THREE ESSAYS RELATED TO BEHAVIORAL FINANCE ISSUES IN THE INDIAN STOCK MARKET

By
Shah Saeed Hassan Chowdhury

A Dissertation Submitted to the Graduate School at Middle Tennessee State University in Partial Fulfillment of the Requirement for the Degree

Doctor of Philosophy/Economics

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IN MEMORY OF MY PARENTS

Shah Fazlul Haque Chowdhury

and

Shawkat Ara Kulsum Begum Chowdhury

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ABSTRACT

This dissertation investigates the behavioral finance issues in the Indian stock market. This consists of five chapters. Chapter two, three, and four present three stand-alone essays on the behavioral issues in the Indian stock market. Chapter one and five provide the introduction and conclusion of the paper, respectively.

The first essay, "Momentum Strategies: Evidence from the Indian Stock Market," investigates the presence of momentum profits on the Indian stock market over the period 1991-2006. I find no observed momentum profits or return reversals when simple non-overlapping medium- and long-term strategies are considered. However, I find significant momentum profits in higher market value and higher turnover portfolios for 6-6 (six-month formation and tracking period) strategies. Results also show return reversals for 3-3 strategies of winner-loser portfolios when I sort small size and low volume firms by market value and turnover criteria, respectively. Finally, I also find return reversals for 1-1 (short-term) strategy for all winner-loser portfolio combinations. Thus, it is possible to earn abnormal return in the Indian stock market by using appropriate trading strategies.

The second essay, "Sources of Momentum and Contrarian Profits in the Indian Stock Market," examines the presence and sources of contrarian and momentum profits in the Indian stock market. Results show that there are contrarian and momentum profits in the short- and medium-term investment horizons, respectively. Further investigation reveals that investors can only earn short-term contrarian profits by investing in small and medium size (and low- and medium-volume of trade) firms. In contrast, large firms (and

high-volume of trade firms) appear to be correctly priced, leaving no opportunity for contrarian profits. As far as sources of contrarian profits are concerned, firm-specific component is the major source of such profits. The role of firm-specific component as the source of contrarian profits for large size and high trade volume firms is very small and this phenomenon explains why large firms do not contribute to contrarian profits. Firm-specific component plays the major role in contrarian profits for small and medium size and low and medium trade volume firms. However, the good news for the Indian stock market is that the contribution of firm-specific component as a source of contrarian profits has decreased dramatically during the period 2000-2006.

In a large stock market such India, firms are highly differentiated in terms of risk factors or other attributes such as size, volume of trade, market-to-book value ratio. Keeping this mind, the third essay, "Lead-Lag Relationships between Stock Returns in the Indian Stock Market," investigates the presence of lead-lag relationships between stock returns in the Indian Stock market using above-mentioned factors as the basis for portfolio selection. Moreover, this essay examines the speed of adjustment of market-wide information into stock prices. The results of the study show that there is weak evidence of lead-lag relationship between large and small firms on the Indian stock market. This size-related lead-lag effect exists for medium and low volume firms, but not for high volume firms. The lead-lag relationship between high and low volume firms is almost nonexistent for both size-volume and MV/BV-volume portfolios. Results of Dimson beta regression find that high volume portfolios respond to market-wide relevant information faster than low volume portfolios. This result is obtained for medium and low MV/BV sorted portfolios only, implying that high volume firms are more efficient than low volume ones. This finding is consistent with the established theory that volume of trade plays an important role in the speed of information adjustment into stock prices.

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CHAPTER ONE

Introduction and Background

1.1 Background and Statement of Research Problem

In traditional finance theory, investors are assumed to be rational and security prices are also assumed to reflect their fundamental value. In its simplest form, this value is the present value of all the expected future cash flows in the form of dividends to be received. Fama (1970) popularized the term "Efficient Market Hypothesis" (EMH), which suggests that in an efficient market all the relevant information is fully reflected in a security's price. To put this statement in another way, a security's price is always in equilibrium, and there is no deviation from its fundamental value.

The implication of EMH is that there is no free lunch in the market and investors cannot consistently earn excess risk-adjusted average return. Financial economists initially welcomed the EMH. The empirical findings of extant literature at that time also supported it. However, during the period of the late 1970s through the early 1990s, researchers discovered several facts suggesting markets were not as efficient as initially thought. One explanation for this phenomenon is the increasing availability of high-frequency data and subsequent development in computational facilities that played a major role in carrying out tests on the EMH. The research showed that investors do not react rationally, a condition that created opportunities for excess risk-adjusted return. In such an environment, investors only need to adopt appropriate trading strategies to earn excess returns. Some of the trading strategies were in the form of the well-known stock price anomalies such as size effects, long-term price reversals, predictive power of price-earnings ratio, momentum effects, stock return seasonality, and underpricing of IPOs.

Some of the early studies provided support for EMH. For example, Ball and Brown (1968) provided evidence that new information is absorbed into stock prices so quickly that there is no possibilities for excess return. Fama et al. (1969) showed that the effect of stock splits is fully reflected in stock prices by the end of the split month. Sunder (1973, 1975) found that changes in an accounting system do not affect firm values.

Other papers challenged the concept of EMH. Banz (1981) and Fama and French (1992) documented that small firms earn significantly higher returns than large firms. French (1980) found significantly negative returns on Mondays. Keim (1983), Reinganum (1983), Roll (1983), and Gultekin and Gultekin (1983) discovered the presence of the so-called year-end effect, a form of pattern or return regularity in stock-price returns. Grinblatt et al. (1984) and Foster and Vickrey (1978) confirmed that dividend and split announcements have an impact on share prices. Over the period 1926 to 1982, DeBondt and Thaler (1985) showed that the average annual return of a past worst-performing portfolio is higher than the average return of the best-performing portfolio over a long investment horizon. On the other hand, Jegadeesh and Titman (1993) found that the best- performing stocks in the previous medium-term investment horizon outperformed the worst-performing stocks (of that period) in the subsequent medium-term investment horizon.

These studies show that the apparent failure of traditional finance theory (EMH) is important and leaves many unanswered questions. The failure of EMH has consequently led a growing number of financial economists to embrace the concept of behavioral finance as a new approach to asset valuation in financial markets. Ritter (2003) defines behavioral finance as the paradigm in which financial markets are studied using models that are less narrow than those based on Von Neumann-Morgenstern expected utility theory and arbitrage assumptions. Behavioral finance has two building blocks: cognitive psychology and limits of arbitrage. Behavioral finance is predicated on the proposition that people make systematic errors in the way they think: they are overconfident, i.e., they put more weight on recent experience.

In the case of financial markets, behavioral finance models take into account the psychological and behavioral aspects of an investor, thus allowing for situations in which agents fail to update their beliefs rationally. Behavioral models even allow those situations in which investors update information correctly but react in an improper or questionable fashion. For example, if there is a large mispricing in the market, investors immediately purchase the stock to take advantage of the opportunity and as a result this opportunity ultimately disappears. However, behavioral finance allows for the possibility that investors may overreact or underreact to information, resulting in further mispricing in the market. Many financial economists—for example, Black, 1986; DeBondt and Thaler, 1985; Kahneman and Tversky, 1979—believe that the behavioral aspect is an integral part of the market since investors often treat noise as information and make trades based on that information, causing prices to move further away from their fundamental value.[1]

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[1] However, Black (1986) claims that noise traders are good for market liquidity since they play roles to facilitate trading.

The literature in the past two decades has documented that stocks suffer from return regularities, which suggests that past return information can be utilized to make future abnormal returns. Simply stated, the market is predictable to some extent. Two types of relatively new return regularities (return patterns) in the cross-section of stocks are especially noteworthy. First is the return reversal as documented in a seminal paper by DeBondt and Thaler (1985, 1987). They show that firms with poor performance in the past three to five years earn abnormal returns in the next three- to five-year investment horizon. Thus, past losers become winners in the long horizon. Returns that occur from this kind of return regularity are called contrarian profits. Second is the return momentum, first documented in a seminal paper by Jegadeesh and Titman (1993). They show that winners in the past three to twelve months outperform losers in the next three to twelve months.

The findings of the presence of contrarian and momentum profits in stock markets have prompted many academicians to investigate the issue in more detail. For example, Daniel et al. (1998) and Hong and Stein (1999) explain how behavioral biases could account for the overreaction and underreaction in the stock market. Rouwenhorst (1998) shows significant momentum returns for the medium-term horizon in European developed markets. Griffin et al. (2003) find that although momentum strategies are profitable in North America, Europe, and Latin America, they are not profitable in Asia.

This study focuses on the Indian stock market because of a number of interesting economic policy activities. As a consequence of the economic liberalization of the Indian economy in the early 1990s, the Indian stock market has attracted both domestic and foreign investors that have made the market attractive to international investors as a new place for investment opportunities. Unfortunately, little is known about this important market, as researchers have tended to focus on developed markets. I investigate three research questions in three distinct but related essays: (1) does opportunity exist for excess return from investing in trading strategies that involve various investment horizons; (2) what are the potential sources of momentum and contrarian profits on the Indian stock market and (3) what is the lead-lag relationship of various firms categorized by risk factors in response to the arrival of information in the Indian stock market? Answers to these questions will provide a better understanding of this emerging market and possibly help investors reduce the presence of information asymmetry in the market. The next section provides an overview of the Indian stock market.

1.2 An Overview of the Indian Stock Market

The Mumbai Stock Exchange (previously known as the Bombay Stock Exchange or BSE) is the dominant stock exchange in India, with approximately 6,000 listed firms. It was established in 1875, making it the oldest stock market in Asia. It is the 10th largest stock exchange in the world and has a market capitalization of US$1.79 trillion as of December 31, 2007. The BSE index (SENSEX) is India's leading and first stock index, which now enjoys an iconic stature and is tracked throughout the world. This index comprises 30 stocks and represents 12 important sectors.[2] Between October 8, 1999 and February 6, 2007, the index experienced a dramatic rise and doubled in value from 5,000 to 10,000. The National Stock Exchange (NSE), also a Mumbai-based stock exchange, was incorporated in 1992. In October, 2007, its market capitalization of listed companies

[2] Source: BSE website, www.bse-india.com.

stood at US$1.46 trillion.[3] The NSE's key index is the S&P CNX Nifty, an index comprising of 50 major stocks weighted by market capitalization.

During the period 2000-2005, the Indian stock market capitalization-to-GDP ratio rose to 77 percent, reflecting the trend in foreign capital inflows and growth in the domestic investor base (Purfield et al., 2006). Foreign investors held about 10 percent of GDP in equity value. The domestic institutional investor base also expanded during this time. Insurance, pension, and mutual fund assets rose to 15 percent of GDP, with significant portions invested in equities (Purfield, 2007). The SENSEX increased at an annual compound rate of 17 percent with inflows of foreign capital at approximately $26 billion. One explanation for this phenomenon is the low interest rate in the U.S. and the growing attractiveness of the Indian stock market. The market experienced high investor confidence as illustrated by a P/E ratio of more than 20 for the overall market and 30 for the technology sector (Purfield, 2007).

