5.31	297.49[a]	5.51	0.62	1.10	4.66[a]	0.68
BVSN	869	233.71[a]	11.98[b]	242.10[a]	6.43	192.75[a]	7.47	75.93[a]	12.38[b]
CHKP	865	358.67[a]	6.64	276.51[a]	5.14	152.42[a]	4.02	127.17[a]	2.82
CKFR	1055	494.07[a]	2.10	333.52[a]	2.63	179.85[a]	2.01	120.54[a]	4.34
CMGI	1423	292.02[a]	12.14[b]	163.99[a]	6.78	76.55[a]	3.06	44.24[a]	6.31
CNCX	589	142.88[a]	11.46[b]	142.88[a]	11.46[b]	85.64[a]	2.20	81.61[a]	11.49[b]
CNET	859	309.17[a]	12.52[b]	199.32[a]	8.32	119.52[a]	5.60	78.66[a]	4.07
COMS	2508	986.94[a]	16.53[a]	239.47[a]	9.74[c]	90.73[a]	5.82	145.60[a]	10.71[c]
CS	2508	795.22[a]	17.47[a]	395.55[a]	6.80	239.10[a]	10.05[c]	131.71[a]	4.13
CTXS	1005	475.44[a]	20.58[a]	192.31[a]	15.17[a]	116.21[a]	13.47[b]	85.68[a]	13.23[a]
CYCH	958	561.58[a]	9.37[c]	415.46[a]	6.11	187.27[a]	4.34	223.64[a]	3.55
EGRP	831	341.99[a]	3.95	269.05[a]	3.43	128.07[a]	5.18	127.12[a]	7.01
ELNK	722	214.19[a]	10.45[c]	177.00[a]	7.25	87.78[a]	9.20	101.49[a]	3.46
GNET	649	95.47[a]	24.97[a]	90.92[a]	31.10[a]	27.54[a]	17.11[a]	111.74[a]	5.90
HRBC	1081	521.99[a]	19.16[a]	302.85[a]	9.16	173.89[a]	12.11[b]	1.09	0.83
INTU	1649	720.91[a]	9.70[c]	185.77[a]	9.52[c]	137.15[a]	6.76	58.41[a]	3.99
LCOS	927	251.61[a]	2.95	193.98[a]	1.88	90.03[a]	2.28	119.61[a]	1.07
MACR	1509	492.10[a]	19.94[a]	182.19[a]	4.39	1.10	0.88	81.54[a]	3.34
MERQ	1528	264.47[a]	2.14	127.52[a]	6.45	0.82	1.50	54.37[a]	18.36[a]
MSPG	938	226.40[a]	5.46	214.59[a]	4.70	116.77[a]	8.70	106.56[a]	5.08
NETA	1795	357.85[a]	6.93	328.54[a]	7.21	104.30[a]	6.01	188.19[a]	8.80
NN	2450	910.59[a]	9.79[c]	291.91[a]	4.57	119.35[a]	3.73	212.13[a]	4.21
NSOL	550	129.85[a]	12.76[b]	129.85[a]	12.76[b]	0.60	1.21	93.84[a]	9.07
NTAP	1016	192.37[a]	6.28	111.67[a]	10.01[c]	44.18[a]	4.10	64.06[a]	16.34[a]
OMKT	890	433.46[a]	7.88	358.40[a]	4.26	128.43[a]	3.00	195.97[a]	7.40
PAIR	1571	692.05[a]	13.19[b]	432.94[a]	4.04	196.35[a]	2.06	223.47[a]	2.68
PSIX	1160	476.73[a]	7.48	213.88[a]	1.67	124.05[a]	2.50	88.50[a]	6.49
QCOM	2013	743.41[a]	6.54	316.32[a]	1.12	192.86[a]	1.76	124.96[a]	1.34
QWST	616	134.05[a]	4.29	134.05[a]	4.29	79.12[a]	3.59	1.06	0.72
RNWK	510	179.26[a]	1.93	179.26[a]	1.93	58.66[a]	7.19	112.20[a]	6.39
RSAS	1255	519.45[a]	8.48	268.17[a]	6.35	168.29[a]	10.85[c]	69.90[a]	2.73
SE	944	381.92[a]	22.94[a]	307.62[a]	14.04[b]	71.50[a]	16.09	141.16[a]	15.84[a]
SFA	2508	916.23[a]	8.79	0.33	0.43	149.23[a]	4.66	91.78[a]	5.90
SONE	890	187.49[a]	5.52	156.06[a]	2.74	83.56[a]	3.65	76.19[a]	5.44
SPLN	515	1.46	0.75	1.46	0.75	51.14[a]	4.51	179.90[a]	1.36
SPYG	1120	828.45[a]	11.42[b]	555.75[a]	5.57	211.99[a]	3.43	1.12	0.99
SUNW	2508	778.98[a]	10.14[c]	120.60[a]	9.63[c]	89.58[a]	5.92	43.90[a]	3.81
TCMS	526	117.83[a]	5.67	117.83[a]	5.67	17.77[a]	4.86	81.78[a]	5.38
TSG	793	190.85[a]	4.61	180.27[a]	1.28	67.47	3.24	111.99[a]	3.13
USWB	501	167.25[a]	20.31[a]	167.25[a]	20.31[a]	77.01[a]	4.90	108.10[a]	19.11[a]
YHOO	919	331.79[a]	2.49	178.54[a]	1.55	113.82[a]	3.80	75.52[a]	3.10

[c] Significant at 10%
[b] Significant at 5%
[a] Significant at 1%

5.5.3.1 Linear Granger Causality

The results from Table 5-3 show that all but one stock displays a strong volume to price linear causality. Of the 45 stocks that display linear causality, 23 display bi-directional causality, while 22 display unidirectional causality from volume to price. It is important to note that the causality from volume to price is very strong compared to that in the reverse direction. This result is inconsistent with the observed relationship for the US Index and individual equities as explored by most other researchers (see Karpoff, 1987). However, these results are consistent for markets that are smaller in size (and liquidity) and are emerging in nature.

A similar pattern is observed for the late IPO stocks with 7 of the 8 stocks showed atleast unidirectional causality from volume to price (3 with bi-directional causality). Although 22 of the 38 stocks retain their direction of causality, 14 stocks that displayed bi-directional causality change to unidirectional causal relationship from volume to price during the overall period of increased market activity (*LowVol*). This implies that during market activity volume changes results in price changes in most cases, though as market volatility increases it effects volume.

5.5.3.2. Non-linear Granger Causality

The results from non-linear causality show that the overall sample period shows that 70% (32 of 46) of the stocks display causality in at least one direction. Of the 32 stocks that display any non-linear relationship, most of the causality (87.5%) is either bi-directional or from volume to price, a results similar to the linear causality tests. However, of the 38 firms with earlier IPO dates, 20 retained their direction of causality, with a large proportion of stocks (21 of 32) displaying volume leading prices and another 5 showing bi-directional causality.

The significance of causality running primarily from volume to price lends support to the low liquidity in this market and to the fact that there seems to be high level of heterogeneity amongst the traders on the informational content (or lack of it) in the market place.

Table 5-5: Non-Linear Causality results

The table below provides results from the Non-linear Causality testing for each firm over each sample period. The sample periods are described as:

Overall: is the overall sample. The time series start 30 trading days after the stock IPOs till the 3rd of December 1999.

Common: is the common sample for all the stocks and is composed of two sub-samples *LowVol* and *HighVol.*

LowVol: Period of low volatility in the market. 8 late IPO stocks are of shorter unequal time series.

