MARKET MICROSTRUCTURE OF INDIAN STOCK MARKET:

AN EMPIRICAL ANALYSIS

A Thesis Submitted to the University of Hyderabad
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IN

ECONOMICS

BY

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DEDICATED

TO

My Beloved Late Grand Mother

DECLARATION

I, **Mr. Rashmi Ranjan Paital,** hereby declare that this thesis entitled, "**Market Microstructure of Indian Stock Market: An Empirical Analysis"** submitted by me under the supervision of **Prof. Naresh Kumar Sharma** is a bonafide research work which is also free from plagiarism. I also declare that it has not been submitted previously in part or in full to this University or any other University or Institution for the award of any degree or diploma. I hereby agree that my thesis can be deposited in Shodganga/INFLIBNET.

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Rashmi Ranjan Paital

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Abbreviations

2SLS	Two Stage Least Squares
ACC	ACC Ltd.
ACEM	Ambuja Cements Ltd.
ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
APNT	Asian Paints Ltd.
AR	Auto Regressive
ARCH	Autoregressive Conditional Hetroscedasticity
ARCH-LM	ARCH-Lagrange Multiplier
ARIMA	Auto Regressive Integrated Moving Average
AXSB	Axis Bank Ltd.
BHARATI	Bharti Airtel Ltd.
BHEL	Bharat Heavy Electricals Ltd.
BJAUT	Bajaj Auto Ltd.
BOB	Bank of Baroda Ltd.
BPCL	Bharat Petroleum Corporation Ltd.
BRVM	Bourse Régionale des Valeurs Mobilières (South African Index)
BSE	Bombay Stock Exchange
CAIR	Carirn India Ltd.
CIPLA	Cipla Ltd.
COAL	Coal India Ltd.
DF	Dickey Fuller
DLFU	DLF Ltd.
DRRD	Dr. Reddy's Laboratories Ltd.
ECM	Error Correction Model
EGARCH	Exponential GARCH
FDI	Foreign Direct Investment
FII	Foreign Institutional Investment
GAIL	GAIL (India) Ltd.
GARCH:	Generalized Autoregressive Conditional Hetroscedasticity
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
GRASIM	Grasim Industries Ltd.
HCLT	HCL Technologies Ltd.
HDFC	Housing Development Finance Corporation Ltd.
HDFCB	HDFC Bank Ltd.
HMCL	Hero Moto Corp Ltd.
HNDL	Hindalco Industries Ltd.

HUVR	Hindustan Unilever Ltd.
ICICIBC	ICICI Bank Ltd.
IDFC	IDFC Ltd.
IDT	Information-Driven Trading
INFO	Infosys Ltd.
IRF	Impulse Response Function
ITC	ITC Ltd.
JPA	Jaiprakash Associates Ltd.
JSP	Jindal Steel & Power Ltd.
KMB	Kotak Mahindra Bank Ltd.
LB-Q	Ljung-Box Q
LDT	Liquidity-Driven Trading
LPC	Lupin Ltd.
LSE	London Stock exchange
LT	Larsen & Toubro Ltd.
LTP	Last Traded Price
MDH	Mixture Distribution Hypothesis
MM	Mahindra & Mahindra Ltd.
MSIL	Maruti Suzuki India Ltd.
NSE	National Stock Exchange
NTPC	NTPC Limited
NYSE	New York Stock Exchange
OLS	Ordinary Least Square
ONGC	Oil & Natural Gas Corporation Ltd.
PNB	Punjab National Bank
PP	Phillips Peron
PWGR	Power Grid Corporation of India Ltd.
RBXY	Ranbaxy Laboratories Ltd.
RELI	Reliance Infrastructure Ltd
RIL	Reliance Industries Ltd.
S&P	Standard & Poor
SBIN	State Bank of India Ltd.
SC	Schwarz's criteria
SENSEX	Sensitive Index
SESA	Sesa Sterlite Limited
SIAH	Sequential Information Arrival Hypothesis
SIEM	Siemens Ltd.
SUNP	Sun Pharmaceutical Industries Ltd.
TATA	Tata Steel Ltd.
TCS	Tata Consultancy Services Ltd.

TOCOM	Tokyo Commodity Futures Market
TPWR	Tata Power Co. Ltd.
TTMT	Tata Motors Ltd.
UTCEM	Ultra Tech Cement Ltd.
VAR	Vector Auto Regression
VD	Variance Decomposition
VECM	Vector Error Correction Model
WPRO	Wipro Ltd.
WTI	West Texas Intermediate

Chapter 1

Introduction

1.1: Background

Market microstructure is the area of finance that studies the processes by which prices come to impound new information over time. In particular, as information is important in decision making, market outcome is sensitive to the assumed information structure. There are two types of information which lead to price changes i.e., (1) macroeconomic information and (2) trading and firm specific information. The role of macroeconomic factors is very important for price determination in weekly, monthly and yearly stock prices. The macroeconomic indicators like inflation rate, interest rate, GDP, exchange rate, FDI and FII flows, Government policies are the main sources of price changes. But in the case of intra-day, the role of trading information and firm specific information like, liquidity position, leverage ratio, profitability, solvency of the firm, inventory holdings, operating efficiency etc. has a major role to play for stock price movement. A major issue that arises here is how to measure the information flow in the market? In this process, market microstructure research has been focusing on the price-volume and price-spread relationship since this empirical relation helps in understanding the competing theories of information flow in the market.

The empirical price-volume relationship has been developed on the basis of two major underlying hypotheses: The Mixture of Distribution Hypothesis (MDH) and the Sequential Information Arrival Hypothesis (SIAH). Mixture of Distribution Hypothesis (MDH) of Clark (1973), Epps and Epps (1976), Tauchen and Pitts (1983) argues that absolute price change/volatility and trading volume should be positively correlated because they jointly depend on a common underlying variable, which is the rate of information flow in the market. This means that both stock price changes and trading volume simultaneously respond to the arrival of new information in the market and they are contemporaneously correlated. Hence, there exists a positive contemporaneous relation between trading volume and absolute price change/volatility. In MDH equilibrium, prices are immediately established and new information is disseminated simultaneously to all the traders. The implication is that with simultaneous information arrival, there is no information in the past volume that can be used in forecasting future absolute price changes that are not yet contained in the past absolute price changes. Hence, the mixture distribution hypothesis supports only the positive contemporaneous relationship but not the lead-lag relationship between trading volume and absolute price changes.

The sequential information arrival hypothesis (SIAH) proposed by Copeland (1976) and discussed further in Jennings, Starks and Fellingham (1981) and Simrlock and Starks (1978) assume that information is disseminated in the market sequentially rather than simultaneously to all the traders. In the sequential information arrival hypothesis (SIAH), some trader receives the signal ahead of the market and trades on it, thereby creating volume and price changes. Hence, there is a positive contemporaneous relationship between absolute price changes and trading volume. Further, this sequential information flow results in past values of trading volume having the ability to predict future absolute stock price changes/volatility and/or vice versa, which means that a causality relationship may exist in both directions or either direction between absolute price changes/volatility and trading volume. Hence, SIAH suggests both contemporaneous as well as causal relationship between volume and absolute stock price changes.

The market microstructure research has also explored and explained the relationship between bid-ask spread and volatility based on information uncertainty. The intraday variations of bid-ask spread and intraday return volatility are expected to be positively correlated because information arrival is supposed to stimulate an increase in volatility which in turn widens the bid-ask spread.

To understand the influence of spot market on futures market and vice versa and the role of each market segment in price discovery is the key question in the research of market microstructure design. Price discovery is important because it hints at where the informed traders do trade. Were the markets perfectly efficient and frictionless, the price discovery would be instantaneous and contemporaneous. In practice, however, between spot and derivatives segments or across different trading venues of the same stock, price discovery takes place in one market and the other markets follow it. Although spot and futures markets react to the same information, the important question to ask is: which market reacts first?

1.2: Issues

The following issues are identified on the basis of the theoretical background and the review of existing literature:

- There are many studies, empirical and theoretical, on the phenomenon of stock price and volume relationship. Although the majority of those findings have confirmed the existence of positive contemporaneous relationship between trading volume and absolute price changes/volatility, the studies of different stock markets have given mixed results about the causal price-volume relationship. Therefore, there is a scope for further examining the contemporaneous and causal relationship between the price changes and trading volume in India.
- Most of the studies have focused on the arrival of new information and the price-volume relation, whereas, studies on the arrival of new information and the price-spread relation are far fewer and this relationship is not so clearly established at theoretical or at empirical level. Hence there exists some scope for further investigation.
- Several recent studies have shown that futures prices play a crucial role in the discovery and transmission of price formation. Whether this situation holds good for all markets is a question of debate for several years. To answer this question, this study makes an attempt, taking into consideration the S&P CNX Nifty index and its related futures prices.
- Most of the studies are related at the international level, but its relevance to developing economy like India is quite limited. Hence studies specific to the Indian stock market are relevant for deepening and understanding.

1.3: Objectives of the Study

On the basis of the above outlined theoretical background and the issues, the following main objectives have been set for this study.

1. To examine the intraday contemporaneous as well as causal relationship between stock returns, trading volume and bid-ask spread.
2. To investigate whether return-volume relation is different for a rising market than that for a declining market.
3. To examine the intraday contemporaneous as well as causal relationship between stock returns volatility, trading volume and bid-ask spread.
4. To investigate whether information content in trading volume and bid-ask spread captures the volatility persistence in the market.
5. To examine the long run as well as lead-lag relationship between spot and futures market.

1.4: Methodology

First, stationarity of the data series are tested with the help of Dickey Fuller (DF), Augmented Dickey Fuller (ADF) and Phillips Peron (PP) tests.

Second, the contemporaneous relationship between trading volume, bid-ask spread and stock returns/volatility are examined through OLS regression.

Third, the causal relationship between trading volume, bid-ask spread and stock returns/volatility are examined through the Granger causality test.

Fourth, the asymmetric relationship between stock returns and trading volume is empirically investigated through dummy variable OLS regression.

Fifth, the impact of trading volume and bid-ask spreads on conditional volatility are examined by adopting the generalized auto regressive conditional hetroscedasticity (GARCH) model.

Sixth, the long run equilibrium relationship between spot and futures market is empirically investigated through Engle-Granger two step co-integration tests.

Finally, the lead-lag relationship between spot and futures market had been empirically investigated through Vector Error Correction Mechanism (VECM).

1.5: Nature and Sources of Data

The data used for examining the relationship between trading volume, bid-ask spread and stock return/volatility consisted of last trading price (LTP), trading volumes, bid price and ask price for the five-minute intervals from 2nd July 2012 to 31st December 2012 for 50 stocks of S&P CNX Nifty Index listed in National Stock Exchange (NSE), India. All the data were obtained electronically from the Bloomberg terminals. Each of the trading days in the analysis was portioned in to five-minute interval beginning with the opening of the market at 9:15 a.m. to end of the trading day at 3:30 p.m.

To examine the long run as well as the lead-lag relationship between spot and futures market, the study used 5-minutes interval data set of S&P CNX Nifty index prices and CNX Nifty futures index prices from 2nd July 2012 to 31st December 2012. All the data were obtained electronically from the Bloomberg terminals.

Here is the list of 50 stocks of S&P CNX Nifty Index considered for the study.

Table 1.1: S&P CNX NIFTY Index List

S&P CNX NIFTY Index List			
Sl.No.	Company Code	Company Name	Industry
1	ACC	ACC Ltd.	Cement
2	ACEM	Ambuja Cements Ltd.	Cement
3	APNT	Asian Paints Ltd.	Chemicals
4	AXSB	Axis Bank Ltd.	Banks
5	BHARATI	Bharti Airtel Ltd.	Telecommunication services
6	BHEL	Bharat Heavy Electricals Ltd.	Electrical Equipment
7	BJAUT	Bajaj Auto Ltd.	Automobile
8	BOB	Bank of Baroda Ltd.	Banks
9	BPCL	Bharat Petroleum Corporation Ltd.	Oil and Gas
10	CAIR	Carirn India Ltd.	Oil and Gas
11	CIPLA	Cipla Ltd.	Pharmaceuticals
12	COAL	Coal India Ltd.	Metals and Mining
13	DLFU	DLF Ltd.	Real Estate
14	DRRD	Dr. Reddy's Laboratories Ltd.	Pharmaceuticals
15	GAIL	GAIL (India) Ltd.	Energy, Petrochemicals
16	GRASIM	Grasim Industries Ltd.	Building materials
17	HCLT	HCL Technologies Ltd.	IT service; IT consulting
18	HDFC	Housing Development Finance Corporation Ltd.	Financial services
19	HDFCB	HDFC Bank Ltd.	Banks
20	HMCL	Hero MotoCorp Ltd.	Automobile
21	HNDL	Hindalco Industries Ltd.	Metals
22	HUVR	Hindustan Unilever Ltd.	Consumer goods
23	ICICIBC	ICICI Bank Ltd.	Banks
24	IDFC	IDFC Ltd.	Financial services
25	INFO	Infosys Ltd.	IT services, IT consulting

26	ITC	ITC Ltd.	FMCG
27	JPA	Jaiprakash Associates Ltd.	Infrastructure
28	JSP	Jindal Steel & Power Ltd.	Steel, Energy
29	KMB	Kotak Mahindra Bank Ltd.	Banks
30	LPC	Lupin Ltd.	Pharmaceuticals
31	LT	Larsen & Toubro Ltd.	Engineering and construction
32	MM	Mahindra & Mahindra Ltd.	Automotive
33	MSIL	Maruti Suzuki India Ltd.	Automotive
34	NTPC	NTPC Limited	Electric utility
35	ONGC	Oil & Natural Gas Corporation Ltd.	Oil and Gas
36	PNB	Punjab National Bank	Banks
37	PWGR	PowerGrid Corporation of India Ltd.	Electric utility
38	RBXY	Ranbaxy Laboratories Ltd.	Pharmaceuticals
39	RELI	Reliance Infrastructure Ltd	Energy
40	RIL	Reliance Industries Ltd.	Multi-industry
41	SBIN	State Bank of India Ltd.	Banks
42	SESA	Sesa Sterlite Limited	Mining
43	SIEM	Siemens Ltd.	Multi-industry
44	SUNP	Sun Pharmaceutical Industries Ltd.	Pharmaceuticals
45	TATA	Tata Steel Ltd.	Steel
46	TCS	Tata Consultancy Services Ltd.	IT services, IT consulting
47	TPWR	Tata Power Co. Ltd.	Electric utility
48	TTMT	Tata Motors Ltd.	Automotive
49	UTCEM	UltraTech Cement Ltd.	Cement
50	WPRO	Wipro Ltd.	IT services, IT consulting

1.6: Organization of the Thesis

The thesis is divided in to six chapters including the present Chapter 1, which introduces the background of the study, issues, objectives of the study, nature and sources of the data and methodology of the study. The Chapter 2 briefly describes the theoretical models and the background of the study. The Chapter 3 examines the first two objectives of the study i.e. the relationship between stock returns, trading volume and bid-ask spread. The Chapter 4 examines the 3^{rd} and 4^{th} objectives of the study i.e. the relationship between stock returns volatility, trading volume and bid-ask spread. The Chapter 5 examines the 5^{th} and last objective of the study i.e. lead-lag relationship between futures and spot market. The final Chapter 6 concludes with the summary, findings, policy implications and conclusions of the study as whole.

Chapter 2

Theoretical Background of the Study: A Thematic Review

2.1: Introduction

Maureen O'Hara (1995, p.1) defines market microstructure as "the study of the process and outcomes of exchanging assets under a specific set of rules. While much of economics abstracts from the mechanics of trading, microstructure theory focuses on how specific trading mechanisms affect the price formation process." One interesting aspect of market microstructure theory is its evolution. While the initial studies focused on issues relating to demand and supply, latter work in this area focuses more on the information aggregation properties of prices and markets. Focusing on market microstructure research, this chapter briefly discuss the price formation process, the arrival of new information and the role of trading volume and bid-ask spreads in the market.

2.2: Price Formation Processes in the Market

How is price determined? The usual answer to this question in economics theory is- the interaction between demand and supply. The equilibrium price is determined when demand equals to supply. If demand exceeds supply then price will go up and if supply exceeds demand then price will fall down. But how is this equilibrium actually attained in the market? What is the economy that coordinates the desires of demanders and suppliers so that a price emerges and trade occurs?

Demsetz (1968) first observed that market is not frictionless. There are frictions existing in the market. According to his observation, trade may involve some cost. He categorised these costs into explicit costs and implicit costs. Explicit costs include brokerage commissions, fees and taxes whereas implicit costs refer to the costs connected with the immediate execution of trading. The latter are not paid explicitly, but reflect in adverse deviation in price to be paid/received by those who do wish to wait but wish to trade immediately. For example, those who wish to sell a stock immediately may be able to so only at a price lower than the market price; and likewise for the trader wanting to buy stock immediately. In Walrasian auction pricing model, trading has a time dimension.

Over the period, there is a possibility that the number of shares to buy is equal to the number of shares to be sold in the market. But, at a particular point of time, such an outcome may not happen. Suppose, at a point of time, the number of shares demanded by the traders to buy immediately may not be equal to the number of shares supplied in the market. This creates a trade imbalance and that makes it impossible to find a market clearing price or equilibrium price. Demsetz (1968) argued that this lack of equilibrium could be overcome by paying a price for immediacy. He also argued that there are two sources of demand and supply at a particular point of time in the market. On the demand side, there is a demand originating from the buyers who want to execute it immediately whereas another demand arises from the buyers who do not feel the need to execute it at that particular point of time. Similarly, on the supply side, there is one supply emanating from the sellers who want to sell immediately where as another supply coming from the sellers who do not feel the need to do so at that particular point of time.

If demand exceeds supply now, then some buyers have to wait for the sellers to arrive in market or immediately they can offer a higher price to attract those additional sellers to transact now. Similarly, if supply exceeds demand now, a lower price must be set to encourage more buyers to trade now. So, there are two sets of prices, not one demonstrating the equilibrium. One is buy side price and other one is sell side price. If demand exceeds over supply then price will be decided at sell side and if supply exceeds demand then price will be decided at buy side. So, in reality two sets of prices exist.

2.3: Bid-Ask Spread and Price Formation Process

As Demsetz (1968) pointed out that friction exists in the market. But the question arises here is how to measure the friction in the market. Thus, the concept of bid-ask spread comes. Bid price represents the highest price that a buyer or buyers are willing to pay for a security. The ask price represents the minimum price that a seller or sellers are willing to receive for the security. A trade or transaction occurs when the buyer and seller agree on a price for the security. The bid-ask spread is the amount by which the ask price exceeds the bid. The bid-ask spread is the price that impatient traders pay for immediacy. Impatient traders buy at the ask price and sell at the bid price. The spread is the compensation received by the traders who offer immediacy.

The bid-ask spread plays a key role in the investment strategy. The bid-ask spread is the most important factor for investors in trading when they decide whether to submit "limit orders" or "market orders". Limit order is an order placed with a brokerage to buy or sell a set number of shares at a specified price or better. It may not be executed if the price set by the investor cannot be met during the period of time in which the order is left open. Similarly market order is an order to buy or sell a stock at the best available current price.

A market order is likely to be executed because here there is no restriction in price limit as well as time limit. When the spread is wide, immediacy is expensive, market order execution is costly, and limit order submission strategies are attractive. When the spread is narrow, immediacy is cheap, and market order strategies are attractive.

2.4: The Role of Information in Price Formation

In general, when market goes up, most of the investors gain, when it falls, most investors lose. Since market price tends to both rise and fall over time, one might expect that an investor need to play a strategy based on the availability of information to receive extra over the market return. In market we can find two types of traders, the informed traders and the uninformed traders. Informed traders have an informational edge regarding the stocks that other traders do not possess. Informed traders use fundamental information (i.e. information about the economy, a sector or a company) and/or technical information (i.e. stock charts, patterns, etc.) to make trading decision whereas the uninformed traders do not possess such information. Some traders are noise traders, since they trade based on their sentiments and beliefs rather than fundamental information. Informed traders can exploit this informational advantage while trading with others. Information is spread over the market through the trading activities of the informed traders. Informed traders adopt different strategies to maximize their profits. Some investors trade immediately after getting the information before it reaches to others. And in some cases to get maximum profit from their informational superiority over others, informed traders have incentives to slow down the rate at which their trading influences prices. In other words, informed investors use medium-size trades rather than large trades, to prevent information from being too quickly impounded into stock prices.

It is also important to know how prices adjust to new information over time. New information becomes impounded into prices as a result of the trading behaviour of informed and uninformed traders. The price at each point reflects all publicly available information, but not necessarily all private information. Consequently, until prices adjust to the new information value, informed traders earn a return to their information. In market, prices eventually converge to new information values though the actual adjustment time can be infinite. This adjustment process depends on how uninformed traders learn from observing market information. If uninformed traders learn quickly then it will take less time to reflect particular information in the market.

Market moves due to some information but the question to ponder is: how this information is relevant to ultimate fundamental value of the securities? Hence, by looking into a single price change does not help uninformed traders to get the actual true value of the information. Therefore the sequence of prices may provide information that individual prices do not.

With asymmetric information, prices play a dual role of market clearing and information aggregation. This latter role dictates that the sequence of prices can be informative beyond the information provided by individual prices. In this adjustment process, uninformed traders learn from watching market data, and this learning is what allows price to ultimately reflect information.

2.5: Arrival of New Information and the Relationship between Trading Volume and Price Changes

New information causes investors to adapt their expectations and this is the main source of price changes. A major issue arises here is concerned with measurement of the information flow in the market. In this connection, market microstructure research has started to focus on the price-volume and price-spread relationship since this empirical relation helps in understanding the competing theories of dissemination of information flow in the market.

The empirical price-volume relationship is developed based on the two major hypotheses: the Mixture of Distribution Hypothesis (MDH) and the Sequential Information Arrival Hypothesis (SIAH).

2.5.1: Mixture of Distribution Hypothesis (MDH)

Clark (1973) was the first to introduce this hypothesis, and then it was extended by others such as, Epps and Epps (1976), Tauchen and Pitts (1983), Harris (1986) and Lamoureux and Lastrapes (1990). They argue that absolute price changes and trading volumes should be positively correlated because they jointly depend on a common underlying variable, which is normally interpreted as the flow of new information to the market. This means that both absolute price changes and trading volume simultaneously respond to the new information and they are contemporaneously correlated. The more information arrives at the market, the more volume it will create and the more stock prices will tend to fluctuate. MDH implies strong positive contemporaneous relationship between absolute price changes and trading volume.

According to Epps and Epps (1976), there is a positive relationship between the extent of traders disagreement about a security's value (disagreement between buyers and sellers) and the absolute price change. That is an increase in extent to which traders disagree is associated with a larger change in absolute price. The price variability and trading volume relationship arises, because the volume of trading is positively related to the extent to which traders disagree when they revise their reservation prices due to new information. When news reaches the market, some investors interpret it as good while some others interpret it as bad. Those who interpret it as good news buy the stock and those who interpret it as bad news sell the stock. Hence, each individual can be assigned to one of the two groups according to whether he buys or sells. If the disagreement between two groups increases as a result both trading volume and absolute price changes increases. Hence, there is a positive relationship existing between trading volume and absolute price changes.

In MDH equilibrium prices are immediately established and new information is received simultaneously by all the traders. The implication is that with simultaneous information arrival there is no information in the past volume that can be used in forecasting future absolute price changes that are not already contained in the past absolute price changes. Therefore, the mixture distribution hypothesis supports only positive contemporaneous relationship but not the lead-lag relationship between trading volume and absolute price changes.

To support the mixture distribution hypothesis, Clark (1973) finds positive contemporaneous relationship between daily price change variance (as measured by squared price change ΔP^2) and trading volume in corn futures market. Epps and Epps (1976) find positive relation between squared price change and volume for common stocks traded in New York Stock Exchange (NYSE). Tauchen and Pitts (1983) find positive correlation between squared price changes and log volume for the 90-day treasury-bill futures contracts traded at the Chicago Merchantile Exchange. Further support is offered by Harris (1986) who finds a positive correlation between changes in volume (measured as the number of transactions) and change in squared returns for individual stocks in NYSE.

Lamoureux and Lastrapes (1990) have further extended the mixture distribution hypothesis to explain the source of auto regressive conditional hetroscedasticity (ARCH) effects in stock returns. Empirical studies on stock return volatility have found significant evidence of ARCH effects in the volatility of stock returns. But there is little agreement on the sources of these phenomena. One possible theoretical explanation is based on the role of information flows in the market. If current information is related to past information, the current volatility will be related to past volatility. Based on mixture distribution hypothesis (MDH), Lamoureux and Lastrapes (1990) first employed GARCH methodology to investigate the relationship between trading volume and volatility by using daily trading volume as a measure of the information flow in the market. They found that the conditional volatility is positively correlated with trading volume and the autoregressive conditional hetroscedasticity (ARCH) effects disappeared when volume was incorporated in the conditional variance equation of GARCH model. It suggested that trading volume (used as a proxy for the information variable) caused price volatility.

2.5.2: Sequential Information Arrival Hypothesis (SIAH)

The sequential information arrival hypothesis (SIAH) proposed by Copeland (1976) and further discussed by Jennings, Starks and Fellingham (1981) and Simrlock and Starks (1988) assumes that information is disseminated in the market sequentially rather than simultaneously to all the traders. The traders change their trading positions as new information arrives in the market. However, not all traders receive this new information simultaneously at exactly the same point of time. Hence, the trader who observes the information initially, he interprets the news, adapts his expectations and generates transaction volume. Accordingly the price changes and a new temporary equilibrium is achieved. After market arrives at this new temporary equilibrium, the next trader gets informed, adapts his expectations and generates transaction volume, accordingly again market price changes and a new temporary equilibrium is achieved. This process continues till it reaches the final equilibrium. The final equilibrium is established when all traders have received the same information and have made a trading decision based on that information.

SIAH suggests that the gradual dissemination of information means that a series of intermediate equilibria exist before the final equilibrium is established. Below is the process of market reaching its final equilibrium when the information is sequential.

Step 1a: The first trader gets the information.
1b: This trader revises his beliefs and re trades.
1c: The market reaches a new temporary equilibrium.

Step 2a: The second trader gets the information.
2b: This trader revises his beliefs and re trades.
2c: The market reaches a new temporary equilibrium.

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Step Na: The last trader gets the information.
Nb: This trader revises his beliefs and re trades.
Nc: The market reaches the final equilibrium.

This sequential dissemination of information initiates transactions at different price levels during the day, the number of which increases with the rate of information flow to the market. Consequently, both transaction volume and absolute price change increases as the rate of information flow into the market increases which implies the existence of a positive contemporaneous relationship between trading volume and absolute price changes.

Smirlock and Starks (1987) have further extended the hypothesis that as the information comes sequentially rather than simultaneously to all the traders, past values of trading volume may have the ability to predict current absolute price changes or vice versa, which means that a causal relationship may exist between absolute price changes and trading volume. For empirical support, they investigated the causal relationship between trading volume and absolute stock price changes for a large sample of 300 firms in New York stock market and found the evidence that there was a significant causal relationship exist between trading volume and absolute stock price changes at the firm level, suggesting that information arrival follows a sequential rather than a simultaneous process.

Saatcioglu and Starks (1998) in support of the sequential arrival information hypothesis (SIAH), find both positive contemporaneous as well as causal relationship between price changes and trading volume in four of six Latin American markets.

Hence, MDH supports only a positive contemporaneous relationship between absolute stock price changes and trading volume whereas SIAH suggests both contemporaneous as well as lead-lag relationship between absolute stock price changes and trading volume.

In line with sequential information arrival hypothesis (SIAH), several studies have found both positive contemporaneous and causal relationship between price changes and trading volume, these include: Saatciogul and Starks (1998), Ciner (2002), Mcmillan and Speight (2002), Ciner (2003), Fan, Groenewold and Wu (2003), Chen, Firth and Xin (2004), Kamath (2007), Kamath (2008), Medeiros (2008), Khan and Rizwan (2008), Deo, Srinivaasan and Devanadhen (2008), Kumar and Singh (2009), Mahajan and Singh (2009), Sinha and Soni (2011), Ansary and Atuea (2012), Chuang, Liu and Susmel (2012), Darwish (2012), Al-Jafari and Tliti (2013), Attari, Rafiq and Awan (2013), Choi and Kang (2013) and He and Xie (2014).

2.6: The Role of Lagged Volume and Volatility

Wang (2004) developed a model to derive dynamic volume-volatility relation by assuming that there are two kinds of traders present in the market, one of them was referred to as informed traders and other as liquidity traders. The informed traders use information such as macroeconomic information, firm specific information, trading information, etc. as a tool for their investment purpose, where as liquidity traders trade only at the time of liquidity requirement for several reasons like investment opportunity outside the stock market or any other personal commitments or any contingent requirements. Based on these two types of traders, Wang developed the concept of liquidity-driven trading (LDT) and information-driven trading (IDT) to derive the theoretical explanation for lagged relationship between volume and volatility.

2.6.1: Liquidity Driven Trading (LDT)

When liquidity traders sell their stocks, others who are ready to buy those stocks need a compensation for their own loss of liquidity. This compensation is achieved in the form of lower current price and higher future returns. If market price drops below its fundamental value due to liquidly demand, then it will be corrected immediately in the next period and thus come back to the equilibrium level again. Owing to liquidity demand, the price movements in the two successive periods are in opposite direction (price fall in current period and in the subsequent period it will rise to come back to the previous level). Thus, higher liquidity demand in any period, through liquidity-driven trading, causes higher volatility in the subsequent period. Higher liquidity demand (requiring a higher compensation to be made), is followed first by a lowering of price followed by the price rising back to equilibrium level and thus, it leads to a higher volatility in the subsequent period. Likewise, the lower liquidity demand is followed by a lower compensation and lower volatility in the following period. Therefore, we expected to observe a positive relationship between current trading volume and subsequent volatility.

Wang and Huang (2012) also explained this relationship with the help of a numerical example. Assume that there is no information currently available in the market. The current market price is 100 and the current volatility is 0. When there exists only liquidity trading, the current price drops to 98 and the subsequent price returns to 100 (results a liquidity compensation equals 2). The volatility in the subsequent period rises from zero to (2/98). Suppose the current liquidity demand is stronger, we except a sharper drop say to 96 and the subsequent price returns to 100 (results a liquidity compensation equals 4). The subsequent period's volatility rises to a still higher level of 4/96, which is greater than 2/98.

2.6.2: Information Driven Trading (IDT)

When informed investors trade due to better private information, that information will spread in the market through a price signal. For example, informed investors buy a stock when they have favorable private information and the stock price increases. Other investors observe it and buy the stock afterwards as a result of price rise. Since this information is partially incorporated in the stock price at the beginning, the positive price changes in the current period will be followed by another positive price change in the next period. Since price movements in these two successive periods are in the same direction, the volatility is lower. The higher the information flows in the current period (higher volume), the lower will be the change in price in the subsequent period (lower volatility) Therefore, we expect to observe a negative correlation between current trading volume and subsequent volatility.

Wang and Huang (2012) also explained this relationship with the help of a numerical example. Assume that there is no information flow currently in the market. The current stock price is 100 and the current price volatility is 0. Suppose, new information arrives and some investors get informed. As the information is not fully reveled in the beginning, the stock price will eventually rise to 104. If less information is revealed in the current period, the price change will be less in the current period say, 102 and in the subsequent period it moves to 104. The subsequent price volatility will be (2/102). In contrary, if more information is revealed in the current period, the more will be price changes in the current period, say 103 and in the subsequent period it moves to 104. The subsequent price volatility will be (1/103) which is less than (2/102). In terms of volatility it is less.

2.7: Arrival of New Information and the Relationship between Bid-Ask Spread and Price Changes

Research on market microstructure also focused in explaining and exploring bid-ask spread and its relationship with price changes and volatility. Richardson (2000) argues that as firm-specific information has not been publicly disclosed by the firm, the withheld information may be privately available to select investors who invest in costly information acquisition. Due to information uncertainty, market traders increase bid-ask spread to offset the potential losses of trading with informed traders. Therefore, over the period, when the possibility of firm-specific information exists and that information is not completely disclosed, bid-ask spread can be used as proxy for the information asymmetry.

Similarly, Copeland and Galai (1983) and Glosten and Milgrom (1985) explained the bid-ask price behaviour where participants in market are heterogeneously informed (some investors are informed and others are not). There is always risk for uninformed investors to face informed investors in the market who trade by private information. The risk neutral traders fix optimal bid-ask spreads in the market to balance expected gains from the liquidity traders who are equally informed, with potential losses to traders who are better informed. The bid-ask spread widens in the market when risk neutral traders think they are facing greater information uncertainty. They observed larger bid-ask spreads before the advent of the first information event due to greater price uncertainty. They also observed that immediately after each information event, the bid-ask spread widens due to increase in the percentage of informed traders in the market.

Rahman et al. (2002) documented that intraday variations of bid-ask spread and intraday return volatility are expected to be positively correlated because an information arrival is supposed to stimulate an increase in volatility which in turn widens the bid-ask spread.

In line with the microstructure theory, some recent studies also empirically examined the relationship between return volatility and bid-ask spread. Such studies include Hartmann (1998), Wang and Yau (2000), Rahman et al. (2002), and Hussain (2011). They found a significant positive relationship between return volatility and bid-ask spread, suggesting higher spread is associated with rising volatility.

2.8: Summary

This chapter briefly introduces the mixture distribution hypothesis (MDH) and sequential information arrival hypothesis (SIAH) for explaining the arrival of new information and the price-volume relation. MDH assumes simultaneous information arrival whereas SIAH suggests sequential information arrival. Basing on simultaneous information arrival, MDH suggests a positive contemporaneous relationship between trading volume and price changes whereas, sequential information arrival hypothesis suggests a positive contemporaneous as well as a causal relationship between trading volume and price changes. Similarly, theoretical models on bid-ask spread explains that higher information uncertainty leads to higher bid-ask spread and higher price changes.

Chapter 3

Stock Returns, Trading Volume and Bid-Ask Spread

3.1: Introduction

In market microstructure literature, a considerable attention has been paid over some period of time to understand the price-volume relationship. For providing insight into the structure of financial markets such as the rate of information flow to the market and the dissemination of the information, the role of price-volume relationship stands important. The relationship between price and volume can be used to examine the usefulness of the technical analysis. The empirical price-volume relationship is developed basing on two major underlined hypotheses: Mixture Distribution Hypothesis (MDH) of Clark (1973), Epps and Epps (1976), Tauchen and Pitts (1983) and Harris (1986) and the Sequential Information Arrival Hypothesis (SIAH) of Copeland (1976), Jennings, Starks and Fellingham (1981) and Simrlock and Starks (1988). Both the hypotheses suggest a positive contemporaneous relationship between absolute price changes and trading volume however, SIAH additionally also suggests a causal relationship between absolute price changes and trading volume.

The researchers in this area have examined the volume-return relationship in a variety of contexts by employing a range of analytical methods. A good number of extensive and empirical studies are there that support the positive contemporaneous relationship between returns/ absolute returns and trading volume including Jain and Joh (1988), Brailsford (1994), Saatcioglu and Starks (1998), Ciner (2002), Mcmillan and Speight (2002), Lee and Rui (2002), Fan, Groenewold and Wu (2003), Cetin (2003), Chen, Firth and Xin (2004), Tambi (2005), Kamath and Wang (2006), Kamath (2007), Khan and Rizwan (2008), Medeiros (2008), Deo, Srinivasan and Devanadhen (2008), Kamath (2008), Kumar and Singh (2009), Mahajan and Singh (2009), Thammasiri (2010), Sinha and Soni (2011), Mehrabanpoor, Bahador and Jandaghi (2011), Darwish (2012), Chuang, Liu and Susmel (2012), Ansary and Atuea (2012), Attari, Rafiq and Awan (2013), Al-Jafari and Tliti (2013) and He and Xie (2014).

In the recent studies, the focus has moved to causal (dynamic) relationship between price changes and trading volume. That means that the recent studies have started to examine the causal relation by asking questions such as, “does trading volume help forecast stock returns” or “do investors trade more when stock prices go up?” The studies of Saatcioglu and Starks (1998) in Latin America, Ciner (2002) in Japan, Ciner (2003) in US and France, Pisedtasalasai and Gunasekarage (2005) in Singapore, Leon (2007) in West Africa, Medeiros (2008) in Brazil, Ansary and Atuea (2012) in Egypt, He and Xie (2014) in China are some of those recent studies. Moreover, most of these studies assume that volume is a proxy for information arrival to the market. It is found that the information content of volume and sequential processing of information may lead to dynamic relationship between returns and trading volume.

One of the key findings of the previous research has been a positive correlation between trading volume and stock price changes. Some of these attempts have been concerned with the asymmetry of such a relation. The question is: do falling stock markets affect trading volume in a significantly different way in contrast to rising stock markets? A general view is that any given quantum of price change causes a higher level of trading volume in a rising stock market compared to the same quantum of absolute price change in a declining stock market. Market folklore claims that the relationship between trading volume and price movements depends on whether the market has a bull or a bear run. The bulls are more optimistic about the assets value and they respond only to positive information. On the other hand, the bears are more pessimistic about the assets value and respond only to negative information. Jennings et al (1981) state that usually the trading volume is more when the investor is an optimist than pessimist. Since the prices increase with an optimistic buyer and they decrease with a pessimistic seller, it follows that the trading volume is high when price increases and low when price decreases.

Brailsford (1994) opines that the presence of short selling component leads to asymmetric volume-price relationship. Short selling can only be initiated on a zero or up ticks (i.e. on non-negative price changes) whereby the sell price is at least equal to the last transaction price of the stock. Hence, there is a possibility of less number of traders in the market on down ticks (i.e. on negative price changes) than on zero or up ticks (i.e. on non-negative price changes) because of the restriction on short selling. Therefore, we may expect higher average volume on non-negative returns than negative returns.

There are several studies that have attempted to trace the asymmetric behaviour in stock market. However, only a small number of studies confirmed this. Ying (1966) found the earliest evidence in New York Stock Exchange (NYSE). Brailsford (1994) provided evidence that price-volume relationship associated with a positive return is higher than associated with a negative return. Mohamad and Nassir (1995) investigated the cases of the Malaysian stock market, and found the evidence that trading volume associated with a rising price is, on average, higher than the trading volume associated with a falling price. Moosa et al. (2003) detected the presence of temporal asymmetry in the relationship between volume and price in the crude oil futures market. Al-Deehani (2007) found that higher trading volume is associated more with positive price change rather than with negative price change for eight different stock markets: US, UK, France, Spain, Japan, Hong Kong, South Korea and Canada. Sadd (2004) and Saad and Moosa (2008) provided evidence in the emerging market of Kuwait that volume tends to be higher in a rising market than in a falling market.

A few researchers have also examined the role of bid-ask spread on price changes by assuming bid-ask spread as a proxy for information arrival in the market. Studies like McGroarty, Gwilym and Thomas (2009) and Hussain (2011) find positive relationship between bid-ask spread and absolute price changes.

Several studies have been made, both empirically and theoretically, on the phenomenon of stock return and volume relationship. Even though the majority of those findings have confirmed the existence of positive contemporaneous relationship between trading volume and stock returns, the study of different stock markets has given mixed results about the causal return-volume relationship. Similarly in the context of India, there are a few studies that have focused on return-volume relationship. These includes: Tambi (2005), Deo, Srinivasan and Devanadhen (2008), Mahajan and Singh (2009), Kumar and Singh (2009), Tripathy (2011), Sinha and Soni (2011). Except Tripathy (2011), all these studies find positive contemporaneous relationship between returns/absolute returns and trading volume. However the causal relationship is still not clearly established. Deo, Srinivasan and Devanadhen (2008), Mahajan and Singh (2009) and Sinha and Soni (2011) find strong evidence of return causing volume, Tambi (2005) find volume causing return, whereas, Tripathy (2011) find no causal linkages between returns and trading volume. Kumar and Singh (2009) find returns cause volume and that the volume also causes returns albeit to a lesser extent. Interestingly enough, none of the studies have focused on intraday relationship. Similarly, return-spread relationship is also not explored widely and in Indian context no study is done so far. Hence, there is a room left for further study. To fill this gap, the current study empirically investigate the intraday contemporaneous and the causal relationship between stock return and trading volume as well as between stock return and bid-ask spread for a list of 50 stocks listed in S&P CNX NIFTY 50 index of National Stock Exchange, India.

3.2: Review of Literature

Smirlock and Starks (1987) investigated the causal relationship between trading volume and absolute stock price changes in New York stock market for the sample period of 49 trading days from 15th June to 21st August 1981. This was the first kind of study covering a large number of 300 firms in S&P 500 index. By using Granger causality test they found that there was a significant causal relationship exist between trading volume and absolute stock price changes at the firm level. Trading volume causes absolute price changes in 49% of cases whereas absolute price changes cause trading volume in 40% of cases. Their findings seemed to indicate that information arrival to investors tend to follow a sequential rather than instantaneous process.

Jain and Joh (1988) investigated an hourly volume-price relationship in New York Stock Exchanges (NYSE) during 1979-83 and provided evidence of a positive contemporaneous relation between trading volume and absolute returns. The Granger causality test result shows that return granger causing volume within 4 hours. They also found an asymmetric relation between trading volume and returns, suggesting stronger correlation between trading volume and returns for a rising market than a declining market.

Brailsford (1994) empirically examined the contemporaneous and asymmetric relation between stock returns and trading volume in the Australian market for the sample period of 24th April 1989 to 31st December 1993. A positive contemporaneous relationship is established between trading volume and absolute value of returns. The study also found evidence of an asymmetric relationship between trading volume and price changes, suggesting that the price-volume relationship for positive returns is stronger than for negative returns.

Mohamad and Nassir (1995) empirically examined the contemporaneous, asymmetric and causal relationship between price changes and trading volume in the Kula Lumpur Stock Exchange for the sample period from January 1985 to December 1992. The findings suggested that absolute change in price and trading volume are positively correlated. The causality test showed that price changes cause volume not vice versa. They also found an asymmetric relation between price changes and volume, suggesting trading volume associated with a positive price change, on average larger than the trading volume associated with a negative price change.

Moosa and Al-Loughani (1995) empirically examined the price-volume relationship by using monthly data for four Asian markets: Thailand, Malaysia, Singapore and the Philippines. The sample roughly covers the period January 1986 to December 1993 with some variations for individual countries. They found strong evidence of causal relationship running from trading volume to absolute price changes and from price changes to trading volume in the case of Thailand, Singapore and Malaysia and their result shows no causal relationship for Philippines. This finding is theoretically conceivable as information contents of trading volume leads to price changes and large positive price change means higher capital gains which encourage transactions and increase in volume. Furthermore, this evidence is in favor of the hypothesis of sequential information.

Saatcioglu & Starks (1998) investigated the contemporaneous and dynamic relationship between monthly stock returns and trading volume in a set of six Latin American Markets i.e. Brazil, Colombia, Argentina, Chile, Venezuela and Mexico over the period from January, 1986 to April, 1995. They found positive significant contemporaneous relationship between returns and trading volume for all the markets except Mexico and also they found positive significant contemporaneous relationship between absolute returns and trading volume for all the markets except Brazil. In the markets of Brazil, Colombia, Mexico and Venezuela, they found evidence of volume Granger causing returns, in case of Chile, Colombia and Venezuela returns Granger causing volume and in case of Brazil no causality traced.