As of March 2008, India is considered to be the third largest stock market in Asia, smaller than only China and Japan.[4] Although the Chinese market is larger than the Indian market, it is generally believed that Indian stock exchanges are better managed and that their rules comply more with international standards (Ananthanarayanan et al., 2008).[5] State-owned enterprises constitute a substantial part of the Chinese market and rules for state-owned and non–state-owned firms are the same.[6] On the other hand, Securities Exchange Board of India (SEBI), the regulatory body of the Indian capital

[3] Source: NSE website, www.nse-india.com.
[4] As of March 2008, the market capitalization of India, China, and Japan is 4,615, 3,059, and 1,090 billion dollars, respectively. Source: http://www.diehardindian.com/overview/stockmkt.htm.
[5] Available at http://www.isb.edu/CAF/htmls/Sandhya&Sen.pdf.
[6] Chhaochharia, S., Capital market development: The race between China and India. The abstract is available at http://ssrn.com/abstract=1130074.

market has very strong regulatory power over the Indian stock market. The strength of the Indian and Chinese stock markets is exhibited in the way they shielded themselves from the East Asian financial crises that swept through Malaysia, Indonesia, South Korea, Philippines, and Thailand in 1997.

1.3 Research Problems and Related Research Questions

The recent globalization trend has created a new world for investors and entrepreneurs.[7] Using today's technology and financial market liberalization policies of individual countries, portfolio managers can diversity their portfolios across many securities in different countries. This phenomenon has enabled investors to diversify their portfolios over more assets to create more efficient portfolios in terms of risk and return. This is particularly possible due to the low or negative correlation between developed and emerging markets found in previous studies (see for example, Harvey, 1995; Bekaert and Harvey, 1994; Buckberg,1995).

The financial markets liberalization policies adopted by a large number of countries have resulted in greater integration of stock markets among different countries. As a result of these financial reforms, a number of important emerging markets have evolved in Brazil, Russia, India, and China.[8] The study of emerging markets is appealing because they provide another avenue for investors to diversify their portfolios in an international arena. As these markets compete to lure international investors, they will be compelled to

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[7] Financial dictionary at www.dictionary.com describes globalization as the tendency of investment funds and businesses to move beyond domestic and national markets to other markets around the globe, thereby increasing the interconnectedness of different markets. Economic liberalization policy adopted by many countries is the main reason for the recent globalization phenomenon.

[8] Some academicians now abbreviate Brazil, Russia, India, and China as BRIC.

make reforms that will make them more competitive and efficient. As these markets become more efficient and liquid, the cost of capital should decrease, leading to more investment and increased economic growth.

This study examines the behavioral finance aspects of the Indian stock market in three distinct but related essays. The first essay investigates the opportunity for excess returns from using trading strategies that involve various investment horizons. It also investigates how opportunity for excess returns may change when firms are chosen based on size and volume of trade. The second essay addresses two issues in the Indian stock market: the presence and sources of so-called momentum and contrarian returns (profits) and the role that risk factors such as size and volume of trade play in explaining these sources. In an efficient market, the momentum and contrarian excess returns should not exist. A detailed study may pinpoint the sources of such excess returns, which will allow market investors and regulators to know exactly what actions need to be taken to achieve or approach market efficiency. When markets are efficient, less-informed investors feel safe to invest. It is especially true for the Indian market since, like other emerging markets, it is still highly influenced by less-informed noninstitutional investors.

The third essay investigates the lead-lag relation of various firms categorized by risk factors in response to the arrival of new information to the market. If returns of one category of firms lead that of another category of firms systematically, then investors may take advantage of this phenomenon, which ultimately drives inefficiency from the market. Thus, a detailed knowledge of the lead-lag relationship is important for investors, regulators, policymakers, and academicians. Every market consists of stocks that can be differentiated on the basis of volume of trade, size, and market-to-book value. According to standard finance theory, return is supposed to be explained by respective exposure to nondiversifiable market risk. Fama and French (1992) show that the traditional risk factor such as the market return as used in Capital Asset Pricing Model (CAPM) fails to capture all the risk exposure of the cross-section of firms. Thus, it is better to investigate the cross-section of expected returns with risk factors such as size, volume of trade, and market-to-book value ratio, which arguably appear as a better proxy for relevant risk. Firms in different risk classes are expected to behave in different ways. For example, firms in a lower risk class yield less actual return and adjust faster to changes in systematic risk factors compared to those in a higher risk class. Such difference in response to information gives rise to the lead-lag relationship in the direction of large to small firms.

1.4 Research Objectives

The broad objective of this study is to provide an empirical investigation of the behavioral aspects of the Indian stock market with respect to opportunities to make excess returns not supported by the existing risk exposure. The specific objectives of the study are:

(a) to test whether or not investors can devise trading strategies based on past trading information to earn abnormal return;

(b) to examine how sensitive the opportunities are with respect to various investment horizons;

(c) to examine how investors can devise trading strategies with respect to factors such as volume of trade and size (market capitalization);

(d) to test whether or not momentum/contrarian profits exist when alternative portfolio construction is used;

(e) to investigate the sources of momentum/contrarian profits based on returns from portfolios, which are constructed in an alternative framework;

(f) to investigate the sources of momentum/contrarian profits in detail by considering various sub-periods, which can show how the contributions of sources (i.e., firm-specific versus market-related sources) change over time;

(g) to explore how high (large)- and low (small)-volume (size) firms react to information that comes from a common factor and how the direction of reaction to information goes from one type to another (lead-lag effect); and

(h) to explore the lead-lag relationship further by studying the speed of stock price adjustment to new common information when firms are categorized by various proxies for risk such as size, volume of trade, and market-to-book value ratios.

1.5 Contribution of the Study

The contributions of the three essays are interrelated and can be summarized as follows. First, the results of the study may be of help to less-informed domestic and foreign investors by helping them get a better understanding of the nature of the Indian stock market.[9] For example, the findings of this study may show the less-informed foreign investors how large firms are different from small ones in terms of processing the arrival of new information in the stock market. Second, this study contributes to the existing finance literature by providing evidence of momentum and contrarian profits in the Indian stock market. Unlike the extant literature in which the Indian stock market momentum and contrarian phenomenon is explained from the viewpoint of all emerging markets, this paper explains the phenomenon from the viewpoint of the idiosyncratic behavior of the Indian stock market. Moreover, few previous studies (Sehgal and Balakrishnan, 2002; Sehgal and Ilango, 2008; and Tripathi, 2008) have investigated the sources of contrarian and momentum profits in the Indian stock market. Moreover, Sehgal and Ilango (2008) use factor models to address momentum profits and do not consider an important factor, volume of trade, to explain momentum profits. Sehgal and Balakrishnan (2002) use a very simple model to examine momentum profits, ignoring important factors such as firm size and volume of trade.

Tripathi (2008) uses primary data collected from investment analysts to investigate trading strategies in the Indian market. The methodology I use in this study is different from that used in the above-mentioned papers.[10] Thus, an investigation of the sources of momentum and contrarian profits helps regulators and policymakers to better understand the Indian stock market. Third, all the essays in this study are among the first few attempts at investigating the trading issues in the Indian stock market from a behavioral

[9] Domestic institutional investors are assumed to have better understanding of the nature of the market because they are possibly more informed due to local relationship and have qualified stock analysts.
[10] Moreover, none of these papers on the Indian stock market has used data collected from Thomson DataStream, which is considered to be a reliable source.

viewpoint. It is expected that future research efforts will follow the path shown in this study, which will potentially solve many unanswered questions about behavioral issues in the India stock market.

1.6 Significance of the Study

Although a large body of literature has emerged over the past 20 years examining trading strategies, their return characteristics, sources, and lead-lag structure between stocks, these studies have mainly focused on the U.S., European, and some Asian markets. Like other emerging markets, the Bombay (Mumbai) stock market index as a whole exhibits a very low degree of correlation with developed markets' indexes, suggesting this market is isolated from developed markets to a large extent. As pointed out earlier, this phenomenon offers an opportunity for international portfolio managers to diversify their portfolios, which may result in superior mean-variance efficient portfolios.

The research on emerging markets has revealed some stylized facts that conclude that these markets (i) are segmented from, (ii) have higher predictability than, and (iii) are more volatile than developed markets.[11] Furthermore, emerging markets have some stylized characteristics such as lack of liquidity, vulnerability to currency risk, shortage of qualified analysts, and limited participation by institutional investors that make them especially appealing to investigate. Researchers, in the absence of adequate research, use these stylized facts on emerging markets as the benchmark to understand the Indian stock

[11] Harvey (1995) provides an early comprehensive empirical work on emerging markets.

market. However, the fact is that every market is different and findings must be explained considering its own market structure, regulatory and legal framework, and culture.

To date, few studies have investigated the existence of momentum/contrarian trading strategies, their sources, and the lead-lag structure between various categories of stocks in the Indian stock market. The literature on the Indian stock market has concentrated on straightforward efficiency, volatility, and integration issues (see for example, Gupta and Basu, 2007; Banerjee and Sarkar, 2006; Pandey, 2005; Karmakar, 2005; Nath and Verma, 2003; Poshakwale, 1996). This study is the first integrated and comprehensive attempt at investigating the Indian stock market in terms of behavioral finance models. Although some studies—for example, Chui et al., 2005; Griffin et al., 2003; and Harvey, 1995—have used the Indian stock market as a sample in their research of other stock markets around the world, these studies are limited in terms of coverage on any specific market. I believe that further study on this market with its unique features and characteristics will add to the existing body of knowledge on emerging markets. This study contributes to the existing literature by investigating the relationship among portfolios of firms based on attributes such as size, volume of trade, and market-to-book value ratio. The results are expected to indicate the stock pricing efficiency of the Indian stock market for the categories of firms traded.

The results of this study will especially be useful to academicians, practitioners, policymakers, and investors as it provides out-of-sample evidence of excess profits from investment strategies common in the U.S. and other developed markets. The results will also be useful to investment analysts, mutual fund managers, and investors in devising trading strategies that may provide excess returns.

1.7 Limitations of the Study

Like any empirical study, this research also has potential drawbacks that may weaken its findings. Since noninstitutional less-informed investors constitute a large portion of the Indian stock market, findings of this study may be difficult to interpret. Although in an emerging market such as India stock price manipulation is possible, the results may show that the market is efficient when it is not. For example, prices may seem to reflect all the information correctly, whereas the true outcome is that only a few investors gain by manipulation (pre-arranged transaction) in such a way that the market gives the false impression of reflecting all available relevant information, ultimately resulting in the exploitation of uninformed investors. This is plausible because the regulatory authority, SEBI, may not be able to exercise surveillance as effectively as regulatory bodies do in developed markets (such as the Securities Exchange Commission (SEC) in the U.S.). The political instability and interference often disrupt the normal flow of the stock market. Moreover, the cultural framework of India is distinct from that of other countries.[12] Acker and Duck (2008) find that Asian investors are consistently more overconfident than their British counterparts and suggest that such a trait may lead to greater trading activity and higher price volatility. Thus, the Indian stock market may be an appropriate place for noise trading.

Although data are collected from Thomson Datastream, data in the early 1990s is not complete, resulting in the removal of some of the firms from the final dataset. Furthermore, although nonsynchronous trading is a problem also in the data and may be

[12] For example, the Indian people on average may be sensitive and prone to react on rumors due to social indulgence in gossiping and joint-family living.

common in this kind of market, I have taken considerable effort to clean the data to keep this problem to a minimum. The use of monthly data is especially helpful in this regard.