HighVol: This sample time series is common for all 46 stocks during high price increases in the Internet market.

Returns are calculated as the log difference of the closing price on a daily basis.

ΔVolume is calculated as the log difference of the daily trading volume.

Significance level from the test is provided as superscript for each firm.

Stock	obs	*All*		*Common*		*LowVol*		*High Vol*	
		Return	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**
ADBE	2508	a, 0,0	0	a , c	0	0, c, 0	0	b, c, 0	0
AMTD	694	b, a	0	a	0	0	b, c, 0	0	0
AMZN	643	a	a, b, c	a, a, b	a, a, b	0	0	b	0, c, 0
AOL	1948	c, 0, 0	0	a, b, 0	c/0	0	0	0	b, c, 0
ATHM	604	c, 0, c/b	0	c, 0, c/b	0	0	0	0	0
AXNT	911	b, c, 0	0, c, 0	0	0	0	0	0, a, b	c, 0, 0
BVSN	869	a	c, 0, 0	0	b, 0, 0	c, 0, c	0, c, 0	c, b, 0	0
CHKP	865	a	0, c, a	a, a, 0	0	0, b/0, 0	0, 0, c	c, 0, c	0
CKFR	1055	a	0, c/a, a	a, a/c, 0	0	0	0, 0/c, c/0	c	0
CMGI	1423	c, b, a	0	b, c/a, c	0	0	0	0, c, 0	a, c, 0
CNCX	589	0	0, b, c	0	0, b, c	0	0	0	0
CNET	859	0	0	0	0	0, b/a, 0	0	0	c, 0, 0
COMS	2508	a, a, c	0	0	0, b/c, 0	0	0	0	0, c, 0
CS	2508	0	0	0	0	0	0	0	0, c, 0
CTXS	1005	a/c, 0, 0	0	c, 0/c, 0	0	0, c/b, c/b	0	a/c, ?, 0	c/b, a/b, 0
CYCH	958	a/b	a/b, b/c	0	c	0	0, b/c, 0	0	0
EGRP	831	0, c, 0	0	0	0	0	0	0	0
ELNK	722	0	0	0	0	c, b	0	0	0
GNET	649	0	c/b, 0, 0	0	c/b, 0, 0	0	0	0	0
HRBC	1081	0	0	a, c/0, c/0	0	0	c	0	0, 0/c, b/a

Stock	obs	*All*		*Common*		*LowVol*		*High Vol*	
		Return	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**
INTU	1649	0	0	a	0	0	0	a, 0, 0	0
LCOS	927	a	0, 0, c	a	a, 0, 0	0	0	0	0
MACR	1509	a	0	a	0	0	0	0	0
MERQ	1528	0	0	a, b/c, 0	0	0	0	B/c	0
MSPG	938	a	0	a	0	0	0	0	c, b/c, 0/a
NETA	1795	0, c/b, a	0, 0, c	a, a/b, b/c	0	0	0	0	0
NN	2450	a	a/c, 0, 0	0, b/c, 0	0	b/c, c/0, 0	0	0, c/0, c	0
NSOL	550	0	0, c/0, 0	0	0, c/0, 0	0	0	0	a/b, b/c, 0
NTAP	1016	c, a, a	a, b/c, b/a	a	a	0	0	0	0
OMKT	890	0	0, c, b, 0	c, c/0, 0	0	0	0	0	0
PAIR	1571	a	0	a	0	0	0	0, a, a	0
PSIX	1160	0	0	0	0	0	a/c, 0, 0	0	0
QCOM	2013	a	c, 0, 0	0	0	0	c/0, b/c, c	0	0
QWST	616	b/c, 0, 0	0	b/c, 0, 0	0	0	0	0	0
RNWK	510	0	0	0	0	0	0	0	0
RSAS	1255	0, b, b/c	0	0	0	0	0	0	0
SE	944	0	0	0	0	0	0	0	0, c, 0
SFA	2508	a	0, c, 0/c	a, a/0, 0	a/b, 0, 0	0	0	0	0
SONE	890	0	0	0	0	0	0	0	0
SPLN	515	0	0	0	0	0	0	0	0
SPYG	1120	0	0	a, b/a, b/c	0	0	0	0	0
SUNW	2508	a	a, 0	a, c, 0	0	0	0	0	0
TCMS	526	a, c/0, 0	0	a, c/0, 0	0	0	0	0	0
TSG	793	0	0	0	0	0	0	0	0
USWB	501	0	0	0	0	0, c, 0	0	0	0
YHOO	919	a, a/c, 0	0	a, a, b	0	0	0	0	0

[c] Significant at 10% [b] Significant at 5% [a] Significant at 1% [0] indicates that the results were not significant at 10% or less.

Testing changes in relationship during altered market behaviour shows that less than 50% (21 of 46) of stocks changed linear price-volume causality relationship from *LowVol* to *HighVol*. However, the results show two aspects of the change in the relationship. The first is that firms that do show changed linear causality are from price to volume. Secondly, more than 50% of the stocks that do show changed relationship (11 of 21 stocks) are from either volume dominance, or no relationship, to a bi-directional causality. This is interesting, in that, there seems to be a price lead that is more evident than a volume lead during the overall periods. Nonlinear causal testing shows that 18 of 38 stocks show changes in causal relationship. Similar to the results observed for linear relationship, 11 of the 18 stocks show a price lead.

Readers should keep in mind that common breakpoints for all stocks were not chosen on the basis of individual trading characteristics of each firm, rather, by observing general market conditions and changes. It could imply that some stocks are still in the their low volatility period while most of the market is in the higher volatility period, and hence evidence of causal relationship changes may get diluted. However, these results indicate that two interesting aspects of the market. Firstly, it seems that during higher activity periods, liquidity has increased and that changes in prices has an impact on trading volume though not as strong as in the reverse direction. Since higher average volume changes shows that there is higher disagreement on fundamental asset valuation. This period may indicate changes in trading strategies displayed by rational speculators, who may be in the process of joining the extrapolative speculative traders. Secondly, once the volatility effect is taken into consideration, by using volatility-filtered residuals for nonlinear causality testing, there is no further dynamic relationship that exists.

5.5.4. Performance of New Stocks during Volatile Period

If speculators who do not have much fundamental knowledge of the assets are dominant in the Internet market, their preference for trading in a particular stock should be market driven (i.e. extrapolative). Hence, if stocks that IPO in higher market activity period display market trading behaviour similar to those stocks that have had longer trading periods, it may imply that the market is dominated by uninformed traders and/or extrapolative trading behaviour.

Seven of the eight late IPO stocks also displayed strong linear causality running from volume to price changes. Of these three firms show causality in reverse direction as well.

Similar results are observed for non-linear causality where seven of the firms show no causality at all. This shows that stocks in the market, including those without substantial trading history, followed similar causal relationship. This again points to the fact that most of the trading strategies pursued in the Internet equity market may not have been based on fundamental valuations, but rather, due to market hype and "get rich quick" strategies.

5.5.5. Leverage Effect

Finally the leverage effect is observed for all stocks. It is interesting to note that 41 stocks (of 46 stocks) show leverage effect in the overall sample. The number of stocks that display the leverage effect during higher volatility period drops to 33 stocks. Though the number decreases, the magnitude of the jump coefficient is high, indicating a higher level of asymmetry during periods of higher price volatility. This result becomes more enhanced when comparing leverage effect between *LowVol* and *HighVol*. 24 stocks display leverage effect in *LowVol* period compared to only 12 in *HighVol*. Additionally the magnitude of leverage effect is greater in *LowVol* than *HighVol* period.