Moosa and Silvapulle (2000) empirically examined the daily price–volume relationship in the crude oil futures market of the West Texas Intermediate (WTI) covering the period from 2nd January, 1985 to 11th July, 1996. Both linear and nonlinear causality test employed to test the dynamic relationship between trading volume and price changes. The results of the linear causality test revealed the presence of unidirectional causality running from volume to return. While the nonlinear causality test showed a feedback causal relationship between volume and return. Their findings support the sequential information arrival hypothesis (SIAH).

Ciner (2002) empirically examined the relationship between daily return and volume for three commodity futures contracts i.e. gold, rubber and platinum traded on the Tokyo commodity futures market (TOCOM), between 4th January, 1992 and 29th September, 2000. The findings show a positive contemporaneous relationship between absolute returns and trading volume. The relationship is not fully contemporaneous since the lagged volume contains useful information for predicting absolute return. The study also investigates the causal relationship between return per se and trading volume by means of granger causality test and found unidirectional causality running from returns to volume.

Lee and Rui (2002) examined the contemporaneous and the dynamic relationship between daily index returns and trading volume for three developed markets: New York, London and Tokyo. The study covers the period of 1973-99 for New York, 1986-99 for London and 1974-99 for Tokyo and. They found evidence of a positive contemporaneous relationship between stock returns and trading volume in all the three stock markets whereas Granger causality test results revealed that there was no causal relationship existing between stock returns and trading volume in either direction.

Mcmillan and Speight (2002) empirically examined the contemporaneous as well as dynamic relationship between returns and trading volume for FTSE-100 index in UK futures market. They used five-minutes, fifteen-minutes, thirty-minutes, sixty-minutes, half day and full day data set over the period from 24th January 1992 to 30th June 1995. The study conducted both for return per se and absolute value of returns. By using correlation analysis, they found positive and statistically significant contemporaneous relationship between absolute returns and trading volume for all the time intervals. They also found a bi-directional causality between absolute returns and trading volume for most of the time frequencies, consistent with sequential information hypothesis. They also investigated the contemporaneous and causal relationship between return per se and trading volume. For most of the time frequencies they did not establish any contemporaneous correlation between returns per se and trading volume whereas, their study found unidirectional causal relationship running from returns to volume only for half day and full day time intervals.

Fan, Groenewold and Wu (2003) empirically examined the contemporaneous and causal relationship between returns and trading volume for two Chinese indices and ten individual stocks in the energy sector using daily data between 1st January, 1997 and 31st December, 2002. They found a positive contemporaneous relationship between returns and trading volume as well as between absolute returns and trading volume for all the 10 individual shares and two Chinese indices. By using Granger causality test, they found a bi-directional causal relationship between returns and trading volume for both the indices as well as for 4 individual stocks and for remaining 6 stocks they found unidirectional causality from return to volume.

Ciner (2003) investigated the contemporaneous and causal relationship between price changes and trading volume for S&P 600 index of US and for NM index of France. The data covered the sample period from 16th August, 1995 to 25th April, 2002 for S&P 600 and from 2nd January, 1998 to 31st August, 2000 for NM index. The findings indicated a positive contemporaneous relationship between absolute value of returns and trading volume for both the markets. The study also investigated the information content of volume for future returns using linear and non linear causality test. Granger causality test suggested that lagged volume had predictive power for subsequent returns for both the markets.

Moosa et al (2003) investigated the temporal asymmetry in the price-volume relationship in the crude oil futures market of the West Texas Intermediate (WTI) by using daily data from 2nd February, 1985 to 23rd September, 1996. They found asymmetry in opposite direction, as negative price and volume changes have stronger effects than positive price.

Saad (2004) scrutinised the asymmetric relationship between price changes and trading volume for 10 individual stocks traded in the Kuwaiti Stock Exchange. The study was conducted for the period from October 1992 to September 1998 by using daily stock prices and volume. The findings indicated that there was a strong evidence of an asymmetrical relationship between trading volume and price changes, suggesting that the average trading volume is higher in a rising market than a declining market.

Chen, Firth and Xin (2004) empirically investigated the relationship between returns and trading volume for four most heavily traded commodity futures contracts in China. The sample period varied between 1996 and 2002. Both correlation analysis and Granger causality tests were used to study the contemporaneous and causal relationship between trading volume and both signed and absolute return. Though they did not find any significant correlation between returns and trading volume, they found a significant positive relationship between absolute returns and trading volume for all the four contracts. The granger causality test showed no causal relationship between returns and trading volume whereas a significant causal relationship was established from absolute returns to trading volume for all the four contacts. Their findings contradicted (MDH) and supported (SIAH).

Tambi (2005) empirically investigated the contemporaneous as well as lead-lag relationship between stock returns and trading volume for NSE-NIFTY 50 stocks during the period from April 2000 to March 2005. He found the evidence of positive significant contemporaneous relationship between stock returns and trading volume. However, the granger causality test result provided strong evidence of volume causing returns.

Gurgul et al. (2005) examined the contemporaneous and causal price-volume relationship in Polish stock market over the period of 11 years from 1995-2005. They found a positive contemporaneous relationship between stock price changes and trading volume. The

Granger causality test result showed that return granger causing volume not volume granger causing return.

Gunduz and Hatemi-J (2005) empirically examined the causal relationship between weekly stock returns and trading volume for five stock markets i.e. Turkey, Czech Republic, Hungary, Poland and Russia. The sample data approximately covers the period 1988-2002 with some changes for individual countries. They found a bi-directional causality between stock returns and trading volume in case of Hungary and Poland and a unidirectional causality from stock returns to trading volume in case of Russia and Turkey, but there was no causal relationship established in case of Czech Republic.

Pisedtasalasai and Gunasekarage (2005) made a scrutiny of the causal and dynamic relationship between daily trading volume and index returns for five emerging stock markets in South East Asia i.e. Singapore, Indonesia, Thailand, Malaysia and The Philippines. The sample data approximately covers the period 1990-2004 with some changes for individual countries. The study used the Granger causality test, variance decomposition (VD) and impulse response function (IRF) to trace the causal relationship between index returns and trading volume. The Granger causality test results indicated a statistically significant causality running from index returns to trading volume in case of Indonesia, Thailand, Singapore and Malaysia. On the other hand, a statistically significant causal relation from trading volume to index returns was established only for Singapore. Both variance decomposition (VDC) and impulse response function (IRF) supports the Granger causality test that trading volume is influenced by index return rather than index return is influenced by trading volume.

Kamath and Wang (2006) empirically investigated the contemporaneous and causal relationship between stock returns and trading volume on the stock market indices of six developing markets from Asia i.e. Indonesia, Malaysia, South Korea, Hong Kong, Taiwan and Singapore over the period from December 2002 to October 2005. They found a positive contemporaneous relationship between index returns and trading volume as well as between absolute index returns and trading volume. No causal relationship is established between index returns and trading volume in case of four out of six countries i.e. Indonesia, Malaysia, Hong Kong and Singapore. However, they found evidence of causal relationship running from index returns to trading volume in the South Korean market and a completely opposite direction of causality running from trading volume to index returns in the Taiwan stock market.

Al-Deehani (2007) investigated price-volume asymmetry in nine stock market indices in eight different countries i.e. US, UK, Spain ,France, Canada, Japan, Hong Kong and South Korea and. The study found an asymmetric relationship between price changes and transaction volume for all the markets except S&P 500 index. The results indicate that average volume is higher with price increase rather than with price decrease.

Assogbavi et al. (2007) investigated the weekly price-volume relationship of individual stocks in the Russian stock market over the period from 1997 to 2005. They found weak significant positive contemporaneous correlation between absolute returns and volume. A reason for this weak support of positive contemporaneous relationship may be information flows sequentially instead of instantaneously in the Russian market. The Granger causality test results provided evidence of bi-directional causal relationship between stock returns and trading volume which indicated that price changes adjusted to lag volume over a week time interval and that volume also adjusted to lag stock price changes over the same time interval. They gave an explanation for such a finding that most traders in the markets are late in the informational queue and they trade only some times after information reach the market. In general, arrival of new information in the market is likely to be sequential rather than instantaneous. The study also found absence of asymmetric relationship between stock price changes and trading volume. This shows that volume associated with positive price changes is not statistically different from negative price changes.

Leon (2007) studied the causal relationship between absolute returns and trading volume using the daily data over the period from 2nd January 2002 to 29th July 2005 in the regional stock exchange of BRVM. This study conducted Granger causality test between absolute returns and trading volume and found a causal relationship from trading volume to absolute stock returns and not vice versa. This causality test results supported the sequential information hypothesis.

Kamath (2007) empirically investigated the contemporaneous and causal relationship between daily index returns and trading volume changes in Turkish stock market for the period of forty-months from January 2003 to April 2006. This study found that contemporaneous change in volume is positively related with returns as well as absolute returns. The Granger causality result revealed bidirectional causal relationship between daily index returns and daily volume changes.

Floors and Vogues (2007) examined the contemporaneous relationship between returns and trading volume in Greek stock futures market for FTSE/ASE-20 and FTSE/ASE-40 index over the period from 1999 to 2001. However, they did not establish a significant positive contemporaneous relationship between returns and trading volumes as well as between absolute returns and trading volume.

Deo, Srinivasan and Devanadhen (2008) empirically investigated the relationship between index returns and trading volume for seven Asian stock markets i.e., Hong Kong, India, Malaysia, Indonesia, Tokyo, Korea and Taiwan. The study was conducted using daily index price and trading volume for the period from 1 January, 2004 to 31, March 2008. A positive contemporaneous relationship was established between index returns and trading volume in case of Indonesia and Taiwan market whereas a negative relationship was established in case of India. But, there was no contemporaneous relationship established between index returns and trading volume in case of Hong Kong, Malaysia, Korea and Tokyo. In addition, for all the markets they found a positive contemporaneous relationship between absolute returns and trading volume. The Granger causality result revealed that return granger causing volume for all the markets and also volume granger causing return in case of four markets out of seven i.e. Hong Kong, Indonesia, Malaysia and Taiwan. In case of India, Korea and Tokyo past volume does not add any significant predictive power for future returns. Overall the evidence shows stronger causal effect from returns to volume than volume to returns.

Khan and Rizwan (2008) empirically investigated the contemporaneous and causal relationship between daily stock returns and trading volume in Pakistan’s stock market during the period from January 2001 to May 2007. Their study found the evidence of a positive significant contemporaneous relationship between stock returns and trading volume. By using both the Granger causality test and the Vector Auto Regression Model (VAR), the study found a feedback relationship between stock returns and trading volume in Pakistan market.

Kamath (2008) investigated a contemporaneous, asymmetric and dynamic relationship between stock returns and daily trading volume changes in Chilean stock market from January, 2003 to October, 2006. A positive significant contemporaneous relationship was established between stock returns and change in volume. Similarly, the study also found a positive significant contemporaneous relationship between absolute returns and change in volume. By using Granger causality test the study found a unidirectional causal relationship from returns to trading volume changes. This study also provide evidence of an asymmetric relationship between returns and trading volume, suggesting higher volume is associated with a given level price changes in a bull market than a bear market.

Medeiros (2008) empirically investigated the relationship between daily stock returns and trading volume in Brazilian stock market for the period from 3rd January 2003 to 29th December 2005. Both cross-correlation analysis and Granger-causality test were performed to check contemporaneous as well as dynamic relationship between stock returns and trading volume. The cross correlation analysis revealed that the stock return was positively correlated with volume and negatively correlated with lagged volume. Similarly, the Granger causality test showed a unidirectional causal relationship running from trading volume to return in Brazilian stock market.

Saad and Moosa (2008) investigated the price-volume asymmetry in a sample of 36 stocks traded in the Kuwait Stock Exchange by using daily data of closing prices and trading volumes for the period from January 1995 to September 2002. For all the 36 stocks in the sample they found evidence for an asymmetric relation, whereby trading volume is higher when prices rise than when prices fall.

Kumar and Singh (2009) empirically scrutinised the contemporaneous, asymmetric and causal relationship between stock returns and trading volume for NSE Nifty-50 stocks in Indian stock market by using daily data over the period from 2001 to 2008. A positive significant contemporaneous relationship established between absolute value of returns and trading volume in Indian stock markets. The study found stock returns granger cause volume in case of 30 stocks and volume also granger causes stock returns in case of 10 stocks. Overall granger causality results indicated that stock return causes volume and volume also causes stock return albeit to a lesser extent. They also checked the asymmetric behavior of stock returns and trading volume. They looked at whether higher volume was associated with a given price change in a bull market than a bear market. Their findings were mixed in some cases asymmetric behavior traced and some other cases; they did not find any asymmetric relationship between volume and return. Their findings were consistent with the findings of Assogbavi (2007) where it clearly indicated the absence of asymmetric relationship in emerging market.

Mahajan and Singh (2009) empirically examined the contemporaneous and causal relationship between daily index returns and trading volume in Indian stock market (SENSEX) over the sample period from Oct 1996 to Mar 2006. Using cross correlation analysis they found a positive significant contemporaneous correlation between trading volume and index returns and using Granger causality test they found unidirectional causal relationship running from index returns to trading volume.

Mcgroarty, Gwilym and Thomas (2009) empirically investigated the relationship between trading volume, bid-ask spread and absolute returns for 5 foreign exchange spot markets by using 5 minutes interval data set over the period from 1st August 1998 to 4th September 1998 and 1st August 1999 to 3rd September 1999. The contemporaneous relationship examined through correlation coefficients for 5 exchange rates. They found a statistically significant positive but small correlation in between spread and absolute return for 4 out of 5 exchange rates. The average correlation coefficient between bid-ask spread and absolute return are 5%. Similarly, the relationship between volume and absolute return is positive for all the exchange rates. The average correlation coefficient between volume and absolute returns are 16%, which is small but comparatively higher than spread.

Thammasiri (2010) empirically investigated the return-volume relationship of SET50 futures contract traded on TFEX market by using daily closing price and trading volume from April 2006 to December 2008. The study found evidence of a positive significant contemporaneous relationship between returns and trading volume whereas the Granger causality test confirms no causal relationship between them in either direction. Similarly, the study also looks at the relationship between absolute value of returns and trading volume and found a positive contemporaneous relationship as well as bidirectional causality between absolute returns and trading volume. The findings of both the contemporaneous as well as causal relationship between absolute value of returns and trading volume support the Sequential Information Arrival Hypothesis (SIAH) and imply some degree of market inefficiency.

Hussain (2011) empirically examines the intraday relationship between trading volume, bid-ask spread and return volatility for DAX-30 index of Germany for the period from 5th May 2004 to 29th September 2005. In the first step the cross correlation analysis between absolute return, volume and spread indicate a positive contemporaneous relationship between absolute return and volume, and absolute return and spread. However the study found relatively small contemporaneous relationship between absolute returns and spread.

Carl and Muhammad (2011) empirically examined the causal relationship between daily returns and trading volume in Malaysian stock index futures market over the period from 15th December, 1995 to 31st December, 2003. The total period is divided in to four sub periods: a learning period, a recovery period, a crisis period and a stable period. They found causality from trading volume to price index for 3 sub periods for spot contracts whereas for next month contracts no causality was traced.

Sinha and Soni (2011) looked at the daily return-volume dynamics in Indian futures market. They found a positive contemporaneous relationship between volume and absolute return whereas this relationship was established negative in between volume and return per se. The findings of contemporaneous relationship between volume and absolute return were consistent with both mixture of distribution hypothesis (MDH) and sequentially information arrival hypothesis (SIAH). They also found unidirectional causal relationship from return to volume and absolute return to volume. The findings of granger causality test supported the sequentially information arrival hypothesis (SIAH) suggesting that there were several temporary equilibrium before the final informational equilibrium can be reached.

Mehrabanpoor, Bahador and Jandaghi (2011) empirically examined the contemporaneous relationship between monthly index returns and trading volume in Tehran Stock Exchange (TSE) for the sample period from 2003 to 2009. Their study found evidence of a positive significant contemporaneous relationship between index returns and trading volume in Tehran stock market.

Tripathy (2011) investigated the contemporaneous as well as the dynamic relationship between daily index returns and trading volume on BSE-SENSEX for the period from 2005 to 2010. However, the study did not find statistically significant contemporaneous relationship between index returns and trading volume. Granger causality test, variance decomposition (VDC) analysis and impulse response function (IRF) analysis were conducted for this study to trace the causal linkages between index returns and trading volume. However, the results revealed no causal relationship between them.

Darwish (2012) examined the contemporaneous as well as the causal relationship between weekly stock returns and trading volume in Palestine stock market over the sample period from October 2000 to August 2010. Here, both volume and change in volume were considered for the study. The results presented a positive contemporaneous relationship between return and volume for both the measures of volume direct as well as change in volume. The Granger causality test revealed bidirectional causality between trading volume and returns, despite of the measures of trading volume used.

Chuang, Liu and Susmel (2012) empirically examined the contemporaneous and causal relationship between daily trading volume and stock returns for ten Asian markets: Korea, Hong Kong, Japan, Singapore, Thailand, Taiwan, Indonesia, Malaysia, the Philippines and China during the period from 1st January, 1998 to 31st December, 2007. For all the ten Asian markets, they found evidence of a positive significant contemporaneous relationship between stock returns and trading volume. They also found a unidirectional causal relationship running from stock returns to trading volume for eight stock markets and for remaining two markets i.e. China and Taiwan feedback relationship were established.

Ansary and Atuea (2012) studied the contemporaneous and causal relationship between daily stock returns and trading volume in Egyptian stock market for 26 companies listed in EGX30 index over the period from 1st July 2000 to 21st March 2010. They found a positive contemporaneous relationship between stock returns and volume for most of the sample stocks. However, the degree of contemporaneous relationship was weak which indicate presence of noise trading in the Egyptian stock market, and that the Egyptian stock market was informationally inefficient. The result also revealed bidirectional causality between volume and stock returns using two and five days lag period. The causality results are more robust in case of five days lag period than two days, which show the slow response of the Egyptian market to information flow. Their findings also showed Egyptian stock exchange was informationally inefficient as the information arrived to the market sequentially rather than simultaneously and also weak contemporaneous relationship confirms the applicable of Sequential Information Arrival Hypothesis (SIAH) in the Egyptian stock market.

Chen (2012) looked at the contemporaneous and causal relationship between stock returns and trading volume separately for bull market and bear market for S&P 500 price index using monthly data for the period from Feb 1973 to Oct 2008. The study found that index returns and trading volume were negatively correlated in the bear market and positively correlated in the bull market. The study also found causality from index returns to trading volume in both bull and bear markets whereas causality traced from trading volume to index return was established only in bear markets.

Choi and Kang (2013) examined the contemporaneous as well as causal relationship between daily trading volume and stock returns in four Asian markets: China, Korea, Japan and Hong-Kong over the period from 2nd January, 2004 to 28th September, 2012. The study found positive relation between stock returns and trading volume for Korean and Chinese market and negative relation for Hong-Kong and insignificant relation for Japan. It was also found unidirectional causal relationship running from return to volume in case of Japan, Korea and China whereas they found bi-directional causality only for Hong-Kong. Their findings supported the sequential information arrival hypothesis (SIAH) and contradicted with the simultaneous information hypothesis of (MDH).

Attari, Rafiq and Awan (2013) investigated the contemporaneous as well as dynamic relationship between stock returns and trading volume by using weekly data of Karachi

Stock Exchange from January 2000 to March 2012. There, both volume and change in volume were considered in the study. They found a positive statistically significant contemporaneous relationship between stock returns and volume for both the measure of volume direct as well as change in volume. For tracing dynamic relationship, they used the Granger causality test and found bidirectional causality between stock returns and direct volume; though no causal relationship was established between stock returns and change in volume.

Al-Jafari and Tliti (2013) studied the contemporaneous and dynamic relationship between daily stock returns and trading volume in Amman Stock Exchange (ASE) over the period from July 2006 to December 2011. Their study found statistically insignificant but positive contemporaneous relationship between trading volume and return. They used the Granger causality test to trace the causal relationship between return and volume and the result revealed bidirectional causality between trading volume and stock return. They also further conducted variance decomposition (VDC) analysis and impulse response function (IRF) analysis to check the strength of causality between them. The results of both variance decomposition analysis and impulse response function analysis revealed a weak causal relationship between them; however the direction of causality from stock returns to trading volume was stronger than the direction from trading volume to stock returns.

He and Xie (2014) investigated the contemporaneous and causal relationship between daily trading volume and returns in China's agricultural futures market. The study covered the complete histories of these contracts until June 2010. For all the six contracts they found positive contemporaneous relationship between returns and trading volume as well as between absolute returns and trading volume. They found unidirectional causality running from volume to return in case of two futures contract and from return to volume in case of 3 futures contract out of six. And they also found an asymmetric return-volume relationship in China's agricultural futures market that the higher volume is associated with a given level of price changes in bull market than a bear market.

Studies like Wei (1991), Bollerslev and Melvin (1993), Galati (2000), McGroarty, Gwilym and Thomas (2009), Gtifa and Lioune (2013) find positive relationship between exchange rate volatility and bid-ask spread. Likewise, Ding and Chong (1997), Wang and

Yau (2000), Frank and Garcia (2011), Wang, Garcia and Irwin (2014) find positive relationship between return volatility and spread in futures market and Rahman et al. (2002) and Hussain (2011) find positive relationship between return volatility and spread in equity markets.

The findings of the past studies are summarized in the below Table 3.A.

Table 3.A: Empirical Evidence on the Relationship between Trading Volume and Returns/Abs.Returns

Sl. No.	Author(s)	Market	Sample Period	Frequency	Support +Ve Correlation	Support Causality	Volume causes Return/Abs .Return	Return/Abs. Return causes Volume
1	Smirlock and Starks (1987)	US	1981-1981	Daily	-	Yes	49% Cases	40% Cases
2	Jain and Joh (1988)	US	1979-1983	Intraday	Yes	Yes	No	Yes
3	Brailsford (1994)	Australia	1989-1993	Daily	Yes	-	-	-
4	Moosa and Al-Loughani (1995)	Thailand, Malaysia, Singapore &Philippines	1986-1993	Monthly	-	Except Philippines	Singapore, Thailand & Malaysia	Singapore, Thailand& Malaysia
5	Mohamad and Nassir (1995)	Malaysia	1985-1992	Daily	Yes	Yes	No	Yes
6	Saatcioglu and Starks (1998)	Argentina, Chile, Brazil, Mexico, Colombia, & Venezuela	1986-1995	Monthly	Except Brazil	Except Brazil	Brazil, Mexico, Colombia, & Venezuela	Colombia, Chile & Venezuela
7	Moosa and Silvapulle (1999)	West Texas Intermediate (WTI)	1985-1996	Daily	-	Yes	Yes	Yes
8	Ciner (2002)	Tokyo	1992-2000	Daily	Yes	Yes	Yes	Yes
9	Ciner (2003)	US & France	1995-2002 1998-2001	Daily	Yes	Yes	US & France	France
10	Lee and Rui (2002)	Tokyo, New York & London	1973-1999 1994-1999 1986-1999	Daily	Yes	No	No	No
11	Mcmillan & Speight (2002)	UK	1992-1995	Intraday	Yes	Yes	Yes	Yes
12	Fan, Groenewold and Wu (2003)	China	1997-2002	Daily	Yes	Yes	2 Index & 4 Stocks	2 Index & 10 Stocks
13	Chen, Firth and Xin (2004)	China	1996-2002	Daily	Yes	Yes	No	Yes
14	Tambi (2005)	India	2000-2005	Daily	Yes	Yes	Yes	No

15	Gurgul et al.(2005)	Polish	1995-2005	Daily	Yes	Yes	No	Yes
16	Gunduz and Hatemi-J (2005)	Poland, Turkey, Hungary, Russia & Czech Republic	1988-2002	Weekly	-	Except Czech Republic	Poland, Hungary	Poland, Russia, Hungary & Turkey
17	Pisedtasalasai and Gunasekarage (2005)	Singapore, Indonesia, Malaysia Thailand and The Philippines,	1990-2004	Daily	-	Except Philippines	Singapore	Singapore, Malaysia, Indonesia, & Thailand
18	Kamath and Wang(2006)	Six Asian Markets	2002-2005	Daily	Yes	Only for South Korea & Taiwan	South Korea	Taiwan
19	Assogbavi et al (2007)	Russian Market	1997-2005	Weekly	Yes	Yes	Yes	Yes
20	Leon (2007)	West Africa	2002-2005	Daily	-	Yes	Yes	No
21	Kamath (2007)	Turkish	2003-2006	Daily	Yes	Yes	Yes	Yes
22	Floors and Vogues (2007)	Greek	1999-2001	Daily	No	-		
23	Deo, Srinivasan and Devanadhen (2008)	India, Indonesia, Hong Kong, Korea, Malaysia, Tokyo and Taiwan	2004-2008	Daily	Yes	Yes	Indonesia. Hong Kong, Malaysia and Taiwan	India, Indonesia, Hong Kong, Malaysia, Tokyo, Korea and Taiwan
24	Khan and Rizwan (2008)	Pakistan	2001-2007	Daily	Yes	Yes	Yes	Yes
25	Kamath (2008)	Chille	2003-2006	Daily	Yes	Yes	No	Yes
26	Medeiros (2008)	Brazill	2003-2005	Daily	Yes	Yes	Yes	No
27	Kumar and Singh (2009)	India	2001-2008	Daily	Yes	Yes	weak	strong
28	Mahajan and Singh (2009)	India	1996-2006	Daily	Yes	Yes	No	Yes
29	Thammasiri (2010)	Thailand	2006-2008	Daily	Yes	Yes	Yes	Yes
30	Hussain (2011)	German	2004-2005	Intraday	Yes	-	-	-
31	Carl and Muhammad (2011)	Malaysia	1995-2003	Daily	-	Yes	Yes	No
32	Sinha and Soni (2011)	India	NA	Daily	Yes	Yes	No	Yes
33	Mehrabanpoor, Bahador and Jandaghi (2011)	Tehran	2003-2009	Daily	Yes	-	-	-
34	Tripathy (2011)	India	2005-2010	Daily	Yes	No	No	No
35	Darwish (2012)	Palestine	2000-2010	Daily	Yes	Yes	Yes	Yes

36	Chuang, Liu and Susmel (2012)	Hong Kong, Korea, Taiwan, Japan, China, Indonesia, Singapore, Malaysia, Thailand and the Philippines	1998-2007	Daily	Yes	Yes	Taiwan & China	For all the markets
37	Ansary and Atuea (2012)	Egypt	2001-2010	Daily	Yes	Yes	Yes	Yes
38	Chen (2012)	US	1973-2008	Daily	-	Yes	No	Yes
39	Choi and Kang (2013)	Korea, China, Japan, & Hong-Kong	2004-2012	Daily	Korea & China	Yes	Hong-Kong	Korea, China, Japan, & Hong-Kong
40	Attari, Rafiq and Awan (2013)	Pakistan	2000-2012	Weekly	Yes	Yes	Yes	Yes
41	Al-Jafari and Tliti (2013)	Amman Stock Exchange	2006-2011	Daily	Yes	Yes	Yes	Yes
42	He and Xie (2014)	China	up to 2010	Daily	Yes	Yes	2 Cases out of 6	3 Cases out of 6

3.3: Objectives of the Chapter

On the basis of the above outlined theoretical background and issues, the following two objectives are empirically investigated in this chapter.

1. To examine the intraday contemporaneous as well as causal relationship between stock returns, trading volume and bid-ask spread.
2. To investigate whether return-volume relation is different for a rising market than that for a declining market.

3.4: Data, Variables and Methodology

3.4.1: Data

The present objective has been empirically investigated by using high frequency 5 minutes interval data set of last trading price (LTP), bid price, ask price and volume for all the 50 stocks of S&P CNX Nifty Index, India during the period of 2nd July, 2012 to 31st December, 2012.

3.4.2: Description of Variables

Stock return, bid-ask spread and trading volume are relevant for this part of this study. The stock return is calculated by the following formula:

$$R_t = \log\left(\frac{P_t}{P_{t-1}}\right) * 100$$

Where R_t represents the stock return, P_t represents current 5 minutes interval trading price and P_{t-1} is the trading price for immediately preceding five minutes interval.

$|R_t| = \text{Absolute value of stock return}$

The proportionate bid-ask spread have been calculated by the following formula:

$$S = \frac{Ask - Bid}{(Ask + Bid)/2}$$

Where S represents proportionate bid-ask spread, ask price is the minimum selling price and bid price is the maximum buying price. Studies like, Wei (1991), Abhyankar et al. (1997), Kyaw and Hiller (2011) and Hussain (2011) used proportionate bid-ask spread in their study to find the relationship between return volatility and spread.

Trading volume is the total number of shares traded at each five minutes interval. Log volume is used instead of raw volume to improve the normality properties of the series. Tian and Guo (2007) and Al-Jafari and Tliti (2013) used log volume instead of raw volume to improve the normality properties of the series.

$V = \log(\text{Trading volume})$

3.4.3: Methodology of the Study

3.4.3.1: Unit Root Test

The stationarity of the data series is tested with the help of Dickey Fuller (DF), Augmented Dickey Fuller (ADF) and Phillips Peron (PP) tests.

3.4.3.2: Contemporaneous Relation (OLS Regression)

The contemporaneous relations between volume and absolute returns, and spread and absolute returns have been investigated using the following OLS equations respectively.

$$|R_t| = \alpha_1 + \beta_1 V_t + u_t \quad (3.1)$$

$$|R_t| = \alpha_2 + \beta_2 S_t + u_t \quad (3.2)$$

Where, $|R_t|$, V_t and S_t are absolute stock returns, trading volume and spread respectively at time t. u_t is the error term. In Equations (3.1) and (3.2), the estimated constant terms are denoted by α_1 and α_2, respectively, and the estimated coefficients of independent variables V_t and S_t are denoted by β_1 and β_2, respectively. In any stock, if we find β_1 to be significantly positive, it would imply that rising absolute values of stock returns tend to be associated with rising volume and the decreasing absolute values of stock returns tend to be associated with decline in volume. Similarly in any stock, if we find β_2 to be significantly positive, it would imply that rising absolute values of stock returns tend to be associated with widening spread and the decreasing absolute values of stock returns tend to be associated with narrowing spread. The R-square value of the estimated OLS model measures the degree of contemporaneous relationship.

3.4.3.3: Asymmetric Relation (Dummy Variable Regression)

Whether average trading volume is higher in a rising market than in a declining market? To check the asymmetric behaviour in the relationship between trading volume and stock returns investigated through the following dummy variable regression model.

$$V_t = \alpha_1 + \beta_1 D_t + u_t \qquad (3.3)$$

Where, V_t stands for trading volume at time t. Here D_t denotes a dummy variable that equals 1 if the corresponding return is negative and 0 otherwise. The estimated parameter β_1 measures the asymmetry in the relationship. A statistically significant negative value of β_1 in equation (3.3) would indicate that average trading volume is higher in rising market than declining market and a statistically significant positive value of β_1 would indicate that average trading volume is higher in declining market than rising market. An insignificant β_1 indicates there is no difference in the relationship whether market is rising or else falling.

3.4.3.4: Causal Relation (Granger Causality Test)

The pair wise causality between stock returns and trading volume has been checked by Granger causality test by the following unrestricted equations:

$$R_t = c_1 + \sum_{i=1}^{p} \alpha_i R_{t-i} + \sum_{j=1}^{p} \beta_j V_{t-j} + u_{1t} \qquad (3.4)$$

$$V_t = c_2 + \sum_{i=1}^{p} \lambda_i R_{t-i} + \sum_{j=1}^{p} \delta_j V_{t-j} + u_{2t} \qquad (3.5)$$

Where, R_t and V_t are stock returns and trading volume respectively. c_1 and c_2 are intercepts and $\alpha_{i,} \beta_{j,} \lambda_i$ and δ_j are parameters. If some of β_j values are statistically not zero, then volume is said to Granger cause returns. Similarly, if some of λ_i values are statistically not zero, stock returns are said to be Granger cause volume. If both β_j and λ_i are statistically significant then a feedback relationship is said to be existing. The optimum lag length is selected based on Schwarz Information Criterion (SC). Similarly, the causality between stock returns and bid-ask spread is checked by using the Granger causality test.

3.5: Results and Analysis

3.5.1: Descriptive Statistics

To assess the distributional properties of the intraday returns, absolute returns, trading volume and spread, various descriptive statistics are reported in Tables 3.1, 3.2, 3.3 and 3.4 that include mean, standard deviation, kurtosis, skewness and Jarque-bera statistics.

The summary statistics of return series are reported in the Table 3.1. The intraday mean percentage returns of these 50 individual stocks range from -0.00058 to 0.00145. For most of the stocks, mean returns are positive. Most of the return series are positively skewed. The positive skew implies that the intraday return distributions of the trading stocks have a higher probability of earning positive returns. In addition, all the Kurtosis values are much higher than 3, ranging from 14 to 1650. This means that for all series, the distribution of intraday return has fatter tails and sharper peaks at the centre compared to normal distribution. The Jarque-Bera test statistic was also found to have a high value at a significant 1% level, suggesting that all returns distribution is non-normal.

Table 3.2 presents descriptive statistics of intraday 5 minutes absolute return series of all 50 individual stocks. The means of the absolute percentage return series of the 50 individual stocks range from 0.038 to 0.079. The statistics show that intraday absolute return series are positively skewed ranging from 3.4 to 41.6. In addition, all kurtosis values are larger than 3 ranging from 24 to 2336. This proves that the distribution of intraday absolute series have fatter tails compared to normal distribution. The Jarque-bera test suggests that all absolute returns distribution is non-normal.

Table 3.3 offers a descriptive statistics of intraday 5 minutes log-volume series of all 50 individual stocks. The means of the trading volume series of the 50 individual stocks range from 2.7 to 5.2. The statistics shows that the intraday trading volume series are most positively skewed. Furthermore, except two stocks all kurtosis values are larger than 3. This proves that the distribution of intraday trading volume series have fatter tails compared to the normal distribution. The Jarque-bera test statistic was also found to have a high value at a significant 1% level, suggests that all trading volume distribution is non-normal.

Table 3.4 provides descriptive statistics of intraday 5 minutes proportionate bid-ask spread series of all 50 individual stocks. The mean of the bid-ask spread series of the 50 individual stocks range from 0.00017 to 0.00067. The statistics shows that intraday spread series are most positively skewed except five stocks. In addition, all kurtosis values are larger than 3, ranging from 5.5 to 8930. This makes it sure that the distributions of intraday spread series have fatter tails compared to the normal distribution. The Jarque-Bera test statistic was also found to have a high value at a significant 1% level, suggests that all spread distribution is non-normal.

3.5.2: Unit Root Test Results

Before doing time series analysis and applying various models to the data, this study adopts Dickey Fuller, Augmented Dickey fuller and Phillips Perron test to ensure that every variable is under stationarity to avoid spurious relation. DF, ADF and PP test statistics are reported in Tables 3.5, 3.6, 3.7 and 3.8 respectively for return, absolute return, volume and spread. The results show that the null hypothesis that return, absolute return, trading volume and bid-ask spread are non-stationary (i.e. has a unit root) is rejected for all the series (except CAIR and NM where DF with intercept only insignificant). This confirms that all the series are stationary and are therefore, useful for further statistical analysis.

3.5.3: Cross Correlation Analysis

As a first step to investigate the relationship between absolute stock returns, trading volume and spread, we calculate the cross-correlation coefficients for all the stocks. The cross correlation coefficients were reported in Table 3.9. A positive correlation was found between absolute returns and trading volume, and absolute returns and lagged volume for all the stocks.

Similarly, a positive correlation was found between absolute returns and spread, and absolute returns and lagged spread for all the stocks except COAL, LT, TPWR and TTMT. The lagged relation gave an indication for causal relationship.

The average correlation coefficient between absolute returns and trading volume is (.33). While the average correlation coefficient between absolute return and spread is (.13) also indicates a positive but relatively small relationship.

3.5.4: Contemporaneous Relationship between Absolute Returns and Trading Volume

The findings of the contemporaneous relationship between absolute returns and trading volume are reported in Table 3.10. The parameter β_1 measures the contemporaneous relationship between absolute returns and volume and it is found statistically significant positive β_1 for all the 50 stocks, suggesting positive contemporaneous relationship between trading volume and absolute value of returns.

The degree of contemporaneous relationship is measured through R-square values which are reported in Table 3.10. The reported R-square values ranged in between 6% to 20% except DLFU. It is highest (20%) in the case of RELI and lowest (1%) in the case of DLFU.

Finally, the results indicate that the contemporaneous volume explains a relatively small portion of price changes in Indian market as evidenced by low R-square values. This weak positive contemporaneous relationship between absolute returns and trading volume indicate that, the Indian market is informationally inefficient. The information flow in Indian market may well be disseminated sequentially instead of instantaneously as required in Mixture Distribution Hypothesis (MDH). This relationship gives an indication of sequential information flow in Indian market. This results corresponds with the results reached by Saatcioglu & Starks (1998) in Argentina, Chile, Colombia, Mexico and Venezuela, Assogbavi (2007) in Russia, Kamath (2007) in Istanbul, Kamath (2008) in Chille, Deo et al. (2008) in India, Hong-Kong, Indonesia, Malaysia, Korea, Japan and Taiwan, Khan & Rizwan (2008) in Pakistan, Kumar & Singh (2009) in India, El-Ansary & Atuea (2012) in Egypt, and He & Xie (2014) for China.

3.5.5: Contemporaneous Relationship between Absolute Returns and Bid-Ask Spread

The findings of the contemporaneous relationship between absolute returns and spread are reported in Table 3.11. The parameter β_2 measures the contemporaneous relationship between absolute returns and spread and it is found statistically significant positive β_2 in case of 45 stocks out of total 50 and statistically significant negative β_2 for 4 stocks i.e. COAL, LT, TPWR and TTMT and statistically insignificant relationship for 1 stock (HNDL). This finding confirms positive contemporaneous relationship between absolute returns and spread.

The degree of contemporaneous relationship is measured by R-square value. It can be observed from the Table 3.11 that in majority of the stocks the reported R-square values are below 1%, this indicate that the contemporaneous spread, explain a relatively very small portion of stock return in the Indian market. Only 9 stocks in the sample it can be observed a comparatively higher R-square values, namely SBIN (35%), SESA (35%), AXSB (29%), CIPLA (27%), GRASIM (25%), HCLT (24%), HUVR (20%), TTMT (14%) and BHARATI (14%).

As a whole, the R-square values suggest that the degree of contemporaneous relationship between return and spread are more stock specific rather than market as a whole. But, in general the R-square values are comparatively higher in case of volume than spread, suggesting contemporaneous spread is less informative than volume. Hussain (2011) found relatively a small contemporaneous relationship between absolute returns and spread than absolute returns and volume. Similarly, McGroarty, Gwilym and Thomas (2009) found relatively a small correlation between absolute return and spread than absolute return and volume for 5 foreign exchange markets. Like volume this weak contemporaneous relationship between the absolute price changes and spread also gives an indication of sequential information flow in Indian market.

3.5.6: Asymmetry Relationship between Stock Returns and Trading Volume

Whether average trading volume is higher in a rising market than in a declining market? To check the asymmetric relationship the study estimated a dummy variable regression model using equation (3.3) and the results are reported in Table 3.12. The asymmetric behaviour of relation between volume and returns is indicated by coefficient β_1. In most of the cases, β_1 is statistically insignificant, suggesting no asymmetry in the relationship between stock returns and trading volume. Only for 19 stocks we established an asymmetry in the relationship between stock returns and trading volume that to 11 stocks having statistically significant negative β_1, suggesting that average trading volume is higher in a rising market than in a declining market, and 8 stocks having statistically significant positive β_1, suggesting that average trading volume is higher in a declining market than a rising market. For those 11 stocks where we established trading volume is higher in a rising market than in a declining market are AXSB, BOB, HDFCB, ICICIBC, LT, MM, MSIL, PNB, RELI, RIL and TTMT. And for those 8 stocks where we established trading volume is higher in a declining market than in a rising market are: APNT, BHARATI, CAIR, HNDL, INFO, JPA, PWGR and TPWR. All R-square values are very low as well.

As a whole, in Indian market this study could not establish any particular asymmetry pattern in the relationship between trading volume and stock returns whether it was a rising market or a falling market. This may be the reasons for absence of short selling in Indian market or it might be the behaviour of traders in developed market is different from developing market like India. This finding confirms the results of Assogbavi et al. (2007) that clearly indicate the absence of such asymmetric relationship in emerging markets. It shows that trading volume resulting from price increases is not statistically different from trading volume following price decreases. This finding does not support "volume is relatively heavy in bull markets and light in bear markets".

3.5.7: Causal Relation between Stock Returns and Trading Volume

The Granger causality test results between stock returns and trading volume are presented in Table 3.13. Causality test are highly sensitive to the lag order. Lag length for Granger causality test has been chosen on the basis of Schwartz Information Criterion (SC) and the selected lag period for each stock are reported in the last column of the same table.

The null hypothesis that lagged volume does not granger cause returns is rejected in the case of 44 stocks out of total 50 except BHARATI, COAL, HMCL, HUVR, KMB and NTPC. Similarly the null hypothesis that past returns does not granger cause volume is rejected only for 22 stocks out of 50. Among these 22 stocks the study found a feedback relationship in 19 stocks. In case of BHARATI, HMCL and NTPC the study did not find any causal relationship in either direction.

The findings of bidirectional causality in some cases can be explained theoretically: volume, which implies information, leads to price changes, and large positive price changes that implies higher capital gain, encourage transactions by traders leading to increase in volume.

The Granger causality result shows that volume causes returns and that the returns also cause volume albeit to a lesser extent. This finding implies that in the presence of current and past returns, trading volume adds some significant predictive power for future returns.

These results are consistent with those of Moosa & Al-Loughani (1995) in Thailand, Singapore and Malaysia; Saatcioglu & Starks (1998) in Brazil, Colombia, Mexico and Venezuela; Ciner (2003) in US and France; Tambi (2005) in India; Kamath & Wang (2006) in South Korea; Leon (2007) in West Africa; Medeiros (2008) in Brazill; and Carl & Muhammad (2011) in Malaysia. It is found that the information content of volume and sequential processing of information may lead to dynamic relationship between returns and trading volume.

In general, the information arrival in Indian market is likely to be sequential which mean that Sequential Information Arrival Hypothesis (SIAH) is applicable in Indian market not Mixture Distribution Hypothesis (MDH).

3.5.8: Causal Relation between Stock Returns and Bid-Ask Spread

The Granger causality test results between stock returns and spread are reported in Table 3.14. The test result shows that the null hypothesis that lagged spread does not granger cause return is rejected in case of 40 stocks except ACEM, BPCL, CAIR, DRRD, HDFCB, INFO, JPA, PNB, UTCM and WIPRO. Similarly, the null hypothesis that lagged return does not granger cause spread is rejected only in case of 11 stocks i.e. BHEL, BPCL, HDFC, HDFCB, HUVR, JPA, KMB, PNB, SIEM, TCS and WIPRO. In six cases the study established a feedback relationship i.e. BHEL, HDFC, HUVR, KMB, SIEM and TCS.

In case of ACEM, CAIR, DRRD, INFO and UTCEM the study did not establish any causal relationship in either direction.

The Granger causality test result shows a strong evidence of spread causing return rather than return causing spread. This result clearly indicates that in the presence of current and past returns, spread adds some significant predictive power for future returns. In fact, information flows from spread to return rather than return to spread.