1.8 Organization of the Study

Chapter two presents the first essay on the Indian stock market. It investigates the profitability of trading strategies of various investment horizons. Chapter three expands the investigation of momentum/contrarian strategy profits by focusing on their sources and how the contribution of sources to such profits is changing with time. Chapter four investigates how large (high) and small (low) size (volume) firms react to changes in common risk factors and whether or not a lead-lag relationship exists in the market. Chapter five concludes the study with suggestions for future research and presents some recommendations for regulators and policymakers.

CHAPTER TWO

Momentum Strategies: Evidence from the Indian Stock Market

2.1 Introduction

Over the last two decades, a large body of literature has emerged documenting the profitability of two distinct investment strategies – *contrarian* and *momentum* strategies. DeBondt and Thaler (1985, 1987), Jegadeesh and Titman (1993) and others show that stock returns suffer from mean-reversion regularities, the notion that past return information can be utilized to make future abnormal returns. A contrarian strategy or return reversal is the strategy of selling recent "winner" stocks and buying recent "loser" stocks. Initially, contrarian profits were thought to be a long-term phenomenon. However, DeBondt and Thaler (1985, 1987), Jegadeesh (1990), Lehmann (1990), and Chopra et al. (1992) show that contrarian profits also exist in both the short-run (weekly) and long-run (3-5 years) horizons. In this strategy, past losers become winners in the long-term. In general, these studies have attributed investors' overreaction to market news as the primary source of contrarian profits or return reversal.

On the other hand, a momentum strategy is a strategy of buying recent "winner" stocks and selling recent "loser" stocks. Momentum profits are realized from the tendency of a security to continue movement in a single direction. The momentum strategy has been documented by Jegadeesh and Titman (1993, 2001), and Chan et al. (1996) who show that investors routinely underreact to market news so that smart investors can exploit the momentum in the stock prices at intermediate terms of three to six months by buying recent winners and selling recent losers, and, consequently, earning risk-adjusted abnormal returns. In these studies, past winners in the past three to twelve months outperform past losers in the next three to twelve months. Thus, the return in the medium-term is the continuation of past performance. In general, these studies have attributed investors' underreaction to market news as the primary source of price momentum.

Although a large body of literature has emerged over the past 20 years examining contrarian and momentum strategies and their resultant return characteristics, these studies have mainly focused on the U.S., European, and some Asian markets. To date, there has been relatively less effort at investigating the existence of such behavioral phenomenon in emerging stock markets such as India. The research on emerging markets has revealed some stylized facts that conclude that these markets (i) are segmented from developed markets, (ii) have higher predictability than developed markets, and (iii) are more volatile than developed markets.[1] Furthermore, emerging markets have some stylized characteristics such as lack of liquidity, vulnerability to currency risk, and shortage of qualified analysts and limited participation by institutional investors which make them especially appealing to investigate.

To date, few studies (Sehgal and Balakrishnan, 2002; Sehgal and Ilango, 2008; Tripathi, 2008) have analyzed momentum strategies on the Indian stock market. Moreover, Sehgal and Ilango (2008) use factor models to address momentum profits and

[1] Harvey (1995) is an influential paper on emerging stock markets.

do not consider an important factor, volume of trade, to explain momentum profits. Sehgal and Balakrishnan (2002) also use a sorting technique based on the Capital Asset Pricing Model (CAPM) model to examine momentum profits. But while they sort the firms based on return performance, they ignore important factors such as firm size and volume of trade which may weaken their results. Tripathi (2008) uses primary data collected from investment analysts to investigate trading strategies in the Indian market. He finds that there have been substantial changes in investment strategies used by active investors in the Indian stock market over the past five years and that there has been a shift from purely technical analysis based strategies to the mixture of both fundamental and technical analysis.

Recently, Rastogi et al. (2009) and Locke and Gupta (2009) investigate trading strategies in the Indian stock market. Rastogi et al. (2009) use National Stock Exchange-listed firms for the period 1996 through 2008 and present strong evidence of momentum profits in 3-month investment horizon. They also report contrarian profits for medium size firms in the 18- and 24-month investment horizon. Locke and Gupta (2009), using data for the period 1991 through 2004 employ cumulative abnormal return (CAR) and sorting technique to examine contrarian phenomena on the Indian stock market. They find longer-term price reversals. More precisely, they show that contrarian profits are about 75% above market returns. However, all the studies cited above fail to consider volume of trade when they examine momentum and contrarian phenomena. In this study, I use volume of trade because it has been shown to be an important factor contributing to the speed of new information absorption into stock prices and the resultant abnormal returns. [2]

Some studies, for example, Chui et al. (2010) and Griffin et al. (2003), include the Indian stock market as a sample in their research of stock markets around the world. I believe that an emerging stock market such as India needs individual attention. As discussed above, there are only few studies on the behavioral aspects of the Indian stock market. Thus, further study will add to the existing body of knowledge of this important emerging market, which has unique features and a long history in South Asia. I use the traditional non-overlapping trading techniques for various investment horizons to investigate (i) the existence of contrarian and momentum profits on the Indian stock market (ii) if there is, the relationship between such profits and duration of investment and (iii) the effects of size (market value) and volume of trade on such profits.

My motivation for studying the Indian stock market is that the Indian economy is relatively insular. The level of exports, though increasing, has a relatively minor impact on the economy compared to, for example, China, Japan, Malaysia or Hong Kong--countries that have been examined in papers cited earlier. Furthermore, the Mumbai stock market index as a whole exhibits a very low degree of correlation with either the London or the New York stock market indexes, suggesting that overseas market developments have little bearing on the valuation of the Indian stocks. These facts suggest that the results of this study are of special interest to academicians, researchers, regulators as well

[2] Moreover, none of these papers on the Indian stock market has used data collected from DataStream, which is considered to be a reliable source. Lee and Swaminathan (2000) show that volume of trade of firms is an important consideration in investigating momentum and contrarian profits.

as practitioners. It provides an out of sample evidence of momentum profits from investment strategies in the Indian market as documented in the U.S. and other markets. These results can be used by investment analysts, mutual fund managers as well as marginal investors in devising investment strategies which may promise extra-normal returns.

The major findings of the paper are: (i) in general, there are no observed momentum or contrarian profits in the Indian stock market when simple non-overlapping medium-term and long-term strategies and tracking periods are considered; (ii) I find significant momentum profits in higher market value and higher turnover portfolios for 6-6 (6-month formation and 6-month holding period) strategies when firms are sorted by market value and turnover; (iii) I find contrarian profits of winner-loser portfolios for 3-3 strategies when small and low trading volume firms are sorted by market value and turnover criteria, respectively; and (iv) I also find contrarian profits for 1-1 short-term strategy for all winner-loser portfolio combinations. That is, this month's winner (loser) portfolio consistently becomes loser (winner) portfolio in the next month. Thus, an investor could easily devise an investment strategy that would result in abnormal profit by changing the portfolio every month and holding it for one month.

The rest of the study is structured as follows: I provide a brief survey of the literature in section 2. Section 3 discusses data and methodology issues. Section 4 analyzes the empirical results and section 5 summarizes and concludes the paper.

2.2 Literature Review

The literature on the profitability of contrarian and momentum strategies portfolios is largely attributed to the seminal work of DeBondt and Thaler (1985) who show that during the period from the 1920s through the 1980s, abnormal profits were obtained in the U.S. stock markets from portfolio strategies that bought (sold) stocks that were in the extreme bottom (top) performers during a period of three immediate preceding years. DeBondt and Thaler (1987) and Jones (1993) attribute such long-horizon contrarian profits to "price reversal" induced by market overreaction. However, Jegadeesh (1990), Lehmann (1990), Chopra et al. (1992) show that such contrarian profits exist in both the short- (weekly) and long- (three to five years) horizon. As for intermediate horizon (three to twelve months) profits, Jegadeesh and Titman (1993, 2001) show that momentum strategies of buying winners and selling losers yield abnormal returns, which are not explained by the conventional risk-return framework. They attribute the price momentum to investor underreaction to information. Fama and French (1996) also confirm this finding by suggesting that their factor model cannot explain momentum profits either.

Several studies investigating the presence of momentum profits in international markets have found mixed results. Chang et al. (1995) find short-term contrarian momentum profits in the Japanese stock market. Rowenhorst (1998) finds significant momentum returns for the medium-term horizon in developed European markets. Rouwenhorst (1999) finds the presence of momentum returns in six out of twenty emerging equity markets. Hameed and Ting (2000) find short-term momentum profits from contrarian strategies in the Malaysian stock market. Kang et al. (2002) find statistically significant abnormal profits for the Chinese stock market using short-horizon contrarian and intermediate-horizon momentum strategies. Griffin et al. (2003) find that although momentum strategies are profitable in North America, Europe, and Latin America, they are not profitable in Asia. Moreover, Hameed and Kusnadi (2002) find no evidence of momentum profits in six pacific-basin stock markets and conclude that factors that contribute to the momentum phenomenon in developed markets are absent in the Asian markets. Chui et al. (2000) also find that momentum profits in Japan and other Asian stock markets are not significant.

Studies have also attributed the existence of contrarian and momentum strategies profits to price reversals or market overreaction. Conrad and Kaul (1998) argue that momentum returns are due to cross-sectional differences in risk, i.e., variation in expected returns. Moskowitz and Grinblatt (1999) suggest that momentum in industry risk factors explain observed momentum returns. Lee and Swaminathan (2000) show that momentum profits are more prevalent in high-turnover stocks. Hong et al. (2000) find that small firms with low analyst following have more momentum phenomenon. Griffin et al. (2003) find that macroeconomic risk factors cannot explain resultant momentum profit. They show that momentum profits are economically large and exist in both good and bad states and that profits tend to reverse over 1- to 5-year investment horizon. Chui et al. (2010) suggest that momentum is related to individualism, consistent with existing behavioral theories.

Behavioral theories have their background in studies by Daniel, Hirshleifer, and Subrahmanyam (henceforth DHS, 1998) and Hong and Stein (henceforth HS, 1999) who show how they could be the reason for the overreaction (momentum) and underreaction (price reversal) in the stock market. DHS assume that investors have private information and that they highly value their stock selection skills. Hence, investors overreact to the information when it actually comes to the market due to their overconfidence. Because of self-attribution bias, investors overreact to market news after the initial overreaction, taking stock prices further away from their fundamental value. In the long-run, investors realize the overpricing of stocks and correct the prices. Thus, in the short-run, an investor may observe price momentum while in the long-run, he may observe price reversals. HS explain the reason for momentum from a different behavioral perspective. They assume that there are two types of investors: news watchers or informed investors and technical or noise traders who use immediate past price information to make investment decisions. In their model, informed investors are assumed to react quickly to market information although the information itself is assumed to travel slowly, thus causing underreaction. On the other hand, technical traders are assumed to delay their reaction to market information causing upward movement in stock price, resulting in momentum profit.