These results are interesting, in that, the period of lower price variability (and higher volume volatility), may be due to new information that enters the market and the heterogeneous processing of this information by the traders. In part, this higher leverage effect in terms of magnitude and also in terms of the number of stocks displaying this effect lends support to the strong volume to return causality. However, during higher price variability (and lower volume variability), the asymmetry has decreased. This result is attributed in part to lower risk borne by traders due to prices having moved up (32 of

46 stocks had increased mean values). Increased wealth of the market participants leads to lowered leverage effects.

Table 5-4: EGARCH results of the Leverage effects (γ)

The table below provides results from the Non-linear Causality testing for each firm over each sample period. The sample periods are described as:

Overall: is the overall sample. The time series start 30 trading days after the stock IPOs till the 3rd of December 1999.

Common: is the common sample for all the stocks and is composed of two sub-samples *LowVol* and *HighVol.*

LowVol: Period of low volatility in the market. 8 late IPO stocks are of shorter unequal time series.

HighVol: This sample time series is common for all 46 stocks during high price increases in the Internet market.

Returns are calculated as the log difference of the closing price on a daily basis.

ΔVolume is calculated as the log difference of the daily trading volume.

Significance level from the test is provided as superscript for each firm.

Stock	Observations	*All*	*Common*	*LowVol*	*HighVol*
ADBE	2508	-0.055^{a}	-0.097^{a}		-0.090^{b}
AMTD	694	-0.035	-0.040	-0.096	-0.010
AMZN	643	0.945^{a}	-0.058^{c}	-0.029	-0.110^{b}
AOL	1948	-0.049^{a}	-0.079^{c}	-0.162^{b}	-0.101^{c}
ATHM	604	-0.064^{b}	-0.064	-0.178^{a}	-0.052
AXNT	911	-0.092^{a}	-0.093^{b}		
BVSN	869	-0.043^{b}	-0.046^{b}	-0.111^{a}	-0.136
CHKP	865	-0.087^{a}	-0.078^{b}	-0.073	-0.159^{a}
CKFR	1055	-0.060^{a}	-0.058^{b}	-0.096^{a}	-0.090^{c}
CMGI	1423	-0.043^{a}	-0.081^{b}	-0.107^{b}	-0.064
CNCX	589	-0.083^{a}	-0.083^{a}	-0.119^{a}	-0.058
CNET	859	-0.062^{a}	-0.088^{b}	-0.137^{a}	-0.09
COMS	2508	-0.084^{a}	-0.102^{b}	-0.141^{b}	-0.068
CS	2508	-0.052^{a}	-0.024	-0.084	-0.060
CTXS	1005	-0.073^{a}	-0.085	-0.064	-0.049
CYCH	958	-0.061^{b}	-0.069^{c}	-0.076	-0.079
EGRP	831	-0.013	-0.023	-0.156^{b}	0.020
ELNK	722	-0.097^{a}	-0.112^{a}	-0.201^{a}	-0.030
GNET	649	0.016	0.028	0.091	-0.028
HRBC	1081	-0.099^{a}	-0.086^{a}	-0.281^{a}	
INTU	1649	-0.039^{a}	-0.029	-0.113^{a}	-0.040
LCOS	927	-0.080^{a}	-0.133^{a}	-0.203^{a}	-0.066^{a}
MACR	1509	-0.050^{a}	-0.078^{b}		-0.158^{b}
MERQ	1528	-0.087^{a}	-0.045	-0.032	-0.091
MSPG	938	-0.063^{a}	-0.076^{b}	-0.034	-0.060
NETA	1795	-0.090^{a}	-0.092^{a}	-0.110^{b}	-0.103^{b}
NN	2450	-0.066^{a}	-0.047^{c}	-0.104	-0.008
NSOL	550	-0.057^{b}	-0.057^{b}		-0.080^{c}
NTAP	1016	-0.077^{a}	-0.110	-0.038	-0.087
OMKT	890	-0.054^{b}	-0.068^{b}	-0.155^{b}	0.030
PAIR	1571	-0.075^{a}	-0.110^{a}	-0.128^{a}	-0.108^{b}
PSIX	1160	-0.056^{a}	-0.055^{b}	-0.111^{b}	-0.065
QCOM	2013	-0.050^{a}	-0.054	-0.121^{b}	-0.039

Stock	Observations	*All*	*Common*	*LowVol*	*HighVol*
QWST	616	-0.093 [b]	-0.093 [b]	-0.078	
RNWK	510	-0.090[c]	-0.090 [c]	-0.041	-0.090
RSAS	1255	-0.040 [a]	-0.074 [a]	-0.162 [a]	-0.026
SE	944	-0.021	-0.036	-0.083	0.025
SFA	2508	-0.053 [a]		-0.118 [a]	0.036
SONE	890	-0.032 [c]	-0.069 [a]	-0.105 [a]	-0.036
SPLN	515			-0.103	-0.129
SPYG	1120	-0.047 [b]	-0.071 [a]	-0.099 [b]	
SUNW	2508	-0.033[a]	-0.068 [c]	-0.093 [c]	-0.097
TCMS	526	-0.081 [b]	-0.081 [b]	0.248 [b]	-0.104 [b]
TSG	793	-0.112 [a]	-0.149 [a]	-0.179	-0.121 [b]
USWB	501	-0.082 [b]	-0.082 [b]	-0.093 [c]	-0.073
YHOO	919	-0.076 [b]	-0.069 [c]	-0.095	-0.098

c Significant at 10%
b Significant at 5%
a Significant at 1%
a blank space indicates that due to lack of ARCH effect, the EGARCH model was not employed for that stock during the specific sample period.

5.6. Conclusion

The emergence and rise of the 'dot com' phenomena has provided opportunity to examine trading behaviour of markets where stock valuation is difficult, and substantial trading history is not available. Price-volume causal relationships provides us with the ability to gain insight into trading strategies and the efficiency of this emerging market.

The sample consists of daily price volume data of stocks from few of the renowned Internet Indices followed in the market place. The stocks are tested for unit roots, cointegration and ARCH effects. The variables, price and volume, for all stocks were non-stationary at levels and their first difference was stationary. Most stocks, in all sample periods displayed long run relationships between price and volume variables, as well as, conditional volatility. Price and volume models for establishing Granger causality relationship was formed based on each individual stock's characteristics over sample periods common to all stocks. This methodology ensures that the market's trading conditions is imposed on each stock and its trading pattern can be observed. All models account for non-trading days. The model for each stock may differ due to existence of cointegrative relationship amongst the two variables, and/or persistence of conditional volatility. The residuals from the linear model are used in Back and Brock's (1992) methodology (modified by Hiemstra and Jones (1994)) to explore nonlinear causality between the variables.

Finding of this research concur with previous research that Internet stocks, like other emerging markets, show uni-directional linear causality from trading volume to price changes. This causal relationship, though, does not support evidence from other US equities that shows at least a unidirectional causality relationship with price changes leading volume. Similar to the linear causality relationship, results of nonlinear causality displays volume leading prices.

The second part, and the major thrust of this research provide evidence of changes in price volume relationship during periods of higher price variability. It is shown that during "non-normal" market activity price changes does impact volume. This result could imply increased liquidity due to higher number of market participants entering the market. A high degree of extrapolative feedback behaviour based on rising stock prices results in wealth creation for the participants. Such trading strategy leads to lowered risk aversion for assets that are from an emerging industry.