3.6: Summary and Concluding Remarks

This section of the study brings together the results on the contemporaneous as well as causal relationship between price changes, trading volume and bid-ask spread by using 5 minutes interval high frequency data set for 50 stocks of S&P CNX NIFTY Index over the period from 2nd July, 2012 to 31st December, 2012, that has been analyzed in this chapter.

To begin with, the cross correlation analysis exhibits a positive relationship between absolute returns and trading volume, and absolute returns and spread, whereas the relationship is comparatively stronger in case of volume than spread. Similarly we found a positive relationship between absolute returns and lagged volume, and absolute returns and lagged spread. This lagged relationship gives an indication of sequential information flow in Indian market

The present study provides evidence of a positive contemporaneous relationship between absolute returns and trading volume for all the stocks in the sample, suggesting that increasing trading volume is associated with higher price changes and vice versa. The present study also provides evidence of a positive contemporaneous relationship between absolute returns and bid-ask spread for majority of the cases in the sample, suggesting that widening spread is associated with higher price changes and vice versa. However, in both cases the explanatory power of this contemporaneous relation is weak. The contemporaneous relationship between absolute stock returns and spread is found, in general to be stock specific rather than for the market as a whole. In general, contemporaneous volume explains a larger portion of stock returns compared to the extent to which spread explains it. Overall, in Indian market the study found evidence of a weak positive correlation between absolute stock returns and volume, and absolute stock returns and spread. This indicates that the Indian stock market is informationally inefficient and this also gives an indication of sequential information flow in Indian market.

Furthermore, the present study investigated the asymmetric relationship between stock returns and trading volume. No particular asymmetric pattern in the relationship could be established whether it was a rising market or a declining market. These findings are consistent with the findings of Assogbavi (2007) which clearly indicated an absence of asymmetric relationship in emerging markets. Hence, these results do not support the proposition that "volume is relatively heavy in bull markets and light in bear markets".

In addition to studying the contemporaneous relationship we also examined the possibility of causal relationship investigated the information content of volume to predict stock returns by means of Granger causality test and found that for most of the cases, trading volume causes stock returns. This implies that in the presence of current and past returns, trading volume adds some significant powers for future return. In some cases the study also found evidence of bi-directional causality between stock returns and trading volume. The theoretical explanation of this finding is that volume, which implies information, leads to price changes, and large positive price changes that imply higher capital gains, encourage transaction by traders leading to an increase in volume. Overall, our findings demonstrate a strong support of volume causing return. An explanation for this, in Indian market most of the participants are small and marginal traders and they are late in information queue. It takes some time for information to reach them after it arrives at the market and thereafter they do trade and price changes. In a similar manner, the study also investigated the information content of spread to predict stock returns by using the Granger causality test and found that for majority of the cases spread causes stock return. This finding implies that in the presence of current and past return, spread contains some predictive power for future returns.

Overall causality tests make it clear that in the Indian market information flows sequentially rather than instantaneously. The findings support the sequential information arrival hypothesis (SIAH) and contradict the mixture distribution hypothesis (MDH).

This study will help the marginal and uninformed traders who cannot afford a cost for information acquisition; they can keep a close eye on the movements of both volume and spread for their investment decision. In particular this study will help the intraday investors for making their trading strategy.

Table 3.1: Descriptive Statistics of Stock Return Series

Descriptive Statistics of Stock Return						
Stock	Mean	Stdev	Skewness	Excess Kurtosis	Jarque-Bera	Prob.
ACC	0.00061	0.07174	0.49	21	125373	0
ACEM	0.00066	0.07978	0.62	14	46514	0
APNT	0.00061	0.06728	0.24	31	290793	0
AXSB	0.00137	0.11907	0.70	977	362000000	0
BHARATI	0.00019	0.10562	1.20	233	20247138	0
BHEL	-0.00007	0.09266	0.56	20	115212	0
BJAUT	0.00145	0.07234	0.38	20	113637	0
BOB	0.00079	0.08780	1.20	48	790623	0
BPCL	-0.00019	0.08362	1.41	37	445961	0
CAIR	0.00017	0.06944	1.32	57	1112412	0
CIPLA	0.00129	0.10679	4.61	1101	460000000	0
COAL	0.00012	0.06939	0.42	23	148740	0
DLFU	0.00071	0.10416	0.56	23	146406	0
DRRD	0.00050	0.06619	-0.06	21	121445	0
GAIL	0.00006	0.08132	2.50	88	2737711	0
GRASIM	0.00085	0.08223	-0.40	582	128000000	0
HCLT	0.00125	0.09944	1.72	677	173000000	0
HDFC	0.00114	0.06806	-0.35	59	1217513	0
HDFCB	0.00087	0.05738	0.05	16	68496	0
HMCL	-0.00058	0.07195	-0.37	22	144548	0
HNDL	0.00044	0.09834	2.13	47	740239	0
HUVR	0.00069	0.08662	-0.97	964	353000000	0
ICICIBC	0.00117	0.08290	3.47	94	3148966	0
IDFC	0.00110	0.10049	1.58	34	362726	0

Table 3.1: Continued.

Descriptive Statistics of Stock Return						
Stock	Mean	Stdev	Skewness	Excess Kurtosis	Jarque-Bera	Prob.
INFO	-0.00036	0.08346	-12.90	538	109000000	0
ITC	0.00046	0.06362	-0.37	21	120958	0
JPA	0.00133	0.12411	-0.57	50	831424	0
JSP	-0.00023	0.11687	0.99	31	293457	0
KMB	0.00045	0.07714	0.47	23	158040	0
LPC	0.00058	0.07587	-0.63	20	114803	0
LT	0.00066	0.07890	1.98	84	2492031	0
MM	0.00134	0.07276	0.87	19	100635	0
MSIL	0.00115	0.08759	-2.69	126	5812139	0
NTPC	-0.00010	0.06584	-0.21	23	156562	0
ONGC	-0.00028	0.07344	1.10	33	346392	0
PNB	0.00036	0.08968	0.20	26	211006	0
PWGR	0.00005	0.06653	0.79	16	61755	0
RBXY	0.00015	0.07820	0.06	14	46910	0
RELI	-0.00034	0.10387	0.57	16	61769	0
RIL	0.00066	0.06719	1.43	27	224367	0
SBIN	0.00050	0.12629	0.13	1615	993000000	0
SESA	0.00008	0.15902	-0.85	1650	1040000000	0
SIEM	-0.00045	0.07515	-0.57	26	210949	0
SUNP	0.00071	0.07267	-0.12	27	212200	0
TATA	-0.00016	0.08534	2.24	50	854400	0
TCS	-0.00008	0.06971	0.42	46	711361	0
TPWR	0.00024	0.09661	0.56	88	2750382	0
TTMT	0.00122	0.11552	0.63	237	20994782	0
UTCEM	0.00129	0.07476	0.87	84	2501713	0
WPRO	-0.00007	0.07665	0.27	26	204354	0

Table 3.2: Descriptive Statistics of Absolute Return Series

Descriptive Statistics of Absolute Return						
Stock	Mean	Stdev	Skewness	Excess Kurtosis	Jarque-Bera	Prob.
ACC	0.046	0.055	4.1	42.6	624228	0
ACEM	0.051	0.061	3.5	24.3	191334	0
APNT	0.042	0.053	4.9	60.9	1318249	0
AXSB	0.057	0.105	31.7	1565.5	934000000	0
BHARATI	0.057	0.089	14.1	422.9	67672402	0
BHEL	0.059	0.071	4.4	39.0	525356	0
BJAUT	0.044	0.057	4.2	35.0	417584	0
BOB	0.055	0.069	6.4	106.0	4116301	0
BPCL	0.051	0.066	5.3	74.9	2018450	0
CAIR	0.039	0.057	6.9	100.6	3709898	0
CIPLA	0.046	0.097	32.6	1580.9	953000000	0
COAL	0.043	0.055	4.3	41.3	587214	0
DLFU	0.068	0.079	4.5	48.7	829853	0
DRRD	0.041	0.052	4.1	38.3	502060	0
GAIL	0.048	0.066	7.5	180.1	12068017	0
GRASIM	0.043	0.070	23.3	1031.7	405000000	0
HCLT	0.046	0.088	24.7	1043.5	414000000	0
HDFC	0.040	0.055	7.0	112.0	4610425	0
HDFCB	0.038	0.043	3.8	32.9	362859	0
HMCL	0.044	0.057	4.4	40.7	572571	0
HNDL	0.063	0.076	6.0	109.9	4424336	0
HUVR	0.040	0.077	30.6	1496.6	853000000	0
ICICIBC	0.049	0.067	9.5	190.1	13509341	0
IDFC	0.066	0.076	5.3	80.1	2311951	0
INFO	0.041	0.073	21.6	872.3	289000000	0

Table 3.2: Continued.

Descriptive Statistics of Absolute Return						
Stock	Mean	Stdev	Skewness	Excess Kurtosis	Jarque-Bera	Prob.
ITC	0.041	0.049	4.2	40.4	562102	0
JPA	0.079	0.096	6.7	111.8	4589368	0
JSP	0.072	0.092	5.0	60.4	1295262	0
KMB	0.050	0.059	4.4	49.7	863294	0
LPC	0.048	0.059	4.0	37.8	487418	0
LT	0.050	0.061	8.9	196.8	14463984	0
MM	0.046	0.056	4.1	35.3	423152	0
MSIL	0.047	0.074	10.3	221.7	18429538	0
NTPC	0.042	0.051	4.3	46.0	735911	0
ONGC	0.045	0.058	5.2	65.3	1522110	0
PNB	0.057	0.069	5.0	54.6	1055254	0
PWGR	0.042	0.052	3.5	27.3	244608	0
RBXY	0.052	0.059	3.4	26.8	233854	0
RELI	0.070	0.077	4.0	32.2	348592	0
RIL	0.043	0.052	5.0	57.1	1157224	0
SBIN	0.052	0.115	41.1	2278.1	1980000000	0
SESA	0.066	0.145	41.6	2336.1	2080000000	0
SIEM	0.048	0.058	4.5	55.7	1091047	0
SUNP	0.044	0.058	4.7	47.2	780178	0
TATA	0.054	0.066	7.0	110.0	4449829	0
TCS	0.042	0.055	6.5	91.9	3081066	0
TPWR	0.057	0.078	8.5	178.3	11846212	0
TTMT	0.063	0.097	14.6	444.3	74704891	0
UTCEM	0.043	0.061	8.0	160.8	9594317	0
WPRO	0.046	0.062	4.7	44.9	704561	0

Table 3.3: Descriptive Statistics of Trading Volume Series

Descriptive Statistics of Volume						
Stock	Mean	Stdev	Skewness	Excess Kurtosis	Jarque-Bera	Prob.
ACC	3.3	0.44	-0.09	3.6	148.4	0
ACEM	4.3	0.44	-0.29	4.0	516.5	0
APNT	2.7	0.50	-0.21	4.1	569.2	0
AXSB	4.3	0.36	0.14	3.1	35.0	0
BHARATI	4.6	0.42	0.33	3.5	264.1	0
BHEL	4.5	0.39	0.26	3.1	106.3	0
BJAUT	3.5	0.42	0.21	3.6	188.4	0
BOB	3.7	0.43	0.10	3.2	35.4	0
BPCL	3.8	0.45	-0.12	3.7	220.4	0
CAIR	4.4	0.40	0.40	5.1	1906.6	0
CIPLA	4.1	0.46	-0.06	3.4	80.3	0
COAL	4.2	0.43	0.06	3.5	93.5	0
DLFU	4.8	0.38	0.17	2.8	65.3	0
DRRD	3.4	0.45	-0.03	3.9	340.8	0
GAIL	3.8	0.46	-0.08	3.9	330.8	0
GRASIM	2.7	0.55	-0.39	4.3	925.5	0
HCLT	3.9	0.44	0.22	4.4	801.6	0
HDFC	4.4	0.38	0.25	5.5	2507.3	0
HDFCB	4.3	0.37	0.11	4.0	428.1	0
HMCL	3.5	0.41	-0.09	3.8	248.9	0
HNDL	4.8	0.38	0.09	3.0	13.3	0
HUVR	4.3	0.37	0.44	4.1	760.7	0
ICICIBC	4.5	0.35	0.04	6.3	4041.5	0
IDFC	4.7	0.35	0.05	3.2	26.9	0
INFO	4.0	0.38	0.51	3.8	605.5	0

Table 3.3: Continued.

Descriptive Statistics of Volume						
Stock	Mean	Stdev	Skewness	Excess Kurtosis	Jarque-Bera	Prob.
ITC	4.7	0.39	0.30	3.7	319.3	0
JPA	5.2	0.35	0.13	2.9	32.2	0
JSP	4.3	0.47	0.19	2.8	67.9	0
KMB	3.7	0.47	-0.09	4.4	804.1	0
LPC	3.8	0.44	0.01	3.7	175.0	0
LT	4.1	0.33	0.32	3.3	182.1	0
MM	4.0	0.39	0.08	3.2	22.3	0
MSIL	3.8	0.43	0.32	3.7	364.3	0
NTPC	4.2	0.47	0.14	3.8	247.8	0
ONGC	4.4	0.40	0.33	3.6	306.1	0
PNB	3.8	0.45	0.92	8.8	13994.0	0
PWGR	4.3	0.45	0.08	3.4	67.6	0
RBXY	3.8	0.45	0.00	3.2	10.0	0
RELI	4.3	0.36	0.13	3.0	27.1	0
RIL	4.4	0.35	0.30	3.3	174.1	0
SBIN	4.4	0.35	0.34	3.2	187.9	0
SESA	4.2	0.40	0.10	3.3	55.8	0
SIEM	3.1	0.57	0.04	3.4	75.9	0
SUNP	3.8	0.42	0.04	3.8	264.4	0
TATA	4.6	0.34	0.30	3.0	135.8	0
TCS	4.0	0.39	0.22	3.3	110.6	0
TPWR	4.4	0.43	0.20	3.6	212.1	0
TTMT	5.0	0.34	0.33	3.7	347.0	0
UTCEM	2.9	0.57	-0.43	5.0	1811.1	0
WPRO	4.1	0.42	0.34	3.7	353.9	0

Table 3.4: Descriptive Statistics of Bid-Ask Spread Series

Descriptive Statistics of Bid-Ask Spread						
Stock	Mean	Stdev	Skewness	Excess Kurtosis	Jarque-Bera	Prob.
ACC	0.00042	0.00035	3.6	69.5	1710655	0
ACEM	0.00049	0.00032	2.8	24.5	187826	0
APNT	0.00051	0.00038	1.2	6.3	6403	0
AXSB	0.00023	0.00128	92.9	8801.0	29600000000	0
BHARATI	0.00032	0.00059	78.2	6989.2	18700000000	0
BHEL	0.00034	0.00020	3.3	46.2	730010	0
BJAUT	0.00033	0.00030	1.8	10.7	27750	0
BOB	0.00042	0.00034	1.9	17.2	82353	0
BPCL	0.00052	0.00039	4.4	84.7	2576604	0
CAIR	0.00029	0.00021	3.5	50.6	885702	0
CIPLA	0.00037	0.00099	85.6	7893.3	23800000000	0
COAL	0.00032	0.00031	-22.4	1412.2	759000000	0
DLFU	0.00035	0.00020	2.9	24.3	185121	0
DRRD	0.00037	0.00046	34.6	2305.4	2030000000	0
GAIL	0.00049	0.00039	2.7	24.5	187796	0
GRASIM	0.00066	0.00112	74.6	6558.2	16400000000	0
HCLT	0.00036	0.00097	82.4	7490.8	21400000000	0
HDFC	0.00021	0.00059	81.5	7390.1	20900000000	0
HDFCB	0.00025	0.00022	2.3	13.8	52013	0
HMCL	0.00036	0.00039	21.3	1120.4	478000000	0
HNDL	0.00053	0.00024	-6.1	323.4	39259901	0
HUVR	0.00025	0.00031	35.6	2358.9	2120000000	0
ICICIBC	0.00017	0.00016	1.9	14.0	51846	0
IDFC	0.00044	0.00022	3.3	29.9	292505	0
INFO	0.00022	0.00022	2.6	30.7	302893	0

Table 3.4: Continued.

Descriptive Statistics of Bid-Ask Spread						
Stock	Mean	Stdev	Skewness	Excess Kurtosis	Jarque-Bera	Prob.
ITC	0.00027	0.00018	4.0	48.3	807425	0
JPA	0.00066	0.00025	27.5	1628.6	1010000000	0
JSP	0.00037	0.00028	4.7	118.6	5135145	0
KMB	0.00048	0.00038	3.0	38.1	484330	0
LPC	0.00038	0.00031	2.2	18.2	95780	0
LT	0.00020	0.00040	-70.1	6066.6	14100000000	0
MM	0.00026	0.00025	3.0	30.5	303050	0
MSIL	0.00030	0.00027	2.0	14.2	53857	0
NTPC	0.00050	0.00029	3.7	43.3	640631	0
ONGC	0.00036	0.00027	6.7	161.3	9644447	0
PNB	0.00042	0.00031	2.8	38.4	490781	0
PWGR	0.00057	0.00027	2.6	17.1	86141	0
RBXY	0.00040	0.00029	1.2	5.5	4818	0
RELI	0.00033	0.00070	78.7	7046.9	19000000000	0
RIL	0.00020	0.00019	4.4	82.6	2451947	0
SBIN	0.00017	0.00118	93.9	8930.9	30500000000	0
SESA	0.00053	0.00143	89.2	8331.0	26500000000	0
SIEM	0.00067	0.00044	1.6	10.7	26389	0
SUNP	0.00036	0.00030	1.9	12.0	36433	0
TATA	0.00023	0.00018	10.6	400.4	60496798	0
TCS	0.00021	0.00023	9.6	347.6	45494982	0
TPWR	0.00067	0.00066	-66.8	5691.0	12400000000	0
TTMT	0.00027	0.00087	-90.7	8528.5	27800000000	0
UTCEM	0.00058	0.00049	1.7	10.3	25028	0
WPRO	0.00037	0.00026	1.9	12.8	42236	0

Table 3.5: Unit Root Test Results for Return Series

Unit Root Test for Return Series						
Stock	Intercept			Intercept with Trend		
	DF	ADF	PP	DF	ADF	PP
ACC	-24.59*	-44.82*	-101.75*	-35.21*	-44.82*	-101.76*
ACEM	-4.51*	-43.99*	-97.92*	-8.90*	-43.99*	-97.92*
APNT	-3.95*	-44.49*	-107.71*	-7.89*	-44.52*	-107.76*
AXSB	-7.39*	-45.64*	-123.28*	-14.24*	-45.64*	-123.29*
BHARATI	-12.18*	-43.58*	-107.35*	-21.34*	-43.60*	-107.41*
BHEL	-15.99*	-41.93*	-94.72*	-26.63*	-41.93*	-94.72*
BJAUT	-17.26*	-44.05*	-102.85*	-28.79*	-44.06*	-102.86*
BOB	-12.63*	-42.99*	-100.28*	-21.70*	-43.03*	-100.31*
BPCL	-4.59*	-43.68*	-98.47*	-9.02*	-43.69*	-98.47*
CAIR	-1.58	-43.15*	-101.25*	-3.44**	-43.16*	-101.27*
CIPLA	-4.73*	-45.23*	-124.88*	-9.37*	-45.23*	-124.88*
COAL	-42.92*	-44.11*	-102.91*	-43.81*	-44.11*	-102.91*
DLFU	-14.36*	-44.03*	-97.17*	-24.85*	-44.02*	-97.16*
DRRD	-2.78***	-42.86*	-103.12*	-5.65*	-42.86*	-103.12*
GAIL	-7.86*	-44.83*	-102.23*	-14.78*	-44.83*	-102.23*
GRASIM	-4.41*	-47.20*	-122.37*	-8.71*	-47.24*	-122.60*
HCLT	-4.20*	-45.61*	-121.84*	-8.43*	-45.62*	-121.86*
HDFC	-8.31*	-42.69*	-100.75*	-15.85*	-42.69*	-100.74*
HDFCB	-4.86*	-44.44*	-102.29*	-9.43*	-44.44*	-102.29*
HMCL	-10.02*	-44.69*	-97.45*	-18.32*	-44.71*	-97.47*
HNDL	-7.04*	-43.52*	-99.46*	-12.63*	-43.53*	-99.47*
HUVR	-19.16*	-47.50*	-123.92*	-31.55*	-47.52*	-123.97*
ICICIBC	-5.12*	-43.84*	-102.74*	-10.06*	-43.83*	-102.73*
IDFC	-12.99*	-42.80*	-98.19*	-22.70*	-42.79*	-98.19*
INFO	-7.69*	-42.56*	-95.16*	-14.72*	-42.55*	-95.15*

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 3.5: Continued.

Unit Root Test for Return Series						
Stock	Intercept			Intercept with Trend		
	DF	ADF	PP	DF	ADF	PP
ITC	-12.58*	-43.78*	-98.32*	-21.34*	-43.77*	-98.32*
JPA	-38.29*	-43.84*	-95.56*	-42.09*	-43.84*	-95.56*
JSP	-10.23*	-43.22*	-99.27*	-19.12*	-43.26*	-99.27*
KMB	-4.36*	-44.56*	-105.72*	-8.63*	-44.56*	-105.72*
LPC	-22.86*	-44.43*	-102.11*	-33.09*	-44.43*	-102.11*
LT	-25.64*	-44.52*	-103.34*	-36.39*	-44.52*	-103.34*
MM	-1.71	-42.63*	-100.20*	-3.62*	-42.62*	-100.19*
MSIL	-17.33*	-43.62*	-101.18*	-28.49*	-43.62*	-101.18*
NTPC	-19.15*	-44.74*	-100.21*	-30.40*	-44.75*	-100.22*
ONGC	-9.28*	-43.83*	-102.88*	-17.22*	-43.83*	-102.88*
PNB	-5.37*	-42.55*	-98.32*	-10.35*	-42.58*	-98.34*
PWGR	-7.21*	-44.40*	-104.13*	-13.76*	-44.41*	-104.15*
RBXY	-2.56**	-44.75*	-100.25*	-5.20*	-44.76*	-100.26*
RELI	-43.30*	-43.45*	-96.98*	-42.81*	-43.47*	-96.98*
RIL	-29.34*	-43.93*	-99.42*	-22.92*	-43.92*	-99.42*
SBIN	-5.21*	-46.84*	-136.47*	-10.16*	-46.86*	-136.58*
SESA	-6.40*	-47.92*	-139.93*	-12.43*	-47.94*	-140.12*
SIEM	-18.70*	-44.99*	-104.05*	-30.21*	-45.00*	-104.06*
SUNP	-11.42*	-44.50*	-102.85*	-20.79*	-44.50*	-102.84*
TATA	-23.37*	-43.23*	-96.76*	-34.73*	-43.27*	-96.79*
TCS	-10.74*	-45.12*	-104.01*	-19.24*	-45.12*	-104.00*
TPWR	-8.46*	-44.24*	-105.87*	-15.75*	-44.26*	-105.89*
TTMT	-3.19*	-44.18*	-107.62*	-6.45*	-44.19*	-107.61*
UTCEM	-19.98*	-44.62*	-107.39*	-29.78*	-44.64*	-107.41*
WPRO	-7.92*	-42.81*	-98.59*	-14.94*	-42.85*	-98.60*

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 3.6: Unit Root Test Results for Absolute Return Series

Unit Root Test for Absolute Return Series						
Stock	Intercept			Intercept with Trend		
	DF	ADF	PP	DF	ADF	PP
ACC	-34.05*	-34.45*	-83.11*	-34.43*	-34.48*	-82.98*
ACEM	-4.28*	-34.68*	-84.47*	-8.33*	-34.79*	-84.11*
APNT	-4.16*	-32.25*	-83.89*	-8.39*	-32.40*	-83.29*
AXSB	-11.48*	-37.24*	-67.51*	-20.65*	-37.35*	-67.32*
BHARATI	-18.64*	-35.21*	-76.89*	-27.27*	-35.21*	-76.88*
BHEL	-25.28*	-34.36*	-92.32*	-31.24*	-34.36*	-92.31*
BJAUT	-27.79*	-32.50*	-86.04*	-31.61*	-32.60*	-85.64*
BOB	-18.43*	-34.09*	-89.97*	-26.62*	-34.09*	-89.96*
BPCL	-4.57*	-34.36*	-86.85*	-9.11*	-34.48*	-86.44*
CAIR	-1.52	-33.01*	-90.81*	-3.32*	-33.36*	-89.39*
CIPLA	-7.20*	-36.34*	-65.68*	-13.41*	-36.36*	-65.56*
COAL	-20.77*	-32.07*	-83.66*	-26.57*	-32.18*	-83.22*
DLFU	-21.71*	-36.05*	-90.23*	-29.71*	-36.05*	-90.22*
DRRD	-2.62***	-32.95*	-90.52*	-5.37*	-32.95*	-90.51*
GAIL	-9.41*	-33.93*	-80.90*	-17.37*	-34.03*	-80.51*
GRASIM	-6.10*	-35.01*	-66.91*	-11.80*	-35.03*	-66.88*
HCLT	-5.91*	-36.06*	-69.44*	-11.06*	-36.13*	-69.29*
HDFC	-10.15*	-33.50*	-90.60*	-17.18*	-33.75*	-89.56*
HDFCB	-4.76*	-33.31*	-89.34*	-9.33*	-33.39*	-89.04*
HMCL	-12.35*	-34.81*	-82.40*	-20.91*	-34.82*	-82.36*
HNDL	-7.65*	-36.01*	-90.64*	-11.53*	-36.02*	-90.62*
HUVR	-36.59*	-36.61*	-51.01*	-36.61*	-36.61*	-51.01*
ICICIBC	-5.50*	-37.30*	-86.17*	-10.80*	-37.31*	-86.15*
IDFC	-18.81*	-36.10*	-91.18*	-28.56*	-36.14*	-91.01*
INFO	-8.79*	-35.76*	-91.86*	-16.25*	-35.78*	-91.79*

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 3.6: Continued.

Unit Root Test for Absolute Return Series						
Stock	Intercept			Intercept with Trend		
	DF	ADF	PP	DF	ADF	PP
ITC	-17.45*	-33.38*	-90.02*	-24.70*	-33.39*	-89.98*
JPA	-25.36*	-36.34*	-90.05*	-31.61*	-36.38*	-89.94*
JSP	-13.29*	-33.00*	-85.81*	-22.40*	-33.06*	-85.52*
KMB	-4.65*	-35.57*	-86.77*	-9.23*	-35.58*	-86.73*
LPC	-31.82*	-31.82*	-87.30*	-31.80*	-31.82*	-87.30*
LT	-37.00*	-37.76*	-86.37*	-37.07*	-37.98*	-85.82*
MM	-1.46	-34.38*	-86.40*	-3.21*	-34.43*	-86.23*
MSIL	-27.64*	-35.76*	-83.15*	-34.71*	-36.13*	-81.98*
NTPC	-30.08*	-33.12*	-87.73*	-32.07*	-33.12*	-87.71*
ONGC	-12.05*	-34.10*	-85.99*	-21.51*	-34.31*	-85.24*
PNB	-5.63*	-35.76*	-89.10*	-10.80*	-35.76*	-89.10*
PWGR	-8.24*	-33.29*	-85.66*	-15.55*	-33.38*	-85.35*
RBXY	-2.26**	-35.87*	-87.87*	-4.71*	-36.07*	-87.29*
RELI	-18.42*	-37.33*	-89.63*	-26.65*	-37.58*	-88.96*
RIL	-31.23*	-34.77*	-91.04*	-20.33*	-34.77*	-91.03*
SBIN	-8.44*	-37.93*	-62.21*	-15.77*	-37.92*	-62.20*
SESA	-10.97*	-38.45*	-61.63*	-19.78*	-38.45*	-61.63*
SIEM	-30.79*	-33.80*	-86.97*	-33.73*	-34.03*	-86.17*
SUNP	-15.33*	-33.24*	-82.51*	-23.53*	-33.27*	-82.40*
TATA	-36.77*	-36.77*	-87.55*	-36.75*	-36.85*	-87.37*
TCS	-14.17*	-33.37*	-83.46*	-23.34*	-33.48*	-83.07*
TPWR	-11.05*	-35.53*	-80.90*	-19.90*	-35.60*	-80.68*
TTMT	-3.46*	-35.89*	-80.07*	-6.96*	-35.89*	-80.05*
UTCEM	-29.79*	-31.79*	-88.91*	-30.17*	-31.92*	-88.26*
WPRO	-9.41*	-32.75*	-82.75*	-16.41*	-32.75*	-82.73*

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 3.7: Unit Root Test Results for Volume Series

Unit Root Test for Volume Series						
Stock	Intercept			Intercept with Trend		
	DF	ADF	PP	DF	ADF	PP
ACC	-17.53*	-20.05*	-65.84*	-19.53*	-20.16*	-65.58*
ACEM	-18.59*	-18.59*	-66.17*	-18.20*	-18.64*	-66.21*
APNT	-13.15*	-20.08*	-68.73*	-17.71*	-20.25*	-68.46*
AXSB	-6.69*	-20.51*	-56.95*	-12.64*	-20.92*	-56.82*
BHARATI	-15.50*	-18.37*	-60.69*	-17.41*	-18.37*	-60.69*
BHEL	-6.74*	-17.60*	-51.81*	-11.26*	-17.60*	-51.82*
BJAUT	-9.28*	-19.31*	-73.14*	-15.60*	-19.72*	-73.39*
BOB	-12.84*	-19.00*	-64.17*	-15.84*	-19.13*	-64.27*
BPCL	-13.98*	-20.44*	-68.48*	-18.41*	-20.61*	-68.45*
CAIR	-3.90*	-18.28*	-51.50*	-7.29*	-18.28*	-51.49*
CIPLA	-17.47*	-18.50*	-64.87*	-17.92*	-18.60*	-64.97*
COAL	-18.94*	-18.97*	-66.11*	-18.85*	-18.97*	-66.11*
DLFU	-18.89*	-20.79*	-62.41*	-19.11*	-21.16*	-62.27*
DRRD	-11.62*	-19.44*	-69.81*	-16.17*	-19.45*	-69.81*
GAIL	-19.18*	-21.22*	-68.53*	-20.09*	-21.23*	-68.51*
GRASIM	-16.89*	-22.47*	-81.19*	-20.01*	-22.47*	-81.19*
HCLT	-13.85*	-18.37*	-67.32*	-16.78*	-18.37*	-67.32*
HDFC	-18.55*	-18.79*	-56.32*	-18.11*	-18.87*	-56.37*
HDFCB	-20.01*	-21.82*	-58.12*	-20.98*	-21.83*	-58.11*
HMCL	-11.47*	-20.42*	-59.06*	-16.75*	-20.47*	-58.90*
HNDL	-10.18*	-20.18*	-54.71*	-14.74*	-20.20*	-54.71*
HUVR	-16.70*	-18.84*	-60.72*	-18.32*	-18.87*	-60.72*
ICICIBC	-5.85*	-20.28*	-57.39*	-11.50*	-21.10*	-56.96*
IDFC	-17.09*	-20.80*	-63.31*	-19.07*	-20.90*	-63.05*
INFO	-15.24*	-18.39*	-51.60*	-17.19*	-18.39*	-51.60*

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 3.7: Continued.

Unit Root Test for Volume Series						
Stock	Intercept			Intercept with Trend		
	DF	ADF	PP	DF	ADF	PP
ITC	-12.98*	-18.75*	-53.48*	-15.93*	-18.79*	-53.48*
JPA	-11.50*	-21.54*	-59.63*	-16.03*	-21.72*	-59.34*
JSP	-10.42*	-18.58*	-55.19*	-15.15*	-18.61*	-55.22*
KMB	-17.05*	-30.78*	-112.68*	-24.14*	-31.79*	-107.70*
LPC	-15.48*	-18.26*	-74.51*	-16.91*	-18.32*	-74.57*
LT	-8.61*	-22.17*	-56.81*	-14.86*	-22.32*	-56.53*
MM	-6.90*	-18.61*	-58.26*	-11.10*	-18.67*	-58.29*
MSIL	-9.89*	-17.82*	-61.35*	-15.99*	-18.36*	-62.08*
NTPC	-14.13*	-19.74*	-71.78*	-16.90*	-19.90*	-71.75*
ONGC	-17.40*	-19.98*	-58.84*	-18.13*	-20.03*	-58.84*
PNB	-9.58*	-18.53*	-55.22*	-13.15*	-18.53*	-55.22*
PWGR	-19.66*	-20.12*	-66.81*	-20.11*	-20.20*	-66.82*
RBXY	-13.02*	-20.51*	-59.67*	-18.21*	-20.66*	-59.71*
RELI	-8.75*	-24.15*	-57.50*	-15.46*	-24.43*	-57.01*
RIL	-15.33*	-20.23*	-50.63*	-18.47*	-20.23*	-50.63*
SBIN	-8.00*	-22.96*	-57.20*	-14.47*	-23.29*	-56.65*
SESA	-11.79*	-20.25*	-56.91*	-18.48*	-20.92*	-56.43*
SIEM	-13.57*	-20.98*	-74.90*	-17.83*	-20.99*	-74.89*
SUNP	-18.02*	-20.14*	-64.92*	-19.16*	-20.14*	-64.91*
TATA	-11.68*	-21.59*	-51.98*	-17.18*	-21.64*	-51.94*
TCS	-10.20*	-17.75*	-49.84*	-15.04*	-17.88*	-50.02*
TPWR	-7.23*	-17.84*	-58.12*	-11.26*	-17.87*	-58.12*
TTMT	-8.30*	-20.20*	-51.40*	-13.56*	-20.23*	-51.40*
UTCEM	-19.39*	-19.81*	-74.65*	-19.35*	-21.05*	-74.10*
WPRO	-19.01*	-19.18*	-66.96*	-18.78*	-19.26*	-66.92*

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 3.8: Unit Root Test Results for Bid-Ask Spread Series

Unit Root Test for Bid-Ask Spread Series						
Stock	Intercept			Intercept with Trend		
	DF	ADF	PP	DF	ADF	PP
ACC	-16.87*	-31.75*	-109.50*	-24.14*	-31.81*	-109.25*
ACEM	-29.47*	-33.12*	-107.95*	-32.20*	-33.32*	-106.76*
APNT	-13.02*	-30.42*	-110.67*	-19.90*	-30.65*	-109.74*
AXSB	-40.27*	-42.40*	-95.65*	-38.46*	-42.40*	-95.65*
BHARATI	-24.42*	-40.36*	-95.70*	-30.68*	-40.35*	-95.70*
BHEL	-21.88*	-35.85*	-100.08*	-27.76*	-35.87*	-100.01*
BJAUT	-8.99*	-31.51*	-112.69*	-16.40*	-31.57*	-112.44*
BOB	-4.76*	-32.87*	-109.82*	-9.18*	-32.87*	-109.81*
BPCL	-12.51*	-32.00*	-112.37*	-20.46*	-32.00*	-112.35*
CAIR	-32.24*	-33.51*	-102.08*	-31.52*	-33.66*	-101.23*
CIPLA	-40.92*	-42.06*	-94.03*	-40.53*	-42.12*	-94.06*
COAL	-18.19*	-35.58*	-101.85*	-24.76*	-35.69*	-101.47*
DLFU	-25.45*	-37.98*	-100.24*	-30.95*	-38.54*	-98.45*
DRRD	-29.27*	-35.09*	-106.00*	-30.44*	-35.09*	-105.99*
GAIL	-31.11*	-33.32*	-102.73*	-32.96*	-33.39*	-102.44*
GRASIM	-10.73*	-38.83*	-95.71*	-19.07*	-38.84*	-95.57*
HCLT	-40.11*	-40.45*	-95.42*	-38.44*	-40.45*	-95.41*
HDFC	-36.65*	-41.25*	-95.13*	-39.73*	-41.25*	-95.13*
HDFCB	-32.66*	-33.08*	-102.52*	-23.66*	-33.09*	-102.19*
HMCL	-18.00*	-36.56*	-103.04*	-26.92*	-36.59*	-102.94*
HNDL	-12.67*	-37.88*	-97.78*	-21.92*	-37.87*	-97.77*
HUVR	-12.55*	-36.04*	-103.56*	-19.93*	-36.17*	-103.10*
ICICIBC	-27.85*	-34.60*	-102.57*	-28.63*	-34.73*	-102.09*
IDFC	-29.40*	-36.14*	-104.53*	-31.40*	-38.08*	-97.22*
INFO	-27.46*	-33.54*	-103.24*	-31.18*	-33.55*	-103.18*

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 3.8: Continued.

Unit Root Test for Bid-Ask Spread Series						
Stock	Intercept			Intercept with Trend		
	DF	ADF	PP	DF	ADF	PP
ITC	-26.13*	-35.02*	-100.87*	-27.94*	-35.50*	-98.75*
JPA	-32.28*	-33.02*	-127.71*	-35.49*	-37.69*	-106.73*
JSP	-7.79*	-35.63*	-103.95*	-13.83*	-35.80*	-103.08*
KMB	-10.91*	-20.65*	-71.01*	-17.32*	-21.21*	-70.53*
LPC	-13.39*	-30.51*	-115.38*	-21.02*	-30.55*	-115.19*
LT	-32.73*	-41.45*	-95.04*	-38.08*	-41.51*	-95.09*
MM	-18.71*	-32.80*	-110.84*	-18.56*	-32.93*	-110.22*
MSIL	-31.15*	-32.27*	-108.76*	-31.34*	-32.31*	-108.63*
NTPC	-27.46*	-36.09*	-101.49*	-33.96*	-36.20*	-100.81*
ONGC	-20.43*	-33.71*	-99.98*	-26.76*	-33.90*	-98.99*
PNB	-9.11*	-35.96*	-101.45*	-15.77*	-36.02*	-100.95*
PWGR	-25.80*	-35.90*	-97.90*	-30.77*	-36.21*	-96.65*
RBXY	-14.74*	-32.40*	-112.16*	-22.39*	-32.49*	-111.37*
RELI	-32.73*	-42.39*	-95.42*	-39.45*	-42.40*	-95.42*
RIL	-9.08*	-36.03*	-102.71*	-17.74*	-36.53*	-100.52*
SBIN	-40.67*	-42.48*	-95.79*	-42.02*	-42.48*	-95.79*
SESA	-42.54*	-42.54*	-95.72*	-42.20*	-42.66*	-95.79*
SIEM	-7.51*	-30.00*	-111.83*	-14.27*	-30.20*	-110.56*
SUNP	-25.55*	-32.77*	-110.12*	-29.19*	-32.82*	-109.88*
TATA	-21.97*	-39.22*	-94.69*	-29.60*	-39.32*	-94.47*
TCS	-12.58*	-35.03*	-102.65*	-20.30*	-35.04*	-102.59*
TPWR	-33.79*	-41.20*	-94.50*	-38.09*	-41.27*	-94.49*
TTMT	-42.44*	-43.06*	-95.64*	-42.81*	-43.07*	-95.65*
UTCEM	-2.97***	-27.21*	-115.49*	-6.02*	-27.57*	-114.27*
WPRO	-15.94*	-30.55*	-113.04*	-23.17*	-30.61*	-112.80*

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 3.9: Correlation Results

Cross Correlation Coefficients					
Stock	|R|↔V	|R|↔S	|R|↔V(-1)	|R|↔S(-1)	V↔S
ACC	0.343	0.130	0.221	0.117	-0.021
ACEM	0.321	0.112	0.206	0.114	-0.064
APNT	0.365	0.123	0.243	0.099	-0.008
AXSB	0.279	0.539	0.169	0.544	0.030
BHARATI	0.316	0.373	0.207	0.390	0.013
BHEL	0.435	0.044	0.259	0.097	0.000
BJAUT	0.323	0.113	0.216	0.160	-0.018
BOB	0.340	0.087	0.234	0.112	-0.036
BPCL	0.320	0.158	0.198	0.126	-0.051
CAIR	0.331	0.098	0.222	0.117	-0.015
CIPLA	0.243	0.515	0.174	0.561	0.019
COAL	0.322	-0.022	0.226	-0.004	-0.028
DLFU	0.460	0.020	0.211	0.091	0.020
DRRD	0.273	0.129	0.201	0.107	0.006
GAIL	0.303	0.154	0.195	0.173	-0.016
GRASIM	0.240	0.496	0.161	0.480	0.009
HCLT	0.237	0.490	0.166	0.497	0.022
HDFC	0.360	0.129	0.254	0.107	0.056
HDFCB	0.281	0.121	0.215	0.172	0.004
HMCL	0.365	0.060	0.246	0.166	0.008
HNDL	0.392	0.010	0.218	0.051	-0.081
HUVR	0.261	0.443	0.189	0.453	0.054
ICICIBC	0.346	0.040	0.212	0.091	0.055
IDFC	0.360	0.071	0.178	0.115	0.026
INFO	0.324	0.064	0.224	0.071	0.004

Table 3.9: Continued.

Cross Correlation Coefficients					
Stock	|R|↔V	|R|↔S	|R|↔V(-1)	|R|↔S(-1)	V↔S
ITC	0.354	0.078	0.248	0.115	0.049
JPA	0.430	0.040	0.189	0.064	-0.007
JSP	0.428	0.093	0.274	0.116	-0.045
KMB	0.262	0.117	0.164	0.129	-0.074
LPC	0.331	0.094	0.217	0.110	-0.047
LT	0.383	-0.212	0.213	-0.170	-0.031
MM	0.315	0.115	0.215	0.148	-0.023
MSIL	0.351	0.071	0.235	0.132	-0.041
NTPC	0.289	0.171	0.208	0.114	0.007
ONGC	0.324	0.110	0.222	0.121	0.000
PNB	0.386	0.033	0.248	0.085	-0.042
PWGR	0.282	0.127	0.196	0.128	-0.023
RBXY	0.436	0.027	0.251	0.078	-0.066
RELI	0.451	0.058	0.206	0.072	0.027
RIL	0.372	0.048	0.243	0.106	0.014
SBIN	0.281	0.595	0.144	0.593	0.033
SESA	0.250	0.591	0.135	0.589	0.018
SIEM	0.295	0.167	0.196	0.149	-0.070
SUNP	0.308	0.111	0.207	0.141	-0.009
TATA	0.423	0.062	0.239	0.118	0.046
TCS	0.356	0.163	0.259	0.188	0.026
TPWR	0.325	-0.238	0.229	-0.214	-0.046
TTMT	0.380	-0.377	0.221	-0.351	-0.024
UTCEM	0.240	0.187	0.167	0.152	-0.106
WPRO	0.322	0.110	0.240	0.138	-0.054
Abs. Avg of 50	**0.334**	**0.137**	**0.212**	**0.157**	**0.031**

Table 3.10: OLS Regression Results between Absolute Returns and Volume

$\lvert R_t \rvert = \alpha_1 + \beta_1 V_t + u_t$					
Stock	α_1	t-statistics	β_1	t-statistics	R-squared
ACC	-0.098	-23.6	0.043*	34.9	0.118
ACEM	-0.141	-23.7	0.045*	32.5	0.103
APNT	-0.062	-22.1	0.039*	37.5	0.133
AXSB	-0.292	-23.2	0.081*	27.8	0.078
BHARATI	-0.257	-26.0	0.067*	31.9	0.100
BHEL	-0.304	-38.6	0.080*	46.3	0.190
BJAUT	-0.113	-23.3	0.045*	32.7	0.104
BOB	-0.149	-25.1	0.055*	34.6	0.115
BPCL	-0.127	-22.8	0.046*	32.3	0.102
CAIR	-0.172	-27.3	0.048*	33.6	0.110
CIPLA	-0.163	-18.6	0.051*	24.0	0.059
COAL	-0.128	-24.3	0.041*	32.5	0.104
DLFU	0.068	83.6	0.076*	9.7	0.010
DRRD	-0.065	-16.5	0.031*	27.2	0.075
GAIL	-0.117	-21.5	0.043*	30.5	0.092
GRASIM	-0.039	-11.1	0.031*	23.7	0.058
HCLT	-0.142	-17.6	0.048*	23.4	0.056
HDFC	-0.192	-30.5	0.052*	36.9	0.129
HDFCB	-0.103	-20.4	0.032*	28.1	0.079
HMCL	-0.129	-27.7	0.050*	37.5	0.133
HNDL	-0.304	-33.6	0.077*	40.7	0.153
HUVR	-0.191	-21.3	0.054*	25.9	0.068
ICICIBC	-0.251	-29.4	0.067*	35.3	0.119
IDFC	-0.303	-30.2	0.078*	36.9	0.129
INFO	-0.205	-27.3	0.062*	32.8	0.105

Note: *Significant at 1% level

Table 3.10: Continued.