Aguiar et al. (2006) use fuzzy set theory to study overreaction and underreaction phenomena in Brazilian stock market.[3] Their results show evidence of overreaction and underreaction for petrol/petrochemical and textile sectors, respectively. Wu (2004) shows that a pure contrarian strategy produces positive excess returns and on average outperforms a pure momentum strategy. Ng and Wu (2007) analyze the trading behavior of 4.74 million individual and institutional investors across mainland China and find that

[3] This paper is available at www.atlantis-press.com/php/paper-details.php?id=26

Chinese institutional investors are momentum investors, while less wealthy Chinese individual investors are contrarian investors. He and Tan (2007) use data from 1994 to 2004 for the Chinese market and report the presence of contrarian profits.[4] They also find higher cross-sectional variance and time-series predictability. Muga and Santamaria (2007) report the presence of momentum profits in the Latin American emerging markets. Results from bootstrap procedure also support their findings. Naughton et al. (2007) provide evidence of substantial momentum profits in the Chinese stock market during the period 1995 through 2005. Ornelas and Fernandes (2008) examine momentum and contrarian profits in 15 emerging markets for the period 1995 through 2005. Their findings show that there are significant contrarian profits in most of the emerging stock markets even after systematic risk and size effects are adjusted for. Kenourgios and Samitas (2009) report evidence of contrarian and momentum profits on the Balkan (Bulgaria, Romania, Croatia, and Turkey) stock markets. This study provides additional evidence on the profitability of momentum and contrarian strategies in the Indian Stock market.

2.3 Data and Methodology

I use monthly stock price index data covering the period January 1991 through December 2006 collected from DataStream International. After screening for firms that have data throughout the study period, I end up with a sample of 254 firms. I calculate the rate of return on each firm as the log difference in the stock index. Then using the

[4] This paper is available at http://www.docstoc.com/docs/14224306/Momentum-Reversal-and-Overreaction-Empirical-Results-from

average returns, I construct portfolios of the stocks in the previous J non-overlapping (J = 1, 3, 6, 9, 12, and 24) months. I then organize the stock portfolios in descending order and divide them into five categories (quintiles) based on past performance. The best performing stocks are those in the top 20% while the worst performing stocks are those in the lowest 20% during the formation (ranking) period. These portfolios are equally-weighted at formation. Using a strategy of buying the top 20% (winner) stocks and selling the worst 20% (loser) stocks, I construct winner-loser portfolios. I then group the portfolios into 3 term-wise categories and track their performance while keeping their composition unchanged during the K subsequent (K = 1, 3, 6, 9, 12, and 24) months. The investment in the portfolio with J (formation or ranking period) = 1 and K (tracking period) = 1 is the short-run strategy. The investment in the portfolios with J = 3, 6, and 9 and K = 3, 6, and 9 is the medium-term strategy while the investment in the portfolios with J = 12 and 24 and K = 12 and 24 is the long-term strategy.

To capture the fact that foreign investors are interested in large firms because they provide less information asymmetry, I sort my sample of firms into groups of high and low market value stocks. I do this by sorting the firms into three categories (best, average, and worst) in descending order where the best performing stocks and worst performing stocks form winner and loser portfolios, respectively. Using this process, I produce size-momentum portfolios for 1-, 3- and 6-month strategies. Since the volume of trade is positively related to information dissemination, volume may affect momentum and contrarian strategies. Thus, I sort the firms also based on volume of trade in local currency the same way I sort firms based on market value. This process produces volume-momentum portfolios.

2.4 Analyses of Empirical Results

Table 2.1 presents descriptive statistics of the Indian stock market returns for the period 1991-2006. The mean monthly return is 1.43%, suggesting the presence of high earnings opportunity for investors during the study period. The standard deviation of 7.68% indicates high market volatility. The Jarque-Bera value of 14.21 suggests that returns are not normally distributed. Consistent with findings in other emerging markets, a significant first order serial correlation of 0.30 suggests that the Indian market is also predictable. The serial correlation of returns at other lags is not significant.

Table 2.1
Descriptive Statistics of Indian Stock Market Returns

Mean	1.4305	
Std. Dev.	7.6816	
Skewness	0.1780	
Kurtosis	4.2465	
Jarque-Bera	14.2136	
Serial Correlation (1)	0.3020	(4.0988)*
Serial Correlation (6)	0.1298	(1.7198)
Serial Correlation (12)	-0.1131	(-1.5581)

t-statistic is given in parenthesis. Asterisk indicates significance at 5% level. International Financial Statistics index data are used for descriptive analysis.

Table 2.2 presents momentum returns for the long-term (12-month and 24-month) trading strategies. In three out of four possible winner-loser portfolio strategies, momentum returns are negative and have low *t*-values suggesting insignificant return reversals. Only the 24-12 trading strategy has a positive return (0.6590). However, since data covers only 15 years, I do not investigate longer periods than the 2-year investment strategies.

Table 2.2
Momentum Returns of Quintile Portfolios for the Long-Term Strategies

		Holding Period (*K*)	
Ranking Period (*J*)		12	24
12	Winner	0.7833	1.1081
	Loser	0.9849	1.3255
	Winner-Loser	-0.2016	-0.2174
	(*t*-statistic)	(-0.2868)	(-0.4261)
24	Winner	3.0978	0.9439
	Loser	2.4387	1.0411
	Winner-Loser	0.6590	-0.0972
	(*t*-statistic)	(0.7313)	(-0.1883)

Firms are sorted based on the average return obtained in the past 12 and 24 months. Due to small sample size of firms, the quintile portfolios are constructed based on past performance. Firms are sorted out in descending order from the best to the worst performing ones. Best performing firms are winners and worst performing firms are losers. I then construct Winner-Loser portfolios by buying the winner stocks and selling the loser stocks. Firms are equally weighted in the winner and loser portfolios. Finally, I tracked the Winner-Loser portfolios are tracked in the following 12 and 24 months.

Table 2.3 presents momentum returns for 9 (3 x 3) different medium-term trading strategies. For example, the 6-month/6-month strategy return is 0.4659% per month and the 9-month/3-month strategy return is 0.6648% per month, respectively. Although I find evidence that most winner-loser returns in the table are positive, these returns are not significant. This finding implies that momentum strategies are not profitable in the Indian stock market and are different from momentum profits found in developed markets. Hameed and Kusnadi (2002) and Chui et al. (2000) find similar results in other Asian markets. Since the presence of momentum and contrarian profits can be partially explained by investor behavior, this finding suggests that cultural features of the Indian stock market may be one of the reasons for the absence of such profit opportunities.

Table 2.3
Momentum Returns of Quintile Portfolios for the Medium-Term Strategies

		Holding Period (*K*)		
Ranking Period (*J*)		3	6	9
3	Winner	1.1731	1.3475	1.4410
	Loser	1.7943	1.2368	1.8997
	Winner-Loser	-0.6212	0.1107	-0.4587
	(*t*-statistic)	(-1.0999)	(0.2489)	(-0.8655)
6	Winner	0.6061	2.3711	2.3531
	Loser	0.3948	1.9052	2.0196
	Winner-Loser	0.2113	0.4659	0.3335
	(*t*-statistic)	(0.2569)	(0.8412)	(0.7372)
9	Winner	2.6663	3.3175	1.8882
	Loser	2.0015	3.3874	1.1617
	Winner-Loser	0.6648	-0.0699	0.7265
	(*t*-statistic)	(0.7552)	(-0.1211)	(1.2200)

Firms are sorted based on the average return in the past 3, 6, and 9 months. Due to small sample of firms, Quintile portfolios are constructed based on the past performance. Firms are sorted as the best to worst performing ones. Best performing firms are winners and worst performing firms are losers. Winner-Loser portfolios are constructed by buying the winner stocks and selling the loser stocks. The firms have equal weights in the winner and loser portfolios. Finally, the Winner-Loser portfolio returns are tracked in the following 3, 6, and 9 months.

Table 2.4 presents the winner, loser, and winner-loser momentum returns of quintile portfolios for 1-month ranking and 1-month tracking period. All loser portfolios, namely, P2...P5, earn positive returns in the next month. All of the various winner-loser portfolio combinations I have used show significant return reversals. While it is difficult to explain why medium-term and long-term momentum reversions are absent whereas short-term reversions exist in this market, it is important to note that the Indian stock market is highly dominated by uninformed and less-informed non-institutional investors, a fact which may create consistent noise in the market. Since the sample period covers a period when the Indian stock market was bullish, individual investors continuously glorified their stock holdings, creating overshooting of stock prices in one period and correcting some part of their irrational exuberance the next period. Furthermore, since the Indian market is not as liquid as developed markets and surveillance may not be as strong, stock price manipulation by syndicates of investors may be a factor contributing to the presence of return reversals.

Table 2.4
Momentum Returns of Quintile Portfolios for 1-month Strategies

Ranking Period ($J = 1$) and Holding Period ($K = 1$)				
Portfolio Combination	Winner	Loser	Winner-Loser	*t*-statistic
P1 and P5	-1.3382	1.9382	-3.2765	-5.5558*
P1 and P4	-1.3382	0.6714	-2.0097	-3.8701*
P1 and P3	-1.3382	1.0113	-2.3495	-4.5561*
P1 and P2	-1.3382	0.2718	-1.6100	-3.9862*

Firms are sorted from best to worst into quintile portfolios based on the average return performance in the last month. Best performing firms are winners and worst performing firms are losers. Winner-Loser portfolios are constructed by buying the winner stocks and selling the loser stocks. Firms are equally weighted in the winner and loser portfolios. Finally, the Winner-Loser portfolio returns are tracked in the following month. In this table, I only consider the winner portfolio (P1), other (loser) portfolios (P2, P3, P4, P5) and the difference between winner and loser portfolios. Asterisks indicate significance at 5% level.

Although not reported here, I also regress winner-loser portfolio returns against market returns and find that regression coefficients are not significant which implies that market risk factors cannot account for the momentum profits that I found. This finding is consistent with Kang et al. (2002) study that find that return reversals occur at very short-term investment horizon in the Chinese stock market. Chang et al. (1995) also find short-term contrarian profits in the Japanese stock market. These findings imply that there may be some cultural and market factors which may account for the differences between Asian and Western markets.

Hong et al. (2000) suggest that in the U.S., momentum profits are stronger for smaller firms and in general have a negative relationship with firm size. Their explanation is that information disseminates slowly for small firms, thus making the scope for momentum profit. However, it is difficult to compare the U.S. momentum results to Indian momentum results because the two markets are different in many aspects such as legal structure, regulatory structure, and market microstructure. For example, since culture plays a role in investor behavior, there will be a notable difference in the risk-taking behavior between the U.S. investors and Indian investors.

International investors have also played an important role in the Indian stock markets since it began its economic liberalization in the early 1990s. However, because of information asymmetries, these investors are more inclined to invest in large firms and to avoid smaller firms. Since firm size has an effect on momentum profits as shown in the studies above, I separately examine this relationship for larger firms and smaller firms using market capitalization.

Chan et al. (2000) argue that momentum profits are higher for a portfolio with higher lagged volume of trade than for a portfolio with lower lagged volume of trade. In other words, return continuation may be supported by higher volume of trade. Lee and Swaminathan (2000) show that the general level of interest in a stock can be reflected in its volume of trade which in turn may influence the behavior of return momentum. Thus, I also sort firms using turnover in local currency (rupees) as a proxy for volume of trade to further investigate the presence of momentum profits.