This chapter provides insight into the area of speculative pricing and causality changes due to changes in market trading patterns. This research provides evidence of speculative traders (both rational and irrational) in the Internet equity market and feedback trading strategies being employed in the period with high price variability. This study further shows that lower liquidity in the Internet stocks than that observed in the NYSE, cause trading volume to lead price changes. As liquidity increases in the market, price volatility does impact on trading volume and results in a bi-directional linear causality. This would point towards market inefficiency and provide support to technical trading by formulating models that employ volume to predict returns.

Chapter 6: Concluding Remarks

Many historians rank the Technology / Internet bubble ahead of earlier US manias such as radio and investment trusts in the 1920s, conglomerate stocks in the late 1960s and early 1970s and oil shocks and gold in the late 1970s and early 1980s (The Wall Street Journal, 2nd January, 2001).

The idea for this thesis was first conceived towards the end of 1999 when the Internet Technology stock prices had increased about 500% in a period of 2 years. There were also high levels of euphoria amongst the US investors, while media reported young engineers and information professionals who became millionaires overnight. At that time a few academics and investment professionals were predicting a crash of the Internet bubble. However, most empirical studies and research utilised high quality, and often proprietary, data such as fundamental valuation techniques, firm specific data and high frequency trading data. It is interesting to note that a large proportion of small investors and noise traders had flooded the market and created this irrational exuberance in the IT sector. These investors were also the ones who did not have either the opportunity to access, or the ability to use, such data to form rational future expectations. Additionally, behavioural finance also points to the fact that such investors often reject their own opinions in favour of that followed by the larger investment community.

6.1 Summary of Results

This research utilises theories on price and volume relationship to model various aspects of an emerging market (or segment of a market) during a speculative bubble event. Specifically, three aspects of the IT bubble are analysed.

First, this research evaluates the source of information that was used by investors to formulate opinions with regards to the pricing of assets. Three sources of information were identified: information from trading during normal hours, information from after-hours trading and the trading turnover. The interaction between the three sources of information was considered in a simultaneously evolving setting and the analysis used contemporaneous, and lagged period's information from each source. In this portion of the study, information is proxied by variability of prices, while volume turnover is the proportion of shares on issue that are bought and sold in a trading day. These time series variables are calculated using adjusted opening and closing prices, and volume turnover for the current period, and closing prices for the last period. This tri-factor relationship is evaluated over the rise and fall of the Internet bubble for portfolios of firms selected on the basis of market size, returns and liquidity.

The analysis for the first part of the research shows that investors use information from past trading volume in pricing of assets during the bubble formation period. It also reveals that information from price variability during trading hours and after-hours trading are not very different in magnitude. However, daytime price variability was found not to be dependant upon information generated from the previous day(s) after-hours trading or lagged period(s) volume of trading. However, overnight price variability does depend upon previous period(s) trading volume. Further, firms with the high returns, are liquid and with the largest capitalisation were not affected by other firms in the same market. Finally, investors were trend chasers during rising markets but invested in large capitalised firms during the downturn in the market.

The second aspect of this study was motivated by the results of the first study, with results that indicated that there was certain degree of irrationality found in the Internet sector. This part of the study evaluated the level of speculation amongst investors within the Internet industry. The level of speculative and private trading is modelled using Lloente, Michaely, Saar and Wang's (2002) rational expectation model. The study analyses if the level of speculation changes over the rise and fall of the sector and if such speculative behaviour was pervasive throughout the industry. This part of the study also introduces an exogenous shock (9/11 attack) to observe if any changes to the level of speculation do take place. Information asymmetry was considered to be the difference between informed and uninformed agents, and thus analysis is conducted on size-based and maturity-based portfolios to explore intertemporal investor behaviour.

The evidence from the second part of the study revealed that asymmetry of information played a less significant role than revealed by LMSW (2002), whose study was also based on the US market and agreed with the results during the bubble formation period. During the formation of the bubble, there was a higher level of speculative interest in smaller firms. This relationship was weakly significant. However, results for the deflation phase of the bubble are similar to those described in Grihchenenko, Litov and Mei's (2002) study of emerging markets. Results for the period when the Internet bubble crashed showed that trading was much more speculative and private information based in firms that were large and more mature. These results were significant and showed that investors chose to stay with assets that had a higher chance of success.

The third part of this research tried to model the linear and non-linear dynamics of the price and volume relationship during the formation of the Internet bubble. The model created during lower volatility period was reconsidered during periods of higher volatility for each firm in the sample. The modelling of this relationship considered long run and short run dynamics in a simultaneous setting. Additionally, a small sample of firms that went public during the hot market conditions of 1999, were also considered to observe if trading behaviour for such firms differed from those that were trading in the market for a longer period. Such modelling, and its breakdown during changed market conditions, is an important aspect to consider by both the investing community and the regulators. It is also important to note that such modelling uses commonly available market data for each firm and hence investors who have financial modelling ability may be able to predict changes in market behaviour and perhaps the formation of an asset bubble.

Results from this analysis revealed that most firms revealed long term dynamics between prices and volume traded. Linear and non-linear causal relationship showed unidirectional relationship similar to that observed in previous research on emerging markets. Mature markets, such as evidence from the US shows that price leads volume, while emerging markets reveal volume leads prices. However, during periods of higher price volatility, price changes lead volume, and bi-directional causality was observed amongst a higher number of firms. These results show that feedback behaviour, where price changes affect trading volume which then affect price changes, were important in the formation of the IT bubble.

Results in this thesis points to the importance of price-volume relationship, and its applicability in determining and evaluating various aspects of the market undergoing a bubble phase.

6.2 Contribution to Literature

This research adds to the body of knowledge in several ways. First, although much theoretical and empirical work has been focused on the Internet bubble, this is the first comprehensive research that utilises price-volume relationship for an emerging market – the Internet firms in the US. Past research was either based upon the broader US market, or other developed markets, while few studies contemplated this relationship in an emerging market conditions. Some studies also considered price-volume relationship for non-equity assets. Hence past research was lacking in evaluating such a relationship for emerging sector in a mature market that underwent speculative bubble condition.

Second, this research is innovative in attempting to evaluate flows of information from various sources to distinguish those information set used by investors to price assets during the formation and collapse of the bubble. Prior research in this area is concentrated with the microstructure literature that uses high frequency trade data. This study uses daily data to understand such information flows and its value to investors during a speculative event.

Third, most prior research was based upon linear price-volume relationship in established equity markets, though few studies do consider developing markets and non-equity assets. It is important to realise that such relationship is not only linear but non-linear dynamics do play a part in this relationship. Thus a study to analyse linear and non-linear dynamics during bubble formation stage warranted empirical evidence. In considering such a relationship, short run and long run dynamics are included in the modelling process, as it was ignored in many of the past research.

6.3 Limitations of this Research

The scope of this thesis was also its limitation, though time and data availability were the other constrains on the analysis conducted. The scope of the thesis was limited to a single event – the Internet bubble of the late 1999 and early 2000. The analysis was conducted over a sample of firms that were represented by various indices and were considered to be part of the index over the period of analysis. This methodology introduced a survivorship bias, since only the larger and more liquid assets in the Internet sector were employed in the sample. Additionally, changes to the constituents of the index over the whole sample period were ignored due to unavailability of such data.