$\lvert R_t \rvert = \alpha_1 + \beta_1 V_t + u_t$					
Stock	α_1	t-statistics	β_1	t-statistics	R-squared
ITC	-0.167	-29.1	0.044*	36.3	0.126
JPA	-0.536	-39.7	0.118*	45.6	0.185
JSP	-0.284	-36.0	0.083*	45.4	0.183
KMB	-0.070	-15.0	0.033*	26.0	0.069
LPC	-0.123	-24.0	0.045*	33.6	0.110
LT	-0.246	-32.9	0.072*	39.7	0.147
MM	-0.137	-23.6	0.046*	31.7	0.099
MSIL	-0.182	-28.3	0.060*	35.9	0.123
NTPC	-0.092	-19.7	0.031*	28.9	0.083
ONGC	-0.163	-25.5	0.047*	32.8	0.105
PNB	-0.166	-29.6	0.060*	40.1	0.149
PWGR	-0.099	-19.6	0.032*	28.1	0.079
RBXY	-0.166	-35.2	0.057*	46.4	0.190
RELI	-0.342	-40.0	0.097*	48.4	0.204
RIL	-0.198	-31.4	0.054*	38.3	0.138
SBIN	-0.353	-24.3	0.093*	28.0	0.079
SESA	-0.314	-20.3	0.090*	24.7	0.063
SIEM	-0.045	-14.1	0.030*	29.6	0.087
SUNP	-0.118	-22.4	0.042*	30.9	0.095
TATA	-0.321	-38.2	0.082*	44.7	0.179
TCS	-0.158	-28.6	0.050*	36.5	0.127
TPWR	-0.200	-25.5	0.059*	32.9	0.106
TTMT	-0.473	-34.6	0.108*	39.3	0.144
UTCEM	-0.032	-10.0	0.026*	23.6	0.057
WPRO	-0.148	-24.8	0.048*	32.6	0.104

Note: *Significant at 1% level

Table 3.11: OLS Regression Results between Absolute Returns and Spread

$\lvert R_t \rvert = \alpha_2 + \beta_2 S_t + u_t$					
Stock	α_2	t-statistics	β_2	t-statistics	R-squared
ACC	0.037	41.9	20.7*	12.6	0.017
ACEM	0.041	35.7	21.1*	10.8	0.013
APNT	0.033	36.4	17.0*	11.8	0.015
AXSB	0.047	50.1	44.2*	61.3	0.291
BHARATI	0.039	39.6	56.5*	38.5	0.139
BHEL	0.054	36.9	15.6*	4.3	0.002
BJAUT	0.037	42.3	21.4*	10.9	0.013
BOB	0.047	41.2	17.8*	8.4	0.008
BPCL	0.037	32.7	26.9*	15.3	0.025
CAIR	0.032	31.3	26.4*	9.4	0.010
CIPLA	0.027	29.0	50.1*	57.5	0.265
COAL	0.044	53.1	-3.8**	-2.1	0.00047
DLFU	0.066	38.9	8.0***	1.9	0.0004
DRRD	0.036	52.3	14.5*	12.4	0.017
GAIL	0.035	32.5	25.8*	15.0	0.024
GRASIM	0.022	29.7	31.3*	54.7	0.247
HCLT	0.030	34.9	44.4*	53.8	0.240
HDFC	0.037	60.9	12.1*	12.5	0.017
HDFCB	0.032	47.0	23.9*	11.7	0.015
HMCL	0.041	51.5	8.8*	5.8	0.004
HNDL	0.061	31.7	3.1	0.9	0.00010
HUVR	0.013	13.9	108.5*	47.3	0.196
ICICIBC	0.046	45.5	16.4*	3.8	0.002
IDFC	0.055	30.6	24.9*	6.8	0.005
INFO	0.036	33.9	20.8*	6.1	0.004

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 3.11: Continued.

$\lvert R_t \rvert = \alpha_2 + \beta_2 S_t + u_t$					
Stock	α_2	t-statistics	β_2	t-statistics	R-squared
ITC	0.035	37.7	21.2*	7.5	0.006
JPA	0.069	24.5	15.3*	3.8	0.002
JSP	0.061	38.8	30.5*	8.9	0.009
KMB	0.041	41.9	18.2*	11.3	0.014
LPC	0.041	41.7	18.0*	9.1	0.009
LT	0.056	80.2	-32.4*	-20.7	0.045
MM	0.039	45.9	25.9*	11.1	0.013
MSIL	0.041	35.4	19.7*	6.8	0.005
NTPC	0.027	25.7	29.6*	16.6	0.029
ONGC	0.037	36.3	24.1*	10.6	0.012
PNB	0.054	45.1	7.3*	3.1	0.001
PWGR	0.028	21.9	24.8*	12.3	0.016
RBXY	0.049	46.8	5.6*	2.6	0.001
RELI	0.068	76.5	6.3*	5.5	0.003
RIL	0.041	51.5	13.3*	4.6	0.002
SBIN	0.042	43.6	57.9*	70.8	0.354
SESA	0.035	26.7	60.0*	70.2	0.350
SIEM	0.033	30.2	22.2*	16.2	0.028
SUNP	0.036	38.0	21.3*	10.6	0.012
TATA	0.048	42.2	23.2*	6.0	0.004
TCS	0.034	43.1	39.8*	15.8	0.027
TPWR	0.076	67.2	-28.3*	-23.4	0.057
TTMT	0.075	76.3	-42.0*	-38.9	0.142
UTCEM	0.029	29.9	23.5*	18.2	0.035
WPRO	0.036	32.8	25.9*	10.6	0.012

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 3.12: Results for Asymmetric Relationship between Return and Volume

$V_t = \alpha_1 + \beta_1 D_t + u_t$					
Stock	α_1	t-statistics	β_1	t-statistics	R-squared
ACC	3.4	531	-0.0117	-1.3	0.000178
ACEM	4.3	696	-0.002	-0.2	0.000005
APNT	2.7	367	0.0177***	1.7	0.000313
AXSB	4.3	819	-0.0166**	-2.2	0.000539
BHARATI	4.6	782	0.0174**	2.0	0.000429
BHEL	4.5	817	-0.0033	-0.4	0.000018
BJAUT	3.5	587	-0.0063	-0.7	0.000057
BOB	3.8	610	-0.022*	-2.5	0.000661
BPCL	3.9	590	-0.0062	-0.7	0.000047
CAIR	4.4	789	0.0157***	1.9	0.000384
CIPLA	4.1	624	0.0141	1.5	0.00023
COAL	4.2	688	0.0022	0.2	0.000006
DLFU	4.7	871	0.0036	0.5	0.000023
DRRD	3.4	525	-0.0034	-0.4	0.000014
GAIL	3.8	585	0.0053	0.5	0.000032
GRASIM	2.7	339	-0.0047	-0.4	0.000018
HCLT	3.9	634	-0.0048	-0.5	0.00003
HDFC	4.4	813	-0.0128	-1.6	0.000282
HDFCB	4.3	810	-0.0193*	-2.5	0.000662
HMCL	3.5	578	0.0103	1.2	0.000156
HNDL	4.7	881	0.021*	2.6	0.000742
HUVR	4.3	814	0.0046	0.6	0.000039
ICICIBC	4.5	888	-0.0169**	-2.3	0.000595
IDFC	4.7	951	0.0112	1.5	0.000252
INFO	4	719	0.0154***	1.9	0.0004

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 3.12: Continued.

$V_t = \alpha_1 + \beta_1 D_t + u_t$					
Stock	α_1	t-statistics	β_1	t-statistics	R-squared
ITC	4.7	860	0.0051	0.6	0.000042
JPA	5.2	1068	0.0137***	1.9	0.00038
JSP	4.3	616	-0.0119	-1.2	0.000159
KMB	3.7	541	-0.0159	-1.6	0.000283
LPC	3.8	609	0.0138	1.5	0.000245
LT	4.1	860	-0.0132***	-1.9	0.000408
MM	4	710	-0.0149***	-1.8	0.000366
MSIL	3.8	610	-0.0217*	-2.4	0.000636
NTPC	4.2	656	0.0092	0.9	0.000095
ONGC	4.4	779	0.0065	0.8	0.000067
PNB	3.8	577	-0.0175***	-1.9	0.000384
PWGR	4.3	717	0.0255*	2.7	0.000773
RBXY	3.8	584	0.0066	0.7	0.000055
RELI	4.3	807	-0.0159**	-2.1	0.000489
RIL	4.5	866	-0.0186*	-2.5	0.000693
SBIN	4.4	854	-0.0068	-0.9	0.000097
SESA	4.2	730	-0.0034	-0.4	0.000018
SIEM	3.1	377	0.0042	0.4	0.000014
SUNP	3.8	629	-0.014	-1.6	0.000272
TATA	4.6	911	0.0042	0.6	0.000038
TCS	4	690	-0.0028	-0.3	0.000013
TPWR	4.4	741	0.0271*	3.0*	0.000958
TTMT	5	1016	-0.0124***	-1.7	0.00033
UTCEM	2.9	359	0.0114	0.9	0.000098
WPRO	4.1	688	0.0041	0.5	0.000023

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 3.13: Granger Causality Test Results between Return and Volume

Granger Causality Test between Return and Volume							
Stock	Volume does not Granger Cause Return			Return does not Granger Cause Volume			Lag Length
	F-Stat	Prob.	Null Hypothesis	F-Stat	Prob.	Null Hypothesis	
ACC	2.1***	0.06	Rejected	1.9***	0.098	Rejected	5
ACEM	5.2*	0	Rejected	4.6*	0	Rejected	4
APNT	2.6**	0.02	Rejected	2.3**	0.04	Rejected	5
AXSB	4.4*	0	Rejected	0.9	0.46	Not Rejected	4
BHARATI	1.4	0.22	Not Rejected	1.3	0.26	Not Rejected	6
BHEL	2.9**	0.03	Rejected	0.5	0.75	Not Rejected	4
BJAUT	3.4*	0.01	Rejected	2.2***	0.07	Rejected	4
BOB	4.6*	0	Rejected	3.3*	0.01	Rejected	4
BPCL	3.2*	0.01	Rejected	1.9***	0.1	Rejected	4
CAIR	5.9*	0	Rejected	1.8	0.13	Not Rejected	4
CIPLA	10.5*	0	Rejected	5.7**	0.02	Rejected	4
COAL	0.9	0.46	Not Rejected	1.9***	0.10	Rejected	5
DLFU	3*	0.01	Rejected	1	0.43	Not Rejected	5
DRRD	2.4**	0.05	Rejected	2***	0.09	Rejected	4
GAIL	4.5*	0	Rejected	0.8	0.55	Not Rejected	4
GRASIM	6.3*	0	Rejected	1.9***	0.08	Rejected	5
HCLT	5.9*	0	Rejected	1.5	0.17	Not Rejected	6
HDFC	3.2**	0.02	Rejected	2.2***	0.09	Rejected	3
HDFCB	2.6**	0.05	Rejected	4.4*	0	Rejected	3
HMCL	0.1	0.99	Not Rejected	1.1	0.35	Not Rejected	4
HNDL	5.6*	0	Rejected	0.5	0.68	Not Rejected	3
HUVR	0.5	0.76	Not Rejected	5.1*	0	Rejected	5
ICICIBC	6.8*	0	Rejected	0.4	0.84	Not Rejected	5
IDFC	2.9*	0.01	Rejected	3.1*	0.01	Rejected	5
INFO	2**	0.09	Rejected	0.4	0.8	Not Rejected	4

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 3.13: Continued.

Granger Causality Test between Return and Volume							
Stock	Volume does not Granger Cause Return			Return does not Granger Cause Volume			Lag Length
	F-Stat	Prob.	Null Hypothesis	F-Stat	Prob.	Null Hypothesis	
ITC	3.5*	0.01	Rejected	1	0.41	Not Rejected	4
JPA	3.3*	0.01	Rejected	1.4	0.23	Not Rejected	5
JSP	2.9*	0.01	Rejected	2.9*	0.01	Rejected	5
KMB	1.1	0.35	Not Rejected	2.9**	0.02	Rejected	4
LPC	3.1*	0.01	Rejected	0.4	0.88	Not Rejected	5
LT	8.8*	0	Rejected	2.1***	0.10	Rejected	3
MM	14.2*	0	Rejected	0.9	0.48	Not Rejected	4
MSIL	2.4**	0.03	Rejected	3.8*	0	Rejected	5
NTPC	1.5	0.18	Not Rejected	0.6	0.72	Not Rejected	5
ONGC	2.3**	0.05	Rejected	1.6	0.16	Not Rejected	4
PNB	3**	0.02	Rejected	1.9***	0.10	Rejected	4
PWGR	1.9***	0.10	Rejected	0.8	0.50	Not Rejected	4
RBXY	3.4*	0.01	Rejected	0.4	0.84	Not Rejected	4
RELI	3.8*	0.01	Rejected	0.5	0.67	Not Rejected	3
RIL	2.1***	0.08	Rejected	0.6	0.64	Not Rejected	4
SBIN	2.5**	0.03	Rejected	0.8	0.53	Not Rejected	5
SESA	7.8*	0	Rejected	0.8	0.54	Not Rejected	4
SIEM	2.7**	0.03	Rejected	2.6**	0.034	Rejected	4
SUNP	5.1*	0.00	Rejected	1.6	0.18	Not Rejected	4
TATA	7.1*	0	Rejected	0.4	0.739	Not Rejected	3
TCS	3.9*	0.004	Rejected	1	0.405	Not Rejected	4
TPWR	4.7*	0.0003	Rejected	1	0.4353	Not Rejected	5
TTMT	10.2*	0	Rejected	1.4	0.241	Not Rejected	4
UTCEM	2.2***	0.06	Rejected	2.3**	0.04	Rejected	5
WPRO	1.8***	0.10	Rejected	3.1*	0.01	Rejected	5

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 3.14: Granger Causality Test Results between Return and Bid-Ask Spread

Granger Causality Test between Return and Spread							
Stock	Spread does not Granger Cause Return			Return does not Granger Cause Spread			Lag Length
	F-Stat	Prob.	Null Hypothesis	F-Stat	Prob.	Null Hypothesis	
ACC	2.8**	0.02	Rejected	0.5	0.81	Not Rejected	5
ACEM	0.6	0.73	Not Rejected	1.0	0.41	Not Rejected	5
APNT	6.8*	0	Rejected	1.6	0.18	Not Rejected	4
AXSB	2065*	0	Rejected	0.2	0.64	Not Rejected	1
BHARATI	836.6*	0	Rejected	1.3	0.25	Not Rejected	1
BHEL	10.3*	0	Rejected	3.1**	0.02	Rejected	3
BJAUT	3.4*	0.01	Rejected	0.8	0.5	Not Rejected	4
BOB	2***	0.06	Rejected	1.6	0.15	Not Rejected	6
BPCL	0.5	0.76	Not Rejected	3.1*	0.01	Rejected	5
CAIR	0.7	0.61	Not Rejected	1.0	0.39	Not Rejected	4
CIPLA	2356*	0	Rejected	1.9	0.17	Not Rejected	1
COAL	31.9*	0	Rejected	1.7	0.18	Not Rejected	2
DLFU	17*	0	Rejected	0	0.97	Not Rejected	1
DRRD	1.7	0.16	Not Rejected	0.7	0.54	Not Rejected	3
GAIL	5.8*	0	Rejected	1.3	0.27	Not Rejected	3
GRASIM	624.5*	0	Rejected	0.6	0.53	Not Rejected	2
HCLT	715.1*	0	Rejected	0.2	0.8	Not Rejected	2
HDFC	13.4*	0	Rejected	69.9*	0.00	Rejected	7
HDFCB	0.5	0.71	Not Rejected	2.3***	0.08	Rejected	3
HMCL	9.5*	0	Rejected	1.4	0.24	Not Rejected	3
HNDL	6.3*	0.01	Rejected	0	0.95	Not Rejected	1
HUVR	263.1*	0	Rejected	4.9*	0	Rejected	3
ICICIBC	2.8**	0.04	Rejected	1.8	0.15	Not Rejected	3
IDFC	12.7*	0	Rejected	0.7	0.52	Not Rejected	2
INFO	1.4	0.22	Not Rejected	0.1	0.98	Not Rejected	5

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 3.14: Continued.

Granger Causality Test between Return and Spread							
Stock	Spread does not Granger Cause Return			Return does not Granger Cause Spread			Lag Length
	F-Stat	Prob.	Null Hypothesis	F-Stat	Prob.	Null Hypothesis	
ITC	5.8*	0	Rejected	0.3	0.73	Not Rejected	2
JPA	1.3	0.22	Not Rejected	5.6*	0.0	Rejected	8
JSP	31.2*	0	Rejected	2.3	0.13	Not Rejected	1
KMB	2***	0.08	Rejected	3.3*	0.01	Rejected	5
LPC	1.9***	0.08	Rejected	1.1	0.33	Not Rejected	6
LT	190.4*	0	Rejected	2.3	0.13	Not Rejected	1
MM	6.3*	0	Rejected	1.2	0.31	Not Rejected	4
MSIL	8.4*	0	Rejected	1.4	0.21	Not Rejected	5
NTPC	4.2*	0.01	Rejected	2.1	0.12	Not Rejected	2
ONGC	2.6**	0.05	Rejected	1.8	0.15	Not Rejected	3
PNB	1.3	0.28	Not Rejected	3.9**	0.02	Rejected	2
PWGR	4.1*	0.01	Rejected	1.3	0.27	Not Rejected	3
RBXY	3.9*	0	Rejected	1.4	0.21	Not Rejected	5
RELI	7.4*	0	Rejected	0.9	0.46	Not Rejected	4
RIL	4*	0.01	Rejected	0.2	0.89	Not Rejected	3
SBIN	2589.5*	0	Rejected	0.0	0.96	Not Rejected	1
SESA	2421.8*	0	Rejected	0.1	0.77	Not Rejected	1
SIEM	3.2*	0.004	Rejected	1.8***	0.098	Rejected	6
SUNP	2***	0.078	Rejected	1.4	0.232	Not Rejected	5
TATA	27.9*	0	Rejected	2	0.158	Not Rejected	1
TCS	31.2*	0	Rejected	2.7**	0.043	Rejected	3
TPWR	324.1*	0	Rejected	1.6	0.201	Not Rejected	1
TTMT	860*	0	Rejected	1.3	0.26	Not Rejected	1
UTCEM	1.5	0.18	Not Rejected	1.0	0.41	Not Rejected	7
WPRO	1.1	0.37	Not Rejected	1.9***	0.09	Rejected	5

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Chapter 4

Returns Volatility, Trading Volume and Bid-Ask Spread

4.1: Introduction

Many empirical studies have been carried out on the relation between stock return volatility and trading volume over the past years. The major inspiration for these studies is the central role played by trading volume in the pricing of financial assets through the arrival of new information. Information plays a crucial role in decision making, and market outcome is highly sensitive to the assumed information structure. Trading volume is considered as a critical piece of information in the stock market because it can either activate or deactivate the price movements.

Several studies have focused on how to determine the relationship between price variability and trading volume, both at a theoretical and at an empirical level. It has been proposed that there exists a positive contemporaneous relationship between trading volume and price volatility in financial markets. At the theoretical level, the existence of such a positive contemporaneous relationship is explained mainly by two theories; the Mixture of Distribution Hypothesis (MDH) and the Sequential Information Arrival Hypothesis (SIAH). In addition, the SIAH assumes that the dissemination of information is sequential and this sequential information flow results in past values of trading volume having the ability to predict stock returns volatility and/or vice versa, which means that a causality relationship could exist in both directions or either direction between stock return volatility and trading volume.

The contemporaneous and causal relationship between trading volume and stock return volatility has also been the subject of a substantial stream of empirical studies. Lee and Rui (2002) found a positive contemporaneous as well as a feedback relationship between trading volume and volatility in US, UK and Japanese markets. Leon (2007) found that trading volume had predictive power for stock returns volatility in the regional stock exchange of the West African Economic and Monetary Union. Khan and Rizwan (2008) found both a positive contemporaneous and bidirectional causality between trading volume and volatility in Pakistan's stock market. Medeiros (2008) found both a positive contemporaneous and bidirectional causality between trading volume and volatility in Brazilian stock market. Mahajan and Singh (2009) traced a positive contemporaneous relationship between trading volume and volatility in the Indian stock market. Their study also provided evidence of one-way causality from volatility to trading volume. Thammasiri (2010) found a positive contemporaneous relationship between trading volume and volatility in TFEX market, however, no causal relation from volume to volatility was claimed to have been established. Tripathy (2011) found a positive contemporaneous as well as bidirectional causal relationship between trading volume and volatility in Indian market. Chuang, Liu and Susmel (2012) found a positive contemporaneous relationship for 6 out of 10 Asian markets. Their study also provided some evidence of bidirectional causal relation for 4 out of 10 markets. Choi and Kang (2013) found a positive volume-volatility relationship for four Asian markets: Korea, Japan, China and Hong-Kong. Their study found volume causes volatility in cases of Hong-Kong, China and Japan whereas volatility causes volume in cases of Hong-Kong, China and Korean market. Celik (2013) also found a positive relationship between volume and volatility in Istanbul stock market both in pre-crisis and post crisis periods whereas bidirectional causality was traced in post crisis period and in pre-crisis period no causality was established.

Empirical studies on stock return volatility have indicated significant evidence of Autoregressive Conditional Hetroscedasticity (ARCH) effects in the stock returns. But there is little agreement on the sources of this phenomenon. One possible theoretical explanation concerns the role of information flows in the market. If current information is related to past information, the current volatility will be related to past volatility. Based on the mixture distribution hypothesis (MDH), Lamoureux and Lastrapes (1990) first employed the Generalized Autoregressive Conditional Hetroscedasticity (GARCH) methodology to investigate the relationship between trading volume and volatility using daily trading volume as a measure of the information flow in the market. They found that the autoregressive conditional hetroscedasticity (ARCH) effects disappeared and the volatility persistence reduced significantly when trading volume was included an explanatory variable in the conditional variance equation of GARCH model, suggesting that using trading volume as a proxy for the information variable causes price volatility. Brailsford (1994), Pyun, Lee and Nam (2000), Miyakoshi (2002), Bhol and Henke (2003) also obtained results similar to those of Lamoureux and Lastrapes (1990).

Unlike the study by Lamoureux and Lastrapes (1990), Huang and Yang (2001), Salman (2002), Arago and Nieto (2005), Wagner and Marsh (2005), Wang, Wang and Liu (2005), Baklaci and kasman (2006), Floors and Vogues (2007), Tian and Guo (2007), Deo, Srinivaasan and Devanadhen (2008), Medeiros (2008), Mahajan and Singh (2009), Choi, Jiang, Kang, Yoon 2012), Choi and Kang (2013), Ananzeh, Jdaitawi and Al-Jayousi (2013) found that volatility persistence remained strong when current volume was included in the conditional variance equation of GARCH model. These authors traced a significant positive relation between trading volume and price volatility, which is consistent with the theoretical models of both mixture distribution hypothesis (MDH) and sequential information arrival hypothesis (SIAH).

Following the work of Lamoureux and Lastrapes (1990), a number of studies investigated the impact of trading volume on volatility persistence across the markets. However, the studies were not consistent. Even in Indian context, Kumar and Singh (2009) found significant reduction in volatility persistence when trading volume was included in conditional variance equation whereas, Mahajan and Singh (2009) did not find any substantial reduction in volatility persistence. Hence, the relationship has still remained an interesting field for investigation in different sets of financial markets with different perspectives.

In line with microstructure theory, a group of researchers like Wei (1991), Bollerslev and Melvin (1993), Ding and Chong (1997), Galati (2000), Wang and Yau (2000), Pelrou, Gopikrishnan and Stanley (2005), McGroarty, Gwilym and Thomas (2009), Kyaw and Hillier (2011), Gitfa and Liouane (2013), Wang, Garcia and Irwin (2014) examined volatility-spread relationship in the financial markets and found evidence of a positive contemporaneous relationship in-between them.

Following Lamoureux and Lastrapes (1990), few studies like Rahman et al. (2002), Worthington and Higgs (2003) and Hussain (2011) incorporated bid-ask spread as an additional information variable in the conditional variance equation of GARCH model to check whether the information content of bid-ask spread can absorb the volatility persistence in the financial markets. However, all those studies in contrast to Lamoureux and Lastrapes (1990) found that the volatility persistence remained strong even after incorporation of bid-ask spread in the conditional variance of GARCH model.

A considerable amount of efforts has been made, empirically and theoretically, to understand the relationship between stock return volatility and trading volume. Although the majority of the findings have confirmed the existence of a positive contemporaneous relationship between trading volume and return volatility, the studies of different stock markets have given mixed results about the causal relationship between return volatility and trading volume. Spread-volatility relation has not been explored widely and thus the relationship is unclear. Therefore, in the present study, we empirically investigate the intraday contemporaneous as well as the causal relationship between return volatility, trading volume and bid-ask spread for 50 stocks of S&P CNX NIFTY index to fill this gap and understand better the microstructure of Indian stock market.

4.2: Review of Literature

4.2.1: Review of Literature (Volume and Volatility)

Clark (1973) was first to introduce the mixture of distribution hypothesis (MDH). For empirical support, the study examined the relationship between daily price change variance (as measured by squared price change: ΔP^2) and trading volume during the period from 17th January, 1947 to 10th February, 1955 in corn futures market and traced a significant positive relationship between them.

Epps and Epps (1976) carried out an empirical investigation and verified the mixture distribution hypothesis for 20 common stocks traded at New York Stock Exchange (NYSE) during the month of January, 1971. They found a positive relation between price change variance and volume for 16 out of 20 cases.

Tauchen and Pitts (1983) examined the relationship between the daily volume and the square of the price change based on mixture of distribution hypothesis during the period from 6th January, 1976 to 30th June, 1979 for the 90-day T-bill futures contracts traded at Chicago Merchantile Exchange (CME). The study found a positive contemporaneous relationship between log value of squared price changes and log volume and supported the mixture of distribution hypothesis (MDH).

Lamoureux and Lastrapes (1990) tried the relationship between trading volume and stock returns volatility for 20 heavily traded stocks in US over the period from 1980 to 1985. The GARCH model had been employed to trace the impact of volume on conditional volatility. The result showed a positive contemporaneous relationship between trading volume and conditional volatility for all the 20 stocks. By including daily trading volume as a proxy for information arrival in the variance equation of GARCH model, the volatility persistence reduced significantly and the GARCH coefficient turned zero for 17 cases out of 20. The overall findings supported the mixture distribution hypothesis (MDH) and confirmed daily trading volume as a good proxy for information arrival in the US market for explaining the return volatility.

Brailsford (1994) empirically examined the volume-volatility relationship in the Australian stock market for the sample period of 24th April, 1989 to 31st December, 1993. He used squared return as a measure of volatility. By using OLS regression, he found a positive contemporaneous relationship between return volatility (squared return measure as volatility) and volume. Similarly, the study also conducted GARCH (1,1) model to investigate the relationship between conditional volatility and volume. By including trading volume as a proxy for information arrival in the variance equation of GARCH model, the study found a significant positive relationship between conditional volatility and volume. The result also showed that the GARCH coefficient became insignificant when trading volume was included in the variance equation, indicating that trading volume is a appropriate proxy for information flow in the Australian stock market. Overall, the findings support the mixed distribution hypothesis (MDH) that volume contained information and explained volatility.

Sharma, Mougoue and Kamath (1996) examined the relationship between trading volume and conditional volatility in the New York Stock Exchange (NYSE) index over the period from 1986 to 1989. By taking into account trading volume as a proxy for information flow in the conditional variance of GARCH model, they found a notable reduction of volatility persistence. However, the GARCH effect did not completely vanish in the model when trading volume was incorporated in the variance equation. Their findings were weaker than those of Lamoureux and Lastrapes (1990).

Phylaktis, Kavussanos and Manalis (1996) empirically examined the relationship between trading volume and conditional volatility in the Athens Stock Exchange (ASE) from 1988 to 1993. They divided the sample period in to two sub-periods with respect to size of the market to examine and compare the relationship between conditional volatility and trading volume. They found that trading volume was a good proxy for information flow in the Athens Stock market, since the volatility of persistence reduced significantly after adding trading volume in the variance equation of GARCH model. Comparing the results of two sample periods, they concluded that, with the size of the market being increased, the information content of trading volume also increased.

Pyun, Lee and Nam (2000) empirically examined the volume-volatility relationship by assuming volume as a proxy for information arrival for 15 individual stocks traded in Korean stock market over the period from 1990 to 1994. Adding volume as an explanatory variable in the conditional variance equation of GARCH model, they found that for all the stocks, the volume effect on conditional volatility was statistically significant and positive. The result showed that the volatility of persistence decreased substantially after incorporating trading volume as a proxy for the rate of information arrival in the conditional variance equation of GARCH model. This finding indicates that volume data (i.e. the rate of arrival information) is a source of the Autoregressive Conditional Hetroscedasticity (ARCH) effect, and that the mixture distribution hypothesis is applicable in the Korean stock market.

Gallo and Pacini (2000) studied the contemporaneous as well as lagged trading volume effect on stock return volatility using GARCH and EGARCH model for 10 actively traded US stocks over a period from 2nd January 1985 to 1st December 1995. Both GARCH (1, 1) and EGARCH (1, 1) confirm a significant positive relationship between volume and conditional volatility for all the sample stocks. Their findings suggested that volatility persistence was substantially decreased after including trading volume as an information variable in the variance equation. Similarly, they also investigated the lagged volume effect on conditional volatility by incorporating lagged trading volume as an explanatory variable in the variance equation of both GARCH and EGARCH model. Only for 4 out of 10 stocks in the sample, they found significant lagged relationship (sometimes with wrong sign) and volatility of persistence remained high even after the introduction of lagged volume (i.e as a proxy for information flow) in the variance equation. However, the overall findings suggest that information contained in volume is useful for explaining volatility than lagged volume.

Huang and Yang (2001) empirically examined the mixture distribution hypothesis (MDH) in Taiwan stock exchange using 5 minute interval data set for the sample period starting from 1st September, 1989 to 30th June, 1993. For volume-volatility relationship, they estimated GARCH (1, 1) model by including volume as an explanatory variable in the conditional variance equation and found a positive significant relationship between volume and conditional volatility. However, the volatility persistence remained dominant even after they introduced trading volume as a proxy for information flow in market in the variance equation. For majority of the cases, there was a nominal reduction in the volatility persistence. GARCH result revealed that MDH could not explain the ARCH phenomenon in Taiwan stock market.

Miyakoshi (2002) investigated the influence of volume on conditional volatility for both individual stocks and the market index of the Tokyo Stock Exchange (TSE). He found significant decrease in volatility persistence both for individual stocks and the market index when trading volume was incorporated in the GARCH model. The results are consistent with the view that trading volume is a good proxy for information flow in Tokyo stock market.

Salman (2002) empirically investigated the risk-return and volume relationship in the Istanbul Stock exchange (ISE) for the period from 2nd January, 1992 to 29th May, 1998. By considering lagged volume as a proxy for information flow in the market, the study found a positive relationship between lagged volume and conditional volatility. However, the volatility persistence remained high even after adding lagged volume as an information variable in the variance equation of GARCH (1, 1) model. The overall findings suggest that volume has limited information to explain volatility persistence in the Istanbul market.

Lee and Rui (2002) empirically investigated volume-volatility relationship for three developed markets: London, New York and Tokyo during the period of 1973 to 1999. By including trading volume in the variance equation of GARCH (1, 1) model as a proxy for information flow in market, they found a significant positive relationship between conditional volatility and trading volume in all these three markets. The Granger causality test was conducted to trace the causality between trading volume and volatility (both squared return and conditional volatility) and the results showed a positive feedback relationship between trading volume and volatility in all the three markets irrespective of measures of volatility. Their overall findings suggest that information content in trading volume is useful in improving forecasts of return volatility.

Bhol and Henke (2003) relying on the mixture distribution hypothesis (MDH), this study examined volume-volatility for 20 Polish stocks during the period from 4th January 1999 to 31st October 2000. The GARCH model confirmed a positive significant relationship between trading volume and conditional return volatility for all the sample stocks. In most of the cases, volatility persistence tends to vanish when trading volume is added in the GARCH model. The overall findings suggest that the mixture distribution hypothesis (MDH) provides to a large extent, a valid theoretical explanation for the Polish stock market volatility.

Arago and Nieto (2005) empirically investigated the influence of trading volume on volatility persistence for seven major stock market indices i.e. France, Germany, US, UK, Italy, Switzerland, Japan and Spain during the period from 1995 to 2000. By adding trading volume in the conditional variance of GARCH model as a proxy for information flow, they did not observe a substantial reduction in volatility persistence.

Wagner and Marsh (2005) empirically investigated the relationship between trading volume and conditional volatility for seven major stock markets in the world i.e. France, German, Holland, Hong Kong, Japan, UK and US over the period from 1988 to 1997. They found that there was a significant positive relationship existing between trading volume and conditional volatility. However, including trading volume in the conditional variance of GARCH model as a proxy for information flow, gave rise to a moderate decrease in volatility persistence across the markets.

Wang, Wang and Liu (2005) empirically examined volume-volatility relationship for 22 individual stocks traded in the Chinese stock market as well as market index over the period from 2nd Jan 1995 to 31st Dec 2002. By including trading volume in the conditional variance of GARCH model as a proxy for information flow, they found a positive and statistically significant relationship between conditional volatility and volume. They also observed a significant decrease in volatility persistence for individual stocks. The average volatility persistence decreased (62%) when trading volume was included in the GARCH model. But in case of market index, they did not observe any significant reduction in volatility persistence. Their overall findings suggest that trading volume can be a good proxy for information flow for individual stocks, but not for the market indices.

Baklaci and Kasman (2006) studied volume-volatility relationship for 25 individual stocks using daily data from Turkish stock market during the period from 1998 to 2005. For majority of the cases they found a positive significant contemporaneous relationship between conditional volatility and trading volume. On the other hand the volatility persistence does not diminish for majority of stocks even after introduction of trading volume as information flow variable in the conditional variance equation of GARCH model, which challenges the validity of mixture distribution hypothesis in Turkish stock market.

Floors and Vogues (2007) investigated the relationship between trading volume and return volatility in Greek stock futures market for FTSE/ASE-20 and FTSE/ASE-40 index over the period from 1999 to 2001. By using GARCH, they found a positive contemporaneous relationship between trading volume and conditional volatility for both FTSE/ASE-20 and FTSE/ASE-40 indices. However, the volatility persistence remained strong even after the inclusion of trading volume as an explanatory variable in the conditional variance equation of GARCH model. The overall findings suggest that volume has limited effect on volatility in Greek stock market.

Tian and Guo (2007) investigated the empirical relationship between intra-day return volatility and trading volume for a sample of 39 stocks from Shanghai Stock Exchange. The study is conducted by using 5 minutes interval data set for the period from 1st

January 2000 to 31st December 2000. Their study used both GARCH and EGRACH models to check the lagged volume effect on conditional volatility and they found a positive relationship between conditional volatility and lagged trading volume. However, the volatility persistence remained high even after incorporating lagged trading volume in the variance equation of both GARCH and EGARCH models. Their results suggest that volume as an information variable has limited impact on intraday return volatility in the Shanghai stock Market.

Leon (2007) studied the causal relationship between return volatility and trading volume in the BRVM over the period from 2nd January 2002 to 29th July 2005. In this study squared return was used as a measure of volatility. The study conducted Granger causality test and found evidence of volume granger causing volatility. This finding is in support with the sequential information arrival hypothesis (SIAH).

Khan and Rizwan (2008) empirically investigated the volume-volatility relationship in Pakistan's stock market during the period from Jan 2001 to May 2007. By employing the GARCH (1, 1) model, their study found a significant positive contemporaneous relationship between volume and conditional volatility. Similarly, using the Granger causality test and VAR model, they found the evidence of a bi-directional causal relationship between conditional volatility and volume.

Deo, Srinivaasan and Devanadhen (2008) empirically investigated daily volume-volatility relationship for seven Asian markets including India for the period from 1st January 2004 to 31st March 2008. They found a significant relationship between conditional volatility and lagged volume by including lagged volume in the conditional variance equation of EGARCH (1, 1) model. However, the volatility persistence remained strong even after incorporating lagged volume as an information variable in the conditional variance equation. Their overall findings suggest that volatility explained by volume is limited.

Medeiros (2008) empirically examined the volume-volatility relationship in Brazilian stock market for the sample period from 2003 to 2005. Both cross-correlation analysis and the Granger-causality test were carried out to check the contemporaneous as well as dynamic relationship between volatility (squared return used as a measure of volatility) and volume in Brazilian stock market. The correlation coefficient between return volatility and volume was positive and statistically significant which indicated a significant positive contemporaneous relationship between them. Similarly, the correlation coefficient between lagged volume and return volatility was also positive and significant which gave a clear indication of a causal relationship between them. The Granger causality test result showed a bi-directional causality between them. With regard to conditional volatility, his findings supported a positive contemporaneous relationship between trading volume and conditional volatility. However, the volatility persistence remained high even after the introduction of trading volume in the conditional variance equation of GARCH (1, 1) model which can be seen as a signal that either trading volume as a rough proxy for information or the assumption of MDH that information flows simultaneously in to the market might be incorrect.

Kumar and Singh (2009) empirically examined volume-volatility relationship in Indian stock market using daily data over the period from 2001 to 2008. By using squared returns as a measure of volatility they found a positive contemporaneous relationship between volume and volatility. Similarly, they also checked the contemporaneous relationship between conditional volatility and volume by including trading volume in the variance equation of GARCH (1, 1) model and found a positive significant contemporaneous relationship for most of the sample stocks. In majority of the cases either the ARCH effect reduced significantly or it became insignificant when trading volume was added in the variance equation. According to MDH, information content on volume would absorb the volatility of persistence completely. However, the result shows that volatility persistence was not completely vanished. Overall, they did neither fully reject the MDH or nor gave an unconditional support.

Mahajan and Singh (2009) studied the contemporaneous and causal relationship between volatility and volume in Indian stock market using daily closing prices and volume data over the period from October 1996 to March 2006. By including volume in the conditional variance equation of GARCH (1, 1) model, they found a positive contemporaneous relationship between volume and volatility. However, the volatility persistence reduced marginally when volume was incorporated in the variance equation. It means that small degree of persistence is absorbed by the volume series. Therefore, their findings showed weak support for the MDH model. Their study also investigated the causal relationship between volume and volatility by means of the Granger causality test and found a unidirectional causality running from volatility to volume. Their overall findings suggest that causality running from return volatility to trading volume can be seen as some evidence that arrival of new information may follow a sequential rather than simultaneous process.

Thammasiri (2010) tested the daily volatility-volume relationship for SET50 futures contract traded in TFEX market for the period from April 2006 to December 2008. By including both volume and lagged volume in GARCH (1, 1) model, he found a positive significant relationship between volume and volatility, though the relationship between lagged volume and volatility was found to be statistically insignificant.

Tripathy (2011) investigated the contemporaneous and dynamic relationship between return volatility (squared return used as a measure of volatility) and trading volume in Indian stock market using regression model, VECM, VAR, IRF and Johansen's co integration test. The study was conducted for the period from 2005 to 2010 and she found a positive contemporaneous relationship as well as bidirectional causal relationship between return volatility and trading volume in Indian market.

Choi, Jiang, Kang, Yoon (2012) investigated volume-volatility relationship in the Korean market between Jan 2000 and Dec 2010. By using GARCH and EGARCH models, they found a positive contemporaneous relationship between trading volume and conditional volatility. Similarly, they also checked the lagged volume impact on conditional volatility by incorporating lagged volume in the variance equation and found a negative relationship between them. However, the volatility persistence remained high even after inclusion of volume and lagged-volume in the conditional variance equation. This indicated that both volume and lagged volume had less information content to absorb volatility persistence in the Korean stock market.

Chuang, Liu and Susmel (2012) empirically investigated the contemporaneous as well as causal relationship between trading volume and conditional return volatility in ten Asian stock markets: Japan, Singapore, Hong Kong, Taiwan, China, Korea Indonesia, Malaysia, Thailand and the Philippines. They found a positive contemporaneous relationship between conditional volatility and trading volume in 6 out of 10 markets: Singapore, Indonesia, Hong Kong, Korea, China and Thailand and negative contemporaneous relation for Taiwan and Japan. In case of the Philippines and Malaysia, no significant contemporaneous relationship was established. They also found a bi-directional causal relationship for 4 out of 10 markets: Korea, China, Hong Kong and Singapore.

Choi and Kang (2013) examined the contemporaneous and dynamic relationship between trading volume and conditional return volatility in four Asian markets: China, Japan, Korea and Hong-Kong. The study conducted both GARCH (1, 1) and Granger causality test to trace the relationship. By including volume in the conditional volatility equation as a proxy for information arrival in the market, they found a significant positive relationship between the trading volume and conditional volatility. However, the volatility of persistence remained dominant even after the addition of volume as an explanatory variable in the conditional variance equation of GARCH model. This implied that the return volatility was not totally explained by volume and linking volatility to volume did not extract all the information. Their study also focused on the causal relationship between trading volume and conditional volatility using the Granger causality test and found bidirectional causality between volume and conditional volatility in the cases of Hong Kong and China whereas volume granger caused volatility in the case of Japan and volatility granger caused volume in the case of Korea.

Al-Jafari and Tliti (2013) studied the relationship between daily return volatility and trading volume in the banking sectors of Amman Stock Exchange (ASE) for the period of July 2006 to December 2011. They used squared return as a measure of volatility. They found a positive contemporaneous relationship between stock return volatility and trading in Amman stock market, suggesting that higher trading volume was associated with rising volatility.

Ananzeh, Jdaitawi and Al-Jayousi (2013) empirically investigated the relationship between daily return volatility and trading volume for 27 individual stocks from Amman Stock Exchange (ASE) over the period from 2002 to 2012. Their study used the GARCH model and found a positive contemporaneous relationship between volume and volatility for 26 out of 27 stocks, however, for the remaining 1 stock the relationship was negative.