Table 2.5
Momentum Returns of Market Value and Turnover Sorted Portfolios with 3-3 and 6-6 Strategy

Portfolio (Strategy)	Winner	Loser	Winner-Loser	*t*-statistic
Panel A. Portfolios Sorted by Market Value in Rupee				
Large (3-3)	0.9486	0.9625	-0.0139	-0.0276
Small (3-3)	0.657	2.3361	-1.6792	-2.6132*
Large (6-6)	2.3155	1.3493	0.9662	2.2657*
Small (6-6)	2.1517	1.9631	0.1886	0.3568
Panel B. Portfolios Sorted by Turnover in Rupee				
High (3-3)	1.1273	0.9459	0.1813	0.3234
Low (3-3)	0.7047	2.3787	-1.6741	-2.6777*
High (6-6)	2.5192	1.4732	1.0460	2.4786*
Low (6-6)	1.8859	1.7942	0.0917	0.1766

Firms are first sorted into two categories – large and small - by market value or by trading volume in local currency. Within each category, firms are sorted based on the average return in the past 3 or 6 months. Due to the small number of firms in the sample, firms are sorted into high, medium and low performing groups where high performing firms are winners and low performing firms are losers. I then construct Winner-Loser portfolios by buying winner stocks and selling loser stocks. Firms are equally weighted in the winner and loser portfolios. Finally the performance of Winner-Loser portfolio is tracked for the next 3 and 6 months. Asterisks indicate significance at 5% level.

Table 2.5 presents the momentum returns of portfolios formed by size (market value) and turnover where I consider only 3-month ranking and 3-month tracking and 6-month ranking and 6-month tracking periods. For size-sorted winner-loser portfolios, I find significant contrarian profit of -1.6792% per month for the 3-3 strategy for small firms. I also find significant momentum profit of 0.9662% per month for the 6-6 strategy for large firms. My finding contradicts the Hong et al. (2000) study, which finds no momentum profit for large firms. For volume-sorted winner-loser portfolios, I find significant contrarian momentum profit of -1.6741% per month for the 3-3 strategy for less-traded stocks. I also find significant momentum profit of 1.046% per month for the 6-6 strategy for the high-volume winner-loser portfolio. My finding supports the study by Chan et al. (2000) who find momentum profits in high volume winner-loser portfolios.

Table 2.6
Momentum Returns of Market Value and Volume Sorted Portfolios with 1-1 Strategy

Portfolio	Winner	Loser	Winner-Loser	*t*-statistic	Average (medium)	Winner-Average	*t*-statistic
Panel A. Portfolios Sorted by Market Value in Rupee							
Small	1.0499	2.1155	-1.0656	-2.8334*	0.7246	0.3253	1.0422
Large	-1.3638	0.4941	-1.8579	-3.6269*	0.0472	-1.4110	-3.3904*
Panel B. Portfolios Sorted by Turnover in Rupee							
Low	1.0192	2.1222	-1.1029	-2.9524*	0.7261	0.2931	0.9516
High	-1.3782	0.5103	-1.8885	-3.6925*	0.0674	-1.4456	-3.4778*

Firms are first sorted into two categories - large and small - by market value or by trading volume in local currency (rupees). Within each category, firms are sorted based on the average return in the past month. Due to the small number of firms in the sample, firms are then sorted into high, medium (average) and low categories. Best performing firms are winners and worst performing firms are losers. Winner-Loser portfolios are constructed by buying the winner stocks and selling the loser stocks. The average firms are those that have returns between winner and loser portfolios. Winner-Average portfolios are constructed by buying winner and selling average firms. The firms are equally weighted in the winner, average, and loser portfolios. Finally, the performance of Winner-Loser portfolio and Winner-Average is tracked in the next month. Asterisks indicate significance at 5% level.

Table 2.6 presents momentum returns of 1-1 (short-term) strategy. The firms are first sorted into small and large portfolios by market value and/or as high and low volume of trade. Firms are further sorted into winner, medium (average), and loser categories and then finally into winner-loser and winner-average portfolios. Table 2.6 shows that for size-momentum and volume-momentum portfolios, the winner-loser portfolio returns are significantly negative, supporting the results in Table 2.5. Even winner-average portfolio returns are also negative for large size and high turnover firms. Thus, the evidence of short-term return reversal seems to be strong and does not change when firm size or volume of trade criteria are used.

2.6 Conclusion

The objective of this study is to investigate the existence of momentum and contrarian profits in the Indian stock market during the period 1991-2006 using short-, medium- and long-term investment strategies. The results of the study show that there are no observed momentum profits or return reversals in the Indian stock market for the period 1991-2006 when simple non-overlapping medium-term and long-term strategies and tracking periods are considered. However, when I sort firms by market value and turnover, I find significant momentum profits in higher market value and higher turnover portfolios for 6-6 (6-month formation and 6-month holding period) strategies. For 3-3 strategies, I find return reversals of winner-loser portfolios when I sort small and low trading volume firms by market value and turnover criteria, respectively. The results also show the presence of return reversals for 1-1 strategy for all winner-loser portfolio combinations. That is, last month's winner (loser) portfolio consistently becomes loser (winner) portfolio in the following month.

The results on firm size and volume of trade suggest that price continuation is stronger for the firms with higher volume of trade in the 6-month trading strategy. I find significant momentum profits for 6-month investment strategies when I sort firms by size, suggesting that investors process information of large firms slowly. For small firms, I find that investors overreact in 3-month investment horizon resulting in contrarian profits. I also find significant price reversals for 1-month investment horizon. In conclusion, my results are similar to other previous findings in the Asian markets.

I hope to extend this study by conducting further study of the Indian stock market in the following ways: First, non-informed individual investors play a more significant role in the Indian market than institutional investors because of their larger number.[5] Since the presence of non-institutional investors is more likely to cause noise in asset pricing which may result in higher frequency of stock price correction, how does this impact short-term contrarian profits? Second, capital inflows and outflows from foreign institutional investors (FII) had a significant impact on the Indian stock market during the study period because of external factors such as low U.S. interest rates. What impact did capital flows have on momentum profits? Last but not least, although the Indian Securities and Exchange Commission banned short-selling in 2001, it was lifted in December 2007. What impact did the re-introduction of short selling have on momentum profits? I believe that finding plausible answers to these questions will provide additional insights to the understanding of an emerging market such as India.

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[5] The total assets under the management of foreign institutional investors and the Indian mutual funds amount to about 18% of the market capitalization (Kumar, 2007).

CHAPTER THREE

Sources of Momentum and Contrarian Profits in the Indian Stock Market

3.1 Introduction

Extant literature has shown the existence of various forms of return regularities (or patterns) in developed as well as emerging markets. Among these, the two most notable regularities—contrarian and momentum profits—are of major concern for both practitioners and academicians. Contrarian profits arise when the previous period's best (worst) performing stocks systematically become worst (best) performing stocks in the next period. Momentum profits arise when the previous period's best-performing stocks systematically continue to do well in the next period.

The purpose of this study is to investigate the sources of momentum and contrarian profits in the Indian stock market. Early studies (for example, Ball and Brown, 1968; Sunder, 1973) have supported the notion of the random walk hypothesis in stock returns, which implies that stock returns are unpredictable. However, other studies—including French, 1980; Keim, 1983; DeBondt and Thaler, 1985, 1987; and Lo and MacKinlay, 1988—indicate that historical stock prices do not follow random walk, implying predictability of stock returns to some extent. Thus, investors may earn abnormal returns from the market by adopting appropriate investment strategies.

DeBondt and Thaler (1985, 1987) are the first to provide evidence of contrarian profits in the U.S. market in the long-run investment horizon. Thus, investors may benefit from buying past losers and selling past winners. Jegadeesh (1990), Lehman

(1990), and Chopra et al. (1992) also provide evidence in favor of short- and long-term contrarian profits. Jegadeesh and Titman (1993, 2001) are also the first to show the existence of momentum opportunity in the U.S. market in the medium-term investment horizon. More recently, other research findings also support the presence of momentum profits in the U.S. market. In general, contrarian and momentum profits are attributed to overreaction and underreaction of investors to market information, respectively.

Daniel, Hirshleifer, and Subrahmanyam (hereafter DHS, 1998) and Hong and Stein (hereafter HS, 1999) provide a detailed behavioral analysis of stock market over- and under-reaction. In their model, DHS assume that investors have their own information and that they value their stock selection skills very highly in the short-run. This overconfidence leads these investors to overreact to new information, driving the price from its true value. However, in the long run, the market realizes that stocks are overvalued and takes necessary corrective measures. This phenomenon causes momentum profits in the short-run and contrarian profits in long-run. In their model, HS assume that there are two types of investors: (1) well-informed investors about the market and (2) technical analysts who use past information to make investment strategies. The informed investors first react to new information and set into motion the initial prices. Then the prices set by this group, coupled with the subsequent reaction of technical analysts to new information causes stock prices to move further in the same direction. Thus, if there is any good news about a firm, the stock price will go up in two phases, resulting in underreaction to information in the first phase and then momentum profits in the second phase.

Finance theory has shown that predictable behavior of stock returns is not a good outcome for a stock market because in such a market only a handful of large institutional investors will almost always exploit the resultant profit opportunities, leaving a significant dent in the wealth and confidence of small investors. In emerging markets such as India where small investors constitute the largest portion of market participants, it is important to protect small investors to ensure the integrity and efficiency of the overall market by making sure that large institutional investors do not exploit their information advantage. This study makes a contribution in this area by highlighting the sources of momentum and contrarian profits so that regulators can take appropriate action to enact rules and regulations to protect small investors and less-informed foreign traders.

Up to the 1990s, numerous studies had been done to detect the sources of momentum and contrarian profits mainly in developed markets. However, since the early 1990s, academicians have conducted studies in emerging capital markets to investigate the possibility of diversification benefits[1] that can be exploited from the low correlation of such markets with developed markets.

Most studies that have been done of the Indian stock market to date have tended to focus primarily on efficiency issues, stock-price predictability, return volatility, and stock market integration with other markets. However, little work has been done on behavioral issues related to momentum and contrarian profits because these are relatively new ideas[2] in this emerging market.

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1 Portfolio diversification benefits can be achieved through the construction of portfolio of assets so that the portfolio is further mean-variance efficient.

2 See chapter one.

The Bombay (Mumbai) Stock Exchange (BSE) and National Stock Exchange (NSE) account for most of the trading volume in the Indian stock market. The BSE is the 10th largest stock exchange in the world and had a market capitalization of US$1.79 trillion[3] as of December 31, 2007. Because of its size and the opportunity the market offers investors to make a profit, it is no surprise that international portfolio investors are interested in investing in this market.

In this paper, I consider both contrarian and momentum strategies in an integrated framework for the Indian stock market. The paper follows the methodology of Lo and MacKinlay (1990) to form portfolios with a weighted relative strength scheme (WRSS). I then use the procedure followed by Jegadeesh and Titman (1995) to decompose the contrarian/momentum profits into three elements: compensation for cross-sectional risk, lead-lag effect in time series with respect to the common factor, and time pattern of stock returns. This paper investigates the presence of contrarian or momentum profits, their sources, and the robustness of the results with regard to various risk factors and changes in the behavior of the sources of such profits over time period 1991 - 2006.

This study makes at least two important contributions to existing literature on the Indian stock market: First, few studies (Sehgal and Balakrishnan, 2002; Sehgal and Ilango, 2008; and Tripathi, 2008) have investigated the sources of momentum and contrarian profits in the Indian stock market. Moreover, the methodologies used in the above-mentioned papers have some drawbacks (see chapter two).[4] Furthermore, I use

[3] This information is collected from the official BSE website, www.bse-india.com.