Secondly, during the early period of research, the quality of data was not of high quality with many inconsistencies when compared against alternate data sources. This may have introduced errors in the analysis conducted. It is unknown if the errors existed systematically across the initial data set.

6.4 Avenues for Further Research

I have identified three areas of further research, as follows:

1. Analysis using High Frequency Transaction Data

The previous section mentions that this study was conducted using end-of-day transactions summary for each firm in the sample that includes adjusted daily closing and opening prices, and traded volume. However, daily data loses idiosyncrasies of investor behaviour and market microstructure due to aggregation, and analysis of investor behaviour cannot be modelled with much accuracy. Tick data on a 5-minute interval can be employed for each of the three research objectives to obtain further details of the types of investors and their associated behaviour during the bubble period. Also, estimates of various parameters, such as volume for the buy-side and sell-side, serial correlation of returns, and volatility can be obtained with precision that will help in modelling asymmetric behaviour predicted by prospect theory.

2. Analysis Across Industries

This research was conducted for a single event but results may not be applicable across various industries such as commodities, fixed income securities, derivatives, closed ended funds and specially less liquid and alternate asset classes such as art, real estate markets, antiques and wines. Recently, prices of oil, real estate, and uranium increased rapidly, and it is of interest to compare the price-volume relationship across various assets and asset classes, while incorporating market effects and period of the particular event in the study. It will provide additional insight into the behaviour of investors that engage in speculative pricing, and the conditions necessary for herding behaviour.

3. Analysis Across Various Markets

This research considered the price-volume relationship for an emerging asset class, the information technology sector, within a developed and mature market. However, rapid price increases in the Technology sector were not restricted to the United States, but were also observed in many developed countries in Europe and Japan. It is of interest to note the differences in investors' trading behaviour across the various developed markets, since market participants may be culturally influenced in their behaviour.

Additionally, a few developing countries, such as the Indian market, also showed signs of rapid price increases in the Technology sector. Interestingly, the Technology sector in India is comparatively more mature and intrinsic to the national market than it is in the United States. However, most of the large Indian technology firms are also listed on the NASDAQ. This provides for an interesting comparison of how investors price assets in the two markets, and the role of these developed markets in the technology bubble of the US.

Appendix A

Table A-1: Descriptive Statistics

The table below describes the descriptive statistics for each firm over each sample period. The sample periods are described as:

Overall: is the overall sample. The time series start 30 trading days after the stock IPOs till the 3rd of December 1999.

Common: is the common sample for all the stocks and is composed of two sub-samples *LowVol* and *HighVol.*

LowVol: Period of low volatility in the market. 8 late IPO stocks are of shorter unequal time series.

HighVol: This sample time series is common for all 46 stocks during high price increases in the Internet market.

Returns are calculated as the log difference of the closing price on a daily basis.

ΔVolume is calculated as the log difference of the daily trading volume.

		All		*Common*		*LowVol*		*High Vol*	
		Return	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**
ADBE	Mean	0.0009	0.0005	0.0021	0.0016	0.0002	0.0014	0.0045	0.0017
	Std. Dev.	0.035	0.612	0.0321	0.5977	0.0311	0.5882	0.033	0.6079
	Skewness	0.3194	0.3109	0.0916	0.5153	0.2477	0.6635	0.3492	0.3825
	Kurtosis	12.753	3.9175	5.3059	4.3448	5.9472	4.3727	4.6582	4.3122
	Jarque-Bera	9867.9	126.9	131.542	70.5835	109.04	44.503	40.067	28.554
AMTD	Mean	0.0045	0.0065	0.0049	0.0064	0.0029	0.0014	0.0069	0.0113
	Std. Dev.	0.0678	0.7318	0.0708	0.6891	0.047	0.7591	0.882	0.6135
	Skewness	1.0993	0.4888	1.0759	0.5181	0.6257	0.4073	0.9655	0.7136
	Kurtosis	10.855	4.747	10.223	4.4302	7.5126	3.846	7.7748	5.163
	Jarque-Bera	1843.9	111.06	1396.6	76.683	267.73	16.8439	328.28	83.11
AMZN	Mean	0.0066	0.0076	0.006	0.0061	0.0069	0.0095	0.0051	0.0027
	Std. Dev.	0.0611	0.5474	0.0607	0.533	0.0567	0.5799	0.0646	0.4833
	Skewness	0.169	0.2083	0.1388	0.223	0.1568	0.1138	0.1349	0.3924
	Kurtosis	4.1238	3.3611	4.163	3.5074	4.8998	3.1697	3.6251	3.867
	Jarque-Bera	35.237	7.7781	35.152	11.221	45.268	0.9852	5.7372	16.926
AOL	Mean	0.0035	0.0031	0.0048	0.0046	0.0035	0.0062	0.0062	0.0031
	Std. Dev.	0.04	0.8494	0.0407	0.4156	0.0343	0.4521	0.0461	0.3768
	Skewness	0.1684	0.4303	0.0054	0.3709	0.5244	0.4178	0.1829	0.2734
	Kurtosis	4.8856	7.7698	4.8824	4.2374	6.4016	4.1371	3.8965	4.0286
	Jarque-Bera	293.37	1871.2	86.967	51.091	154.69	24.312	11.565	16.739
ATHM	Mean	0.0028	0.0058	0.0028	0.0058	0.0031	0.0048	0.0026	0.0068
	Std. Dev.	0.0553	0.5934	0.0553	0.5934	0.0515	0.6551	0.0587	0.5304
	Skewness	0.2204	0.5355	0.2204	0.5355	0.5406	0.5643	0.019	0.4637
	Kurtosis	5.1615	3.9475	5.1615	3.9475	7.7007	3.8703	3.615	3.5933
	Jarque-Bera	116.59	48.995	116.59	48.995	269.49	23.528	4.6994	15.001
AXNT	Mean	5.87E-05	0.0037	0.0002	0.0037	0.0003	0.0013	0.0002	0.006
	Std. Dev.	0.0565	0.7835	0.0606	0.6419	0.0432	0.7021	0.0739	0.5776
	Skewness	4.6203	0.5461	5.681	0.7996	0.2449	0.6213	6.2868	1.0905
	Kurtosis	79.113	7.4104	88.8637	6.0681	5.3284	4.2619	79.4747	9.2711
	Jarque-Bera	216038.8	758.69	184416.2	294.29	69.121	38.298	74330.2	545.54
BUSN	Mean	0.0049	0.0052	0.0067	0.008	0.0019	0.0114	0.0115	0.0047
	Std. Dev.	0.0586	1.105	0.0623	0.7859	0.057	0.9847	0.0669	0.5218
	Skewness	0.3297	0.0073	0.2601	0.3544	1.0209	0.3147	0.2645	0.2758
	Kurtosis	7.8665	6.8007	7.8025	5.6005	10.5433	4.3307	6.427	3.2031
	Jarque-Bera	844.14	505.59	573.64	178.61	745.59	26.456	148.8	4.276