They did not observe any significant reduction in volatility persistence for most of the sample stocks, challenging the implication of the mixed distribution hypothesis (MDH) in Amman stock exchange.

Celik (2013) examined the volume-volatility relationship in Istanbul Stock Exchange (ISE) using intraday data for the period from 4^{th} February, 2005 to 30^{th} April, 2010. The study used squared return as a measure of volatility and the relationship was conducted for both pre-crisis period and post-crisis period. The study found a positive contemporaneous relationship between volume and volatility for both the pre-crisis and the post-crisis period. No causal relationship was established between volume and volatility in pre-crisis period whereas a bi-directional causality existed in the post-crisis period. Overall, the findings supported the mixture distribution hypothesis (MDH) in pre-crisis period and the sequential information arrival hypothesis (SIAH) in post-crisis period.

Table (4.A) summarizes the previous studies on the contemporaneous and causal relation between volume and volatility and table (4.B) highlights the studies relating to volume and volatility persistence.

Table 4.A: Empirical Evidence on the Contemporaneous and Causal Relationship between Volume and Volatility

Sl. No	Author(s)	Market	Sample Period	Frequency	Support +Ve Correlation	Volume causes Volatility	Volatility causes Volume
1	Clark (1973)		1947-1955	Daily	Yes	-	-
2	Epps and Epps (1976)	US	1971-1971	Daily	Yes	-	-
3	Tauchen and Pitts (1983)	US	1976-1979	Daily	Yes	-	-
4	Lee and Rui (2002)	US, Japan, UK	1973-1999	Daily	Yes	Yes	Yes
5	Leon (2007)	West Africa	2002-2005	Daily	-	Yes	No
6	Medeiros (2008)	Brazil	2003-2005	Daily	Yes	Yes	Yes
7	Khan and Rizwan (2008)	Pakistan	2001-2007	Daily	Yes	Yes	Yes
8	Mahajan and Singh (2009)	India	1996-2006	Daily	Yes	No	Yes
9	Thammasiri (2010)	TFEX	2006-2008	Daily	Yes	No	-
10	Tripathy (2011)	India	2005-2010	Daily	Yes	Yes	Yes

11	Chuang, Liu and Susmel (2012)	Hong Kong, Japan, Korea, Indonesia, Taiwan, Singapore, China, Malaysia, Thailand and the Philippines	1998-2007	Daily	Six out of ten	Korea, Japan, Taiwan,, and Singapore	Korea, Taiwan, Japan, and Singapore
12	Choi et al. (2012)	Korea	2000-2010	Daily	Yes	-	-
13	Al-Jafari and Tliti (2013)	Amman	2006-2011	Daily	Yes	-	-
14	Celik (2013)	Turkey	2005-2010	Intraday	Yes	Only Post Crisis Period	Only Post Crisis Period
15	Ananzeh et al. (2013)	Amman	2002-2012	Daily	Yes		
16	Choi and Kang (2013)	Asian	2004-2012	Daily	Yes	Except Korea	Except Japan

Table 4.B: Empirical Evidence on the Relationship between Volume and Volatility Persistence

Sl. No.	Author(s)	Market	Sample Period	Frequency	Support +Ve Correlation	Volume impact on volatility persistence
1	Lamoureux and Lastrapes (1990)	US	1980-1985	Daily	Yes	High
2	Brailsford (1994)	Australia	1989-1993	Daily	Yes	High
3	Sharma et al. (1996)	US	1986-1989	Daily	Yes	High
4	Phylaktis et al. (1996)	Greece	1988-1993	Daily	Yes	High
5	Pyun et al. (2000)	Korea	1990-1994	Weekly	-	High
6	Gallo and Pacini (2000)	US	1985-1995	Daily	Yes	High
7	Huang and Yang (2001)	Taiwan	1989-1993	Intraday	Yes	Small
8	Salman (2002)	Turkey	1992-1998	Daily	Yes	Small
9	Miyakoshi (2002)	Japan	NA	NA	Yes	High
10	Bhol and Henke (2003)	Polish	1999-2000	Daily	Yes	High
11	Wang, Wang and Liu (2005)	China/Individual stocks	1995-2002	Daily	Yes	High
12	Wang, Wang and Liu (2005)	China/Index	1995-2002	Daily	Yes	Small
13	Wagner and Marsh (2005)	France, Hong Kong, German, Holland, Japan, US and UK	1988-1997	Weekly	Yes	Moderate

14	Arago and Nieto (2005)	France, Germany, UK, Italy, US, Switzerland, Japan and Spain	1995-2000	Daily	Yes	Small
15	Baklaci and kasman(2006)	Turkey	1998-2005	Daily	Yes	Small
16	Floors and Vogues (2007)	Greece	1999-2001	Daily	Yes	Small
17	Tian and Guo (2007)	Shanghai	2000-2000	Intraday	Yes	Small
18	Deo et al. (2008)	India, Indonesia, Malaysia, Hong Kong, Korea, Tokyo and Taiwan	2004-2008	Daily	Yes	Small
19	Medeiros (2008)	Brazil	2003-2005	Daily	Yes	Small
20	Mahajan and Singh (2009)	India	1996-2006	Daily	Yes	Small
21	Kumar and Singh (2009)	India	2001-2008	Daily	Yes	High
22	Choi et al. (2012)	Korea	2000-2010	Daily	Yes	Small
23	Choi and Kang (2013)	Asian	2004-2012	Daily	Yes	Small
24	Ananzeh et al. (2013)	Amman	2002-2012	Daily	Yes	Small

4.2.2: Review of Literature (Spread and Volatility)

Wei (1991) empirically studied the effect of exchange rate volatility on bid-ask spread over the period from 1983 to 1990. The study used percentage bid-ask spread for examining the relationship between exchange rate volatility and spread. Using OLS regression, the study found a positive contemporaneous relationship between exchange rate volatility and bid-ask spreads. An increase in exchange rate volatility was found to be widening bid-ask spreads, though the magnitude was small. She also found an increase in trading volume also widens bid-ask spread.

Bollerslev and Melvin (1993) examined the relationship between bid-ask spread and volatility in foreign exchange market over the period from April 1989 to June 1989 using GARCH (1, 1) model and found the evidence of a strong positive contemporaneous relationship between exchange rate volatility and spread.

Ding and Chong (1997) empirically examined the intraday relationship between bid-ask spread, trading volume and volatility in Nikkei stock index futures market. The bid-ask spreads was found to be negatively correlated related with trading volume and positively related with exchange rate volatility.

Galati (2000) in a study on the market microstructure of foreign exchange markets, empirically investigated the relationship between volatility, trading volumes and bid-ask spreads. In this study, he used squared return as a measure of volatility. This study was undertaken for 8 foreign exchange markets for the sample period from 1st January 1998 to 30th June 1999. The study found a significant positive contemporaneous relationship between conditional volatility and volume, and conditional volatility and spread for most of the markets.

Wang and Yau (2000) investigated the relationship between volatility, volume and bid-ask spread in futures market. Using the Generalized Method of Moments (GMM) estimation procedure, they found a negative correlation between bid-ask spreads and volume and a positive correlation between bid-ask spreads and volatility. The positive relation between bid-ask spreads and return volatility shows that an increase in liquidity (narrowing spreads) would reduce price volatility.

Rahman et al. (2002) empirically examined the intraday relationship between return volatility, volume and bid-ask spread for a sample of 30 NASDAQ stocks using 5 minutes interval data set during the period from 1st January, 1999 to 31st March, 1999. After including trading volume, lagged trading volume, bid-ask spread and lagged bid-ask spread separately in the variance equation of GARCH model, they found a positive and statistically significant but numerically very small effect of each information variable on conditional volatility. Furthermore, their results recommended that none of the exogenous information variables significantly decreased volatility persistence effects for their sample returns.

Worthington and Higgs (2003) tested the intraday relationship between return volatility, trading volume and bid-ask spread in the Australian market using five-minute interval data set over the period from 31st December 2002 to 4th March 2003 for 50 stocks of S&P/ASX 50 index. The study found conditional volatility was positively related to contemporaneous volume and negatively related to contemporaneous spread for majority of cases. In similar fashion, the conditional volatility was found to be negatively related to lagged volume. However, lagged spread was insignificant for majority of cases. The results showed strong persistence in volatility for all the fifty stocks even after inclusion of contemporaneous volume, lagged volume, contemporaneous spread and lagged spread simultaneously in the variance equation of GARCH model. Their study found trading volume and bid-ask spread as proxies for the rate of information arrival in the Australian market has limited effect on return volatility.

Plerou, Gopikrishnan and Stanley (2005) empirically investigated the relationship between absolute stock price changes, bid-ask spread and trading volume for the 116 most actively traded stocks in the New York Stock Exchange (NYSE) over the period from 1994 to 1995. Their study found significant logarithmic relationship between trading volume and spread as well as absolute stock price changes and spread.

McGroarty, Gwilym and Thomas (2009) empirically investigated the relationship between trading volume, bid-ask spread and return volatility for 5 foreign exchange spot markets: USD/JPY, EUR/JPY, USD/CHF, UUR/CHF and EUR/USD using 5 minutes interval data set over the period from 1st August 1998 to 4th September 1998 and 1st August 1999 to 3rd September 1999. The contemporaneous relationship was examined through correlation coefficients for 5 exchange rates. Their study found a statistically significant positive but small correlation between bid-ask spread and exchange rate volatility for 4 out of 5 exchange rates, however, the relationship between trading volume and exchange rate volatility was positive for all the exchange rates. The average correlation coefficient between bid-ask spread and exchange rate volatility is 5%. The average correlation coefficient between trading volume and exchange rate volatility is 16%, which is small but comparatively higher than spread.

Frank and Garcia (2011) using Generalized Method of Moments (GMM) empirically investigated the relationship between bid-ask spread, trading volume and volatility on two futures contracts i.e. live cattle and lean hogs trading in the CME group between January 2005 and October 2008. They found trading volume and return volatility were simultaneously determined and both were significantly related to the bid-ask spread.

Kyaw and Hillier (2011) investigated to find whether the relationship between trading volume, bid-ask spread and return volatility at the portfolio level was similar to the relationship at the individual security level of all firms listed on the London Stock Exchange (LSE) from 21st December, 1993 to 31st July, 2003. This study was conducted for 3 portfolios as well as individual companies. They found a positive relationship between return volatility and spread for 2 portfolios (Top-250 and Small-cap) however a negative relationship was established for Top-100 portfolio. Similarly they found a positive relationship between return volatility trading volume for all the three portfolios as well as individual companies.

Hussain (2011) empirically examined the intraday behavior of bid-ask spread, trading volume and return volatility for DAX-30 index using 5-minutes interval data set over the period from 5th May, 2004 to 29th September, 2005. In his study, EGARCH model was used to test the contemporaneous as well as lagged effect of trading volume and bid-ask spread on conditional volatility. The study found statistically significant but numerically small effect of both contemporaneous and lagged spreads and volume on return volatility. It was also found that both spread and lagged spread had positive impact on conditional volatility whereas volume and lagged volume had negative impact on the conditional volatility. However, introduction of both the information variables i.e. volume and spread in the conditional variance equation of GARCH model does not explain the volatility persistence in German stock returns.

Gtifa and Liouane (2013) empirically examined the relationship between volatility, order size and bid-ask spread in the foreign exchange market covering the period of 15th December, 2009 to 15th January, 2010. Their study focused on the rates of the USD versus TND and EUR versus TND, the most actively traded currencies pairs in Tunisia exchange market. They found that exchange rate volatility of EUR/TND affected spreads significantly and furthermore, they also found the evidence of a positive relationship between bid-ask spreads and exchange rate volatility, though order size and bid-ask spread were unrelated.

Wang, Garcia and Irwin (2014) examined the relationship between bid-ask spreads, trading volume and volatility for corn futures market for the period from 14th Jan 2008 to 29th Jan 2010. Their study found a positive contemporaneous relationship between spread and volatility as well as volume and volatility. However, the negative impact of lagged volume on volatility was also found. In addition both volume and spread were found to be negatively related.

4.3: Objectives of the Chapter

1. To examine the intraday contemporaneous as well as causal relationship between stock returns volatility, trading volume and bid-ask spread.

2. To investigate whether information contents in trading volume and bid-ask spread captures the volatility persistence in the market.

4.4: Data, Variables and Methodology

4.4.1: Data

In order to investigate the relationship between return volatility, volume and spread, the present study has used intraday high frequency 5 minutes interval data set of last trading price (LTP), bid price, ask price and volume from 2^{nd} July, 2012 to 31^{st} December, 2012 for 50 stocks of S&P CNX Nifty Index.

4.4.2: Description of Variables

Earlier studies like Clark (1973), Epps and Epps (1976), Tauchen and Pitts (1983) and Harris (1986) used squared price changes as measures of price variance/volatility to explain the mixture distribution hypothesis. Likewise, the recent studies like Brailsford (1994), Leon (2007), Medeiros and Doornik (2008), Kumar (2009), Tripathy (2011), Jafari & Tliti (2013) used squared return as measures of price volatility. In this part of the study, we have used squared return as measures of price volatility.

Both the log volume and proportionate spread are defined in the same manner as in the previous Chapter-3.

4.4.3: Methodology of the Study

4.4.3.1: Unit Root Test

The stationarity of the data series is tested with the help of Dickey Fuller (DF), Augmented Dickey Fuller (ADF) and Phillips Peron (PP) tests.

4.4.3.2: Contemporaneous Relation (OLS Regression)

The contemporaneous relations between volume and return volatility, and spread and return volatility have been investigated using the following OLS equations respectively.

$$R_t^2 = \alpha_1 + \beta_1 V_t + u_t \quad (4.1)$$

$$R_t^2 = \alpha_2 + \beta_2 S_t + u_t \quad (4.2)$$

Where, R_t^2, V_t and S_t are squared return (i.e. used as a measure of volatility), trading volume and spread respectively at time t. u_t is the error term. In equations (4.1) and (4.2), the estimated constant terms are denoted by α_1 and α_2 respectively, and the estimated coefficients of independent variables V_t and S_t are denoted by β_1 and β_2, respectively. In any stock, if we find β_1 to be significantly positive, it would imply that rising volatility of stock returns tends to be associated with rising volume and the decreasing volatility of stock returns tend to be associated with decline in volume. Similarly in any stock, if we find β_2 to be significantly positive, it would imply that rising volatility of stock returns tend to be associated with widening spread and the decreasing volatility of stock returns tend to be associated with narrowing spread. The R-square value of the estimated OLS model measures the degree of contemporaneous relationship.

4.4.3.3: Causal Relation (Granger Causality Test)

The pair wise causality between squared returns and trading volume has been checked by the Granger causality test by means of the following unrestricted equations:

$$R_t^2 = c_1 + \sum_{i=1}^{p} \alpha_i R_{t-i}^2 + \sum_{j=1}^{p} \beta_j V_{t-j} + u_{1t} \quad (4.3)$$

$$V_t = c_2 + \sum_{i=1}^{p} \lambda_i R_{t-i}^2 + \sum_{j=1}^{p} \delta_j V_{t-j} + u_{2t} \quad (4.4)$$

Where, R_t^2 and V_t are squared return (volatility) and trading volume respectively. c_1 and c_2 are intercepts and $\alpha_{i,} \beta_{j,} \lambda_i$ and δ_j are parameters. If some of β_j values are statistically not zero, then trading volume is said to granger cause return volatility. Similarly if some of λ_i values are statistically not zero, then stock returns volatility are said to Granger cause volume. If both β_j and λ_i are statistically significant then a feedback relationship is said to exist. The optimum lag length is selected based on Schwarz Information Criterion (SC). Similarly we checked the causality between stock return volatility and bid-ask spread.

4.4.3.4: Conditional Volatility (GARCH)

The conditional volatility of the returns is measured through GARCH model developed by Bollerslev (1986). Let r_t be the return at time t. The GARCH (1, 1) model is given by:

$$r_t = c + b_i r_{t-i} + \varepsilon_t \qquad (4.5)$$

$$\varepsilon_t \sim (0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} \qquad (4.6)$$

Equation (4.5) represents the mean equation. Where r_t is the return at time t, c stands for constant, b_i is the autoregressive coefficient and ε_t is the random error at time t, is approximately distributed $\varepsilon_t \sim (0, h_t)$. The autoregressive order of the mean equation is decided based on minimum AIC and SC criterion.

Equation (4.6) represents the conditional variance equation. Where h_t is the conditional variance of ε_t at time t. α_0 is a constant, α_1 reflects the influence of past squared residuals, ε_{t-1}^2 on current volatility and α_2 reflects the influence of previous periods volatility on current volatility. Here α_1 , $\alpha_2 > 0$ and sum of $(\alpha_1 + \alpha_2) < 1$. The aggregation of α_1 and α_2 coefficients measures the degree of continuity or persistence of volatility. The greater is the sum; the greater is the persistence of volatility. If the degree of persistence is close to one, this implies that the current volatility of intraday returns is affected by past volatility and that tends to persist over time. There is some evidence that normal GARCH model cannot capture the full extent of excess kurtosis in high frequency data (Tian and Guo, 2007). For this GARCH with Generalized Error Distribution (GED) employed in this study.

The presence of conditional volatility in the market is due to the serial correlation in arrival of information in the market. If current information is related to past information, the current volatility will be related to past volatility. Basing on the mixture distribution hypothesis (MDH), Lamoureux and Lastrapes (1990) used trading volume as measures of information flow in market and empirically verified that adding volume in the conditional variance equation of GARCH model leads to a very significant decrease in persistence in volatility measured by $(\alpha_1 + \alpha_2)$ and the ARCH effects tend to disappear when volume is included in the variance equation. They found information contained in volume absorbed the volatility persistence in the market.

Similarly, Najand and Yung (1991) included lagged volume to explain volatility. Studies like Rahman et al.(2002), Worthington and Higgs (2003) and Hussain (2011) considered bid-ask spread, lagged bid-ask spread along with volume and lagged volume as proxy for information arrival in their studies to explain conditional volatility.

Similarly, we also examined the impact of volume, lagged volume, spread and lagged spread on conditional volatility in Indian market by the following unrestricted GARCH (1, 1) model:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 V_t \quad (4.7)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 V_{t-1} \quad (4.8)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 S_t \quad (4.9)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 S_{t-1} \quad (4.10)$$

Where, V_t, V_{t-1}, S_t and S_{t-1} represent volume, lagged volume, spread and lagged spread respectively. The coefficient α_3 measures the influence of V_t , V_{t-1} , S_t and S_{t-1} on conditional volatility in the respective equations. If α_3 is found to be positive and trading volume/spread is serially correlated, α_1 and α_2 should be small and statistically insignificant, and their sum (the persistence of volatility) will be negligible.

4.5: Results and Analysis

4.5.1: Summary Statistics

Table 4.1 provides descriptive statistics of intraday 5 minutes squared return series of all 50 individual stocks. The means of the squared return series of the 50 individual stocks range from 0.0033 to 0.0253. The statistics shows that intraday squared return series are positively skewed ranging from 13 to 76.9. In addition, all kurtosis values are larger than 3 ranging from 246.6 to 6761. This shows that the distribution of intraday squared return series have fatter tails compared to normal distribution. The Jarque-Bera test suggests that all squared returns distribution is non-normal.

The presence of serial correlation in intraday volume series is important in implementing the mixture distribution hypothesis (MDH) with GARCH specification (Lamoureux and Lastrapes, 1990), since it is hypothesized in the mixture distribution hypothesis that serial correlation in the volume series (i.e. the rate of information arrival) causes the conditional hetroscedasticity of stock returns. For testing the serial correlation, we estimated the LB-Q statistic for volume and spread series up to the 10^{th} lag length and the LB-Q statistic are reported in Table 4.2. The LB-Q statistics are generally large and highly significant at 1% level for all the 50 stocks, confirming the presence of serial correlation in volume series. Hence, the rate of information arrival in the Indian market measured by the trading volume is serially correlated. In the similar manner, LB-Q statistics for spread series are also statistically significant except AXSB, SBIN and TTMT, suggesting the presence of serial correlation in spread series.

4.5.2: Unit Root Test Results

Table 4.3 reports the results of DF, ADF and PP test statistics of return volatility (squared return) for all the 50 stocks. The DF, ADF and PP statistics are significant at 1% level for all the stocks (except CAIR, MM and RBXY where DF is insignificant) and we reject the null hypothesis that return volatility has a unit root. It confirms that the volatility series is stationary for every one of the stocks therefore, suitable for further statistical analysis. CAIR, NM and RBXY series are considered in level as ADF and PP statistics are significant.

4.5.3: Cross Correlation Analysis

As the first step, to investigate the relationship between return volatility, trading volume and spread, we computed the cross-correlation coefficients for all the stocks. The correlation coefficients are reported in Table 4.4. We found return volatility is positively related with trading volume as well as with lagged trading volume in case of all the stocks. Similarly, we also found return volatility is positively related with spread as well as with lagged spread in case of 90% of the stocks. The lagged correlation gives an indication for causal relationship.

4.5.4: Contemporaneous Relationship between Return Volatility and Trading Volume

The results of the contemporaneous relationship between return volatility and trading volume are reported in Table 4.5. The parameter β_1 measures the contemporaneous relationship between trading volume and return volatility and it is found statistically significant positive for all the stocks. This indicates a positive contemporaneous relationship between return volatility and trading volume. It suggests that a higher trading volume is associated with an increase in stock return volatility and vice versa.

The degree of contemporaneous relationship is measured through R-square value. The reported R-square values for all the stocks are below 10%, which indicates that the contemporaneous volume explain a relatively small portion of return volatility in Indian market.

4.5.5: Contemporaneous Relationship between Return Volatility and Spread

The results of the contemporaneous relationship between return volatility and bid-ask spreads are reported in Table 4.6. The parameter β_2 measures the contemporaneous relationship between spread and return volatility and it was found that statistically significant positive β_2 for 40 stocks out of total 50, suggesting a positive contemporaneous relationship between them. We also found statistically significant negative β_2 for 5 stocks (COAL, ICICIBC, LT, TPWR and TTMT) and statistically insignificant relationship for remaining 5 stocks (DLFU, HNDL, INFO, PNB and RBXY).

Overall result shows there is a positive contemporaneous relationship exists between return volatility and spread in Indian market.

The degree of contemporaneous relationship is measured by R-square value. It can be observed from the Table 4.6 that, in majority of the stocks the reported R-square values are less than 5%, which indicates that the contemporaneous spread, explains relatively a very small portion of volatility in Indian market. Only for 11 stocks in the sample, we can observe a relatively high R-square values, namely SBIN(50%), SESA(49%), AXSB(48%), TTMT(46%), GRASIM(45%), HCLT(43%), CIPLA(38%), BHARATI(36%), TPWR(35%), HUVR(27%) and LT(16%).

The R-square values suggest that the degree of contemporaneous relationship between return volatility and spread are stock-specific rather than market, as a whole. But in general, the R-square values are comparatively higher in case of volume than spread, suggesting contemporaneous volume explains comparatively more portion of return volatility comparatively to spread.

4.5.6: Causal Relation between Return Volatility and Trading Volume

The Granger causality test results are presented in Table 4.7. Lag length for the causality test has been determined on the basis of Schwartz Information Criterion (SC) and the selected lag period for each stock are reported in the same table. The null hypothesis that lagged volume does not granger cause return volatility is rejected in case of 44 stocks except AXSB, BHARATI, GRASIM, HUVR, SBIN and SESA. On the other hand, the null hypothesis that past return volatility does not granger cause volume is rejected only for 35 stocks out of 50. For all these 35 stocks, we also found feedback relationship. Only in case of 6 stocks: AXSB, BHARATI, GRASIM, HUVR, SBIN and SESA, no causality is traced in either direction. The Granger causality result shows that volume causes volatility and that the volatility also causes volume but in lesser number of cases. This finding implies that in the presence of current and past volatility, trading volume adds some significant predictive power for future volatility.

4.5.7: Causal Relation between Return Volatility and Spread

The Granger causality test results between return volatility and bid-ask spreads are reported in Table 4.8. The test results show that the null hypothesis that lagged spread does not granger cause return volatility is rejected in case of 49 stocks except INFO, whereas the null hypothesis that lagged volatility does not granger cause spread is rejected only for 24 stocks. For all these 24 stocks, we also found feedback relationship between return volatility and spread. Only in case of INFO, no causality was traced in either direction. This clearly indicates that in the presence of current and past volatility, spread adds some significant predictive power for future returns. In general, information flows from spread to return volatility rather than return volatility to spread.

4.5.8: Conditional Return Volatility

Before GARCH, we estimated the conditional mean return equation for all the 50 stocks. The estimated coefficients and the t-stat values are reported in Table 4.9. However, AR(1) model was selected for 41 stocks, AR(2) model for DLFU and RELI, AR(3) model for DRRD and INFO, AR(4) model for JPA, AR(14) model for TATA and AR(28) model for BHEL. AR models were selected on the basis of minimum AIC and SC lag selection criterion and the AIC and SC values are reported in the last two columns in the same mean equation table. All the selected AR coefficients of the mean equation are statistically significant at various levels of significance (1-10%). In high frequency series, there are also chances of getting higher order autoregressive return series. We observed the same in the case of TATA and BHEL.

The ARCH-LM test was performed before an estimation of GARCH model to check whether the ARCH effect was present in the return series or not. Engle (1982) had introduced the concept in which the error variance depends on the lagged squared error term. We performed ARCH-LM test up to 20 lag periods and the ARCH-LM test results are reported in Table 4.10. For all the stocks, F-statistics were significant at 1% level of significance, and so we reject the null hypothesis i.e. there is homoscedasticity in error variance. So, there is ARCH effect present in the return series. To capture the ARCH effect, we switch to GARCH.

Moreover, the GARCH (1, 1) model has been used in order to explain the conditional variance and volatility clustering. The estimated results of GARCH (1, 1) model for each stock are reported in Table 4.11. The coefficients α_1 and α_2 represent ARCH and GARCH terms, respectively, and are shown to be statistically significant. It is also found that for all the stocks the conditional volatility is time varying and shows persistence. Our results also indicate that the persistence in volatility, as measured by the sum of $(\alpha_1 + \alpha_2)$ in the GARCH (1, 1) model, ranging from 0.703 to 0.998 with an average of .878, is fairly close to one, suggesting a strong presence of ARCH and GARCH effects. This indicates a high degree of volatility persistence in Indian stock market as observed in developed markets.

In order to check the source of conditional volatility, we included contemporaneous volume, contemporaneous spread, lagged volume and lagged spread as proxy for information arrivals in the conditional variance equation of GARCH model. The model results are discussed in the following sections.

4.5.9: Relationship between Conditional Volatility and Volume

In order to investigate the contemporaneous volume impact on conditional volatility we estimated the GARCH (1, 1) cum volume model including volume as an exogenous proxy for information arrival. Table 4.12 reports the coefficient estimates of the GARCH (1, 1) cum volume model. Here both ARCH coefficient (α_1) and GARCH coefficient (α_2) are significant and also the coefficients of trading volume (α_3) are positive and statistically significant for all the 50 stocks.

For comparison with baseline GARCH (1, 1) model, we reported all the models (GARCH with volume, lagged volume, spread and lagged spread) result together in Table 4.16 and it include sum of volatility persistence ($\alpha_1 + \alpha_2$) for all the models and its percentage change with baseline GARCH (1, 1). We also calculated the average sum of volatility persistence of all the 50 companies which is shown in the last row of the same comparison table.

The results in the comparison table show that in majority of cases, there is a substantial reduction in the volatility persistence ($\alpha_1 + \alpha_2$) after including trading volume in the conditional variance equation except for five stocks in the sample, namely, CAIR, DRRD, HDFC, ICICIBC and SUNP, where it can be observed that a marginal reduction exists in volatility persistence (i.e. below 10%). It can also be observed that, for a few stocks, the impact of volume on volatility persistence is comparatively high, namely, IDFC (82%), CIPLA (77%), HCLT (75%), TPWR (67%), TATA (61%), AXSB (58%) and RBXY (53%). The average sum of volatility persistence ($\alpha_1 + \alpha_2$) of the 50 individual stocks is reduced from (0.88) to (0.62). The average reduction in volatility persistence is 30%.

Our results ascertain that when trading volume is included in the variance equation, as a proxy for information flow, some moderate to high level reduction are observed in the volatility persistence.

4.5.10: Relationship between Conditional Volatility and Lagged Volume

Table 4.13 shows the estimation results of GARCH model, when lagged trading volume is included in the conditional variance equation. The result shows that the both ARCH coefficient (α_1) and GARCH coefficient (α_2) are statistically significant and the coefficients of lagged trading volume (α_3) are positive and statistically significant for all the 50 stocks. It clearly indicates that a positive lagged relationship exists between volume and conditional volatility.

However, in 50% cases, where the lagged volume impact is comparatively higher, the average reduction in volatility persistence is 25%. Similarly, for remaining 50% cases where the impact is less, the average reduction in volatility persistence is 6%. The average sum of volatility persistence $(\alpha_1 + \alpha_2)$ is reduced from (0.88) to (0.74). The average reduction is 15%. The volatility of persistence absorbed by lagged volume is the highest in the cases of TPWR (90%), MM (63%), RIL (40%), HNDL (32%) and RELI (31%).

Our results suggest that when lagged trading volume is included in the variance equation, the degree of volatility persistence is reduced but comparatively lesser than volume. Hence, contemporaneous volume has more information content than lagged volume to absorb the volatility of persistence in the Indian market.

4.5.11: Relationship between Conditional Volatility and Spread

Rahman et al. (2002), Worthington and Higgs (2003) and Hussain (2011) add spread as an explanatory variable in the GARCH model to examine if spread can capture the volatility persistence in the market. In the similar manner we examine the role of bid-ask spread on return volatility in the Indian market.

Table 4.14 provides the coefficient estimates of the GARCH (1, 1) cum spread model. Here, both the ARCH coefficient (α_1) and GARCH coefficient (α_2) are statistically significant and the coefficients of spread (α_3) are positive and statistically significant for 41 stocks, negative and statistically significant for 7 stocks (BHARATI, CIPLA, HCLT, HUVR, LT, TPWR and TTMT) and the spread coefficient is insignificant in case of GRASIM and HNDL. The overall result suggests a positive contemporaneous relationship between volatility and spread for most of the cases.

However, the results also show that in majority of cases, there is a very small decrease in the volatility persistence $(\alpha_1 + \alpha_2)$. Only for five stocks in the sample, namely AXSB, KMB, SBIN, SESA and SEIM, we can observe 10% or larger decrease in volatility persistence and it is highest (13%) in the case of SBIN. The average sum of volatility persistence $(\alpha_1 + \alpha_2)$ of 50 stocks is marginally reduced from (0.88) to (0.83) by the inclusion of spread in variance equation. The average reduction in volatility persistence is found to be only 5%. Hence, including spread in the conditional variance equation does not result in a significant reduction of volatility persistence for most samples. So, spread has less information content to absorb volatility persistence in the Indian market.

The whole result suggests a positive and statistically significant but numerically very small effect on conditional volatility. Rahaman et al. (2002) reported some similar findings in NASDAQ stocks.

4.5.12: Relationship between Conditional Volatility and Lagged Spread

Table 4.15 reports the coefficient estimates of the GARCH (1, 1) cum lagged spread model. Here both the ARCH coefficient (α_1) and GARCH coefficient (α_2) are statistically significant and the coefficients of lagged spread (α_3) are positive and statistically significant for all the stocks except HNDL. It clearly indicates that a positive significant lagged relationship exists between spread and volatility.

However, in most of the cases, it can be observed that there is only a marginal reduction in the volatility persistence ($\alpha_1 + \alpha_2$). The volatility persistence reduction is highest (12%) in cases of ICICIBC. The average sum of volatility persistence ($\alpha_1 + \alpha_2$) of 50 stocks is reduced from (0.88) to (0.84) and the average reduction in volatility persistence is only 4%. Hence lagged spread has very less information content to absorb volatility persistence in the Indian market.

Both contemporaneous and lagged spreads show a very limited impact on volatility. The overall result suggests a positive and statistically significant but numerically very small effect on conditional volatility. Rahaman et al. (2002) also reported positive and statistical significant but numerically very small impact of both contemporaneous spread and lagged spread along with volume and lagged volume in NASDAQ stocks.

4.6: Summary and Concluding Remarks

This chapter of the study investigated the contemporaneous as well as causal relationship between return volatility, trading volume and spread using 5-minutes interval high frequency data from 50 stocks of S&P CNX NIFTY Index over the period from 2nd July, 2012 to 31st December, 2012.

We find evidence of a positive contemporaneous relationship between volume and volatility measured by squared return, suggesting that higher trading volume was associated with an increase in stock return volatility and vice versa. Similarly, the study also found positive contemporaneous relationship between return volatility (squared return) and spread, suggesting that widening spread is associated with an increasing stock return volatility and vice versa. Overall, the findings suggested that in particular stocks, the contemporaneous spread explained a relatively higher portion of return volatility, though in general, contemporaneous volume explained return volatility to a larger extent compared to what the spread could explain.

The current study also investigated the information content of volume for future returns volatility by using Granger causality test and found that for the majority of the cases trading volume causes return volatility. In a similar manner, the current study also investigated the information content of spread for future returns volatility and found that for the majority of the cases spread caused return volatility. Overall, our findings demonstrate a strong support of volume causing return/return volatility. An explanation for this, in Indian market most of the participants are small and marginal traders and they are late in information queue. It takes some time for information to reach them after it arrives at the market and thereafter they do trade and changes in price/volatility.

These results seem to indicate that information arrival to investors tends to follow a sequential rather than simultaneous process. The findings support the sequential information arrival hypothesis (SIAH) and contradict the mixture distribution hypothesis (MDH). Our study examines the efficient market hypothesis from the perspective of price-volume and price-spread relationships in Indian market. We find that Indian market is to some extent predictable using historical information contained in the past volume and the past spread, and is informationally, not as efficient as the efficient market hypothesis suggests.

The present study provides evidence of strong volatility persistence in the Indian stock market. The current volatility can be explained by past volatility that tends to persists over time. Based on Lamoureux and Lastrapes (1990) study, we add volume as an explanatory variable in the GARCH model to examine if the information contents of volume can capture the volatility persistence in the Indian market. It was observed that a moderate to high degree of reduction in volatility persistence could be achieved when contemporaneous volume is included in variance equation of GARCH model, It was also observed that a small to moderate level of reduction in volatility persistence could be achieved when lagged volume was included in variance equation of GARCH model. We then substitute the bid ask spread for volume in the conditional volatility equation to examine if the latter can capture the volatility persistence. The results show that the volatility persistence remained strong for many of the securities after the introduction of both the contemporaneous and lagged spread.

Table 4.1: Descriptive Statistics of Squared Return Series

Descriptive Statistics of Squared Return						
Stock	Mean	Stdev	Skewness	Excess Kurtosis	Jarque-Bera	Prob.
ACC	0.0051	0.023	29.0	1309.2	653000000	0
ACEM	0.0064	0.023	13.0	246.6	22915489	0
APNT	0.0045	0.025	38.1	2071.3	1640000000	0
AXSB	0.0142	0.443	66.6	4483.5	7680000000	0
BHARATI	0.0112	0.170	56.4	3433.6	4500000000	0
BHEL	0.0086	0.038	18.9	536.5	109000000	0
BJAUT	0.0052	0.023	17.0	418.1	66251277	0
BOB	0.0077	0.053	43.8	2374.9	2150000000	0
BPCL	0.0070	0.042	48.5	3402.6	4420000000	0
CAIR	0.0048	0.036	35.5	1760.9	1180000000	0
CIPLA	0.0114	0.378	64.4	4279.8	6990000000	0
COAL	0.0048	0.022	23.8	813.4	252000000	0
DLFU	0.0108	0.050	26.6	1005.4	385000000	0
DRRD	0.0044	0.020	21.5	641.5	156000000	0
GAIL	0.0066	0.062	76.9	6761.0	17500000000	0
GRASIM	0.0068	0.163	66.7	4489.8	7690000000	0
HCLT	0.0099	0.257	62.6	4058.7	6290000000	0
HDFC	0.0046	0.035	42.8	2464.1	2320000000	0
HDFCB	0.0033	0.013	19.7	606.2	140000000	0
HMCL	0.0052	0.024	20.9	634.4	153000000	0
HNDL	0.0097	0.065	62.3	4957.0	9380000000	0
HUVR	0.0075	0.233	66.7	4494.1	7710000000	0
ICICIBC	0.0069	0.066	41.5	2093.5	1670000000	0
IDFC	0.0101	0.058	51.9	3727.8	5300000000	0
INFO	0.0070	0.161	64.8	4316.1	7110000000	0

Table 4.1: Continued.

Descriptive Statistics of Squared Return						
Stock	Mean	Stdev	Skewness	Excess Kurtosis	Jarque-Bera	Prob.
ITC	0.0040	0.018	23.0	797.1	242000000	0
JPA	0.0154	0.107	43.2	2458.2	2310000000	0
JSP	0.0137	0.074	35.5	1932.3	1420000000	0
KMB	0.0060	0.028	29.7	1226.5	573000000	0
LPC	0.0058	0.025	27.4	1230.6	577000000	0
LT	0.0062	0.057	50.4	3014.9	3470000000	0
MM	0.0053	0.023	18.2	473.9	85210014	0
MSIL	0.0077	0.086	46.3	2510.7	2410000000	0
NTPC	0.0043	0.020	32.9	1747.6	1160000000	0
ONGC	0.0054	0.031	37.2	2045.1	1600000000	0
PNB	0.0080	0.041	23.1	702.4	188000000	0
PWGR	0.0044	0.017	18.7	583.2	129000000	0
RBXY	0.0061	0.022	21.3	866.8	286000000	0
RELI	0.0108	0.041	15.0	308.9	36091397	0
RIL	0.0045	0.023	28.0	1076.0	441000000	0
SBIN	0.0159	0.641	67.1	4532.5	7840000000	0
SESA	0.0253	1.027	67.4	4563.5	7950000000	0
SIEM	0.0056	0.029	44.2	2886.2	3180000000	0
SUNP	0.0053	0.027	26.0	1109.4	469000000	0
TATA	0.0073	0.051	37.4	1825.6	1270000000	0
TCS	0.0049	0.033	29.5	1048.0	418000000	0
TPWR	0.0093	0.087	50.5	2979.9	3390000000	0
TTMT	0.0133	0.205	58.6	3718.7	5280000000	0
UTCEM	0.0056	0.051	50.6	2975.8	3380000000	0
WPRO	0.0059	0.029	21.3	664.1	168000000	0

Table 4.2: LB-'Q' statistics for Volume and Spread Series

Stock	LB-'Q' statistic of Volume (up to lag 10)	LB-'Q' statistic of Spread (up to lag 10)
ACC	21815*	1422.7*
ACEM	25588*	959.95*
APNT	20149*	2056.8*
AXSB	21915*	0.9597
BHARATI	27769*	36.709*
BHEL	31897*	380.65*
BJAUT	23741*	1654.8*
BOB	25586*	1124.4*
BPCL	21175*	1162.5*
CAIR	29806*	786.1*
CIPLA	26319*	5.9093*
COAL	24061*	437.86*
DLFU	20381*	157.54*
DRRD	22368*	433.8*
GAIL	18353*	1180.8*
GRASIM	13398*	114.51*
HCLT	26456*	37.399*
HDFC	26655*	13.234*
HDFCB	19709*	1010.4*
HMCL	21487*	331.23*
HNDL	23814*	137.07*
HUVR	25755*	381.06*
ICICIBC	22298*	619.05*
IDFC	20009*	361.24*
INFO	28441*	796.2*

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.2: Continued.

Stock	L-B 'Q' statistic of Volume (up to lag 10)	L-B 'Q' statistic of Spread (up to lag 10)
ITC	27389*	512.98*
JPA	18028*	1086.8*
JSP	27851*	380.07*
KMB	1711.7*	19261*
LPC	25491*	1956.9*
LT	18339*	21.348*
MM	27938*	1303.8*
MSIL	29669*	1209.6*
NTPC	20899*	394.68*
ONGC	23464*	766.31*
PNB	27395*	384.66*
PWGR	21843*	599.16*
RBXY	22108*	1125.6*
RELI	13617*	3.1143**
RIL	23360*	497.4*
SBIN	16140*	0.7267
SESA	22710*	3.5318**
SIEM	17968*	2427.4*
SUNP	21973*	1136*
TATA	20060*	171.3*
TCS	32269*	675.18*
TPWR	28814*	17.292*
TTMT	23134*	1.5315
UTCEM	21266*	4736.4*
WPRO	23432*	1863*

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.3: Unit Root Test Results for Squared Return Series

Unit Root Test for Squared Return Series						
Stock	Intercept			Intercept with Trend		
	DF	ADF	PP	DF	ADF	PP
ACC	-37.8*	-39.6*	-84.9*	-39.2*	-39.6*	-84.9*
ACEM	-4.7*	-39.2*	-84.1*	-9.2*	-39.2*	-84.0*
APNT	-5.6*	-29.6*	-94.1*	-10.8*	-29.7*	-93.8*
AXSB	-36.1*	-36.5*	-51.7*	-36.4*	-36.5*	-51.7*
BHARATI	-39.0*	-39.1*	-57.5*	-39.1*	-39.1*	-57.5*
BHEL	-38.4*	-38.4*	-92.2*	-38.4*	-38.4*	-92.2*
BJAUT	-38.2*	-38.4*	-89.6*	-38.3*	-38.5*	-89.5*
BOB	-39.9*	-40.7*	-90.6*	-40.5*	-40.7*	-90.6*
BPCL	-8.0*	-40.8*	-90.8*	-15.3*	-40.9*	-90.8*
CAIR	-1.3	-39.3*	-93.4*	-2.8***	-39.4*	-93.4*
CIPLA	-34.7*	-37.8*	-53.6*	-36.9*	-37.8*	-53.5*
COAL	-35.3*	-38.5*	-81.4*	-37.2*	-38.5*	-81.4*
DLFU	-38.9*	-39.4*	-88.8*	-39.3*	-39.4*	-88.8*
DRRD	-2.3**	-39.4*	-92.4*	-4.7*	-39.4*	-92.4*
GAIL	-31.1*	-41.7*	-93.1*	-38.5*	-41.7*	-93.1*
GRASIM	-29.0*	-36.2*	-50.9*	-33.9*	-36.2*	-50.9*
HCLT	-30.1*	-38.1*	-53.8*	-35.5*	-38.1*	-53.8*
HDFC	-30.1*	-40.4*	-93.4*	-36.3*	-40.5*	-93.3*
HDFCB	-6.3*	-38.1*	-92.4*	-12.2*	-38.1*	-92.4*
HMCL	-28.8*	-39.6*	-87.3*	-36.3*	-39.6*	-87.2*
HNDL	-21.5*	-42.0*	-94.0*	-21.2*	-42.0*	-94.0*
HUVR	-36.6*	-36.6*	-51.0*	-36.6*	-36.6*	-51.0*
ICICIBC	-16.9*	-41.4*	-86.6*	-27.8*	-41.4*	-86.5*
IDFC	-40.2*	-41.5*	-93.5*	-41.3*	-41.5*	-93.5*
INFO	-39.1*	-42.4*	-94.8*	-41.7*	-42.4*	-94.8*

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.3: Continued.