[4] Moreover, none of these papers on the Indian stock market has used data collected from DataStream, which is considered to be a reliable source.

a methodology that is more in line with current techniques that have been used in the finance literature over the past few years.[5]

Second, the results of this study will provide both domestic and foreign investors with more information and knowledge of the Indian stock market in regard to sources of momentum and contrarian profits. Third, the results of this study will help regulators obtain a better understanding of the Indian stock market microstructure so that they can undertake appropriate actions to enact rules and regulations to protect small investors and less-informed foreign traders. Finally, arbitrageurs may use the results of this study to develop trading strategies that may earn abnormal profits thereby eliminating inefficiencies from the market.

The results of this study show that (i) there are contrarian profits in the short run, (ii) contrarian profits turn into momentum profits when portfolios are held for medium horizons of six to twelve months, (iii) small and medium-size firms and low- and medium-volume of trade firms exhibit contrarian phenomena, (iv) firm-specific sources are the main component of contrarian profits, and finally (v) large (high volume of trade) firms are more correctly priced than small and medium size firms and those with low and medium volume of trade..

The rest of the paper is structured as follows. Section 2 provides a brief survey of the literature. Section 3 discusses the data and methodology I use in the study. Section 4 analyzes the results. Section 5 concludes the study.

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[5] For example, unlike other papers on the Indian stock market, I use weighted relative strength scheme (WRSS) to address the sources of contrarian and momentum profits.

3.2 Literature Review

DeBondt and Thaler (1985) were the first to discover that past winners (losers) ultimately become losers (winners) in the 3- to 5-year investment horizon. Subsequent researchers, including DeBondt and Thaler (1987) and Jones (1993), find similar results. Jegadeesh and Titman (1995) argue that contrarian profits occur due to overreaction in firm-specific information. Jegadeesh and Titman (1993) first present momentum returns in the U.S. market for the intermediate horizon of three to twelve months. They find that momentum phenomenon still exists in the market even after considering several risk factors.

Moskowitz and Grinblatt (1999) suggest that momentum in industry risk factors explains observed momentum returns. Lee and Swaminathan (2000) show that momentum profits are more prevalent in high-turnover stocks. Hong et al. (2000) find that small firms with low analyst following have more momentum phenomenon. Griffin et al. (2003) find that macroeconomic risk factors cannot explain momentum profit. They show that momentum profits are large and exist in both good and bad states of the economy and that profits tend to reverse over the one- to five-year investment horizon.

Recent research has concentrated on emerging markets and the sources of momentum and contrarian profit. Antoniou et al. (2003) investigate the sources of contrarian profits in the London Stock Exchange and find that the magnitude of the contribution of delayed reactions is small compared to that of the firm-specific component. Du and Denning (2005) use lagged Fama-French factors in their model for sources of momentum profits and report that industry momentum is mainly due to common factors, not industry-specific risk. Chou et al. (2007) investigate profitability of contrarian strategies in the Tokyo stock exchange in the short-term and find that contrarian profits mainly occur due to cross-autocorrelations among firm-specific error components of the Fama-French three-factor model.

Wang (2002) reports that zero-investment portfolios in the Chinese stock market earn negative returns in the 6 to 24 month investment horizon. However, when the Fama-French three factor model is used, such returns disappear. Galariotis (2004) uses a method similar to Jegadeesh and Titman (1995) and find evidence of contrarian profits in the Athens Stock Exchange. They attribute overreaction to the firm-specific component as the main source of contrarian profits. Antonios et al. (2005) provide evidence of serial correlation in equity returns in the Athens Stock Exchange and show that contrarian profits decline as one moves from small stocks to large stocks, even after market friction is accounted for. Moreover, they find that firm-specific component is the main source of contrarian profits.

Kang et al. (2002) find short-term contrarian and medium-term momentum profit for the Chinese stock market. They also report that negative serial correlation contributes to momentum profit. Hameed and Ting (2000) examine the effect of volume of trade on contrarian profits and find that contrarian profits from more actively traded firms are higher than those from less-traded firms. Mengoli (2004) investigates the sources of contrarian and momentum profits in the Italian equity market and finds that momentum profits are more likely to be generated by stock returns time series sources rather than by cross-sectional sources. He and Tan (2007) use data from 1994 to 2004 for the Chinese market and find evidence of contrarian profits. They also find higher cross-sectional variance and time-series predictability. He and Su (2009) also find that momentum profit is created by manipulators and chased by speculators in the Chinese stock market. They also attribute the sources of momentum to positive own autocorrelation. Using a sample of both developed and emerging markets, Urrutia and Vu (2005) find that momentum profits are larger for emerging markets than for developed markets. They also show that momentum profits occur mainly due to the low correlation between emerging markets and developed markets.

Ding et al. (2008) show that high-volume firms are more likely to experience price reversals than low-volume ones in the Asia-Pacific markets. McInish et al. (2008) show that short-run trading strategies based on past return are not profitable in Pacific Basin markets (except for Japan and Hong Kong, where contrarian profits have been found).

3.3 Data and Methodology

3.3.1 Data

I use monthly stock price index, volume, and number of shares outstanding data of Indian stocks from Thomson Datastream over the period January 1991 through December 2006. Since the interest in emerging markets is a relatively recent phenomenon, the data in early years contains some missing values for returns, volume of trade, and number of shares outstanding. Because of missing data, I drop many firms from the initial dataset. Hence, I only include in my usable dataset firms that have been regularly traded and have survived for the whole study period. After screening the dataset in this manner, I end up with a final dataset of 254 firms that I use in the study. I calculate stock returns as the log difference in the stock price indices times 100.

3.3.2 Methodology

3.3.2.1 *Construction of Portfolios*

I use the weighted relative strength scheme (WRSS) of Lo and MacKinlay (1990a) to construct portfolios where the formation and holding periods are of 1-, 2-, 3-, 6-, 9-, and 12-month duration, respectively. Thus, there are 36 trading strategies. Under this portfolio formation strategy, the stocks with positive (negative) return (i.e., higher return than the market or average return) over the formation period are bought (sold). The positive (negative) return stocks with respect to the market return are considered to be the winners (losers). The stocks that have higher positive (negative) return in the formation period have larger positive (negative) weights in the portfolios. Thus, the weight of an individual stock depends on the magnitude of its performance in the formation period. During each study period, each stock is assigned the weight of

$$w_{i,t} = \frac{1}{N}\left(r_{i,t-1} - \bar{r}_{t-1}\right), \qquad (1)$$

where $r_{i,t-1}$ is the return of stock *i* at time *t*-1, *N* is the number of stocks at period *t*-1, and $\bar{r}_{t-1}$ is the market return at time *t*-1. Thus the total weight of the portfolio becomes zero when individual stock weights are added. The momentum or contrarian profit, π_t, is given by

$$\pi_t = \frac{1}{N}\sum_{i=1}^{N} r_{i,t}\left(r_{i,t-1} - \bar{r}_{t-1}\right). \tag{2}$$

I create the portfolios considering the performance of the past 1, 2, 3, 6, 9, or 12 months. This is called the formation or ranking period. The performance of the portfolio is evaluated during the next 1, 2, 3, 6, 9, or 12 months. This duration is called the evaluation or holding period. Thus, there are 36 trading strategies that involve short to medium-run trading horizons. After forming each portfolio, I calculate its cumulative momentum/contrarian return in the holding period. The momentum/contrarian profit in each observation period k = 1, 2, 3, 6, 9, and 12 months is given by

$$\pi_{j,t}(k) = \sum_{i=1}^{N_j} w_{i,t}\, r_{i,t+k}, \tag{3}$$

where $J = L$ (loser portfolio), W (winner portfolio), C (contrarian portfolio), $w_{i,t}$ is the weight of respective stocks in the portfolio, and N_j is the number of stocks in the portfolio during the ranking (formation) period. $r_{i,t+k}$ is the average return of firm i for period k. The weight of individual stocks does not change during the holding (observation) period.

The study also investigates the robustness of the results with respect to size and volume of trade of firms. I construct the size portfolios based on the average market capitalization of firms during the sample period. The highest market value firms are large. Likewise, the lowest market value firms are small. Firms in the middle in terms of market capitalization are medium. In the same manner, I construct volume of trade portfolios based on the average volume of trade.[6] Trade volume portfolios are categorized as high, medium, and low. The numbers of large, medium, and small firms are 85, 85, and 84, respectively. The numbers of high, medium, and low volume of trade firms are 85, 85, and 84, respectively. Finally, I form the WRSS portfolios and respective returns and finally decompose them (returns) using the method described below.

3.3.2.2 *Decomposition of Contrarian/Momentum Profits*

The decomposition of momentum and contrarian profits given by Jegadeesh and Titman (1995) is

$$\pi^m = \sigma_\mu^2 + \delta\sigma_f^2 + \Omega \tag{4a}$$

$$\pi^c = -\sigma_\mu^2 - \delta\sigma_f^2 - \Omega, \tag{4b}$$

where π^m and π^c are momentum and contrarian profit, respectively, and σ_f^2 is the variance of the factor (market portfolio return).

Momentum profits can be decomposed into different components that give a better idea about how investors may exploit this information to formulate a trading

[6] In this paper, volume of trade is measured as the number of stocks traded times the price (in Rupee) of stocks.

strategy. Jegadeesh and Titman (1995) develop the following framework to find the sources of momentum and contrarian profits.[7]

They estimate

$$r_{i,t} = \mu + b_{0,i} f_t + b_{1,i} f_{t-k} + \varepsilon_{i,t} \tag{5}$$

where $r_{i,t}$ is the return of individual stock *i* at time *t*; f_t is the market return (equally weighted) at time *t*, which happens to be the common factor for all the stocks; f_{t-k} is the market return (equally weighted) during *t-k* period; *k* is the observation period; and $b_{0,i}$ and $b_{1,i}$ are the estimated parameters. As shown in Jegadeesh and Titman (1995), I calculate the following components of contrarian/momentum returns from the factor model:

(i) Cross-sectional risk component:

$$\sigma_{\mu}^{2} = \frac{1}{N}\sum_{i=1}^{N}(\mu_i - \overline{\mu})^2 \,, \tag{6}$$

(ii) Lead-lag effect component:

$$\delta = \frac{1}{N}\sum_{i=1}^{N}(b_{0,i} - \overline{b}_0)(b_{1,i} - \overline{b}_1) \,, \tag{7}$$

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[7] Recently, McInish et al. (2008) use similar methodology to find sources of momentum and contrarian profits in the Asian markets.

(iii) Time-series pattern component:

$$\Omega = \frac{1}{N}\sum_{i=1}^{N} Cov(\varepsilon_{i,t}, \varepsilon_{i,t-1}), \tag{8}$$

where μ_i is the intercept of the regression for an individual stock; $b_{0,i}$ and $\overline{b}_0$ are the regression coefficient and mean (cross-sectional) regression coefficients, respectively; $b_{1,i}$ and $\overline{b}_1$are the second regression coefficient and mean (cross-sectional) of that, respectively; $\varepsilon_{i,t}$ is the error-term of the regression equation.

After using equations (6), (7), and (8), I use equation (4a) and (4b) to decompose the expected contrarian/momentum profits into three components: (i) the cross-sectional variance of expected returns, (ii) the contrarian or momentum profits attributable to time difference in reacting to a common factor, and (iii) the stock price adjustment to idiosyncratic information.

Since the study also investigates the robustness of results with respect to size and volume of trade, I also sort portfolios based on these factors and then apply the same decomposition framework. Since data are monthly, the sources correspond to only monthly contrarian or momentum returns and not to longer investment horizon returns.