		All		*Common*		*LowVol*		*High Vol*	
		Return	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**
CHKP	Mean	0.0022	0.0009	0.0031	9.77E-05	0.001	0.001	0.0071	0.0011
	Std. Dev.	0.0522	0.7005	0.0531	0.6493	0.0503	0.707	0.0555	0.5881
	Skewness	0.1064	0.2272	0.1255	0.2915	0.3617	0.4693	0.5254	0.0204
	Kurtosis	7.351	3.7103	7.4953	4.3205	6.7734	4.4373	8.1896	3.6608
	Jarque-Bera	661.04	24.77	498.33	51.224	180.21	35.979	346.95	5.4245
CKFR	Mean	0.001	0.0013	0.0024	0.0033	0.002	0.0037	0.0069	0.0032
	Std. Dev.	0.0523	0.8381	0.0589	0.738	0.052	0.7814	0.0647	0.6938
	Skewness	0.7395	0.2985	1.0768	0.4958	3.2326	0.5885	0.0334	0.3588
	Kurtosis	16.442	4.2112	196.7	4.1956	41.108	4.5775	5.3857	3.4391
	Jarque-Bera	7818.4	77.967	4728.5	59.325	18240.1	47.295	70.489	8.7625
CMGI	Mean	0.0044	0.0059	0.0072	0.0124	0.0059	0.0141	0.0088	0.0103
	Std. Dev.	0.0587	1.1515	0.0671	0.6216	0.063	0.7104	0.0718	0.4974
	Skewness	0.3296	0.3184	0.33	0.273	0.1588	0.199	0.702	0.4672
	Kurtosis	5.8005	5.8361	5.2108	5.2696	5.1698	4.9994	5.0195	3.5043
	Jarque-Bera	480.79	490.78	119.77	122.61	58.709	50.741	62.265	11.606
CNCY	Mean	0.0026	0.007	0.0026	0.007	0.0017	0.0081	0.0034	0.006
	Std. Dev.	0.0588	0.7898	0.0588	0.7898	0.0555	0.8809	0.0616	0.7009
	Skewness	0.4692	0.203	0.4692	0.203	0.7572	0.0062	0.2732	0.5577
	Kurtosis	4.399	3.465	4.399	3.465	4.4878	2.942	4.2879	4.0772
	Jarque-Bera	66.226	8.8919	66.226	8.8919	49.39	0.0385	24.225	29.757
CNET	Mean	0.0034	0.0032	0.0036	0.0057	0.0018	0.0056	0.0053	0.0059
	Std. Dev.	0.0637	0.9768	0.0694	0.7819	0.0621	0.9459	0.0759	0.5778
	Skewness	0.6604	0.318	0.6359	0.3872	1.0155	0.376	0.3944	0.285
	Kurtosis	7.0136	5.4654	6.2924	4.9668	6.3135	4.1274	5.9652	3.9533
	Jarque-Bera	617.46	224.19	306.26	109.84	184.4	22.423	116.5	15.267
COMS	Mean	0.001	0.0014	0.0004	0.0004	0.0018	0.0011	0.0009	0.0002
	Std. Dev.	0.0373	0.5953	0.0372	0.4936	0.0359	0.4776	0.03855	0.5097
	Skewness	0.8501	0.3811	0.1281	0.5491	0.4179	0.4094	0.1174	0.6604
	Kurtosis	14.803	4.7221	5.1528	3.645	4.6032	3.299	5.5944	3.8793
	Jarque-Bera	14689.8	366.38	115.55	39.884	39.91	9.2807	83.982	31.162
CS	Mean	0.0009	0.0019	0.0007	0.0011	0.0038	0.0016	0.0023	0.0006
	Std. Dev.	0.0334	0.647	0.0452	0.5351	0.0407	0.5176	0.0492	0.5527
	Skewness	1.4298	0.2194	1.181	0.4051	2.9666	0.4427	0.225	0.3737
	Kurtosis	23.408	4.6364	15.586	3.493	30.593	3.7233	7.6364	3.292
	Jarque-Bera	43866.9	296.51	4031.8	22.113	9725.2	15.961	268.52	7.9712
CTXS	Mean	0.0031	0.0044	0.0031	0.0019	0.0027	0.0033	0.0035	0.0004
	Std. Dev.	0.0585	0.6813	0.0424	0.5979	0.0401	0.6142	0.0447	0.5823
	Skewness	3.0882	0.4591	0.2213	0.348	0.5555	0.4877	0.0234	0.1846
	Kurtosis	68.777	4.4608	5.0705	4.1387	6.2373	3.2379	4.2428	5.2085
	Jarque-Bera	177503.4	121.07	110.2	43.787	143.01	12.31	19.148	62.0515
CYCH	Mean	0.0012	0.0019	0.0009	0.0002	0.0021	0.0023	0.0001	0.0028
	Std. Dev.	0.058	0.7161	0.0602	0.6664	0.0537	0.7016	0.0661	0.631
	Skewness	0.7285	0.5256	0.7619	0.7157	0.8143	0.8217	0.6988	0.5679
	Kurtosis	7.8418	4.3037	8.7196	4.8673	7.3618	5.4206	8.7815	3.9077
	Jarque-Bera	989.64	108.56	861.3	136.1	264.65	104.51	437.82	26.164

		All		*Common*		*LowVol*		*High Vol*	
		Return	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**
EGRP	Mean	0.0028	0.0028	0.0023	0.0033	0.0016	0.0012	0.0063	0.0078
	Std. Dev.	0.0611	0.6786	0.0648	0.5848	0.0565	0.6346	0.072	0.5323
	Skewness	0.543	0.4262	0.5188	0.3589	0.3824	0.344	0.5085	0.3839
	Kurtosis	6.0644	8.2753	5.7896	3.3604	8.1558	3.4103	4.4358	2.9716
	Jarque-Bera	353.23	954.25	217.77	15.8625	331.66	7.8352	38.312	7.3056
ELNK	Mean	0.0027	0.0069	0.0038	0.0072	0.0069	0.0108	0.0008	0.0036
	Std. Dev.	0.056	0.835	0.0573	0.6709	0.054	0.7776	0.0604	0.547
	Skewness	0.1635	0.2738	0.2563	0.0593	0.184	0.0303	0.5973	0.2839
	Kurtosis	6.0248	5.5214	5.722	3.8482	6.3933	3.5419	5.3556	3.1006
	Jarque-Bera	267.29	192.24	188.61	18.036	142.23	3.6303	86.33	4.1165
GNET	Mean	0.0057	0.0044	0.0063	0.0121	0.0024	0.0148	0.0101	0.0095
	Std. Dev.	0.0674	1.0385	0.0673	1.0016	0.0532	1.2678	0.0787	36407
	Skewness	1.5635	0.0867	1.6328	0.1082	0.4915	0.0706	1.8038	1.3272
	Kurtosis	13.4388	6.9715	13.946	7.5288	4.3476	5.2946	13.623	9.5714
	Jarque-Bera	306.67	408.24	3207.7	505.37	33.973	64.524	1557.7	621.59
HRBC	Mean	0.001	0.0016	0.0002	0.0023	0.0037	0.0026	0.0031	0.0021
	Std. Dev.	0.0537	1.0331	0.0599	0.826	0.0545	0.8378	0.0647	0.8156
	Skewness	0.5517	0.1462	1.1465	0.3265	1.0393	0.4046	1.2453	0.2428
	Kurtosis	17.904	4.2906	17.471	3.6935	13.1873	3.767	19.1292	3.607
	Jarque-Bera	9790.9	76.769	5277.9	22.313	1319.7	15.179	3296.1	7.4802
INTV	Mean	0.0015	0.0028	0.0032	0.0025	0.0018	0.0034	0.0045	0.0016
	Std. Dev.	0.0397	0.7791	0.0471	0.616	0.0456	0.6839	0.0486	0.5419
	Skewness	0.2047	0.6053	0.1511	0.1235	0.234	0.1393	0.0735	0.082
	Kurtosis	8.7472	6.4454	4.791	3.31	6.3001	3.2042	3.6258	2.9964
	Jarque-Bera	2303.1	925.26	81.107	3.8632	135.63	1.4575	5.1152	0.3334
LCOS	Mean	0.0028	0.0033	0.0044	0.0052	0.0045	0.0084	0.0044	0.002
	Std. Dev.	0.0652	0.7373	0.0696	0.5967	0.06763	0.6446	0.0717	0.5463
	Skewness	0.3593	0.1645	0.2819	0.223	0.1654	0.0984	0.6516	0.4122
	Kurtosis	6.4488	4.38	6.7326	4.3239	5.8231	4.4888	7.4028	3.6845
	Jarque-Bera	464.36	75.315	350.33	47.981	98.641	27.534	260.9	14.212
MACR	Mean	0.0014	0.0021	0.0036	0.0005	0.0021	0.0046	0.0052	0.0057
	Std. Dev.	0.0494	0.8158	0.0497	0.6494	0.0454	0.6921	0.0537	0.6055
	Skewness	0.1342	0.275	0.2079	0.3745	0.359	0.3524	0.0904	0.409
	Kurtosis	6.82	4.9542	3.9498	3.5771	4.3837	3.2123	3.5891	4.0287
	Jarque-Bera	904.33	254.17	26.431	21.987	29.671	6.616	4.6992	21.378
MERQ	Mean	0.0014	0.0023	0.004	0.001	0.003	0.0086	0.0051	0.0067
	Std. Dev.	0.0456	1.1009	0.0462	0.7286	0.0389	0.8009	0.0527	0.6478
	Skewness	0.8215	0.0488	1.0152	0.3569	0.0849	0.364	1.3802	0.3456
	Kurtosis	8.7197	5.5502	9.4509	3.6587	4.3691	3.5105	10.12	3.5128
	Jarque-Bera	2211.9	406.81	1105.3	22.802	23.237	9.6554	697.35	8.8586
MPSG	Mean	0.0034	0.0044	0.0044	0.0057	0.0074	0.0092	0.0014	0.0023
	Std. Dev.	0.053	0.6966	0.0585	0.6037	0.0497	0.6782	0.066	0.521
	Skewness	0.3566	0.4903	0.2956	0.4482	3.37E-05	0.4387	0.4684	0.4203
	Kurtosis	4.8518	5.1325	4.4481	4.0189	4.0511	3.6774	4.2534	4.0094
	Jarque-Bera	149.15	208.67	60.152	45.278	13.4885	15.002	30.302	21.3559