Unit Root Test for Squared Return Series						
Stock	Intercept			Intercept with Trend		
	DF	ADF	PP	DF	ADF	PP
ITC	-36.5*	-38.8*	-91.8*	-37.8*	-38.8*	-91.8*
JPA	-39.4*	-41.3*	-90.4*	-40.6*	-41.3*	-90.4*
JSP	-32.2*	-38.0*	-85.5*	-36.7*	-38.1*	-85.5*
KMB	-7.4*	-39.3*	-69.9*	-14.2*	-39.4*	-69.9*
LPC	-35.5*	-36.8*	-86.6*	-36.3*	-36.8*	-86.6*
LT	-40.7*	-41.3*	-79.6*	-41.1*	-41.3*	-79.6*
MM	-0.7	-39.1*	-91.1*	-2.0	-39.2*	-91.1*
MSIL	-41.1*	-41.1*	-85.9*	-41.1*	-41.2*	-85.9*
NTPC	-38.6*	-39.0*	-92.0*	-38.8*	-39.0*	-92.0*
ONGC	-30.7*	-39.9*	-90.4*	-37.5*	-39.9*	-90.3*
PNB	-10.2*	-40.6*	-86.1*	-18.6*	-40.6*	-86.1*
PWGR	-15.0*	-38.4*	-87.1*	-25.2*	-38.4*	-87.1*
RBXY	-1.4	-39.0*	-91.2*	-3.1**	-39.2*	-91.0*
RELI	-35.3*	-40.9*	-90.1*	-38.5*	-41.0*	-90.1*
RIL	-37.3*	-39.3*	-92.4*	-21.8*	-39.3*	-92.4*
SBIN	-35.3*	-36.4*	-51.4*	-36.1*	-36.4*	-51.4*
SESA	-35.9*	-36.3*	-51.3*	-36.2*	-36.3*	-51.3*
SIEM	-40.0*	-40.4*	-92.2*	-40.1*	-40.5*	-92.1*
SUNP	-35.3*	-39.0*	-84.4*	-37.8*	-39.0*	-84.4*
TATA	-40.9*	-41.7*	-90.3*	-41.3*	-41.7*	-90.3*
TCS	-35.3*	-38.1*	-76.0*	-37.6*	-38.1*	-75.9*
TPWR	-34.8*	-39.7*	-61.6*	-38.5*	-39.7*	-61.6*
TTMT	-12.1*	-38.4*	-56.2*	-21.2*	-38.4*	-56.2*
UTCEM	-39.3*	-39.6*	-90.2*	-39.6*	-39.6*	-90.1*
WPRO	-21.4*	-38.1*	-89.5*	-30.4*	-38.1*	-89.5*

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.4: Correlation Results

Cross Correlation Coefficients					
Stock	R^2 ↔V	R^2 ↔S	R^2 ↔V(-1)	R^2 ↔S(-1)	V↔S
ACC	0.214	0.066	0.143	0.073	-0.021
ACEM	0.237	0.084	0.163	0.094	-0.064
APNT	0.208	0.045	0.141	0.043	-0.008
AXSB	0.048	0.694	0.035	0.699	0.030
BHARATI	0.082	0.603	0.054	0.635	0.013
BHEL	0.285	0.041	0.182	0.083	0.000
BJAUT	0.222	0.048	0.145	0.118	-0.018
BOB	0.157	0.025	0.102	0.059	-0.036
BPCL	0.170	0.074	0.099	0.071	-0.051
CAIR	0.200	0.034	0.106	0.066	-0.015
CIPLA	0.062	0.618	0.048	0.719	0.019
COAL	0.195	-0.159	0.147	-0.162	-0.028
DLFU	0.249	0.010	0.121	0.111	0.020
DRRD	0.172	0.072	0.138	0.085	0.006
GAIL	0.118	0.043	0.070	0.091	-0.016
GRASIM	0.058	0.670	0.037	0.639	0.009
HCLT	0.059	0.656	0.045	0.655	0.022
HDFC	0.217	0.100	0.125	0.062	0.056
HDFCB	0.200	0.073	0.167	0.164	0.004
HMCL	0.226	0.032	0.160	0.188	0.008
HNDL	0.176	0.001	0.095	0.040	-0.081
HUVR	0.056	0.522	0.050	0.495	0.054
ICICIBC	0.162	-0.024	0.101	0.030	0.055
IDFC	0.179	0.036	0.095	0.103	0.026
INFO	0.113	0.007	0.065	0.016	0.004

Table 4.4: Continued.

Cross Correlation Coefficients					
Stock	R^2 ↔V	R^2 ↔S	R^2 ↔V(-1)	R^2 ↔S(-1)	V↔S
ITC	0.237	0.038	0.172	0.100	0.049
JPA	0.187	0.021	0.081	0.046	-0.007
JSP	0.224	0.124	0.143	0.115	-0.045
KMB	0.158	0.040	0.112	0.087	-0.074
LPC	0.210	0.038	0.136	0.079	-0.047
LT	0.152	-0.394	0.098	-0.305	-0.031
MM	0.214	0.053	0.157	0.131	-0.023
MSIL	0.148	0.021	0.096	0.069	-0.041
NTPC	0.167	0.171	0.140	0.078	0.007
ONGC	0.196	0.054	0.130	0.076	0.000
PNB	0.220	0.007	0.161	0.073	-0.042
PWGR	0.197	0.069	0.154	0.097	-0.023
RBXY	0.295	0.005	0.170	0.066	-0.066
RELI	0.297	0.056	0.155	0.067	0.027
RIL	0.214	0.027	0.146	0.090	0.014
SBIN	0.047	0.706	0.031	0.695	0.033
SESA	0.047	0.702	0.029	0.676	0.018
SIEM	0.173	0.065	0.122	0.090	-0.070
SUNP	0.203	0.039	0.137	0.106	-0.009
TATA	0.200	0.060	0.123	0.103	0.046
TCS	0.191	0.216	0.143	0.246	0.026
TPWR	0.130	-0.595	0.101	-0.488	-0.046
TTMT	0.102	-0.675	0.072	-0.632	-0.024
UTCEM	0.122	0.061	0.091	0.039	-0.106
WPRO	0.212	0.047	0.160	0.089	-0.054
Abs Avg-correlation	0.172	0.180	0.114	0.203	0.032

Table 4.5: OLS Regression Results between Volume and Volatility

$R_t^2 = \alpha_1 + \beta_1 V_t + u_t$					
Stock	α_1	t-statistics	β_1	t-statistics	R-squared
ACC	-0.033	-17.9	0.011*	20.9	0.046
ACEM	-0.047	-20.4	0.012*	23.3	0.056
APNT	-0.023	-16.7	0.010*	20.4	0.043
AXSB	-0.242	-4.4	0.060*	4.6	0.002
BHARATI	-0.144	-7.3	0.033*	7.9	0.007
BHEL	-0.117	-26.4	0.028*	28.4	0.081
BJAUT	-0.038	-19.0	0.012*	21.8	0.049
BOB	-0.065	-13.5	0.020*	15.2	0.025
BPCL	-0.054	-14.5	0.016*	16.6	0.029
CAIR	-0.075	-18.3	0.018*	19.5	0.040
CIPLA	-0.196	-5.6	0.050*	5.9	0.004
COAL	-0.038	-16.8	0.010*	19.0	0.038
DLFU	-0.147	-22.9	0.033*	24.6	0.062
DRRD	-0.021	-13.7	0.007*	16.7	0.029
GAIL	-0.053	-10.0	0.016*	11.4	0.014
GRASIM	-0.039	-4.7	0.017*	5.6	0.003
HCLT	-0.126	-5.2	0.035*	5.6	0.003
HDFC	-0.084	-20.1	0.020*	21.3	0.047
HDFCB	-0.027	-17.3	0.007*	19.6	0.040
HMCL	-0.040	-19.5	0.013*	22.2	0.051
HNDL	-0.133	-15.9	0.030*	17.1	0.031
HUVR	-0.143	-5.1	0.035*	5.4	0.003
ICICIBC	-0.133	-14.9	0.031*	15.7	0.026
IDFC	-0.129	-16.1	0.029*	17.4	0.032
INFO	-0.182	-10.4	0.047*	10.9	0.013

Note: *Significant at 1% level

Table 4.5: Continued.

$R_t^2 = \alpha_1 + \beta_1 V_t + u_t$					
Stock	α_1	t-statistics	β_1	t-statistics	R-squared
ITC	-0.047	-21.5	0.011*	23.4	0.056
JPA	-0.283	-17.2	0.057*	18.2	0.035
JSP	-0.138	-19.9	0.035*	22.0	0.050
KMB	-0.029	-12.6	0.009*	15.3	0.025
LPC	-0.040	-17.9	0.012*	20.6	0.044
LT	-0.102	-13.8	0.026*	14.7	0.023
MM	-0.044	-18.7	0.012*	21.0	0.046
MSIL	-0.105	-13.3	0.030*	14.3	0.022
NTPC	-0.027	-13.8	0.007*	16.2	0.028
ONGC	-0.061	-17.5	0.015*	19.2	0.039
PNB	-0.067	-19.1	0.020*	21.6	0.048
PWGR	-0.028	-16.5	0.007*	19.2	0.039
RBXY	-0.049	-26.1	0.015*	29.6	0.087
RELI	-0.135	-27.4	0.034*	29.7	0.088
RIL	-0.058	-19.4	0.014*	21.0	0.046
SBIN	-0.361	-4.3	0.087*	4.5	0.002
SESA	-0.481	-4.2	0.120*	4.5	0.002
SIEM	-0.021	-13.1	0.009*	16.8	0.030
SUNP	-0.044	-17.6	0.013*	19.9	0.041
TATA	-0.129	-18.5	0.030*	19.6	0.040
TCS	-0.058	-17.2	0.016*	18.7	0.037
TPWR	-0.106	-11.5	0.026*	12.6	0.017
TTMT	-0.292	-9.3	0.061*	9.8	0.010
UTCEM	-0.026	-9.6	0.011*	11.8	0.015
WPRO	-0.055	-18.6	0.015*	20.7	0.045

Note: *Significant at 1% level

Table 4.6: OLS Regression Results between Bid-Ask Spread and Volatility

$R_t^2 = \alpha_2 + \beta_2 S_t + u_t$					
Stock	α_2	t-statistics	β_2	t-statistics	R-squared
ACC	0.0033	8.7	4.4*	6.4	0.0044
ACEM	0.0035	8.0	6.0*	8.1	0.0070
APNT	0.0031	7.2	2.9*	4.3	0.0020
AXSB	-0.0399	-11.8	240.8*	92.4	0.4820
BHARATI	-0.0443	-27.5	174.2*	72.3	0.3633
BHEL	0.0060	7.7	7.6*	3.9	0.0017
BJAUT	0.0040	11.3	3.7*	4.6	0.0023
BOB	0.0060	6.7	4.0*	2.4	0.0006
BPCL	0.0028	3.8	8.1*	7.1	0.0055
CAIR	0.0032	5.0	5.7*	3.2	0.0011
CIPLA	-0.0766	-23.1	235.5*	75.2	0.3818
COAL	0.0086	25.6	-11.5*	-15.5	0.0254
DLFU	0.0099	9.2	2.6	1.0	0.0001
DRRD	0.0033	12.5	3.0*	6.9	0.0052
GAIL	0.0033	3.2	6.8*	4.1	0.0019
GRASIM	-0.0580	-39.5	97.8*	86.3	0.4487
HCLT	-0.0533	-24.6	173.7*	83.3	0.4309
HDFC	0.0034	8.7	6.0*	9.6	0.0100
HDFCB	0.0022	10.8	4.3*	7.0	0.0053
HMCL	0.0045	13.2	2.0*	3.0	0.0010
HNDL	0.0096	5.7	0.2	0.1	0.0000
HUVR	-0.0900	-33.8	387.7*	58.6	0.2726
ICICIBC	0.0086	8.5	-9.9*	-2.3	0.0006
IDFC	0.0059	4.3	9.5*	3.4	0.0013
INFO	0.0059	2.5	4.8	0.6	0.0000

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.6: Continued.

$R_t^2 = \alpha_2 + \beta_2 S_t + u_t$					
Stock	α_2	t-statistics	β_2	t-statistics	R-squared
ITC	0.0030	8.9	3.7*	3.6	0.0014
JPA	0.0096	3.0	8.9**	2.0	0.0004
JSP	0.0016	1.3	32.8*	11.9	0.0153
KMB	0.0045	9.5	3.0*	3.8	0.0016
LPC	0.0046	10.9	3.1*	3.6	0.0014
LT	0.0176	28.8	-55.9*	-41.1	0.1555
MM	0.0040	11.8	4.8*	5.1	0.0028
MSIL	0.0056	4.1	6.8**	2.0	0.0004
NTPC	-0.0016	-3.9	11.9*	16.6	0.0292
ONGC	0.0032	6.0	6.2*	5.1	0.0029
PNB	0.0077	10.8	0.9	0.7	0.0001
PWGR	0.0019	4.6	4.4*	6.6	0.0047
RBXY	0.0060	15.0	0.4	0.5	0.0000
RELI	0.0097	20.4	3.3*	5.3	0.0031
RIL	0.0039	11.0	3.3*	2.5	0.0007
SBIN	-0.0493	-10.3	382.9*	95.4	0.4981
SESA	-0.2398	-29.5	505.3*	94.3	0.4923
SIEM	0.0028	5.2	4.2*	6.2	0.0042
SUNP	0.0040	9.2	3.5*	3.8	0.0016
TATA	0.0032	3.7	17.3*	5.8	0.0036
TCS	-0.0018	-3.9	31.1*	21.2	0.0468
TPWR	0.0621	59.5	-79.0*	-70.9	0.3542
TTMT	0.0565	34.1	-159.8*	-87.6	0.4556
UTCEM	0.0019	2.3	6.4*	5.9	0.0037
WPRO	0.0039	7.5	5.3*	4.5	0.0022

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.7: Granger Causality Test Results between Volatility and Volume

Granger Causality Test between Squared Return (Volatility) and Volume							
Stock	Volume does not Granger Cause Squared Return (Volatility)			Squared Return (Volatility) does not Granger Cause Volume			Lag Length
	F Stat	Prob.	Null Hypothesis	F Stat	Prob.	Null Hypothesis	
ACC	24.0*	0.00	Rejected	6.7*	0.00	Rejected	5
ACEM	43.7*	0.00	Rejected	15.2*	0.00	Rejected	4
APNT	16.9*	0.00	Rejected	3.8*	0.00	Rejected	6
AXSB	0.9	0.56	Not Rejected	0.5	0.86	Not Rejected	10
BHARATI	1.5	0.20	Not Rejected	1.1	0.34	Not Rejected	5
BHEL	66.1*	0.00	Rejected	11.0*	0.00	Rejected	4
BJAUT	41.5*	0.00	Rejected	7.1*	0.00	Rejected	4
BOB	21.9*	0.00	Rejected	2.4**	0.05	Rejected	4
BPCL	21.5*	0.00	Rejected	2.8**	0.03	Rejected	4
CAIR	22.2*	0.00	Rejected	7.6*	0.00	Rejected	4
CIPLA	2.0***	0.06	Rejected	1.0	0.43	Not Rejected	6
COAL	27.4*	0.00	Rejected	4.3*	0.00	Rejected	5
DLFU	22.0*	0.00	Rejected	6.2*	0.00	Rejected	5
DRRD	41.4*	0.00	Rejected	5.4*	0.00	Rejected	4
GAIL	11.0*	0.00	Rejected	0.8	0.52	Not Rejected	4
GRASIM	0.6	0.84	Not Rejected	1.0	0.43	Not Rejected	10
HCLT	2.9*	0.01	Rejected	0.9	0.52	Not Rejected	6
HDFC	46.7*	0.00	Rejected	5.8*	0.00	Rejected	**3**
HDFCB	78.1*	0.00	Rejected	10.6*	0.00	Rejected	3
HMCL	46.9*	0.00	Rejected	7.1*	0.00	Rejected	4
HNDL	34.6*	0.00	Rejected	3.5*	0.01	Rejected	3
HUVR	1.2	0.32	Not Rejected	1.4	0.17	Not Rejected	9
ICICIBC	2.4**	0.04	Rejected	6.8*	0.00	Rejected	5
IDFC	18.8*	0.00	Rejected	3.6*	0.00	Rejected	5
INFO	10.2*	0.00	Rejected	0.6	0.63	Not Rejected	4

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.7: Continued.

Granger Causality Test between Squared Return (Volatility) and Volume							
Stock	Volume does not Granger Cause Squared Return (Volatility)			Squared Return (Volatility) does not Granger Cause Volume			Lag Length
	F Stat	Prob.	Null Hypothesis	F Stat	Prob.	Null Hypothesis	
ITC	63.9*	0.00	Rejected	10.2*	0.00	Rejected	4
JPA	14.8*	0.00	Rejected	1.7	0.13	Not Rejected	5
JSP	24.8*	0.00	Rejected	3.2*	0.01	Rejected	5
KMB	12.8*	0.00	Rejected	2.1***	0.08	Rejected	4
LPC	23.2*	0.00	Rejected	3.9*	0.00	Rejected	5
LT	20.1*	0.00	Rejected	1.3	0.27	Not Rejected	3
MM	39.7*	0.00	Rejected	8.5*	0.00	Rejected	5
MSIL	12.6*	0.00	Rejected	0.4	0.85	Not Rejected	5
NTPC	32.2*	0.00	Rejected	4.2*	0.00	Rejected	5
ONGC	33.8*	0.00	Rejected	8.1*	0.00	Rejected	4
PNB	48.7*	0.00	Rejected	4.5*	0.00	Rejected	**4**
PWGR	42.6*	0.00	Rejected	9.3*	0.00	Rejected	4
RBXY	28.8*	0.00	Rejected	7.6*	0.00	Rejected	6
RELI	70.6*	0.00	Rejected	10.9*	0.00	Rejected	3
RIL	41.9*	0.00	Rejected	5.5*	0.00	Rejected	4
SBIN	1.1	0.39	Not Rejected	0.4	0.96	Not Rejected	11
SESA	0.5	0.93	Not Rejected	0.4	0.96	Not Rejected	12
SIEM	33.7*	0.00	Rejected	2.8**	0.02	Rejected	4
SUNP	29.9*	0.00	Rejected	6.4*	0.00	Rejected	4
TATA	48.6*	0.00	Rejected	3.5**	0.02	Rejected	3
TCS	26.0*	0.00	Rejected	2.8**	0.02	Rejected	4
TPWR	8.1*	0.00	Rejected	0.6	0.69	Not Rejected	5
TTMT	4.2*	0.00	Rejected	0.7	0.66	Not Rejected	5
UTCEM	14.9*	0.00	Rejected	2.0***	0.08	Rejected	5
WPRO	45.4*	0.00	Rejected	4.0*	0.00	Rejected	5

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.8: Granger Causality Test Results between Volatility and Spread

Granger Causality Test between Squared Return (Volatility) and Spread							
Stock	Spread does not Granger Cause Squared Return (Volatility)			Squared Return (Volatility) does not Granger Cause Spread			Lag Length
	F Stat	Prob.	Null Hypothesis	F Stat	Prob.	Null Hypothesis	
ACC	6.8*	0.00	Rejected	2.02***	0.06	Rejected	6
ACEM	14.2*	0.00	Rejected	3.44*	0.00	Rejected	5
APNT	5.1*	0.00	Rejected	1.64	0.13	Not Rejected	6
AXSB	485.6*	0.00	Rejected	0.84	0.50	Not Rejected	4
BHARATI	1464.9*	0.00	Rejected	4.85*	0.01	Rejected	2
BHEL	22.1*	0.00	Rejected	0.40	0.75	Not Rejected	3
BJAUT	19.3*	0.00	Rejected	1.04	0.40	Not Rejected	7
BOB	8.7*	0.00	Rejected	0.40	0.81	Not Rejected	4
BPCL	9.0*	0.00	Rejected	0.86	0.50	Not Rejected	5
CAIR	6.7*	0.00	Rejected	2.51**	0.02	Rejected	6
CIPLA	969.4*	0.00	Rejected	4.29*	0.00	Rejected	4
COAL	66.1*	0.00	Rejected	7.86*	0.00	Rejected	3
DLFU	112.6*	0.00	Rejected	1.23	0.27	Not Rejected	1
DRRD	20.5*	0.00	Rejected	0.15	0.93	Not Rejected	3
GAIL	27.2*	0.00	Rejected	6.58*	0.00	Rejected	3
GRASIM	114.6*	0.00	Rejected	12.99*	0.00	Rejected	6
HCLT	313.1*	0.00	Rejected	7.69*	0.00	Rejected	6
HDFC	4.2*	0.00	Rejected	913.3*	0.00	Rejected	8
HDFCB	51.1*	0.00	Rejected	1.68	0.14	Not Rejected	5
HMCL	112.9*	0.000	Rejected	3.31*	0.019	Rejected	3
HNDL	14.8*	0.00	Rejected	0.57	0.45	Not Rejected	1
HUVR	40.8*	0.00	Rejected	9.64*	0.00	Rejected	8
ICICIBC	4.0*	0.01	Rejected	2.91**	0.03	Rejected	3
IDFC	95.8*	0.00	Rejected	5.11**	0.02	Rejected	1
INFO	0.9	0.49	Not Rejected	0.12	0.99	Not Rejected	5

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.8: Continued.

Granger Causality Test between Squared Return (Volatility) and Spread							
Stock	Spread does not Granger Cause Squared Return (Volatility)			Squared Return (Volatility) does not Granger Cause Spread			Lag Length
	F Stat	Prob.	Null Hypothesis	F Stat	Prob.	Null Hypothesis	
ITC	15.6*	0.00	Rejected	0.41	0.87	Not Rejected	6
JPA	2.5*	0.01	Rejected	1.78***	0.08	Rejected	8
JSP	20.4*	0.00	Rejected	0.56	0.73	Not Rejected	5
KMB	16.1*	0.00	Rejected	9.69*	0.00	Rejected	5
LPC	7.7*	0.00	Rejected	1.70***	0.10	Rejected	7
LT	658.7*	0.00	Rejected	1.09	0.30	Not Rejected	1
MM	38.5*	0.00	Rejected	2.85**	0.02	Rejected	4
MSIL	10.3*	0.00	Rejected	1.07	0.38	Not Rejected	5
NTPC	23.1*	0.00	Rejected	2.99**	0.05	Rejected	2
ONGC	16.1*	0.00	Rejected	0.67	0.57	Not Rejected	3
PNB	24.1*	0.00	Rejected	0.83	0.43	Not Rejected	2
PWGR	25.2*	0.00	Rejected	2.03	0.11	Not Rejected	3
RBXY	7.2*	0.00	Rejected	0.53	0.81	Not Rejected	7
RELI	37.1*	0.00	Rejected	0.44	0.51	Not Rejected	1
RIL	24.3*	0.00	Rejected	0.16	0.92	Not Rejected	3
SBIN	420.7*	0.00	Rejected	0.18	0.95	Not Rejected	4
SESA	152.5*	0.00	Rejected	2.48**	0.02	Rejected	6
SIEM	12.4*	0.00	Rejected	0.65	0.69	Not Rejected	6
SUNP	22.6*	0.00	Rejected	0.72	0.61	Not Rejected	5
TATA	91.4*	0.00	Rejected	3.42***	0.06	Rejected	1
TCS	74.6*	0.00	Rejected	1.99***	0.06	Rejected	6
TPWR	513.2*	0.00	Rejected	9.66*	0.00	Rejected	2
TTMT	1148.9*	0.00	Rejected	1.04	0.35	Not Rejected	2
UTCEM	2.9*	0.00	Rejected	2.15**	0.04	Rejected	7
WPRO	15.6*	0.00	Rejected	0.96	0.44	Not Rejected	5

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.9: Mean Equation

$r_t = c + b_i r_{t-i} + \varepsilon_t$							
Stock	Order	c	t-Statistics	b_i	t-Statistics	AIC	SC
ACC	AR(1)	0.0006	0.87	-0.0576*	-5.5	-2.43	-2.43
ACEM	AR(1)	0.0007	0.85	-0.0217**	-2.1	-2.22	-2.22
APNT	AR(1)	0.0006	1.01	-0.1091*	-10.5	-2.57	-2.57
AXSB	AR(1)	0.0014	1.37	-0.2282*	-22.4	-1.42	-1.42
BHARATI	AR(1)	0.0002	0.18	-0.1149*	-11.1	-1.67	-1.67
BHEL	AR(28)	-0.0002	-0.16	0.0234**	2.2	-1.92	-1.92
BJAUT	AR(1)	0.0015	2.07	-0.0712*	-6.8	-2.42	-2.42
BOB	AR(1)	0.0008	0.88	-0.0473*	-4.5	-2.03	-2.03
BPCL	AR(1)	-0.0002	-0.19	-0.0273*	-2.6	-2.13	-2.13
CAIR	AR(1)	0.0001	0.14	-0.0492*	-4.7	-2.51	-2.51
CIPLA	AR(1)	0.0013	1.46	-0.244*	-24.1	-1.64	-1.64
COAL	AR(1)	0.0001	0.18	-0.0671*	-6.4	-2.5	-2.5
DLFU	AR(2)	0.0007	0.63	-0.0174***	-1.7	-1.69	-1.68
DRRD	AR(3)	0.0005	0.76	0.0194***	1.9	-2.6	-2.59
GAIL	AR(1)	0.0001	0.09	-0.0607*	-5.8	-2.18	-2.18
GRASIM	AR(1)	0.0009	1.24	-0.1973*	-19.3	-2.2	-2.2
HCLT	AR(1)	0.0012	1.46	-0.2176*	-21.4	-1.83	-1.83
HDFC	AR(1)	0.0011	1.67	-0.0511*	-4.9	-2.54	-2.54
HDFCB	AR(1)	0.0009	1.59	-0.0617*	-5.9	-2.88	-2.88
HMCL	AR(4)	-0.0005	-0.72	-0.0298*	-2.9	-2.43	-2.43
HNDL	AR(1)	0.0005	0.47	-0.0397*	-3.8	-1.8	-1.8
HUVR	AR(1)	0.0007	0.95	-0.2237**	-22	-2.11	-2.1
ICICIBC	AR(1)	0.0011	1.41	-0.0672*	-6.4	-2.15	-2.15
IDFC	AR(1)	0.0011	1.06	-0.0253*	-2.4	-1.76	-1.76
INFO	AR(3)	-0.0004	-0.44	0.0202***	1.9	-2.13	-2.13

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.9: Continued.

$r_t = c + b_i r_{t-i} + \varepsilon_t$							
Stock	ARIMA	c	t-Statistics	b_i	t-Statistics	AIC	SC
ITC	AR(1)	0.0005	0.72	-0.0263*	-2.5	-2.67	-2.67
JPA	AR(4)	0.0013	1.05	-0.0346*	-3.3	-1.34	-1.33
JSP	AR(1)	-0.0002	-0.17	-0.0356*	-3.4	-1.46	-1.46
KMB	AR(1)	0.0004	0.57	-0.0935*	-9	-2.3	-2.29
LPC	AR(1)	0.0006	0.78	-0.062*	-6	-2.32	-2.32
LT	AR(1)	0.0007	0.85	-0.0746*	-7.2	-2.25	-2.24
MM	AR(1)	0.0013	1.74	-0.0401*	-3.9	-2.42	-2.41
MSIL	AR(1)	0.0011	1.32	-0.0549*	-5.3	-2.03	-2.03
NTPC	AR(1)	-0.0001	-0.15	-0.0445*	-4.3	-2.6	-2.6
ONGC	AR(1)	-0.0003	-0.37	-0.0657*	-6.3	-2.39	-2.39
PNB	AR(1)	0.0003	0.36	-0.0266*	-2.5	-1.99	-1.98
PWGR	AR(1)	0.0001	0.09	-0.0723*	-6.9	-2.59	-2.59
RBXY	AR(1)	0.0001	0.11	-0.0409*	-3.9	-2.27	-2.26
RELI	AR(2)	-0.0003	-0.33	-0.0234**	-2.2	-1.69	-1.69
RIL	AR(1)	0.0007	0.98	-0.0398*	-3.8	-2.56	-2.56
SBIN	AR(1)	0.0005	0.48	-0.2989*	-30	-1.39	-1.39
SESA	AR(1)	0.0001	0.05	-0.3062*	-30.8	-0.94	-0.94
SIEM	AR(1)	-0.0004	-0.6	-0.0728*	-7	-2.34	-2.34
SUNP	AR(1)	0.0007	0.99	-0.0687*	-6.6	-2.41	-2.41
TATA	AR(14)	-0.0002	-0.21	0.0175***	1.7	-2.08	-2.08
TCS	AR(1)	-0.0001	-0.11	-0.0771*	-7.4	-2.49	-2.49
TPWR	AR(1)	0.0002	0.24	-0.097*	-9.3	-1.85	-1.84
TTMT	AR(1)	0.0013	1.19	-0.1144*	-11	-1.49	-1.49
UTCEM	AR(1)	0.0013	1.85	-0.1145*	-11	-2.36	-2.36
WPRO	AR(1)	-0.0001	-0.11	-0.0292*	-2.8	-2.3	-2.3

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.10: ARCH-LM Test Results

ARCH-LM Test						
	Lag-1		Lag-10		Lag-20	
Stock	F-Statistics	Prob.	F-Statistics	Prob.	F-Statistics	Prob.
ACC	193.5*	0	37.1*	0	19.26*	0
ACEM	198.8*	0	22.8*	0	11.59*	0
APNT	72.4*	0	141.4*	0	73.74*	0
AXSB	2504.2*	0	321.7*	0	160.48*	0
BHARATI	2032.1*	0	257.4*	0	128.7*	0
BHEL	50.5*	0	12.5*	0	6.45*	0
BJAUT	73.9*	0	13.1*	0	6.72*	0
BOB	28.6*	0	4.2*	0	2.24*	0
BPCL	28.8*	0	3.8*	0	1.93*	0
CAIR	19.3*	0	8.1*	0	4.22*	0
CIPLA	2707.7*	0	336.3*	0	167.82*	0
COAL	311.6*	0	33.4*	0	16.77*	0
DLFU	82.4*	0	11.6*	0	6.29*	0
DRRD	42.3*	0	9.6*	0	5.34*	0
GAIL	34.2*	0	7.8*	0	4.21*	0
GRASIM	2795*	0	335.1*	0	167.22*	0
HCLT	2140.2*	0	255.5*	0	127.47*	0
HDFC	18.5*	0	8.3*	0	4.33*	0
HDFCB	44.8*	0	13.1*	0	6.73*	0
HMCL	114.5*	0	14.1*	0	7.42*	0
HNDL	28.6*	0	10.1*	0	5.32*	0
HUVR	2626.4*	0	299.9*	0	149.65*	0
ICICIBC	80.8*	0	8.2*	0	4.11*	0
IDFC	6.1*	0	5.3*	0	3.64*	0
INFO	86.8*	0	25.1*	0	14.63*	0

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.10: Continued.

ARCH-LM Test						
	Lag-1		Lag-10		Lag-20	
Stock	F-Statistics	Prob.	F-Statistics	Prob.	F-Statistics	Prob.
ITC	41.4*	0	10.2*	0	5.26*	0
JPA	34.3*	0	3.9*	0	2.02*	0
JSP	166.6*	0	21*	0	10.98*	0
KMB	954.2*	0	99.1*	0	49.68*	0
LPC	180.2*	0	28.5*	0	14.38*	0
LT	233.1*	0	23.7*	0	11.86*	0
MM	100.4*	0	13.5*	0	7.68*	0
MSIL	104.1*	0	11.5*	0	5.82*	0
NTPC	28.8*	0	10.3*	0	5.35*	0
ONGC	35.2*	0	7.9*	0	4.01*	0
PNB	152.3*	0	16.7*	0	8.57*	0
PWGR	124.9*	0	17.7*	0	8.98*	0
RBXY	87.8*	0	29.1*	0	14.83*	0
RELI	40.9*	0	5.3*	0	2.91*	0
RIL	50.1*	0	13.7*	0	7.04*	0
SBIN	2009.6*	0	217.1*	0	108.33*	0
SESA	1867.5*	0	197.7*	0	98.64*	0
SIEM	29.4*	0	5.5*	0	5.16*	0
SUNP	144.9*	0	17*	0	9.17*	0
TATA	31.8*	0	3.4*	0	1.71**	0.03
TCS	487.1*	0	50.9*	0	25.48*	0
TPWR	1417*	0	169.4*	0	84.63*	0
TTMT	2141.1*	0	288.6*	0	143.97*	0
UTCEM	62.8*	0	8.9*	0	4.51*	0
WPRO	76.2*	0	15.4*	0	7.92*	0

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.11: Results of GARCH (1, 1) Models

$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1}$							
Stock	α_0	z-Statistic	α_1	z-Statistic	α_2	z-Statistic	$\alpha_1 + \alpha_2$
ACC	0.0006*	12.4	0.306*	13.6	0.629*	35.1	0.935
ACEM	0.0012*	10.6	0.256*	10.9	0.582*	20.7	0.838
APNT	0.0006*	12.6	0.298*	11.9	0.608*	28.6	0.906
AXSB	0.0013*	14.6	0.201*	10.7	0.630*	31.5	0.831
BHARATI	0.0014*	12.9	0.351*	11.8	0.536*	22.1	0.887
BHEL	0.0014*	10	0.164*	10.2	0.651*	23.7	0.815
BJAUT	0.0005*	11.6	0.341*	13.3	0.646*	35.9	0.986
BOB	0.0009*	10.6	0.239*	12.8	0.664*	31.3	0.902
BPCL	0.0008*	11.2	0.298*	11.9	0.631*	28.7	0.929
CAIR	0.0005*	12.6	0.389*	14.5	0.583*	30.6	0.972
CIPLA	0.001*	15.2	0.345*	13.7	0.483*	21.4	0.828
COAL	0.0005*	11.4	0.321*	12.4	0.636*	31.9	0.957
DLFU	0.0015*	8.9	0.120*	8.7	0.725*	29	0.845
DRRD	0.0005*	24.7	0.280*	26.5	0.621*	57.8	0.901
GAIL	0.0008*	13.4	0.390*	14.1	0.554*	28	0.944
GRASIM	0.0007*	12.3	0.367*	12.2	0.551*	23	0.918
HCLT	0.0007*	13.8	0.473*	14.3	0.520*	28	0.993
HDFC	0.0004*	11.3	0.339*	13.5	0.641*	34.5	0.980
HDFCB	0.0004*	10.1	0.215*	11.5	0.670*	29.4	0.885
HMCL	0.0007*	12.6	0.317*	13.2	0.579*	26.7	0.896
HNDL	0.0015*	8.5	0.127*	9.1	0.694*	23.6	0.820
HUVR	0.0004*	12.4	0.318*	15.4	0.620*	31.9	0.938
ICICIBC	0.0016*	10.8	0.182*	8.5	0.521*	13.7	0.703
IDFC	0.0017*	8.3	0.155*	9.6	0.666*	21.1	0.821
INFO	0.0007*	12.7	0.377*	14.1	0.548*	24.1	0.925

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.11: Continued.

$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1}$							
Stock	α_0	z-Statistic	α_1	z-Statistic	α_2	z-Statistic	$\alpha_1 + \alpha_2$
ITC	0.0005*	29.7	0.250*	38.7	0.669*	88.6	0.919
JPA	0.0037*	12.9	0.156*	9.8	0.540*	17.8	0.696
JSP	0.002*	12.2	0.326*	12.5	0.561*	23.1	0.887
KMB	0.0007*	10.3	0.201*	11.5	0.689*	32.8	0.890
LPC	0.0006*	11.6	0.339*	12.1	0.637*	32.2	0.975
LT	0.0012*	8.8	0.138*	7.9	0.645*	18.7	0.783
MM	0.0007*	10.5	0.288*	11.6	0.615*	25.2	0.903
MSIL	0.0008*	12.8	0.393*	14.1	0.562*	27.6	0.954
NTPC	0.0005*	10.5	0.229*	12.1	0.667*	30.5	0.896
ONGC	0.0007*	11.3	0.284*	12.4	0.608*	25.5	0.892
PNB	0.0014*	11.1	0.229*	11.48	0.602*	22.8	0.832
PWGR	0.0007*	11.5	0.317*	11.6	0.566*	22.5	0.884
RBXY	0.0011*	11.7	0.219*	10.8	0.608*	24.7	0.827
RELI	0.003*	8	0.124*	8	0.573*	12.5	0.697
RIL	0.0007*	10.7	0.214*	11.6	0.629*	25.5	0.843
SBIN	0.0015*	11.2	0.149*	8.6	0.603*	19.9	0.753
SESA	0.0022*	10.9	0.187*	9.5	0.604*	21.4	0.790
SIEM	0.0006*	11.1	0.284*	13.1	0.632*	29.8	0.915
SUNP	0.0007*	13.1	0.451*	14.1	0.526*	24.1	0.977
TATA	0.0014*	10.1	0.157*	10.6	0.605*	19.2	0.762
TCS	0.0007*	11.7	0.290*	11.9	0.591*	24.3	0.881
TPWR	0.0019*	15	0.337*	13	0.449*	19	0.786
TTMT	0.002*	11.8	0.173*	8.9	0.616*	21.8	0.789
UTCEM	0.0003*	11.2	0.341*	15.4	0.642*	42.9	0.983
WPRO	0.0007*	12.5	0.468*	13.5	0.530*	24.9	0.998

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.12: Results of GARCH (1, 1) Models with Trading Volume

$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 V_t$									
Stock	α_0	z-Statistic	α_1	z-Statistic	α_2	z-Statistic	α_3	z-Statistic	$\alpha_1 + \alpha_2$
ACC	-0.0021*	-57.3	0.31*	10.1	0.29*	8.0	0.001208*	43.3	0.598
ACEM	-0.0027*	-14.5	0.25*	9.9	0.45*	13.5	0.001047*	14.8	0.700
APNT	-0.0004*	-23.7	0.31*	11.4	0.45*	16.7	0.000494*	21.5	0.752
AXSB	-0.0096*	-32.5	0.19*	9.5	0.15*	4.5	0.003197*	29.9	0.346
BHARATI	-0.0061*	-31	0.29*	10	0.42*	13.7	0.00179*	25.7	0.712
BHEL	-0.0057*	-13.6	0.12*	8.6	0.59*	19.3	0.001634*	13.4	0.716
BJAUT	-0.0021*	-17.5	0.36*	12	0.49*	19.1	0.000843*	16.4	0.858
BOB	-0.005*	-24.2	0.25*	10.3	0.34*	11	0.002022*	22.2	0.594
BPCL	-0.0025*	-28.9	0.30*	10.7	0.48*	17.2	0.001057*	21.7	0.785
CAIR	-0.0013*	-25.4	0.34*	14.4	0.57*	39.1	0.000411*	26.4	0.914
CIPLA	-0.0039*	-38.1	0.08*	16.7	0.11*	2.7	0.001788*	26.8	0.190
COAL	-0.002*	-19.2	0.35*	11.6	0.5*	19.4	0.000679*	17.8	0.851
DLFU	-0.01*	-19	0.08*	7.2	0.6*	19.4	0.00261*	17.4	0.685
DRRD	-0.0008*	-48	0.26*	26.4	0.57*	63.5	0.000621*	44.1	0.836
GAIL	-0.0023*	-25.8	0.41*	12.1	0.42*	16.4	0.000981*	21.7	0.832
GRASIM	-0.0005*	-17.1	0.35*	10.9	0.44*	15.5	0.000583*	21	0.784
HCLT	-0.0043*	-44.3	0.13*	9.4	0.12*	3.8	0.002233*	31.7	0.251
HDFC	-0.0009*	-11.4	0.27*	12.9	0.66*	38.6	0.000301*	13.1	0.932
HDFCB	-0.0015*	-21.3	0.23*	10.5	0.54*	19.5	0.000502*	18	0.768
HMCL	-0.0016*	-23.8	0.29*	13.7	0.45*	23.6	0.000801*	22.2	0.737
HNDL	-0.0127*	-39.6	0.06*	5.5	0.49*	88.7	0.003393*	39.6	0.549
HUVR	-0.004*	-23.6	0.37*	14	0.24*	9.5	0.001282*	23.1	0.612
ICICIBC	-0.0033*	-21.6	0.23*	8.9	0.44*	12.3	0.001131*	22.8	0.670
IDFC	-0.0132*	-63.8	0.13*	7	0.01*	0.5	0.00427*	38.6	0.145
INFO	-0.0039*	-20.6	0.38*	12.4	0.25*	8.3	0.001373*	19.8	0.633

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.12: Continued.