3.4 Analyses of Empirical Results

Table 3.1 presents the returns of winner, loser, and relative strength (WRSS) portfolios of different ranking and holding periods. The table gives 36 mean returns for the whole period for each winner, loser, and WRSS portfolio. The mean return of WRSS portfolio is strongly negatively significant for 1x1 (ranking period x holding period), 1x2, 1x3, and 1x6 strategies, but becomes insignificant at higher holding periods. When the holding period is nine and twelve months, there are no significant contrarian profits. One interesting result shown in the table is that for all the ranking periods the initial WRSS (or total portfolio) return is always negative, whereas as the holding period increases the contrarian profits tend to become significantly positive. This is probably an indication that investors are uncertain about the stock performance initially, resulting in current-period over-pricing and next-period correction. However, in the relatively longer horizons of nine and twelve months, investors are less uncertain about the stocks. It is also possible that since holding period returns are cumulative, there could be a tendency for ups and downs to cancel each other out, resulting in smaller returns. I also observe significantly positive momentum returns when both ranking and holding periods are of relatively longer horizons of three to twelve months.

Table 3.1
WRSS Portfolio Returns for All Trading Strategies

Ranking Period	Holding Period / Portfolio	1 Mean Ret.	1 t-stat.	2 Mean Ret.	2 t-stat.	3 Mean Ret.	3 t-stat.	6 Mean Ret.	6 t-stat.	9 Mean Ret.	9 t-stat.	12 Mean Ret.	12 t-stat.
1	WRSS	-17.74	-6.69*	-19.85	-5.32*	-18.54	-4.33*	-12.31	-2.35*	-9.23	-1.54	-3.80	-0.59
	Winner	-3.90	-0.81	-0.01	0.00	6.65	0.76	25.07	2.15*	39.07	2.63*	56.86	3.27*
	Loser	-13.83	-3.36*	-25.18	-3.28*	-19.84	-3.29*	-37.38	-3.27*	-48.30	-3.42*	-60.67	-3.64*
2	WRSS	-9.87	-5.28*	-10.29	-3.93*	-10.10	-3.49*	-3.67	-1.06	0.13	0.03	6.29	1.36
	Winner	-0.39	-0.12	3.61	0.74	7.76	1.34	21.61	2.70*	32.24	3.21*	46.43	3.92*
	Loser	-9.48	-3.39*	-13.90	-3.23*	-17.86	-3.35*	-25.28	-3.21*	-32.12	-3.31*	-40.14	3.51*
3	WRSS	-6.20	-4.04*	-6.76	-3.20*	-5.86	-2.43*	0.10	0.03	4.22	1.18	10.01	2.50*
	Winner	1.02	0.39	4.04	1.05	7.91	1.69	18.25	2.82*	28.20	3.46*	39.27	4.11*
	Loser	-7.22	-3.06*	-10.80	-3.05*	-13.77	-3.08*	-18.15	-2.86*	-23.98	-3.02*	-29.26	-3.20*
6	WRSS	-2.06	-2.06*	-1.32	-0.95	-0.12	-0.07	4.75	2.25*	10.14	3.85*	10.96	3.56*
	Winner	1.54	0.89	3.82	1.46	6.30	1.94	14.34	3.18*	10.67	5.27*	28.37	4.18*
	Loser	-3.60	-2.13*	-5.14	-2.06*	-6.42	-2.07*	-9.59	-2.18*	-0.52	-0.31	-17.41	-2.68*
9	WRSS	-1.09	-1.36	-0.06	-0.05	1.34	0.95	6.64	3.57*	8.83	3.83*	9.74	3.81*
	Winner	1.57	1.11	3.83	1.80	6.32	2.42*	13.41	3.71*	18.83	4.10*	23.69	4.24*
	Loser	-2.66	-1.92	-3.89	-1.86	-4.98	-1.91	-6.77	-1.86	-9.99	-2.15*	-13.96	-2.59*
12	WRSS	-0.28	-0.41	1.17	1.16	2.65	2.13*	5.70	3.46*	0.83	3.90*	4.93	2.76*
	Winner	1.73	1.43	3.03	1.81	5.85	2.62*	10.85	3.43*	1.76	3.86*	14.04	3.34*
	Loser	-2.01	-1.60	-1.86	-1.10	-3.20	-1.40	-5.15	-1.61	-0.93	-2.04*	-9.11	-2.21*

Asterisks indicate significance at the 5% level. Winner, Loser, and WRSS (Winner+Loser) portfolios are constructed using equation (3). Formation and holding periods are 1, 2, 3, 6, 9, or 12 months. Thus, there are 36 trading strategies. Formation period returns are the cumulative returns for the respective period (number of months). Holding-period returns are calculated based on the weight derived from the formation period and cumulative return for the respective holding period where weights of the firms do not change. Winner and Loser portfolio returns are calculated when assigned weights are positive and negative, respectively. Weights of the stocks in the portfolio and corresponding portfolio returns change every month after the initial period when weights are assigned.

Table 3.2 provides the returns of relative-strength portfolios when stocks are sorted and portfolios are constructed based on the market value of individual stocks. I take the average of year-end market capitalization data for the whole study period to select the firms in terms of size. Thus, status of size for individual stocks is fixed for the whole study period. Since the objective of the study is to focus on short-term trading strategies, I consider strategies of only a one- to three-month investment horizon. Therefore, there are nine short-term trading strategies. Panel A of Table 3.2 suggests that there is no contrarian or momentum profit for large firms in the Indian stock market. This finding is consistent across all short-term investment strategies. This result supports finance theory that stock analysts usually follow large stocks more closely and provide more frequent recommendations on these firms. Because of this, foreign investors tend to be major players in the Indian stock market and are mostly invested in large firms because more reliable information is readily available on these firms than on small firms. Moreover, large firms are believed to be more heavily regulated and as a result are more transparent than smaller firms.

Table 3.2

Market Value–Sorted WRSS Portfolio Returns for Short-Term Strategies

Ranking Period	Holding Period / Portfolio	1 Mean Ret.	1 *t*-stat.	2 Mean Ret.	2 *t*-stat.	3 Mean Ret.	3 *t*-stat.
	Panel A: Portfolio of large firms						
1	WRSS	-2.61	-1.09	-2.55	-0.79	0.43	0.11
	Winner	6.62	1.65	12.50	2.23*	19.69	2.91*
	Loser	-9.23	-2.59*	-15.05	-2.88*	-19.26	-2.93*
2	WRSS	-2.26	-0.59	0.63	0.13	3.94	0.72
	Winner	9.61	1.64	19.37	2.36*	15.29	2.81*
	Loser	-11.87	-2.37*	-18.74	-2.46*	-11.36	-2.11*
3	WRSS	0.45	0.09	3.85	0.61	10.26	1.44
	Winner	12.79	1.81	25.13	2.56*	40.61	3.46*
	Loser	-12.35	-1.97*	-21.28	-2.23*	-30.35	-2.52*
	Panel B: Portfolio of medium firms						
1	WRSS	-17.01	-6.02*	-19.75	-5.16*	-15.84	-3.71*
	Winner	-5.55	-1.17	-2.10	-0.29	4.49	0.51
	Loser	-11.45	-2.84*	-17.65	-2.98*	-20.33	-2.74*
2	WRSS	-19.74	-5.38*	-18.65	-3.52*	-17.47	-2.85*
	Winner	-3.12	-0.48	4.09	0.42	10.37	0.87
	Loser	-16.62	-3.03*	-22.73	-2.74*	-27.83	-2.70*
3	WRSS	-15.84	-3.48*	-17.26	-2.64*	-15.16	-2.03*
	Winner	0.35	0.05	7.36	0.63	16.80	1.17
	Loser	-16.20	-2.39*	-24.62	-2.39*	-31.97	-2.41*
	Panel C: Portfolio of small firms						
1	WRSS	-34.96	-7.87*	-38.91	-6.58*	-40.61	-6.16*
	Winner	-13.82	-2.16*	-12.08	-1.32	-6.39	-0.57
	Loser	-21.14	-3.82*	-26.83	-3.42*	-34.22	-3.55*
2	WRSS	-39.33	-6.77*	-45.34	-5.56*	-48.03	-5.20*
	Winner	-10.64	-1.29	-4.64	-0.38	-5.06	-0.58
	Loser	-28.69	-3.97*	-40.69	-3.75*	-42.97	-5.62*
3	WRSS	-41.27	-5.88*	-48.34	-4.96*	-49.18	-4.23*
	Winner	-5.55	-0.56	0.67	0.05	9.87	0.56
	Loser	-35.71	-3.91*	-49.01	-3.74*	-59.05	-3.68*

Asterisks indicate significance at the 5% level. Winner, Loser, and WRSS (Winner+Loser) are constructed using equation (3). First the firms are categorized as large, medium, or small based on the average market capitalization for the sample period. Size status is fixed for the whole period. Similarly, firms are also categorized as high, medium, or low volume (of trade). Formation and holding period are 1, 2, and 3 months. Thus, there are 9 trading strategies. Formation-period returns are the cumulative returns for the respective period (number of months). Holding-period returns are calculated based on the weight derived from the formation period and cumulative return for the respective holding period where weights of the firms do not change. Winner and Loser portfolio returns are calculated when assigned weights are positive and negative, respectively.

Panel B of Table 3.2 provides the results of momentum and contrarian profits for medium-size firms. All the medium-size firms have significant contrarian profits. For all the investment horizons, the contrarian profits are huge. Investors just need to buy the loser stock and sell the winner stock and hold the portfolio for one, two, or three months, depending on their investment horizon preferences, to earn abnormal returns. Panel C shows the opportunity for abnormal returns when only small stocks are chosen in portfolios. Results exhibit highly significant contrarian profits for all the short-term investment horizons. Almost all the portfolios—WRSS, winner, and loser—earn negative returns. It seems that when all portfolios earn negative returns there is no need to distinguish between winner and loser portfolios, and a very raw strategy (regardless of the type) can earn abnormal returns. However, the construction of a WRSS portfolio gives the opportunity to reduce risk by assigning weights appropriately to create a zero-investment portfolio. Results in panels B and C of Table 3.2 also indicate the inefficiency of the market with respect to medium-size and small firms. For achieving a well-functioning market overall, these pricing anomalies must be eradicated. The Securities Exchange Board of India (SEBI) must ensure proper and timely surveillance and financial reporting practices.

Table 3.3 presents the mean return of the portfolios when firms are sorted and portfolios formulated based on the volume of trade of individual firms. I take the average of year-end volume of trade data for the whole study period to select firms in terms of trade volume. Thus, the volume-of-trade status of firms is fixed for the whole study period. Results are close to those found previously, when firms were sorted based on market value. The firms with high volume of trade do not show any opportunity for abnormal returns. Probably high-volume firms are mostly big firms, and higher level of trading offers better opportunity for faster adjustment of prices to new information, which ultimately drives out the possibility of abnormal returns. As with medium-size and small firms, medium- and low-volume firms also exhibit significant contrarian profits.