		All		*Common*		*LowVol*		*High Vol*	
		Return	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**
NETA	Mean	0.0011	0.0021	0.0008	0.0035	0.0005	0.0032	0.0011	0.0037
	Std. Dev.	0.048	1.2224	0.0479	0.5786	0.0351	0.5974	0.0579	0.5604
	Skewness	3203	0.0906	1.3757	0.6031	0.0542	0.5458	1.5543	0.6697
	Kurtosis	8.2598	6.7416	12.738	4.2284	3.7706	3.8983	11.366	4.6098
	Jarque-Bera	2065.9	1032.5	2517.5	72.871	7.3948	24.402	985.78	54.278
NN	Mean	0.009	0.0005	0.0014	0.0026	0.0035	0.0045	0.0007	0.0007
	Std. Dev.	0.0383	0.7156	0.046	0.617	0.0432	0.6037	0.0486	0.6308
	Skewness	0.5969	0.2418	0.7384	0.4889	0.9031	0.7221	0.65	0.2874
	Kurtosis	11.72	5.8337	9.6865	3.5431	7.2245	3.8585	11.0356	3.2657
	Jarque-Bera	7815.8	833.63	1152.7	30.759	257.7	34.462	819.98	4.9647
NSOL	Mean	0.0059	0.0055	0.0059	0.0055	0.0038	0.0022	0.0074	0.0079
	Std. Dev.	0.0706	0.656	0.0706	0.656	0.0569	0.7718	0.0794	0.5544
	Skewness	0.7856	0.219	0.7856	0.219	0.5181	0.2226	0.7976	0.1984
	Kurtosis	6.3736	3.8834	6.3736	3.8834	3.6664	3.6129	6.2185	3.1931
	Jarque-Bera	300.67	21.112	300.67	21.112	14.167	5.3563	159.68	2.4104
NTAP	Mean	0.0029	0.0011	0.0042	0.0031	0.0028	0.0029	0.0056	0.0033
	Std. Dev.	0.0417	0.9198	0.0432	0.7443	0.0348	0.9029	0.0502	35459
	Skewness	0.0999	0.1627	0.1287	0.1393	0.3641	0.0034	0.2413	0.6899
	Kurtosis	5.3668	4.5571	5.3423	4.6595	4.0321	3.5387	4.8977	5.9633
	Jarque-Bera	232.03	104.06	136.5	69.615	19.481	3.5441	47.451	132.23
OMKT	Mean	0.0008	0.0054	0.0023	0.0078	3.81E-05	0.0038	0.0047	0.0117
	Std. Dev.	0.0653	0.7422	0.0695	0.6324	0.0547	0.6342	0.0816	0.6318
	Skewness	1.7089	0.4017	1.9574	0.6744	0.53	0.6524	2.2057	0.6967
	Kurtosis	17.115	4.225	18.234	3.9664	4.8953	3.3569	17.928	4.576
	Jarque-Bera	7566.8	77.003	6082.4	67.694	57.579	22.34	2998.7	54.767
PAIR	Mean	0.0007	0.0011	0.0007	0.0013	0.0035	0.0005	0.002	0.0032
	Std. Dev.	0.0486	0.7337	0.0542	0.6654	0.0451	0.6179	0.0618	0.7102
	Skewness	0.7948	0.3995	1.4829	0.5365	0.3265	0.5532	2.0553	0.5212
	Kurtosis	12.652	5.0031	17.787	3.9679	6.671	3.8734	18.695	3.9067
	Jarque-Bera	6148.2	298.85	5592.1	51.337	169.73	24.262	3257.6	23.626
PSIY	Mean	0.0011	0.0015	0.0031	0.004	0.0013	0.012	0.0046	0.0028
	Std. Dev.	0.0568	0.6808	0.0566	0.5916	0.0565	0.6488	0.0568	0.5384
	Skewness	0.2915	0.2988	0.2202	0.602	0.3079	0.5826	0.1455	0.5951
	Kurtosis	6.2465	4.1635	7.0252	4.2377	9.4982	4.4565	4.9635	3.4212
	Jarque-Bera	512.7	80.634	403.08	73.307	484.65	39.576	52.042	21.057
QCOM	Mean	0.0021	0.0017	0.0047	0.0021	0.0002	0.0003	0.009	0.0038
	Std. Dev.	0.0387	0.6717	0.0411	0.5888	0.0358	0.6438	0.0453	0.5326
	Skewness	0.713	0.307	0.9379	0.37	0.1401	0.2953	1.2025	0.4865
	Kurtosis	7.8345	5.3047	10.635	3.8627	7.5539	3.8808	10.858	3.4269
	Jarque-Bera	2100.2	470.28	1519.8	31.763	248.93	13.451	852.74	14.255
QWST	Mean	0.0025	0.0065	0.0025	0.0065	0.0022	0.0083	0.0027	0.0046
	Std. Dev.	0.0409	0.5662	0.0409	0.5662	0.0408	0.6581	0.0411	0.4604
	Skewness	0.4775	0.5274	0.4775	0.5274	0.0334	0.4219	0.9023	0.7288
	Kurtosis	7.3332	4.6481	7.3332	4.6481	5.6588	3.8109	8.941	5.5543
	Jarque-Bera	481.56	93.651	481.56	93.651	85.474	16.552	477.09	107.03