$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 V_t$									
Stock	α_0	z-Statistic	α_1	z-Statistic	α_2	z-Statistic	α_3	z-Statistic	$\alpha_1 + \alpha_2$
ITC	-0.0068*	-27.8	0.40*	23.7	0.15*	66.4	0.00094*	41.3	0.556
JPA	-0.0208*	-29.1	0.10*	7.2	0.41*	16.8	0.00493*	27.8	0.514
JSP	-0.0103*	-184.3	0.30*	10.5	0.25*	8	0.003519*	51.3	0.557
KMB	-0.0009*	-7.6	0.22*	10	0.49*	14.3	0.000677*	10	0.713
LPC	-0.0025*	-28	0.34*	11.1	0.51*	22.2	0.000928*	24	0.852
LT	-0.0074*	-260.1	0.10*	7.1	0.37*	12.8	0.002303*	130.6	0.477
MM	-0.0032*	-106.4	0.32*	10.5	0.41*	13.4	0.001141*	65.5	0.735
MSIL	-0.0026*	-27.8	0.34*	11	0.42*	14	0.001075*	22.3	0.760
NTPC	-0.0025*	-29.9	0.23*	12.9	0.34*	17.6	0.000943*	27.2	0.572
ONGC	-0.0039*	-20.2	0.32*	10.6	0.40*	12.9	0.001222*	19.3	0.726
PNB	-0.0063*	-43.7	0.23*	9.6	0.28*	11.7	0.002519*	41.7	0.517
PWGR	-0.0021*	-8.8	0.26*	11.4	0.51*	18.6	0.000679*	10.9	0.771
RBXY	-0.0045*	-33.5	0.18*	7.6	0.22*	4.6	0.001987*	23.1	0.392
RELI	-0.0135*	-35.2	0.08*	7.4	0.31*	11.7	0.004267*	30.3	0.399
RIL	-0.0044*	-39.2	0.18*	10.2	0.42*	26.4	0.001299*	37.1	0.595
SBIN	-0.0089*	-633.1	0.07*	7.1	0.34*	38.3	0.002649*	247.9	0.402
SESA	-0.0085*	-34.7	0.11*	6.5	0.35*	14.2	0.003067*	30.3	0.458
SIEM	-0.0014*	-27.3	0.32*	14.4	0.36*	59.6	0.001013*	28.4	0.678
SUNP	-0.0014*	-10.1	0.39*	13.8	0.52*	23.6	0.000561*	12.5	0.911
TATA	-0.0147*	-48.5	0.09*	6.9	0.19*	16.2	0.004009*	48.1	0.298
TCS	-0.0026*	-174.4	0.26*	10.2	0.43*	14.8	0.000948*	61.3	0.682
TPWR	-0.0119*	-25.6	0.17*	5.4	0.09*	39.3	0.004433*	25.3	0.258
TTMT	-0.0153*	-407.6	0.14*	7.5	0.28*	9.4	0.003903*	147.2	0.429
UTCEM	-0.0003*	-23.1	0.28*	14.8	0.36*	19.3	0.000479*	35.6	0.647
WPRO	-0.0023*	-9.4	0.41*	13	0.46*	19.4	0.000806*	11.5	0.869

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.13: Results of GARCH (1, 1) Models with Lagged Trading Volume

$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 V_{t-1}$									
Stock	α_0	z-Statistic	α_1	z-Statistic	α_2	z-Statistic	α_3	z-Statistic	$\alpha_1 + \alpha_2$
ACC	-0.0011*	-6.1	0.27*	12.4	0.59*	31.2	0.000892*	9	0.872
ACEM	-0.0021*	-7.4	0.23*	9.8	0.54*	16.6	0.000845*	9.5	0.764
APNT	-0.0004*	-7.9	0.26*	10.6	0.57*	22.8	0.000444*	13.5	0.827
AXSB	-0.006*	-215.3	0.13*	7.9	0.52*	18.9	0.00193*	57.3	0.655
BHARATI	-0.0052*	-10.1	0.29*	10.4	0.49*	17.5	0.001538*	11.6	0.784
BHEL	-0.0072*	-12	0.11*	7.7	0.56*	14.6	0.002097*	11.5	0.675
BJAUT	-0.0013*	-7.2	0.32*	12.2	0.61*	29.2	0.000547*	9.1	0.937
BOB	-0.0027*	-8.9	0.21*	10.8	0.59*	21.1	0.001119*	10.4	0.798
BPCL	-0.0019*	-8.6	0.29*	10.5	0.57*	20.7	0.000823*	10.8	0.854
CAIR	-0.001*	-11.8	0.38*	13.8	0.55*	26.7	0.000367*	13.7	0.932
CIPLA	-0.002*	-17.9	0.29*	12.7	0.40*	14.8	0.000845*	17.9	0.699
COAL	-0.0013*	-7.3	0.3*	11.3	0.61*	26.2	0.000466*	8.9	0.907
DLFU	-0.0104*	-7.9	0.08*	6.1	0.58*	13.3	0.002851*	8.4	0.664
DRRD	-0.0007*	-33.4	0.24*	25	0.64*	60.8	0.000382*	37.5	0.871
GAIL	-0.0013*	-5.5	0.42*	12.3	0.49*	20.9	0.000649*	8.5	0.918
GRASIM	-0.0002	-1.2	0.34*	11.3	0.53*	20.9	0.00038*	7.1	0.862
HCLT	-0.0011*	-8.1	0.44*	13.2	0.52*	26.3	0.000474*	11.6	0.954
HDFC	-0.0011*	-11.8	0.31*	12.1	0.61*	28.6	0.000383*	12.4	0.913
HDFCB	-0.0011*	-15.4	0.18*	10.1	0.66*	27.5	0.000379*	14.6	0.848
HMCL	-0.0014*	-7.4	0.30*	12.18	0.50*	19.7	0.000713*	10.6	0.801
HNDL	-0.0128*	-10.2	0.09*	5.8	0.46*	9	0.003477*	10.2	0.555
HUVR	-0.0017*	-8.6	0.27*	14.4	0.58*	24.5	0.000555*	10.3	0.848
ICICIBC	-0.0025*	-25.4	0.16*	7.1	0.52*	17.1	0.000871*	26.2	0.682
IDFC	-0.0061*	-10.5	0.12*	7.6	0.61*	15.4	0.001813*	10.4	0.730
INFO	-0.0025*	-13.1	0.31*	12.9	0.50*	19.4	0.000863*	14	0.813

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.13: Continued.

$h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 V_{t-1}$									
Stock	α_0	z-Statistic	α_1	z-Statistic	α_2	z-Statistic	α_3	z-Statistic	$\alpha_1 + \alpha_2$
ITC	-0.0046*	-432.6	0.25*	17.6	0.41*	24.3	0.000508*	96.6	0.661
JPA	-0.0119*	-7.2	0.09*	6.9	0.55*	13.7	0.003071*	8.2	0.647
JSP	-0.0078*	-9.5	0.27*	10.3	0.47*	14.7	0.002617*	10.8	0.742
KMB	-0.001*	-4.5	0.20*	10.2	0.61*	23.9	0.000556*	8.4	0.816
LPC	-0.0016*	-8.5	0.29*	11.3	0.64*	32	0.000596*	10.2	0.928
LT	-0.007*	-10	0.08*	5.3	0.51*	10	0.002209*	9.8	0.584
MM	-0.0061*	-30.5	0.16*	6.2	0.17*	3	0.002465*	20.7	0.329
MSIL	-0.002*	-13.9	0.34*	11.5	0.54*	21.7	0.000818*	15.1	0.872
NTPC	-0.0015*	-6.8	0.26*	10.6	0.55*	19.5	0.000563*	8.8	0.817
ONGC	-0.0022*	-9.6	0.26*	11	0.58*	21.7	0.000722*	10.8	0.835
PNB	-0.0054*	-10.8	0.17*	8.5	0.45*	11.2	0.002167*	11.6	0.616
PWGR	-0.0015*	-6.5	0.28*	10.5	0.58*	22.2	0.000529*	8.3	0.859
RBXY	-0.0037*	-11.5	0.16*	8.2	0.49*	14.9	0.0015*	12.5	0.652
RELI	-0.0132*	-12.4	0.06*	4.7	0.43*	9.7	0.004258*	12.8	0.485
RIL	-0.0058*	-182.9	0.18*	8.2	0.33*	9.1	0.001758*	85.4	0.503
SBIN	-0.0084*	-12.3	0.08*	5.6	0.45*	10.6	0.002534*	12.2	0.531
SESA	-0.0077*	-13.4	0.12*	6.9	0.51*	13.8	0.002636*	13.1	0.633
SIEM	-0.0004*	-2.2	0.27*	12	0.61*	25.5	0.000381*	6.2	0.877
SUNP	-0.0011*	-5.1	0.39*	13.6	0.53*	23.7	0.00048*	7.7	0.923
TATA	-0.0088*	-9.7	0.08*	6.5	0.52*	11.6	0.002421*	9.9	0.599
TCS	-0.0025*	-12.4	0.24*	10.1	0.49*	15.4	0.000896*	12.8	0.739
TPWR	-0.0134*	-43.2	0.13*	7.4	-0.04*	-7.4	0.005099*	41.8	0.082
TTMT	-0.0121*	-11.8	0.12*	6.7	0.51*	14.4	0.003072*	12.4	0.628
UTCEM	-0.0001	-1.1	0.32*	15.3	0.63*	44.9	0.000104*	4.5	0.945
WPRO	-0.0022*	-8	0.42*	12.2	0.49*	19.9	0.0008*	9.9	0.907

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.14: Results of GARCH (1, 1) Models with Bid-Ask Spread

$h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 S_t$									
Stock	α_0	z-Statistic	α_1	z-Statistic	α_2	z-Statistic	α_3	z-Statistic	$\alpha_1 + \alpha_2$
ACC	0.0001**	2.3	0.33*	13.3	0.55*	33.5	1.97*	12.4	0.878
ACEM	0.0002	1.3	0.25*	11.1	0.54*	20	2.58*	9.1	0.793
APNT	0.0002*	4.6	0.32*	11.7	0.53*	23.5	1.34*	11.4	0.848
AXSB	0.0008*	5.6	0.20*	10.1	0.53*	17.5	5.16*	10.6	0.733
BHARATI	0.0014*	12.8	0.33*	11.6	0.53*	21.6	-0.1*	-25.6	0.861
BHEL	0.0007*	3.9	0.17*	10.1	0.62*	21.8	2.61*	5.7	0.793
BJAUT	0.0000	0.5	0.34*	13.1	0.58*	32.1	2.28*	14.2	0.921
BOB	0.0004*	4.6	0.27*	12.7	0.59*	26.4	1.98*	8.3	0.860
BPCL	0.0000	-0.4	0.33*	12.1	0.51*	21.7	2.73*	13.3	0.846
CAIR	-0.0002*	-5	0.34*	15.6	0.61*	38.5	2.3*	11.2	0.946
CIPLA	0.0006*	10.7	0.06*	11.2	0.76*	36.3	-0.1*	-14.4	0.815
COAL	0.0003*	8.6	0.31*	12.3	0.63*	34.1	0.16*	8.4	0.940
DLFU	0.0007*	3.1	0.12*	8.6	0.73*	29.6	2.55*	4.5	0.843
DRRD	0.0001*	10.5	0.31*	26.2	0.54*	54.8	1.45*	28.9	0.857
GAIL	-0.0002*	-4.1	0.38*	13.3	0.47*	26.7	3*	15.4	0.855
GRASIM	0.0007*	12.1	0.37*	12.1	0.54*	20.9	0.01	1	0.909
HCLT	0.0006*	12.8	0.47*	13.8	0.52*	27.6	-0.05*	-17.6	0.983
HDFC	0.0000	-0.5	0.34*	12.4	0.56*	28.3	3.5*	11.7	0.902
HDFCB	0.0001*	2.6	0.23*	11.2	0.59*	24.8	2.13*	11	0.827
HMCL	0.0002*	4.3	0.33*	12.9	0.53*	24.7	2.01*	10.5	0.863
HNDL	0.0013*	4.8	0.13*	9	0.69*	23.7	0.42	1.1	0.823
HUVR	0.0008*	14.2	0.25*	12	0.61*	25.5	-0.63*	-16.2	0.862
ICICIBC	0.0007*	6	0.16*	8.3	0.50*	21.9	3.33*	13.6	0.661
IDFC	0.0001	0.2	0.14*	9	0.65*	20.7	4.4*	7.1	0.791
INFO	0.0003*	5.7	0.36*	14.3	0.53*	24.5	2.32*	9.7	0.893

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.14: Continued.

$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 S_t$									
Stock	α_0	z-Statistic	α_1	z-Statistic	α_2	z-Statistic	α_3	z-Statistic	$\alpha_1 + \alpha_2$
ITC	-0.0002*	-9.4	0.26*	37.2	0.61*	78.3	3.47*	35.4	0.866
JPA	0.0002	0.4	0.15*	7.8	0.53*	17.9	4.54*	6.1	0.681
JSP	0.001*	5.2	0.33*	12.6	0.55*	23.1	2.96*	6.3	0.877
KMB	0.0003*	4	0.23*	11.4	0.56*	23.2	2.16*	10.7	0.788
LPC	-0.0001*	-3.8	0.37*	12.9	0.59*	33	2.41*	13.2	0.956
LT	0.0013*	8.5	0.14*	8	0.63*	16.9	-0.22*	-4.5	0.769
MM	0.0002*	3.4	0.31*	11.4	0.51*	20.3	3.74*	11.1	0.819
MSIL	0.0000	0.8	0.39*	14	0.55*	29.7	3.06*	12.4	0.936
NTPC	-0.0003*	-3.3	0.29*	11.2	0.57*	24.5	2.08*	9.5	0.862
ONGC	0.0000	-0.4	0.29*	12.7	0.56*	24.1	2.65*	9.4	0.852
PNB	0.0007*	5.3	0.22*	11.5	0.61*	23.7	1.57*	5.7	0.829
PWGR	-0.0007*	-5.3	0.33*	11.7	0.54*	23.4	2.73*	9.3	0.874
RBXY	0.0008*	7.1	0.23*	10.8	0.57*	24.4	0.89*	3.9	0.817
RELI	0.0014*	4.8	0.10*	7.4	0.56*	17.2	3.57*	6.8	0.665
RIL	0.0005*	6.1	0.22*	11.3	0.59*	21.7	2.01*	6.3	0.808
SBIN	0.0011*	6.4	0.13*	8.4	0.52*	13.4	5.22*	9.1	0.653
SESA	0.0016*	6.2	0.19*	9.3	0.52*	14.8	2.17	9.3	0.712
SIEM	-0.0001*	-11.2	0.33*	15	0.48*	26.4	2.16*	17.4	0.806
SUNP	0.0000	0.1	0.40*	14.3	0.50*	24.8	2.45*	13.1	0.904
TATA	0.001*	6.2	0.14*	9.2	0.60*	18	2.15*	5.3	0.749
TCS	0.0005*	7.4	0.31*	11.5	0.52*	19.4	2.12*	7.4	0.828
TPWR	0.0019*	27.6	0.26*	26.1	0.50*	32.8	-0.37*	-23.5	0.768
TTMT	0.0022*	10	0.18*	8.8	0.59*	17	-0.31*	-3.8	0.768
UTCEM	0.0000*	-17.9	0.44*	16.4	0.47*	35.9	1.65*	19.9	0.904
WPRO	-0.0001	-0.9	0.48*	13.6	0.45*	21.5	3.01*	11.3	0.929

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.15: Results of GARCH (1, 1) Models with Lagged Bid-Ask Spread

$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 S_{t-1}$									
Stock	α_0	z-Statistic	α_1	z-Statistic	α_2	z-Statistic	α_3	z-Statistic	$\alpha_1 + \alpha_2$
ACC	0.0004*	6.1	0.31*	13.3	0.59*	33.5	0.93*	6	0.906
ACEM	0.0006*	4.3	0.27*	10.9	0.53*	18.2	1.71*	6.4	0.796
APNT	0.0004*	7.7	0.30*	11.6	0.58*	26.2	0.61*	5.8	0.882
AXSB	0.0009*	7.7	0.20*	10	0.59*	29.5	2.96*	6.4	0.799
BHARATI	0.0009*	5.9	0.36*	11.5	0.49*	20.1	2.42*	5.3	0.854
BHEL	0.0008*	4.2	0.18*	10.2	0.57*	18.9	3.1*	6.3	0.749
BJAUT	0.0001*	4.1	0.34*	12.9	0.61*	34.1	1.51*	10.2	0.948
BOB	0.0006*	6.5	0.25*	12.6	0.62*	27.6	1.06*	4.9	0.878
BPCL	0.0005*	5.3	0.32*	11.4	0.56*	22.3	1.25*	6.78	0.885
CAIR	0.0000	-0.2	0.33*	15.3	0.62*	38.1	1.54*	8.1	0.950
CIPLA	0.0003*	4.1	0.35*	13.6	0.44*	19.6	2.38*	10.2	0.786
COAL	0.0001*	2.9	0.32*	12.2	0.59*	29.1	1.38*	7.4	0.915
DLFU	0.0008*	3.2	0.12*	8.6	0.70*	26.4	2.87*	5.1	0.824
DRRD	0.0004*	18.5	0.30*	25.6	0.57*	51.9	0.57*	12.5	0.874
GAIL	0.0003*	4.5	0.37*	12.8	0.53*	27.1	1.45*	8.4	0.901
GRASIM	0.0003*	6.5	0.37*	12.1	0.50*	21.3	0.87*	8.1	0.873
HCLT	0.0003*	5.3	0.46*	13.5	0.49*	24.48	1.68*	7.9	0.949
HDFC	0.0001*	3.2	0.35*	12.5	0.56*	27.2	2.54*	9.3	0.911
HDFCB	0.0003*	5.4	0.24*	10.8	0.57*	20.5	1.62*	8.6	0.807
HMCL	0.0005*	6.6	0.36*	12.8	0.48*	21.2	1.71*	8.7	0.845
HNDL	0.0015*	5.3	0.13*	8.9	0.68*	21.6	0.19	0.5	0.806
HUVR	0.0001**	2	0.32*	15.3	0.59*	30.7	1.94*	8.9	0.911
ICICIBC	0.0012*	7.7	0.17*	8	0.44*	12.7	5.33*	9.9	0.613
IDFC	0.0006**	2.1	0.15*	9.1	0.63*	19.1	3.35*	5.9	0.786
INFO	0.0005*	8.3	0.38*	13.8	0.53*	22.9	1.21*	5.8	0.906

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.15: Continued.

$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 S_{t-1}$									
Stock	α_0	z-Statistic	α_1	z-Statistic	α_2	z-Statistic	α_3	z-Statistic	$\alpha_1 + \alpha_2$
ITC	0.0001*	4.3	0.25*	36	0.62*	74.4	2.19*	26.5	0.871
JPA	0.0003	0.8	0.14*	8.1	0.53*	16.9	4.58*	6.3	0.674
JSP	0.0014*	6.6	0.33*	12.6	0.55*	22.9	1.78*	3.8	0.882
KMB	0.0005*	6.1	0.22*	11.2	0.60*	24.7	1.21*	7	0.823
LPC	0.0003*	5.2	0.35*	12	0.60*	29.3	1.13*	6.7	0.959
LT	0.001*	6.5	0.15*	7.9	0.56*	16.28	2.66*	8.6	0.716
MM	0.0005*	6.4	0.31*	11.1	0.53*	19.5	2.18*	7.9	0.837
MSIL	0.0004*	5.4	0.38*	13.9	0.55*	27.7	1.79*	7.8	0.924
NTPC	0.0003*	3.7	0.28*	11.4	0.58*	23.6	0.76*	4.1	0.869
ONGC	0.0003*	2.9	0.29*	11.5	0.57*	22.6	1.72*	6.3	0.865
PNB	0.0009*	5.8	0.24*	11.4	0.57*	21	1.69*	5.9	0.807
PWGR	0.0000	0.2	0.31*	11.2	0.56*	22.6	1.29*	5.3	0.875
RBXY	0.0009*	7.9	0.23*	10.8	0.57*	22.9	0.82*	3.8	0.803
RELI	0.0021*	5.6	0.11*	7.6	0.54*	11.6	4.04*	7.3	0.653
RIL	0.0006*	7.1	0.23*	11.4	0.57*	20.8	1.65*	5.5	0.798
SBIN	0.0011*	6.6	0.15*	8.1	0.55*	17.1	4.15*	6.8	0.703
SESA	0.0017*	6.1	0.19*	9	0.59*	19.9	1.1*	3.2	0.777
SIEM	0.0002*	3.7	0.29*	13.1	0.59*	26.7	0.98*	8.1	0.883
SUNP	0.0002*	4.7	0.41*	13.8	0.53*	25.8	1.4*	8.1	0.942
TATA	0.001*	5.6	0.17*	9.6	0.52*	14.7	3.86*	7.5	0.689
TCS	0.0006*	9.3	0.30*	11.5	0.55*	21.2	0.88*	3.8	0.854
TPWR	0.0008*	3.3	0.34*	12.3	0.42*	16.9	1.93*	5.1	0.757
TTMT	0.0004***	1.7	0.18*	9	0.53*	18.1	7.9*	9.1	0.718
UTCEM	0.0000	-0.3	0.34*	15.3	0.63*	41	1.05*	14.9	0.969
WPRO	0.0003*	4.5	0.47*	13.1	0.49*	22.4	1.53*	6.4	0.968

Note: *Significant at 1% level, **Significant at 5% level and ***Significant at 10% level

Table 4.16: Volatility Persistence Comparison with Baseline GARCH (1, 1) Models

Volatility Persistence Comparison with GARCH(1,1)									
	GARCH	GARH Cum V		GARH Cum V(-1)		GARH Cum S		GARH Cum S(-1)	
Stock	$\alpha_1 + \alpha_2$	$\alpha_1 + \alpha_2$	% Change	$\alpha_1 + \alpha_2$	% Change	$\alpha_1 + \alpha_2$	% Change	$\alpha_1 + \alpha_2$	% Change
ACC	0.935	0.598	-36%	0.872	-6%	0.878	-6%	0.906	-3%
ACEM	0.838	0.700	-17%	0.764	-9%	0.793	-6%	0.796	-5%
APNT	0.906	0.752	-17%	0.827	-9%	0.848	-7%	0.882	-3%
AXSB	0.831	0.346	-58%	0.655	-21%	0.733	-12%	0.799	-4%
BHARATI	0.888	0.712	-20%	0.784	-12%	0.861	-3%	0.854	-4%
BHEL	0.815	0.716	-13%	0.675	-18%	0.793	-3%	0.749	-9%
BJAUT	0.986	0.858	-13%	0.937	-5%	0.921	-7%	0.948	-4%
BOB	0.902	0.594	-34%	0.798	-11%	0.860	-4%	0.878	-2%
BPCL	0.929	0.785	-16%	0.854	-8%	0.846	-9%	0.885	-5%
CAIR	0.972	0.914	-6%	0.932	-4%	0.946	-2%	0.950	-2%
CIPLA	0.828	0.190	-77%	0.699	-16%	0.815	-2%	0.786	-5%
COAL	0.957	0.851	-11%	0.907	-6%	0.940	-2%	0.915	-5%
DLFU	0.844	0.685	-19%	0.664	-21%	0.843	0%	0.824	-2%
DRRD	0.901	0.836	-7%	0.871	-3%	0.857	-5%	0.874	-3%
GAIL	0.944	0.832	-11%	0.918	-2%	0.855	-9%	0.901	-4%
GRASIM	0.918	0.784	-15%	0.862	-6%	0.909	-1%	0.873	-5%
HCLT	0.993	0.251	-75%	0.954	-4%	0.983	-1%	0.949	-4%
HDFC	0.980	0.932	-5%	0.913	-7%	0.902	-8%	0.911	-7%
HDFCB	0.885	0.768	-14%	0.848	-5%	0.827	-7%	0.807	-9%
HMCL	0.896	0.737	-18%	0.801	-11%	0.863	-4%	0.845	-6%
HNDL	0.820	0.549	-33%	0.555	-32%	0.823	0%	0.806	-2%
HUVR	0.938	0.612	-35%	0.848	-10%	0.862	-8%	0.911	-3%
ICICIBC	0.703	0.670	-4%	0.682	-3%	0.661	-6%	0.613	-12%
IDFC	0.821	0.145	-82%	0.730	-11%	0.791	-4%	0.786	-4%
INFO	0.925	0.633	-31%	0.813	-12%	0.893	-3%	0.906	-2%

Table 4.16: Continued.

Volatility Persistence Comparison with GARCH(1,1)									
	GARCH	GARH Cum V		GARH Cum V(-1)		GARH Cum S		GARH Cum S(-1)	
Stock	$\alpha_1 + \alpha_2$	$\alpha_1 + \alpha_2$	% Change	$\alpha_1 + \alpha_2$	% Change	$\alpha_1 + \alpha_2$	% Change	$\alpha_1 + \alpha_2$	% Change
ITC	0.919	0.556	-40%	0.661	-28%	0.866	-6%	0.871	-5%
JPA	0.696	0.514	-27%	0.647	-8%	0.681	-3%	0.674	-4%
JSP	0.887	0.557	-37%	0.742	-17%	0.877	-1%	0.882	-1%
KMB	0.890	0.713	-20%	0.816	-8%	0.788	-11%	0.823	-8%
LPC	0.975	0.852	-13%	0.928	-5%	0.956	-2%	0.959	-2%
LT	0.783	0.477	-39%	0.584	-25%	0.769	-1%	0.716	-8%
MM	0.903	0.735	-18%	0.329	-63%	0.819	-9%	0.837	-7%
MSIL	0.954	0.760	-20%	0.872	-8%	0.936	-1%	0.924	-3%
NTPC	0.896	0.572	-36%	0.817	-9%	0.862	-4%	0.869	-3%
ONGC	0.892	0.726	-18%	0.835	-6%	0.852	-4%	0.865	-3%
PNB	0.832	0.517	-38%	0.616	-26%	0.829	0%	0.807	-3%
PWGR	0.884	0.771	-12%	0.859	-2%	0.874	-1%	0.875	-1%
RBXY	0.827	0.392	-53%	0.652	-21%	0.817	-2%	0.803	-3%
RELI	0.697	0.399	-43%	0.485	-31%	0.665	-5%	0.653	-7%
RIL	0.843	0.595	-29%	0.503	-40%	0.808	-4%	0.798	-5%
SBIN	0.753	0.402	-46%	0.531	-29%	0.653	-13%	0.703	-6%
SESA	0.790	0.458	-42%	0.633	-20%	0.712	-10%	0.777	-2%
SIEM	0.915	0.678	-26%	0.877	-5%	0.806	-12%	0.883	-4%
SUNP	0.977	0.911	-7%	0.923	-6%	0.904	-8%	0.942	-4%
TATA	0.762	0.298	-61%	0.599	-21%	0.749	-1%	0.689	-9%
TCS	0.881	0.682	-23%	0.739	-16%	0.828	-6%	0.854	-3%
TPWR	0.786	0.258	-67%	0.082	-90%	0.768	-3%	0.757	-4%
TTMT	0.789	0.429	-46%	0.628	-21%	0.768	-3%	0.718	-9%
UTCEM	0.983	0.647	-34%	0.945	-4%	0.904	-8%	0.969	-1%
WPRO	0.998	0.869	-13%	0.907	-9%	0.929	-7%	0.968	-3%
Average	0.878	0.624	-30%	0.748	-15%	0.834	-5%	0.839	-4%

Chapter 5

Lead-Lag Relation between Spot Market and Futures Market

5.1: Introduction

The influence of spot market on futures market and vice versa and the role of each market segment in price discovery is a key question in the research of market microstructure design and thus, of greatest importance to the investors, traders, market makers, regulators and researchers. Price discovery is important because it hints at where informed traders trade first, and whether information reflects first in the futures market and the spot market follows it or is it vice versa. Were the markets perfectly efficient and frictionless, the price discovery would be instantaneous and contemporaneous. However, due to market frictions such as transactions costs and capital market microstructure effects (different trading rules in spot and futures market i.e. margin trading, cash settlement, short selling, lot size etc.) significant lead-lag relationship between the two markets have been observed. In practice, between spot and futures markets or across different trading venues of the same stock, price discovery takes place in one market and the other markets follow it. Although futures and spot markets respond to the same information, the important question to ask is: which market reacts first?

A reason that has been advanced for prices to assimilate information faster in futures market than spot market is that the transaction cost in the former is lower and the futures market is more liquid than the spot market. Moreover, investing in a futures contract requires less capital since margin trading is allowed in futures market. For an example, if margin rate is 10%, investors need to pay only 10% of the total transaction amount, whereas in spot market, a total of 100% transaction amounts is needed to be paid immediately. Thus, suppose if an investor acquires new information on the health of the economy, it can be considered as worth acting upon. As a result, the investors have to decide whether to purchase stocks or a stock index futures contract since the purchase of stocks requires a substantial amount of capital whereas purchase of index futures contract, requires a small amount of capital. Therefore, if the investors are willing to trade, the futures transaction is likely one to be chosen. The information will be incorporated in the futures prices. This will widen the differential between the futures and spot price which in turn will attract arbitrageurs. Since arbitrageurs trade simultaneously in cash and futures market the information will be transmitted from the futures to the cash market. Thus, the futures price will lead the cash price.

On the other hand, reason for prices to assimilate information faster in spot market than futures market could be that firm-specific information reveals itself first in stock prices before being transmitted to the futures market. In the emerging markets, the futures trading is less active compared to spot trading, for this reason, spot market reflects new information faster than the futures market. Hence, it is suggested that price is discovered first in spot market than futures market.

There is also a possibility for feedback relationship between the spot market and the futures market since, firm-specific information is revealed first in stock prices and the underlying stock index before being transmitted to the futures market whereas, macro specific information is first reflected in the futures market and then gets transmitted through to the spot market.

In many recent studies, it is observed that futures prices play a significant role in the discovery and the transmission of price information. Whether this situation holds good for all markets, is an ongoing debate for several years. Studies such as: Kawaller (1987), Stoll and Whaley (1990), Brockman and Tse (1995), Alphones (2000), Chris et.al.(2001), Raju and Karande (2003), So (2004), Zhong, Darrat and Otero (2004), Gupta and Belwinder (2006), Pavabutr and Chaihetphon (2010), Theissen(2011), Iiter and Alguner (2013), Yuhan and Fang (2013) and Singhal (2014) backed the hypothesis that the futures markets play an important role in the price discovery process by disseminating new information faster than the cash market. They found that price discovery first takes place in the futures market and then it gets transmitted to underlying cash market.

Turkington and Walash (1999), Kenourgios (2004), Floros (2009), Mallikarjunappa and Afsal (2010), Unlu and Ersoy (2012), Choudhary and Bajaj (2012), Sehgal (2012), Chhajed and Mehta (2013) found a feedback relationship between spot and futures markets.

Wahab and Lashgari (1993), West (1997), Mukherjee and Mishra (2006), Jackline and Deo(2011), Srinivasan and Ibrahim (2011), Zakaria and Shamsuddin (2012), Rajput et al. (2012) found that price discovery first takes position in the spot market and then it is transmitted to the underlying futures market.

Issues like price discovery have been extensively studied for mature markets. Most of the studies have been conducted in developed countries, particularly in the US. Since derivatives trading started in India in 2000, there have been only a small number of studies which have investigated the intraday lead-lag relationship between spot and futures market. In this context, an attempt has been made to revisit the price discovery in Indian market especially focusing on intraday relationship.

5.2: Review of Literature

Although future and spot markets react to the same information, the major question is which market reacts first. Several studies have examined these relationships by using different analytical techniques on different markets which are briefly reviewed here under.

Kawaller and Koch (1987) examined the relationship between spot and futures markets using minute-to-minute high frequency intraday data for both S&P 500 futures and the S&P 500 index for all trading days during 1984 and 1985. Three stage least squares (3SLS) regression was employed to determine the relationship between spot and futures markets. They found stronger lead effect from futures to spot market (by 45 minutes) than spot to futures market (by 1 minute). The lead from futures to spot appeared to be more pronounced compared to the spot to futures lead.

Stoll and Whaley (1990) examined the intraday lead-lag relationship between S&P 500 index and the Major Market Index (MMI) futures using 5 minutes interval data set from 21st April, 1982 to 31st March, 1987. For empirical investigation, serial correlation and ARMA (p, q) process had been employed. The necessary data was obtained from the Chicago Board of Trade (CBOT), Chicago Mercantile Exchange (CME), and Francis Emory Fitch, Inc. (“Fitch”). The study revealed feedback relationship between futures and spot index. Even though they found evidence of feedback relationship, the lead from futures index was stronger than the spot index lead.

Chan et al. (1991) empirically examined the intraday relationship between returns and returns volatility in the S&P 500 and Major Market Index (MMI) futures using Autocorrelation, Cross Correlation and Bivariate GARCH model for the sample period from 1st August, 1984 to 31st December, 1984. They found evidence of a strong bi-directional relationship existing between spot and futures price changes.

Kutner & Sweeney (1991) investigated the causal relationship between the S&P 500 spot and futures index returns using intraday high frequency minute-by-minute data during the period from 10th August, 1987 to 31st December, 1987. Using Granger causality and Sims test they found evidence of futures leading over the spot market

Tang et al. (1992) empirically examined the interrelationship between the Hang Seng spot and futures index for both pre crisis period from 6th May 1986 to 16th October 1987 and post-crash period from 1st November 1987 to 28th February 1989. The Granger causality test results indicated that futures prices caused spot index prices during the pre-crisis period. Similarly, during the post-crash period, the analysis revealed a bi-directional causal relationship between the two markets.

Wahab and Lashgari (1993) empirically examined the causal relationship between daily stock index futures prices and stock index spot prices for both the FTSE 100 and the S&P 500 indices for the period from 1988 to 1992. They found the feedback relationship between spot and futures markets for both the S&P 500 and the FTSE 100 indices; however, the lead from spot to futures appeared to be more pronounced compared to the futures to spot lead.

Brockman and Tse (1995) also empirically examined the price discovery in four agricultural commodities markets in Canada using daily prices between 1978 and 1994. They found long run equilibrium relationship between futures and spot markets for all the 4 commodities. They employed error correction mechanism (ECM) and found futures markets leading the spot market for all the four commodities. Their results suggested that price discovery was mainly performed in the futures market.

West (1997) investigated the intraday lead-lag relationship between futures market and spot market for the period from 1992 to 1996 by using 1 minute interval data set of SPI price Index and AOI futures Index. They found strong evidence of spot market leading futures market by 5 minutes gap. They concluded that the automation of the ASX has enhanced price discovery in the spot market relative to the SPI futures market.

Pizzi et al (1998) examined the relationship between the S&P 500 spot and futures index using intraday high frequency minute by minute data both for three and six month contracts. By using vector error correction model (VECM), they found that the futures market leading over the spot market by at least twenty minutes both for the three and six month contracts. There was existence of bidirectional causality but the leads from futures market to spot market have a stronger effect.

Turkington and Walash (1999) empirically investigated the intra-day price discovery and causality in Australian Market using 5-minutes interval data for the period from 3rd January 1995 to 31st December 1995. They employed bivariate VEC, VAR models and impulse response functions (IRF) to trace out the relationship. The study found that the SPI futures and the spot AOI index were integrated and there is long run equilibrium relationship existing between them. The result showed a bi-directional causality between spot and futures market.

Alphonse (2000) examined the intraday price discovery in French market using 30 seconds interval data set for the period from January 3rd 1995 to March 31st 1995. The result showed that the price discovery process was dominated by the futures market. New information was reflected first in the futures market and then it was transmitted to the spot market through futures market.

Brooks et al. (2001) investigated the intraday lead-lag relationship between the FTSE 100 spot index and futures index using 10-minutes interval data set for the period from June 1996 to December 1997. Having used the Engle-Granger two step co-integration tests they found a long run equilibrium relationship between the spot and futures prices. Using vector error correction model they found a unidirectional causality running from futures market to spot market. The study concluded that the futures market led spot market due to lower transaction costs.

Tan (2002) investigated the causal relationships between spot and futures markets using daily closing prices for both Malaysian stock composite index (MSCI) and Kuala Lumpur futures index (KLFI) for the period from 2nd January 1996 to 29th September 2000. By applying the Johansen co-integration test, they found a long run equilibrium relationship between them. Both Granger causality test and Hsiao's sequential approach model (HSM) revealed a bidirectional causal relationship for the short-run period; while the ECM provided the evidence that the futures market (KLFI) led spot market (MSCI) in the long run.

Raju and Karande (2003) examined price discovery in Indian market for CNX Nifty spot and futures index using daily closing prices for the period from June 2000 till October 2002. By using Engle and Granger two step co-integration test, their study found both the markets were co-integrated and they had a long term equilibrium relationship. The vector error correction model (VECM) result showed that the information gets reflected first in the futures market and thus, the price was discovered first in futures market then it flowed to spot market.

So (2004) examined the intraday price discovery process in Hong Kong market by using 1-minute interval data set for the period from 12th November 1999 to 28th June 2002. The findings showed that the price was discovered first in the futures market and the spot market followed the futures market.

Zhong, Darrat and Otero (2004) investigated the price discovery in the Mexican market using daily closing prices from 15th April 1999 to 24th July 2002. Their study found a long run equilibrium relationship between spot index and futures index. They also found that the futures market led the spot market and price was discovered first in the futures market.

Kenourgios (2004) looked at the relationship between daily spot and futures market in Athens Stock Exchange (ASE) over the period from August 1999 to June 2002. The empirical results provided evidence of bi-directional causal relationship between spot and futures markets; there was an informational connection between spot and futures markets and existence of such an informational connection between them implied that investors using these markets could explore significant arbitrage profits and hedging opportunities.

Mattos and Garcia (2004) empirically examined the lead-lag relationship between daily spot and futures prices in the Brazilian agricultural market. The study has been conducted both for lightly traded markets before 1999 and heavily traded markets after 1999. Their findings are mixed. For lightly traded markets, neither long run equilibrium relationship nor short run lead-lag relationship is established. And for heavily traded markets, they found the evidence of a long run relationship between spot and futures markets. In these cases, futures market appeared to play a more leading role in the pricing process.

Mukherjee and Mishra (2006) investigated the lead-lag relationship between spot and futures market in India using intraday data from April to September 2004. They found evidence of contemporaneous and feedback relationship between the spot market and the futures market in India. However, they observed stronger lead effect from spot to futures than futures to spot. They established almost the similar findings even for some underlying NIFTY stocks. They, however, concluded that the informational efficiency of the Indian equity market had increased due to the onset of derivatives trading.

Gupta and Singh (2006) examined the price discovery mechanism in the NSE spot and futures markets in India using daily closing prices of index future Sand PCNX Nifty, during the period from June 2002 to February 2005. By using vector error correction mechanism (VECM) they found evidence of causality relation from futures to spot index. Hence the price was discovered first in the futures market in India.

Bose (2007) examined to find whether the futures market played a significant role in the absorption of information and price discovery in the Indian stock market. The study was conducted during the period from March 2002 to September 2006 using daily closing prices of CNX Nifty spot and futures indices. She found that there was a significant information flow from the futures market to the spot market in short term, whereas in long term, there existed a bi-directional causality between them. The contributions of both the futures and the spot market to the price discovery process were also almost the same though the futures showed a marginal edge over the spot market.

Floros and Vougas (2007) examined the lead-lag relationship between daily futures and spot markets in Greece. They employed a bivariate GARCH model to examine price discovery over the Greek debt crisis period from August 1999 to August 2001. Empirical findings confirmed that futures market played a dominant role in price discovery during the crisis period, implied that futures index prices contain useful information about spot index prices.

Pradhan and Bhat (2009) examined the causality between the spot and futures prices in India on individual securities using daily closing values during the period from 9th November 2001 to 29th September 2005. They applied both Johansen's co-integration test and VECM model to trace the causal relationship between them. They found lead from futures to spot in case of 9 individual securities, lead from spot to futures in case of 7 individual securities and the feedback relationship in case of 9 individual securities. They did not find any clear evidence of price discovery in Indian market.

Floros (2009) examined the price discovery between spot and futures markets in South Africa using daily closing prices over the period from 2002 to 2006. The empirical results showed that both the markets were co-integrated and there exists a long run equilibrium relationship between them. Furthermore, Granger causality test and vector error correction model results suggested bidirectional causality between spot and futures markets.

Ozen et al. (2009) examined causality between the futures market and the spot market in Turkey for the period from February 2005 to February 2009 by using daily closing prices. They employed cointegration test and vector error correction model (VECM) to investigate the relationship between spot and futures market. The cointegration test results provided evidence of a long run equilibrium relationship between spot and futures markets and the vector error correction model provided evidence of long run causality from futures to spot market and short run causality from spot to futures market.

Mallikarjunappa and Afsal (2010) investigated the intraday lead-lag relationship between spot and futures markets in India using high frequency one-minute interval price data of twelve individual stocks during the period from 3rd July 2006 to 28th December 2006. By employing vector error correction mechanism (VECM) they found a bi-directional lead-lag relationship between the spot and futures markets. Their findings suggest that price discovery occurs in both the markets simultaneously.

Pavabutr and Chaihetphon (2010) studied the price discovery process of the nascent gold futures contracts in the Multi Commodity Exchange of India (MCX) over the period from 2003 to 2007. They employed the vector error correction model (VECM) and their result showed that futures prices of both standard and mini contracts led spot price. They also found that standard and mini futures contracts exhibited a stronger influence over spot prices.

Jackline and Deo (2011) examined the relationship between the futures market and spot market of S&P CNX Nifty using daily price data over the period from January 2003 to September 2010. The cointegration tests and vector error correction models (VECM) were employed in the study to investigate relationship between spot and futures market. The cointegration results provided the evidence of a long run equilibrium relationship between spot and futures market and the vector error correction model provided the evidence of spot market leading futures market. Hence, the price discovery was achieved first in the spot market.

Theissen (2011) examined the price discovery in spot and futures market in Germany using intraday high frequency 15 seconds interval price data during the 1st quarter of 1999. The study employed the vector error correction model (VECM) and found that DAX futures index leads spot index and also DAX futures ETF index leads spot index and hence, price is discovered first in futures market.

Srinivasan and Ibrahim (2011) examined the price discovery process in Gold futures and spot markets of National Commodity Derivatives Exchange (NCDEX) in India using daily price data for the period from November 2010 to January 2011. They employed Johansen's Vector Error Correction Model (VECM) and their empirical results confirmed that the spot market of Gold played a key role and served as an effective price discovery vehicle.

Rahman et al. (2012) studied the market efficiency of the Malaysian crude palm oil prices using monthly price data for the sample period from January 1998 to December 2010. The employed cointegration tests and VECM model to investigate the relationship between spot and futures market. The cointegration results provided the evidence of a long run equilibrium relationship between spot and futures markets and the vector error correction model provided evidence of feedback relationship between spot and futures prices. This implies that the market efficiency hypothesis can be easily rejected.

Rajput et al (2012) examined the lead lag relationship between spot and futures markets in India using daily closing prices for the sample period from January 2003 to March

2011. The cointegration tests and Granger causality test, vector error correction models (VECM) and variance decomposition analysis (VDA) were employed to investigate the short and long-term dynamics between spot and futures markets. The cointegration test results revealed that there was a long run relationship between spot and futures prices. The VECM provided the evidence of spot market leading the futures market and price is discovered first in spot market.

Unlu and Ersoy (2012) investigated the lead lag relationship between foreign currency spot and futures market in Turkey for the period from January 2007 to December 2011. Cointegration test was used and an error correction model (ECM) was developed in order to investigate the causal relationship. The results showed that there was a long run relationship between spot and futures markets. Moreover, there was also a bi-directional causality existing between them both in the long run and short run.

Choudhary and Bajaj (2012) investigated whether spot and futures markets were playing an important role in price discovery in the Indian stock market using intraday 5-minutes interval data set for 31 individual securities during the period from April 2010 to March 2011. They applied both the Johansen's cointegration test and Engle and Granger's residual based cointegration test to investigate the long-run equilibrium relationship between these two markets. Apart from this, the Granger causality test and the Vector Error Correction Model (VECM) were used to determine the direction of causality. The results of the study exhibited that there was a bi-directional information flows between the spot and futures markets. As far as price discovery role is concerned, both spot and futures markets are playing a significant role implying that spot (futures) prices may contain useful information about futures (spot) prices.

Zakaria and Shamsuddin (2012) looked at price discovery mechanism in spot price index and futures price index in Malaysia using daily data from January 2006 to November 2011. The cointegration test results showed that both spot and futures prices in Malaysia were cointegrated indicating a long run relationship between them. By using Granger causality test, they found unidirectional causal relationship running from spot market to futures market. The finding suggests that in an emerging market like Malaysia, where the futures trading is less active, compared to the spot trading, the spot market reveal the new information faster than the futures market. Therefore, in Malaysian market price was discovered first in the spot market.

Sehgal (2012) studied price discovery and causality between futures prices and spot prices for ten agricultural commodities in India using cointegration techniques and Granger causality test for the period from June 2003 to March 2011. The study found long run equilibrium relationship for 9 out of 10 commodities and the results of Granger causality test showed a bidirectional causal relationship between spot and futures in all agricultural commodities except turmeric.

Chhajed and Mehta (2013) examined the price discovery in Indian agriculture commodity markets for nine agriculture commodities i.e. soybean oil, wheat, rubber, gram, soybean oil, potato, jute, mentha oil, rubber, crude palm oil and cardamom during 2009-2010 using monthly data. The Granger causality test was used to test the price discovery i.e., the effect of future market on spot market and vice-versa. The Granger causality test results showed bi-directional causality between spot and future prices for most of the commodities.

Iiter and Alguner (2013) examined the price discovery and lead-lag relationship between stock index (ISE 100) and stock index futures markets in Turkey using daily closing prices over the period from 2006-2011. By using vector error correction model (VECM) they found that price was discovered first in the futures market and then it flowed to the spot market.

Yuhua and Fang (2013) examined the price discovery and causality between oil's futures prices and the spot price in the Chinese market using cointegration test, Granger causality test and error correction model (ECM). They found both futures price and spot price were cointegrated and there was a long run equilibrium relationship existing between them. Both the Granger causality test and the error correction model revealed that the futures market led the spot market and hence, price is discovered first in futures market.