		All		*Common*		*LowVol*		*High Vol*	
		Return	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**
RNWK	Mean	0.0063	0.0054	0.0063	0.0054	0.0049	0.0127	0.0072	0.0009
	Std. Dev.	0.0726	0.6408	0.0726	0.6408	0.0621	0.735	0.0785	0.576
	Skewness	0.3829	0.2913	0.3829	0.2913	0.2191	0.1037	0.4116	0.5029
	Kurtosis	5.3188	3.7152	5.3188	3.7152	5.0227	3.324	5.0906	3.8092
	Jarque-Bera	119.51	17.058	119.51	17.058	32.84	1.1357	62.477	20.627
RSAS	Mean	0.0015	0.0014	6.40E-05	0.0019	0.0041	0.0004	0.0039	0.0034
	Std. Dev.	0.0508	0.9112	0.0546	0.6953	0.0523	0.7569	0.0566	0.63
	Skewness	0.1469	0.028	0.849	0.424	2.0811	0.5422	0.0711	0.2108
	Kurtosis	11.435	6.7819	13.065	4.0475	22.108	4.1383	6.1116	3.473
	Jarque-Bera	3638.9	730.82	2561.3	44.659	4669.03	30.179	120.06	4.9706
SE	Mean	0.0001	0.0022	0.0005	0.0002	0.0003	0.0022	0.0008	0.0019
	Std. Dev.	0.0357	0.7522	0.04	0.7438	0.029	0.8128	0.0485	0.6702
	Skewness	1.5235	0.2927	1.7172	0.3597	0.3729	0.0056	1.8288	0.9691
	Kurtosis	16.117	3.8405	15.418	4.164	6.2662	2.7671	13.378	6.6871
	Jarque-Bera	6913.7	40.001	4081.1	46.04	137.03	0.6635	1498.4	214.72
SFA	Mean	0.0008	0.001	0.0018	0.0008	8.41E-05	0.0008	0.0036	0.0024
	Std. Dev.	0.0322	0.6878	0.0415	0.5826	0.0359	0.5996	0.0463	0.5664
	Skewness	1.2521	0.3384	2.209	0.9241	0.2205	0.9035	3.3096	0.9469
	Kurtosis	25.242	4.078	32.909	5.5363	7.0962	5.0494	40.21	6.1012
	Jarque-Bera	51748.7	167.37	22472	242.13	207.21	91.141	17676.9	163.41
SONE	Mean	0.0014	0.0053	0.0045	0.0063	0.0021	0.0011	0.0069	0.0137
	Std. Dev.	0.0554	1.0567	0.0583	0.8089	0.0557	0.9055	0.0607	0.7021
	Skewness	0.3018	0.0658	0.3658	0.1246	0.7052	0.1154	0.0887	0.1564
	Kurtosis	4.5857	5.1712	4.5083	3.2274	4.9921	3.0503	4.1934	3.0095
	Jarque-Bera	103.28	169.75	69.093	2.8007	72.742	0.6818	18.017	1.2127
SPLN	Mean	0.0032	0.0075	0.0032	0.0075	0.0026	0.0196	0.0035	0.0001
	Std. Dev.	0.0763	0.7063	0.0763	0.7063	0.0629	0.722	0.0838	0.6961
	Skewness	1.4869	0.29	1.4869	0.29	0.0535	0.2845	1.8561	0.2918
	Kurtosis	24.594	3.9137	24.594	3.9137	4.3279	3.9493	26.909	3.8928
	Jarque-Bera	9622.4	23.723	9622.4	23.723	13.976	9.6483	7269.1	14.129
SPYG	Mean	4.90E-05	0.0002	0.0018	0.0046	0.0016	0.0029	0.0019	0.0063
	Std. Dev.	0.0631	0.7534	0.0696	0.7852	0.0599	0.8135	0.0781	0.7576
	Skewness	1.5504	0.8597	1.7634	1.1268	2.4235	1.2973	1.405	0.9149
	Kurtosis	15.457	5.0965	17.002	5.6672	24.713	6.2305	12.937	4.8684
	Jarque-Bera	7491.2	334.22	5125.6	299.75	6042.9	209.6	1319.7	84.634
SUNW	Mean	0.0015	0.0007	0.0031	0.0014	0.0003	0.0003	0.0058	0.0032
	Std. Dev.	0.0323	0.5346	0.0335	0.4372	0.0315	0.4607	0.0351	0.4135
	Skewness	0.2879	0.2431	0.1381	0.4388	0.1721	0.6561	0.1617	0.1409
	Kurtosis	6.7054	4.7062	3.4134	4.6349	3.9314	5.3502	3.0395	3.4272
	Jarque-Bera	1452.5	325.13	6.0788	84.649	12.039	88.462	1.3136	3.2416
TCMS	Mean	0.0034	0.0014	0.0034	0.0014	0.006	0.0049	0.0017	0.0008
	Std. Dev.	0.0554	1.283	0.0554	1.283	0.0551	1.3341	0.0556	1.2497
	Skewness	0.2687	0.2016	0.2687	0.2016	0.2796	0.0608	0.2644	0.4163
	Kurtosis	5.5126	4.1196	5.5126	4.1196	4.9766	2.8877	5.8701	5.1581
	Jarque-Bera	136.72	29.327	136.72	29.327	35.164	0.2283	105.4	66.218

		All		*Common*		*LowVol*		*High Vol*	
		Return	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**	**Return**	**ΔVolume**
TSG	Mean	0.0006	0.0008	0.0007	0.0005	1.43E-05	0.003	0.0015	0.0041
	Std. Dev.	0.0246	0.8462	0.0266	0.8132	0.0221	0.8714	0.0305	0.753
	Skewness	0.5547	0.2107	0.556	0.1611	1.5912	0.0888	1.3025	0.2734
	Kurtosis	11.917	3.7143	11.212	3.4083	15.201	3.3217	8.6963	3.3643
	Jarque-Bera	2570.9	21.901	1688.6	6.6535	1941.1	1.6495	485.52	5.3435
USWB	Mean	0.0028	0.0029	0.0028	0.0029	0.0003	0.0021	0.0042	0.0034
	Std. Dev.	0.063	0.592	0.063	0.592	0.0674	0.6784	0.0603	0.5358
	Skewness	0.075	0.4571	0.075	0.4571	0.1201	0.5857	0.0551	0.2851
	Kurtosis	4.5491	3.6023	4.5491	3.6023	3.3725	3.6427	5.5367	3.0646
	Jarque-Bera	47.639	23.575	47.639	23.575	1.4326	13.02	79.784	4.0772
YHOO	Mean	0.0044	0.0049	0.0055	0.0033	0.0065	0.0068	0.0045	0.0001
	Std. Dev.	0.0493	0.5627	0.0494	0.4557	0.0443	0.4805	0.054	0.4307
	Skewness	0.249	0.4955	0.0794	0.3576	0.2629	0.4308	0.2828	0.2476
	Kurtosis	4.5548	4.5701	4.742	4.3469	6.4961	4.4514	3.7387	4.0468
	Jarque-Bera	98.849	127.85	75.224	57.179	152.59	34.784	10.712	16.597

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