Xie & Huang (2013) empirically examined price discovery in the Chinese market using the daily closing values of the CSI 300 index and its futures index from April 2010 to April 2012. By using Johansen's cointegration test they established a long run equilibrium relationship between spot and futures index. Both vector error correction model (VECM) and an impulse response function (IRF) were conducted for the study to trace the causal relationship between them. The VECM model shows no causality between them either way however, impulse response function (IRF) shows shocks from the spot index have a long impact upon the futures index, but not vice versa.

Edward and Rao (2013) examined the price discovery and causality between turmeric spot and futures markets in India for the period from 1st April 2007 to 31st March 2013 by dividing into three panels of data. The cointegration tests and vector error correction model (VECM) were employed to investigate the relationship between spot and futures markets. The findings suggest that there exists a cointegration relationship between spot and futures turmeric prices for the first two panels (2007-10 and 2010-13), the causality does not exist, but for the third panel (2007-13), the causality is bidirectional. The results show that there is no evidence of which market leads the other in the long run.

Singhal (2014) investigated the causality between crude oil daily spot and future prices in India for the period from 1st January 2009 to 31st December 2011. Using the Granger causality test to determine the lead-lag relationship, the study found that the futures market leads the spot market i.e. the futures crude oil price in India can be used to forecast the spot price. Overall, the findings suggest that the price discovery is much faster in the futures market than in the spot market.

5.3: Objective of the Chapter

1. To examine the long run as well as lead-lag relationship between spot and futures market.

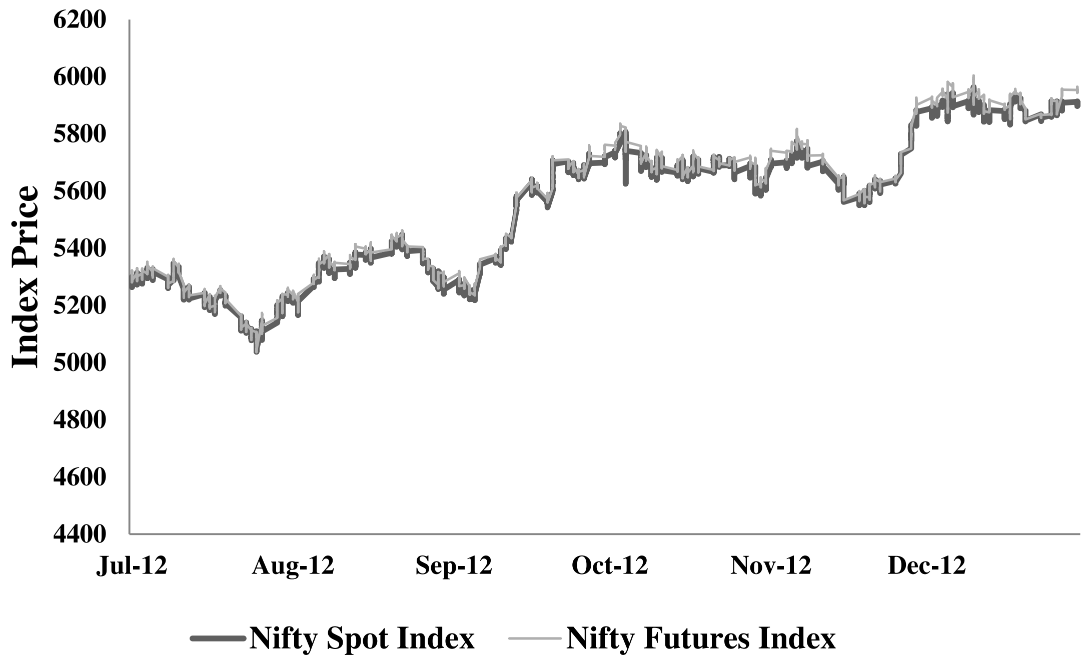
5.4: Data, Variables and Methodology

5.4.1: Data

The sample used in the study consists of 5-minutes interval data set of S&P CNX Nifty index prices and CNX Nifty futures Index prices from 2nd July 2012 to 31st December 2012.

The spot prices and future prices are plotted in Figure 1. It can be observed that the prices are almost the same in the two markets at any given point in time and they share the same trend. They are found to be frequently overlapping, which makes it difficult to distinguish between them.

Fig.1: Time Trend of Nifty Index and Futures Index



5.4.2: Description of Variables

Direct spot index prices and futures index prices are considered in the study.

S_t = Spot Index Price

F_t = Futures Index Price

$\Delta S_t = S_t - S_{t-1}$ (First differences of Spot Index Prices)

$\Delta F_t = F_t - F_{t-1}$ (First differences of Futures Index Prices)

5.4.3: Methodology

5.4.3.1: Stationarity Test

The stationary of the data series is evaluated by Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) tests.

5.4.3.2: Engle-Granger and Augmented Engle Granger Co-integration Test

Since the price series of both the set of data were found to be integrated in an identical order, the Engle-Granger and the Augmented Engle-Granger two step co-integration tests were employed to investigate the long-run relationship between spot and futures prices which is presented below. In the first step we estimate an OLS regression:

$$S_t = \alpha_0 + \beta_1 F_t + u_t \qquad (5.1)$$

Where S_t and F_t are spot prices and futures prices respectively at time t. α_0 and β_1 are the estimated parameters and u_t is the error term.

In the second step, we obtain the residual $(\hat{u}_t)$ series from the above OLS regression and use the DF and ADF test on it. If the estimated residual series $(\hat{u}_t)$ is found to be stationary (i.e., it does not have a unit root), spot prices and futures prices, despite being individually non-stationary, are co-integrated. Hence, there is a long run equilibrium relationship existing between them.

5.4.3.3: Vector Error Correction Model (VECM)

If spot and futures prices are co-integrated, causality must exist at least in one direction (Granger, 1986). In order to test the causality, the following vector error correction model (VECM) is estimated by using ordinary least square (OLS) in each equation.

$$\Delta S_t = a_{S,0} + \sum_{i=1}^{p} a_{S,i}\, \Delta S_{t-i} + \sum_{j=1}^{p} b_{S,j}\, \Delta F_{t-j} + \alpha_S u_{t-1} + \varepsilon_{S,t} \qquad (5.2)$$

$$\Delta F_t = a_{F,0} + \sum_{i=1}^{p} a_{F,i}\, \Delta S_{t-i} + \sum_{j=1}^{p} b_{F,j}\, \Delta F_{t-j} + \alpha_F u_{t-1} + \varepsilon_{F,t} \qquad (5.3)$$

where $\Delta S_{t,}$ ΔF_t are first difference spot and futures prices series respectively; $a_{S,0}$, $a_{F,0}$ are intercept terms; $a_{S,i}$, $b_{S,j}$, $a_{F,i}$, $b_{F,j}$ are the short-run coefficients and u_{t-1} is the error correction term lagged one period from co-integration equation (5.1). The error correction coefficients, α_S and α_F measure the speed of adjustment in response to deviations from the long run equilibrium. Higher absolute values of error correction coefficients indicate higher speeds of adjustment from the short run to long run.

If for instance, the spot price is high in terms of deviations from a long run equilibrium value, a negative price change on the spot and/or a positive price change on the futures market will correct mispricing. To explain let us consider a positive value of $(\hat{u}_{t-1})$. It indicates that either S_{t-1} is higher than what it is expected to be for a given value of F_{t-1} (see equation 5.1), i.e. in same sense, S_{t-1} is seen to be above its long run equilibrium value; or conversely, it can be interpreted that F_{t-1} is below what it is expected to be for a given value of S_{t-1}, i.e. in same sense, F_{t-1} is seen to be below its long run equilibrium value. Thus, we should expect spot price to fall ($\alpha_S < 0$) and or futures price to rise ($\alpha_F > 0$). Thus, we should expect α_S to have a negative sign and α_F to have a positive sign.

On the other hand, the lagged terms of ΔS_t and ΔF_t appear as explanatory variables, and these indicate short run cause and effect relationship between two variables. The spot market Granger causes futures market if the null hypothesis: H_0: $a_{F,1}$ = $a_{F,2}$ =….= $a_{F,p}$= 0 is rejected and similarly, futures market Granger causes spot market if the null hypothesis: H_0: $b_{S,1}$ = $b_{S,2}$ =….= $b_{S,p}$= 0 is rejected. If both variables Granger cause each other, there exists bi-directional causality between spot and futures market.

5.5: Results and Analysis

Table 5.1: Unit Root Test Results

Unit Root Test						
Series in Levels						
Indexes	Intercept			Intercept with Trend		
	DF	ADF	PP	DF	ADF	PP
Spot Index	0.568	-0.674	-0.670	-1.950	-2.430	-2.442
Futures Index	0.533	-0.662	-0.646	-2.012	-2.550	-2.546
Series in First Difference						
Indexes	Intercept			Intercept with Trend		
	DF	ADF	PP	DF	ADF	PP
ΔSpot Index	-30.42*	-46.58*	-97.97*	-39.66*	-46.58*	-97.97*
ΔFutures Index	-42.65*	-42.67*	-97.43*	-42.411*	-42.67*	-97.42*

Note: * denotes 1% level significance

5.5.1: Unit Root Test Results

A necessary requirement to carry out co-integration test in a time series data is that the data have to be non-stationary at the level, but stationary in the differences. To test the stationary properties of spot index prices and futures index prices we conducted DF, ADF and Phillips-Perron test. The test statistics are reported in Table 5.1. It is found that both the series are not stationary at their levels, but are stationary at their first differences. Thus, the variables are integrated in the same order, i.e, I (1).

5.5.2: Cointegration Test Results

In the next step, the Cointegration between the stationary variables has been tested by the two steps Engle-Granger and Augmented Engle Granger Cointegration Test. The results of these tests are reported in Table 5.2.

Table 5.2: Cointegration Test Results

Engel-Granger and Augmented Engle-Granger Cointegration Test			
Panel-A			
Co-integration Equation ($S_t = \alpha_0 + \beta_1 F_t + u_t$)			
Variable	Coefficient	Std. Error	t-Statistic
α_0	114.8*	2.34255	49.04
Futures	0.97*	0.000421	2319
Panel-B			
Unit Root Test of Residuals ($\hat{u}_t$)			
Intercept		Intercept with Trend	
DF	ADF	DF	ADF
-5.141*	-6.411*	-5.575*	-6.402*

Note: * denotes 1% level significance

Initially, we estimated the cointegration equation and obtained the residuals ($\hat{u}_t$). The cointegration equation results are reported in Panel-A (Table 5.2). Next we conducted DF and ADF test on the residual series ($\hat{u}_t$) and found it to be stationary by rejecting the null hypothesis that ($\hat{u}_t$) has a unit root at 1% level. This indicates that both the series are co-integrated and they have a long run equilibrium relationship.

Cointegration equation ($S_t = 114.8 + 0.97F_t + \hat{u}_t$) represents the long-run equilibrium relationship between spot and futures. The result indicates that when the futures price increases by 1%, the spot price will follow the futures price with an increase of 0.97%, ceteris paribus. Alternatively, result can also be understood as when the spot price increases by 1%, the futures price will increase by 1.03% (i.e., the reciprocal of 0.97), ceteris paribus.

5.5.3: Vector Error Correction Model (VECM) Results

The error correction mechanism provides a means whereby a proportion of the disequilibrium is corrected in the next period. Thus error correction mechanism is a means to reconcile the short-run and long-run behavior. The estimation of a vector error correction model (VECM) requires selection of an appropriate lag length. The lag length of eight in the vector error correction model (VECM) of equations (5.2) and (5.3) is chosen on the basis of Akaike's information criteria (AIC) and Schwarz criteria (SC). The VECM estimation results are presented in Table 5.3.

From the Table 5.3 it is observed that the error correction coefficient in futures equation is 0.009857 which shows 0.99% of the short term disequilibrium in futures market is corrected in each 5 minutes time interval and Futures prices have a greater speed of adjustment to the previous period's deviation from long-run equilibrium than the spot price series.

The lagged spot coefficients in the futures equation are statistically significant in 1,2,3,4 and 7 lags and the null hypothesis that spot market does not granger cause futures market is rejected. Similarly, the lagged coefficients of futures to spot market are also statistically significant up to 7 lags and the null hypothesis that futures market does not granger cause spot market is rejected. This result shows a bi-directional information flow between spot and futures markets. As far as price discovery role of spot and futures markets is concerned, both markets play an important role implying that futures (spot) prices may contain useful information about spot (futures) prices.

Even though there exists of a bi-directional causality between spot and futures market, the lead from spot to futures appears to be more pronounced relative to lead from futures to spot market because futures market has a greater speed of adjustment (i.e. $\alpha_F =$

0.009857) to the previous period's deviation from long-run equilibrium than the spot price series.

Table 5.3: Vector Error Correction Model Results

Results: Vector Error Correction Model				
	ΔS_t		ΔF_t	
	Coefficient	t-statistic	Coefficient	t-statistic
u_{t-1}	-0.007803	[-1.36]	0.009857***	[1.77]
ΔS_{t-1}	-0.082035*	[-3.72]	0.069792*	[3.25]
ΔS_{t-2}	-0.145346*	[-6.57]	-0.039571***	[-1.83]
ΔS_{t-3}	-0.35152*	[-15.88]	-0.043654**	[-2.02]
ΔS_{t-4}	-0.176367*	[-7.66]	-0.054685*	[-2.44]
ΔS_{t-5}	-0.111686*	[-4.86]	-0.009547	[-0.42]
ΔS_{t-6}	-0.076856*	[-3.50]	0.006493	[0.30]
ΔS_{t-7}	-0.141703*	[-6.49]	-0.056349*	[-2.65]
ΔS_{t-8}	-0.017146	[-0.79]	0.018597	[0.88]
ΔF_{t-1}	0.059052*	[2.61]	-0.080355*	[-3.66]
ΔF_{t-2}	0.135368*	[5.97]	0.034513	[1.56]
ΔF_{t-3}	0.300107*	[13.22]	0.045963**	[2.08]
ΔF_{t-4}	0.16988*	[7.30]	0.055186*	[2.43]
ΔF_{t-5}	0.090578*	[3.89]	0.007313	[0.32]
ΔF_{t-6}	0.081479*	[3.62]	-0.006103	[-0.27]
ΔF_{t-7}	0.10839*	[4.83]	0.034744	[1.59]
ΔF_{t-8}	0.007049	[0.31]	-0.017315	[-0.80]
Constant	0.075609	[1.36]	0.074311	[1.37]
F-statistic	20.10755*		2.712916*	

Note:*, ** and *** denotes significance level of 1%, 5% and 10% respectively

5.6: Summary and Concluding Remarks

Using 5-minutes interval data set for CNX Nifty index and its futures index for the period from 2nd July 2012 to 31st December 2012 we investigated the lead-lag relationship between spot and futures market in India.

Using DF, ADF and PP test, it was found that both Nifty index and Nifty futures index were not stationary at their levels but they were stationary at their first difference.

The present study applied Engle and Granger's residual based approach to determine the long-run equilibrium between the two markets and found both the markets were co-integrated which showed a long run equilibrium relationship between spot and futures market.

VECM (Vector Error Correction Model) had been used to determine the direction of causality and the leading market. The results of the study depict that there was a bi-directional information flow or feedback between the spot and futures markets. As far as price discovery role of spot and futures markets was concerned, both markets were playing an important role implying that futures (spot) prices might contain useful information about spot (futures) prices.

On the whole, the findings suggest that even though the study revealed a feedback relationship, the lead from spot to futures appeared to be more pronounced relative to the lead from futures to spot market. In an emerging market like India, where the futures market is less active, compared to the spot market, the spot market reacts to the new information faster than the futures market. Therefore, in Indian market the lead from spot to futures appeared to be more pronounced relative to futures to spot market.

One of the implications is that as long as one market leads the other market, the arbitrageur can make a gain by entering both the markets. This section of the study may be useful for the investors, participants and academicians who are keen on observing the trend of the selected market.

Chapter 6

Summary and Conclusion

Market microstructure is the area of finance that studies the processes by which prices come to impound new information over time. A major issue arises here concerning measurement of the information flow in the market. In this process, market microstructure research has been focusing on the price-volume and price-spread relationship since this empirical relation helps in understanding the competing theories of dissemination of information flow in the market. The empirical price-volume relationship is developed based on two major underlying hypotheses: Mixture Distribution Hypothesis (MDH) and the Sequential Information Arrival Hypothesis (SIAH). Both the hypotheses suggest a positive contemporaneous relationship between absolute price changes and trading volume however, SIAH additionally also suggests a causal relationship between absolute price changes and trading volume.

The market microstructure research has also explored and tried to explain the relationship between bid-ask spread and volatility based on information uncertainty. The intraday return volatility and intraday variations of bid-ask spread are expected to be correlated because an information arrival is supposed to stimulate an increase in volatility which in turn widens the bid-ask spread.

To understand the influence of spot market on futures market and vice versa and the role of each market segment in price discovery is the key question in the research of market microstructure design. Price discovery is important because it hints at where the informed traders do trade. Were the markets perfectly efficient and frictionless, the price discovery would be instantaneous and contemporaneous. In practice, however, between spot and derivatives segments or across different trading venues of the same stock, price discovery takes place in one market and the other markets follow it. Although futures and spot markets react to the same information, the important question to ask is: which market reacts first?

Against the above background, the present study attempts to investigate the following objectives:

1. To examine the intraday contemporaneous as well as causal relationship between stock returns, trading volume and bid-ask spread.
2. To investigate whether return-volume relation is different for a rising market than that for a declining market.
3. To examine the intraday contemporaneous as well as causal relationship between stock returns volatility, trading volume and bid-ask spread.
4. To investigate whether information content in trading volume and bid-ask spread captures the volatility persistence in the market.
5. To examine the long run as well as lead-lag relationship between spot and futures market.

6.1: Summary

The present study consists of six chapters. The **first chapter** briefly explains the background of the study, issues, objectives, data and methodology of the study.

Chapter 2 deals with the theoretical background of the study. It briefly discusses the arrival of the new information and the price-volume relation based on mixture distribution hypothesis (MDH) and sequential information arrival hypothesis (SIAH). In the literature, the price-spread relation is also explored based on information uncertainty in the market. We also explored the proposition concerning the lagged volume and volatility relationship based on liquidity driven trading and information driven trading.

Objective specific empirical studies are more extensively reviewed respectively in each chapter of the study concerned with that objective. Studies on stock price changes, trading volume and bid-ask spread are reviewed in Chapter 3. Similarly, empirical studies on stock return volatility, trading volume and bid-ask spread are reviewed in Chapter 4 and the literature related to the lead-lag relationship and price discovery between spot and futures markets is reviewed in Chapter 5. The respective methodologies of the relevant to particular topics in this study are similarly discussed in the specific chapter relevant for that topic (i.e. Chapter 3, Chapter 4 and Chapter 5 include discussions on the topic specific methodologies).

For first four objectives of the thesis, last trading price, bid price, ask price and trading volume are the relevant variables. The study uses intraday high frequency 5-minutes interval data set for a period from 2nd July, 2012 to 31st December, 2012 for 50 stocks of S&P CNX Nifty. In order to examine the last objective, 5-minutes interval trading prices of the Nifty index and Nifty index futures for the near-month have been taken into consideration for the period from 2nd July, 2012 to 31st December, 2012.

Chapter 3 empirically examines the contemporaneous and causal relationship between trading volume, bid-ask spread and stock returns. This chapter has also briefly reviewed the past literature. Both the OLS regression and the Granger causality test are employed to investigate contemporaneous and causal relationship respectively between trading volume, bid-ask spread and stock returns. This chapter also looked at the asymmetric behavior of stock returns and trading volume using dummy variable OLS regression. Before employing the OLS regression and the Granger causality test, the stationarity of the variables is checked through Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) tests.

Chapter 4 empirically examines the contemporaneous and causal relationship between trading volume, bid-ask spread and return volatility measured by squared returns. Both the OLS regression and the Granger causality test have been employed to investigate contemporaneous and causal relationship between trading volume, bid-ask spread and volatility. The stationarity of the variables is checked through Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) tests. The chapter also examines the effect of trading volume and bid-ask spread on conditional volatility. The Generalized autoregressive conditional hetroscedasticity (GARCH) model is employed to investigate the impact of trading volume and bid-ask spread on conditional return volatility.

Chapter 5 has empirically examines the lead-lag relationship between the NSE spot and futures market. The price discovery and the causal relationship between spot and futures prices have been investigated by employing Vector Error Correction Model (VECM).

The stationarity tests have been carried out by using Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) tests. Engle-Granger cointegration test is selected to verify the existence of cointegration between the spot and futures prices. After obtaining the cointegration between the spot and futures prices, price discovery and causality between the two markets are tested with the help of vector error correction model.

Finally, the last (current) chapter summarizes the study. It offers limitations of the study, implications of the study and explores future agenda of research.

6.2: Findings of the Study

There are many studies, empirical and theoretical, on the phenomenon of stock price and volume relationship. Although the majority of those findings have confirmed the existence of positive contemporaneous relationship between trading volume and absolute price changes/volatility, the studies of different stock markets have given mixed results about the causal price-volume relationship. Therefore, there is a scope for further examining the contemporaneous and causal relationship between the price changes and trading volume in India.

Most of the studies have focused on the arrival of new information and price-volume relation, whereas, studies on the arrival of new information and price-spread relation are far fewer and this relationship is not so clear by established at theoretical or at empirical level. Hence, there exists some scope for further investigation.

Several recent studies have shown that futures prices play a crucial role in the discovery and transmission of price formation. Whether this situation holds good for all markets is a question of debate for several years. To answer this question, this study makes an attempt, taking into consideration the S&P CNX Nifty Index and its related futures prices.

With above background to the subject matter of the present study, the main findings of the study are summarized below.

Chapter 3

The present study provides evidence of a positive contemporaneous relationship between absolute returns and trading volume for all the stocks in the sample, suggesting that increasing trading volume is associated with higher price changes and vice versa. The present study also provides evidence of a positive contemporaneous relationship between absolute returns and bid-ask spread for majority of the cases in the sample, suggesting that widening spread is associated with higher price changes and vice versa. The contemporaneous relationship between absolute stock returns and spread is found, in general to be stock specific rather than for the market as a whole. In general, contemporaneous volume explains a larger portion of stock returns compared to the extent to which spread explains it. Overall, in Indian market the study found evidence of a weak positive correlation between absolute stock returns and volume, and absolute stock returns and spread. This indicates that the Indian stock market is informationally inefficient and this also gives an indication of sequential information flow in Indian market.

Furthermore, the present study investigated the asymmetric relationship between stock returns and trading volume. No particular asymmetric pattern in the relationship could be established whether it was a rising market or a declining market. These findings are consistent with the findings of Assogbavi (2007) which clearly indicated an absence of asymmetric relationship in emerging markets. Hence, these results do not support the proposition that "volume is relatively heavy in bull markets and light in bear markets".

In addition to studying the contemporaneous relationship we also examined the possibility of causal relationship. Investigated the information content of volume to predict stock returns by means of Granger causality test and found that for most of the cases, trading volume causes stock returns. In some cases the study also found evidence of bi-directional causality between stock returns and trading volume. The theoretical explanation of this finding is that volume, which implies information, leads to price changes, and large positive price changes that imply higher capital gains, encourage transaction by traders leading to an increase in volume. In a similar manner, the study also investigated the information content of spread to predict stock returns by using the

Granger causality test and found that for majority of the cases spread causes stock return. This finding implies that in the presence of current and past return, spread contains some predictive power for future returns

Chapter 4

We find evidence of a positive contemporaneous relationship between volume and volatility measured by squared return, suggesting that higher trading volume is associated with an increase in stock return volatility and vice versa. Similarly, the study also found positive contemporaneous relationship between return volatility measured by squared return and spread, suggesting that widening spread is associated with an increasing stock return volatility and vice versa. Overall, the findings suggested that in particular stocks, the contemporaneous spread explained a relatively higher portion of return volatility, though in general, contemporaneous volume explained return volatility to a larger extent compared to what the spread could explain.

The current study also investigated the information content of volume for future returns volatility by using Granger causality test and found that for the majority of the cases trading volume causes return volatility. In a similar manner, the current study also investigated the information content of spread for future returns volatility and found that for the majority of the cases spread caused return volatility. Overall, our findings demonstrate a strong evidence of volume causing return/return volatility. An explanation for this, in Indian market most of the participants are small and marginal traders and they are late in information queue. It takes some time for information to reach them after it arrives at the market and thereafter they do trade and changes in price/volatility.

These results seem to indicate that information arrival to investors tends to follow a sequential rather than simultaneous process. The findings support the sequential information arrival hypothesis (SIAH) and contradict the mixture distribution hypothesis (MDH). Our study examines the efficient market hypothesis from the perspective of price-volume and price-spread relationships in Indian market. We find that Indian market is to some extent predictable using historical information contained in the past volume and the past spread, and is informationally, not as efficient as the efficient market hypothesis suggests.

The present study provides evidence of strong volatility persistence in the Indian stock market. The current volatility can be explained by past volatility that tends to persists over time. Based on Lamoureux and Lastrapes (1990) study, we add volume as an explanatory variable in the GARCH model to examine if the information contents of volume can capture the volatility persistence in the Indian market. It was observed that a moderate to high degree of reduction in volatility persistence could be achieved when contemporaneous volume is included in the variance equation of GARCH model. It was also observed that a small to moderate level of reduction in volatility persistence could be achieved when lagged volume was included in the variance equation of GARCH model. We then substitute the bid ask spread for volume in the conditional volatility equation to examine if the latter can capture the volatility persistence. The results show that the volatility persistence remained strong for many of the securities after the introduction of both the contemporaneous and lagged spread.

Chapter 5

As far as price discovery role of spot and futures markets is concerned, both markets are playing an important role implying that futures (spot) prices may contain useful information about spot (futures) prices.

On the whole, the findings suggest that even though the study revealed a feedback relationship, the lead from spot to futures appeared to be more pronounced relative to the lead from futures to spot market. In an emerging market like India, the futures market is less active compared to the spot market, the spot market reacts to the new information faster than the futures market.

6.3: Some Limitations of the Study

- The study could be conducted for a period of six months due to lack of free availability of data set for a period of more than 6 months.
- The findings of this study are subject to the period and data selected, and extending the study for larger and different periods may be needed to confirm these results.

6.4: Implications of the Study

The implications of this study are as follows.

i. The past information of trading volume and bid-ask spread are useful to improve the prediction of future returns and returns volatility. The study suggests that regulators and market participants can use past information for monitoring the stock price movement in the market.

ii. This study could help the marginal and uninformed traders who can not afford the cost of information acquisition; they can keep a close eye on the movements of both volume and spread for their investment decisions.

iii. Especially, this study may help the intraday investors for making their trading strategy.

iv. The results of price discovery indicate that the market can benefit from using the information content in spot prices more efficiently. The information from spot and futures market will help to predict futures prices more accurately for investors.

v. One of the implications is that as long as one market leads the other market, the arbitrageur can profit by entering both the markets.

6.4: Agenda for Future Research

Some lines of future research in this area are indicated as here under:

a. This study has been conducted on the number of shares traded as measures of volume. This can be conducted for the number of transactions (trade) and total value of shares traded (value) as measures of volume.

b. The price-volume and price-spread relation can be investigated in futures market also.

c. This present study has been conducted only for large firms. Future research can provide additional evidence on stock price, volume and spread relation of small firms to determine whether the findings of this study have wider validity.

d. The present study has been conducted only for a period of 6 months. The study can be conducted for a longer period, or several sets of such periods. This may yield valuable insights into evolving nature of Indian stock market.

e. Research on price discovery can be profitably conducted by considering the individual securities.

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A Synopsis of

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Market Microstructure of Indian Stock Market:
An Empirical Analysis

Market microstructure is the area of finance that studies the processes by which prices come to impound new information over time. In particular, as information is important in decision making, market outcome is sensitive to the assumed information structure. A major issue concerns measurement of the information flow in the market. In this process, market microstructure research has been focusing on the price-volume and price-spread relationship since this empirical relation helps in understanding the competing theories of dissemination of information flow in the market.

The empirical price-volume relationship has been developed on the basis of two major underlying hypotheses: The Mixture Distribution Hypothesis (MDH) and the Sequential Information Arrival Hypothesis (SIAH). Mixture of Distribution Hypothesis (MDH) of Clark (1973), Epps and Epps (1976), Tauchen and Pitts (1983) argues that absolute price change/volatility and trading volume should be positively correlated because they jointly depend on a common underlying variable, which is the rate of information flow to the market. This means that both stock price changes and trading volume simultaneously respond to the arrival of new information in the market and they are contemporaneously correlated. Hence, there exists a positive contemporaneous relation between trading volume and absolute price change/volatility. MDH implies strong positive contemporaneous but, no causal linkage between trading volume and price variability. In MDH equilibrium prices are immediately established and new information is disseminated simultaneously to all the traders. The implication is that with simultaneous information arrival, there is no information in the past volume that can be used in forecasting future absolute price changes that are not yet contained in the past absolute price changes. Hence, the mixture distribution hypothesis supports only the positive contemporaneous relationship but not the lead-lag relationship between trading volume and absolute price changes.

Lamoureux and Lastrapes (1990) have further extended the mixture distribution hypothesis to explain the source of autoregressive conditional hetroscedasticity (ARCH) effects in the stock returns. Empirical studies on stock return volatility have found significant evidence of ARCH effects in the stock returns. But there is little agreement on the sources of this phenomenon. One possible theoretical explanation is based on the role of information flows in the market. Based on mixture distribution hypothesis (MDH), Lamoureux and Lastrapes (1990) first employed the GARCH methodology to investigate the relationship between trading volume and volatility using daily trading volume as a measure of the information flow in the market. They found that the conditional volatility is positively correlated with trading volume and the autoregressive conditional hetroscedasticity (ARCH) effects disappeared when volume was included in the conditional variance equation of GARCH model. Their study found information contained in volume absorbed the volatility persistence in the market.

The sequential information arrival hypothesis (SIAH) proposed by Copeland (1976) and discussed further in Jennings, Starks and Fellingham (1981) and Simrlock and Starks (1978) assume that information is disseminated in the market sequentially rather than simultaneously to all the traders. The traders change their trading positions as new information arrives in the market. However, not all traders receive this new information at exactly the same time. Hence, the trader who observes the information initially, he interprets the news, adapts his expectations and generates transaction volume. Accordingly the price changes and a new temporary equilibrium is achieved. After market reaches at this new temporary equilibrium, the next trader becomes informed, adapts his expectations and generates transaction volume, accordingly again price changes and a new temporary equilibrium is achieved. This process will continue till it reaches the final equilibrium. The final equilibrium is established when all traders have received the same information and made a trading decision based on that information. In the sequential information arrival hypothesis (SIAH), some trader receives the signal ahead of the market and trades on it, thereby creating volume and price changes. Hence, there is a positive contemporaneous relationship between absolute price changes and trading volume. Further, this sequential information flow results in past values of trading volume having the ability to predict future absolute stock price change/volatility and/or vice versa, which means that a causality relationship may exist in both directions or either direction between absolute price changes/volatility and trading volume. Hence, SIAH suggests both contemporaneous as well as causal relationship between volume and absolute stock price changes.

One of the key findings of the previous research has been a positive correlation between trading volume and stock price changes. Some of these attempts have been concerned with the asymmetry of such a relation. The question is: do falling stock markets affect trading volume in a significantly different way in contrast to rising stock markets? Market folklore claims that the relationship between trading volume and price movements depends on whether the market has a bull or a bear run. The bulls are more optimistic about the assets value and they respond only to positive information. On the other hand, the bears are more pessimistic about the assets value and respond only to negative information. Jennings *et al* (1981) state that usually the trading volume is more when the investor is an optimist than pessimist. Since the prices increase with an optimistic buyer and they decrease with a pessimistic seller, it follows that the trading volume is high when price increases and low when price decreases. Brailsford (1994) opines that the presence of short selling component leads to asymmetric volume-price relationship. Short selling can only be initiated on a zero or up ticks (i.e. on non-negative price changes) whereby the sell price is at least equal to the last transaction price of the stock. Hence, there is a possibility of less number of traders in the market on down ticks (i.e. on negative price changes) than on zero or up ticks (i.e. on non-negative price changes) because of the restriction on short selling. Therefore, we may expect higher average volume on non-negative returns than negative returns.

The market microstructure research has also explored and tried to explain the relationship between bid-ask spread and volatility based on information uncertainty. The intraday return volatility and intraday variations of bid-ask spread are expected to be positively correlated because arrival of information would be expected to induce an increase in volatility and this would in turn have the effect of widening the bid-ask spread.

To understand the influence of spot market on futures market and vice versa and the role of each market segment in price discovery is the key question in the research of market microstructure design. Price discovery is important because it hints at where the informed traders do trade. Were the markets perfectly efficient and frictionless, the price discovery would be instantaneous and contemporaneous. In practice, however, between spot and derivatives segments or across different trading venues of the same stock, price discovery takes place in one market and the other markets follow it. Although futures and spot markets react to the same information, the important question to ask is: which market reacts first?

Issues

The following issues are identified on the basis of the theoretical background and the review of existing literature:

There are many studies, empirical and theoretical, on the phenomenon of stock price and volume relationship. Although the majority of those findings have confirmed the existence of positive contemporaneous relationship between trading volume and absolute price changes/volatility, the studies of different stock markets have given mixed results about the causal price-volume relationship. Therefore, there is a scope for further examining the contemporaneous and causal relationship between the price changes and trading volume in India.

Most of the studies have focused on the arrival of new information and price-volume relation, whereas, studies on the arrival of new information and price-spread relation are far fewer and this relationship is not so clear by established at theoretical or at empirical level. Hence, there exists some scope for further investigation.

Several recent studies have shown that futures prices play a crucial role in the discovery and transmission of price formation. Whether this situation holds good for all markets is a question of debate for several years. To answer this question, this study makes an attempt, taking into consideration the S&P CNX Nifty Index and its related futures prices.

Objectives of the Study

On the basis of the above outlined theoretical background and the issues, the following main objectives have been set for this study.

1. To examine the intraday contemporaneous as well as causal relationship between stock returns, trading volume and bid-ask spread.

2. To investigate whether return-volume relation is different for a rising market than that for a declining market.

3. To examine the intraday contemporaneous as well as causal relationship between stock returns volatility, trading volume and bid-ask spread.

4. To investigate whether information content in trading volume and bid-ask spread captures the volatility persistence in the market.

5. To examine the long run as well as lead-lag relationship between spot and futures market.

The present study consists of six chapters. The **first chapter** briefly explains the background of the study, issues, objectives, data and methodology of the study.

Chapter 2 deals with the theoretical background of the study. It briefly discusses the arrival of the new information and the price-volume relation based on mixture distribution hypothesis (MDH) and sequential information arrival hypothesis (SIAH). In the literature, the price-spread relation is also explored based on information uncertainty in the market. We also explored the proposition concerning the lagged volume and volatility relationship based on liquidity driven trading and information driven trading.

Objective specific empirical studies are more extensively reviewed respectively in each chapter of the study concerned with that objective. Studies on stock price changes, trading volume and bid-ask spread are reviewed in Chapter 3. Similarly, empirical studies on stock return volatility, trading volume and bid-ask spread are reviewed in Chapter 4 and the literature related to the lead-lag relationship and price discovery between spot and futures markets is reviewed in Chapter 5. The respective methodologies of the relevant to particular topics in this study are similarly discussed in the specific chapter relevant for that topic (i.e. Chapter 3, Chapter 4 and Chapter 5 include discussions on the topic specific methodologies).

For first four objectives of the thesis, last trading price, bid price, ask price and trading volume are the relevant variables. The study uses intraday high frequency 5-minutes interval data set for a period from 2nd July, 2012 to 31st December, 2012 for 50 stocks of S&P CNX Nifty. In order to examine the last objective, 5-minutes interval trading prices of the Nifty index and Nifty index futures for the near-month have been taken into consideration for the period from 2nd July, 2012 to 31st December, 2012.

Chapter 3 empirically examines the contemporaneous and causal relationship between trading volume, bid-ask spread and stock returns. This chapter has also briefly reviewed the past literature. Both the OLS regression and the Granger causality test are employed to investigate contemporaneous and causal relationship respectively between trading volume, bid-ask spread and stock returns. This chapter also looked at the asymmetric behavior of stock returns and trading volume using dummy variable OLS regression. Before employing the OLS regression and the Granger causality test, the stationarity of the variables is checked through Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) tests.

Chapter 4 empirically examines the contemporaneous and causal relationship between trading volume, bid-ask spread and return volatility measured by squared returns. Both the OLS regression and the Granger causality test have been employed to investigate contemporaneous and causal relationship between trading volume, bid-ask spread and volatility. The stationarity of the variables is checked through Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) tests. The chapter also examines the effect of trading volume and bid-ask spread on conditional volatility. The Generalized autoregressive conditional hetroscedasticity (GARCH) model is employed to investigate the impact of trading volume and bid-ask spread on conditional return volatility.

Chapter 5 has empirically examines the lead-lag relationship between the NSE spot and futures market. The price discovery and the causal relationship between spot and futures prices have been investigated by employing Vector Error Correction Model (VECM). The stationarity tests have been carried out by using Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) tests. Engle-Granger cointegration test is selected to verify the existence of cointegration between the spot and futures prices. After obtaining the cointegration between the spot and futures prices, price discovery and causality between the two markets are tested with the help of vector error correction model.

Finally, the last (current) chapter summarizes the study. It offers limitations of the study, implications of the study and explores future agenda of research.

Findings of the Study

With above background to the subject matter of the present study, the main findings of the study are summarized below.

Chapter 3

The present study provides evidence of a positive contemporaneous relationship between absolute returns and trading volume for all the stocks in the sample, suggesting that increasing trading volume is associated with higher price changes and vice versa. The present study also provides evidence of a positive contemporaneous relationship between absolute returns and bid-ask spread for majority of the cases in the sample, suggesting that widening spread is associated with higher price changes and vice versa. The contemporaneous relationship between absolute stock returns and spread is found, in general to be stock specific rather than for the market as a whole. In general, contemporaneous volume explains a larger portion of stock returns compared to the extent to which spread explains it. Overall, in Indian market the study found evidence of a weak positive correlation between absolute stock returns and volume, and absolute stock returns and spread. This indicates that the Indian stock market is informationally inefficient and this also gives an indication of sequential information flow in Indian market.

Furthermore, the present study investigated the asymmetric relationship between stock returns and trading volume. No particular asymmetric pattern in the relationship could be established whether it was a rising market or a declining market. These findings are consistent with the findings of Assogbavi (2007) which clearly indicated an absence of asymmetric relationship in emerging markets. Hence, these results do not support the proposition that “volume is relatively heavy in bull markets and light in bear markets”.

In addition to studying the contemporaneous relationship we also examined the possibility of causal relationship. Investigated the information content of volume to predict stock returns by means of Granger causality test and found that for most of the cases, trading volume causes stock returns. In some cases the study also found evidence of bi-directional causality between stock returns and trading volume. The theoretical explanation of this finding is that volume, which implies information, leads to price changes, and large positive price changes that imply higher capital gains, encourage transaction by traders leading to an increase in volume. In a similar manner, the study also investigated the information content of spread to predict stock returns by using the Granger causality test and found that for majority of the cases spread causes stock return. This finding implies that in the presence of current and past return, spread contains some predictive power for future returns.

Chapter 4

We find evidence of a positive contemporaneous relationship between volume and volatility measured by squared return, suggesting that higher trading volume is associated with an increase in stock return volatility and vice versa. Similarly, the study also found positive contemporaneous relationship between return volatility measured by squared return and spread, suggesting that widening spread is associated with an increasing stock return volatility and vice versa. Overall, the findings suggested that in particular stocks, the contemporaneous spread explained a relatively higher portion of return volatility, though in general, contemporaneous volume explained return volatility to a larger extent compared to what the spread could explain.

The current study also investigated the information content of volume for future returns volatility by using Granger causality test and found that for the majority of the cases trading volume causes return volatility. In a similar manner, the current study also investigated the information content of spread for future returns volatility and found that for the majority of the cases spread caused return volatility. Overall, these results constitute a strong evidence of volume causing return/return volatility. An explanation of such a finding is that most investors in Indian market are late in the informational queue and trade some time after the new information hits the market.

These results seem to indicate that information arrival to investors tends to follow a sequential rather than simultaneous process. The findings support the sequential information arrival hypothesis (SIAH) and contradict the mixture distribution hypothesis

(MDH). Our study examines the efficient market hypothesis from the perspective of price-volume and price-spread relationships in Indian market. We find that Indian market is to some extent predictable using historical information contained in the past volume and the past spread, and is informationally, not as efficient as the efficient market hypothesis suggests.

The present study provides evidence of strong volatility persistence in the Indian stock market. The current volatility can be explained by past volatility that tends to persists over time. Based on Lamoureux and Lastrapes (1990) study, we add volume as an explanatory variable in the GARCH model to examine if the information contents of volume can capture the volatility persistence in the Indian market. It was observed that a moderate to high degree of reduction in volatility persistence could be achieved when contemporaneous volume is included in the variance equation of GARCH model. It was also observed that a small to moderate level of reduction in volatility persistence could be achieved when lagged volume was included in the variance equation of GARCH model. We then substitute the bid ask spread for volume in the conditional volatility equation to examine if the latter can capture the volatility persistence. The results show that the volatility persistence remained strong for many of the securities after the introduction of both the contemporaneous and lagged spread.

Chapter 5

As far as price discovery role of spot and futures markets is concerned, both markets are playing an important role implying that futures (spot) prices may contain useful information about spot (futures) prices.

On the whole, the findings suggest that even though the study revealed a feedback relationship, the lead from spot to futures appeared to be more pronounced relative to the lead from futures to spot market. In an emerging market like India, the futures market is less active compared to the spot market, the spot market reacts to the new information faster than the futures market.

Some Limitations of the Study

- The study could be conducted for a period of six months due to lack of free availability of data set for a period of more than 6 months.
- The findings of this study are subject to the period and data selected, and extending the study for larger and different periods may be needed to confirm these results.

Implications of the Study

The implications of this study are as follows.

i. The past information of trading volume and bid-ask spread are useful to improve the prediction of future returns and returns volatility. The study suggests that regulators and market participants can use past information for monitoring the stock price movement in the market.

ii. This study could help the marginal and uninformed traders who can not afford the cost of information acquisition; they can keep a close eye on the movements of both volume and spread for their investment decisions.

iii. Especially, this study may help the intraday investors for making their trading strategy.

iv. The results of price discovery indicate that the market can benefit from using the information content in spot prices more efficiently. The information from spot and futures market will help to predict futures prices more accurately for investors.

v. One of the implications is that as long as one market leads the other market, the arbitrageur can profit by entering both the markets.

Agenda for Future Research

Some lines of future research in this area are indicated as here under:

a. This study has been conducted on the number of shares traded as measures of volume. This can be conducted for the number of transactions (trade) and total value of shares traded (value) as measures of volume.

b. The price-volume and price-spread relation can be investigated in futures market also.

c. This present study has been conducted only for large firms. Future research can provide additional evidence on stock price, volume and spread relation of small firms to determine whether the findings of this study have wider validity.

d. The present study has been conducted only for a period of 6 months. The study can be conducted for a longer period, or several sets of such periods. This may yield valuable insights into evolving nature of Indian stock market.

e. Research on price discovery can be profitably conducted by considering the individual securities.