Table 3.3
Volume of Trade–Sorted WRSS Portfolio Returns for Short-Term Strategies

		Holding Period					
Ranking Period		1		2		3	
	Portfolio	Mean Ret.	*t-stat.*	Mean Ret.	*t-stat.*	Mean Ret.	*t-stat.*
	Panel A: Portfolio of high volume-sorted firms						
1	WRSS	-4.07	-1.38	-4.62	-1.23	-3.79	-0.80
	Winner	4.07	0.85	8.94	1.35	3.22	0.93
	Loser	-8.14	-1.99*	-13.55	-2.29*	-7.01	-2.08*
2	WRSS	-4.45	-1.05	-4.30	-0.74	-4.32	-0.64
	Winner	6.74	1.00	15.05	1.59	23.50	2.13*
	Loser	-11.19	-1.99*	-19.36	-2.21*	-27.82	-2.52*
3	WRSS	-3.77	-0.69	3.85	0.61	10.26	1.44
	Winner	9.92	1.24	25.13	2.56*	40.61	3.46*
	Loser	-13.69	-1.89	-21.28	-2.23*	-30.35	-2.52*
	Panel B: Portfolio of medium volume-sorted firms						
1	WRSS	-22.13	-6.28*	-24.10	-5.25*	-21.39	-4.37*
	Winner	-5.14	-1.06	0.48	0.06	-0.84	-0.23
	Loser	-16.99	-3.65*	-24.58	-3.69*	-20.55	-5.67*
2	WRSS	-24.01	-5.04*	-23.14	-3.72*	-22.79	-3.32*
	Winner	-1.91	-0.28	9.16	0.87	17.57	1.36
	Loser	-22.10	-3.54*	-32.30	-3.46*	-40.36	-3.55*
3	WRSS	-21.31	-3.78*	-22.46	-2.95*	-22.75	-2.66*
	Winner	4.61	0.56	15.02	1.20	25.14	1.60
	Loser	-25.92	-3.29*	-37.47	-3.31*	-47.89	-3.40*
	Panel C: Portfolio of low volume-sorted firms						
1	WRSS	-28.02	-8.12*	-32.61	-6.24*	-32.84	-5.67*
	Winner	-11.54	-2.15*	-11.07	-1.38	-5.99	-0.64
	Loser	-16.47	-3.78*	-21.54	-3.39*	-26.84	-3.33*
2	WRSS	-32.54	-6.95*	-37.43	-5.47*	-36.92	-4.57*
	Winner	-8.89	-1.27	-5.19	-0.50	-6.09	-0.84
	Loser	-23.65	-4.08*	-32.24	-3.67*	-30.83	-4.62*
3	WRSS	-33.10	-5.73*	-4.64	14.99*	-32.05	-3.22*
	Winner	-7.11	-0.84	-0.08	9.79*	10.16	0.68
	Loser	-25.99	-3.59*	-3.35	7.02*	-42.21	-3.13*

Asterisks indicate significance at the 5% level. Winner, Loser, and WRSS (Winner+Loser) are constructed using equation (3). First the firms are categorized as large, medium, or small based on the average market capitalization for the sample period. Size status is fixed for the whole period. Similarly, firms are also categorized as high, medium, or low volume (of trade). Formation and holding period are 1, 2, and 3 months. Thus, there are 9 trading strategies. Formation-period returns are the cumulative returns for the respective period (number of months).

Holding-period returns are calculated based on the weight derived from the formation period and cumulative return for the respective holding period where weights of the firms do not change. Winner and Loser portfolio returns are calculated when assigned weights are positive and negative, respectively.

It is noticeable that at every short-term investment horizon the WRSS portfolio return is highly significant. Therefore, an investor needs only to sell the previous period's winner and buy the previous period's loser. Nonsynchronous trading may be one of the reasons for such contrarian profits. Since the data are monthly, there should be less nonsynchronous trading. However, some nonsynchronous trading may still exist. Nonsynchronous trading, which is quite typical of any emerging market, keeps stock prices from reflecting new information on a timely basis and gives well-informed traders the opportunity to manipulate the situation so it eventually translates into some sort of observable return regularity. Particularly, SEBI should be vigilant when trading of these stocks resumes after certain periodic gaps. This kind of monitoring should bolster the confidence of less-informed small and foreign investors.

Table 3.4 exhibits the sources of momentum/contrarian portfolio returns. Panel A shows the sources of contrarian profits when firms are sorted based on market value and volume of trade. For market-value sorted portfolios, the cross-sectional risk component plays almost the same role for large-, medium-, and small-size firms. The lead-lag effect—the second component of contrarian or momentum profits—does not have much impact on WRSS portfolios. However, the effects of the lead-lag relationship on small firms are much larger than on large- and medium-size firms. This result implies that small firms follow large firms and not the other way around.

Table 3.4
Sources of Momentum/Contrarian Portfolio Profits

Panel A. Sources of return when firms are sorted based on MV and Volume

Components of profit	Market value–sorted portfolios			Volume of trade–sorted portfolios		
	Large	Medium	Small	High	Medium	Low
Cross-sectional risk	1.0071	1.1178	1.1552	0.8007	0.8993	1.2000
Lead-lag effect	-0.0003	-0.0014	-0.2114	-0.0012	-0.0057	-0.0144
Time-series pattern	-3.8433	-21.3732	-27.8633	-3.3030	-17.1967	-35.2709

Panel B: Sources of return for total and two sub-periods

	1991-06	1991-01	2002-06
Cross-sectional risk	1.1518	1.5433	8.6909
Lead-lag effect	-0.0044	-0.0134	0.0025
Time-series pattern	-18.6794	-18.4969	-7.9238

This table exhibits the sources of momentum/contrarian profits. The expected profits are decomposed using the one-factor (contemporaneous and lagged market return) model shown in equation (5). To estimate the parameters I use equally weighted market return as the proxy for the common factor for the return of individual stocks. The momentum/contrarian profit components, cross-sectional risk, lead-lag effect, and time-series pattern correspond to equations (6), (7), and (8), respectively. Since these numbers are estimated based on monthly returns, results can be treated only as related to monthly contrarian or momentum characteristics. Thus, the components are not valid for investment horizons of more than one month.

The last component, firm-specific error terms, plays the largest role in contrarian profits. The sign of this effect is negative for all three types of firms, which explains why the portfolio return is negative and contrarian profits occur eventually. This effect is relatively small for large firms but large for medium- and small-size firms. This finding also confirms the absence of contrarian returns for large firms exhibited in Table 3.2.

Results do not change that much when firms are categorized by volume of trade. Once again, low-traded firms exhibit higher average covariance of error terms than the other two volume-based firms do. The difference of cross-sectional risk between high- and low-volume firms is more noticeable than that between large- and small-size firms. Probably high-volume firms are even more informationally efficient than large firms. This may indicate that information efficiency is more of a volume- than size-related issue in the Indian stock market. It is plausible since high-volume firms are probably large as well. Cross-sectional risk indicates expected return for the stock concerned. That is, firms with higher (lower) cross-sectional risk should expect higher (lower) returns. Since high-volume firms are less risky due to frequent adjustment of information into stock prices and there is a high degree of correlation between trade volume and size, expected return for high-volume firms is less than that for the low-volume firms.

Panel B shows the sources of contrarian profits for the whole period and two sub-periods, 1991-2001 and 2002-2006. For the whole study period and sample of firms, the lead-lag effect is very small. The cross-sectional component has some effect on contrarian profits, but the firm-specific component is the most important one. When the total period is divided into two sub-periods, there is a noticeable change in the contribution of error terms (time-series pattern or firm-specific component) to contrarian profits. The contribution of the time pattern component is -7.92 during the period 2002-2006 compared to -18.50 during the period 1991-2001, suggesting the market has matured and firm-specific mispricing has declined over time.

Since it has been found that the effect of the time-series pattern has declined in the past few years of the study, I divide the total period further into eight two-year sub-periods to investigate how the contribution of components changes over time. When the sample period is short, there is a tendency to have larger estimated coefficients, resulting in larger values of components as against the case when the whole sample period is considered. Thus, results reported in Table 3.5 may not be directly comparable with results in the other tables. However, the results can be validly used for comparison across various two-year sub-periods. Panel A of Table

3.5 presents the sources of contrarian profits for each of the two-year sub-periods. The cross-sectional component is high during the period 1991-1992, declines during the period 1997-2002, and then rises again after 2003.

Since the Indian stock market was on the bullish trend beginning in 2003 and the cross-sectional component corresponds to the average return of stocks, the value of this component is logically higher in the later period. This happens due to the higher spread of returns between large and small stocks. For example, the bullish period is also accompanied by a higher influx of foreign investors who are mostly interested in large caps, causing an increase in cross-sectional return deviation. Also evident from the table is that the lead-lag effect in the later period is slightly lower than in the initial period. Thus, the quality of response to a common factor does not change noticeably throughout the period. It may indicate higher market efficiency in terms of the lead-lag effect or simply higher segmentation (low correlation) of firms in the market. Overall, it is good to see that the effect of the time-series pattern has dramatically declined despite a few spikes over the period. This scenario implies better reflection of information in the stock prices and consequently less observed autocovariance among error terms. Thus, I may conclude that the market's stock-pricing mechanism has markedly improved.

Table 3.5

Sources of 2-Year Momentum/Contrarian Portfolio Profits

Components of profit	1991-92	1993-94	1995-96	1997-98	1999-00	2001-02	2003-04	2005-06
Panel A: Estimated factor coefficients are based on respective 2-year period regression								
Cross-sectional risk	11.7606	6.9484	12.8951	9.5032	6.6281	6.5569	11.9243	12.7157
Lead-lag effect	-0.0439	-0.0628	0.0629	-0.0202	-0.0373	0.0186	-0.0123	0.0377
Time-series pattern	-32.8101	-23.9467	-17.4374	-31.9206	-38.9811	-25.1367	-15.8253	-13.8357
Panel B: Estimated factor coefficients are based on full period regression								
Time-series	-29.4162	-24.2546	-22.6251	-34.2424	-39.5332	-31.5243	-17.1981	-11.2360

This table exhibits the sources of momentum and contrarian profits when the total period is divided into eight 2-year sub-periods to investigate how the role of components changes over time. The expected profits are decomposed using the one factor (contemporaneous and lagged market return) model shown in equation (5). To estimate the parameters I use equally weighted market return as the proxy for the common factor for the return of individual stocks. The momentum/contrarian profit components, cross-sectional risk, lead-lag effect, and time-series pattern correspond to equations (6), (7), and (8), respectively. Since these numbers are estimated based on monthly returns, results can be treated only as related to monthly contrarian or momentum characteristics. Thus, the components are not valid for investment horizons of more than one month.

Panel B of Table 3.5 reports the estimated time-series pattern for each period when the estimated coefficients for the whole sample period are used. This gives a better comparison across various periods. In this case, the lead-lag and cross-sectional components are not reported since estimated coefficients from the factor model do not change and thus have no impact on those two effects. However, the time-series pattern is sensitive to stock prices at every period, resulting in month-to-month changes. Results show that throughout the sample period the firm-specific factor is a major cause for contrarian profits. Nonetheless, the good news for the Indian market is the fact that this effect has been gradually disappearing in the last few years of the sample period.

3.5 Conclusion

This study investigates the presence and sources of contrarian and momentum profits in the Indian stock market for the period January 1991 through December 2006. The study uses the weighted relative strength scheme (WRSS) of Lo and MacKinlay (1990) methodology and procedure used by Jegadeesh and Titman (1995) to find the components of contrarian or momentum profits.

The results show that there are short-term contrarian profits, which suggests that investors in the Indian stock market tend to correct price departures due to initial overreaction at frequent intervals. This is not surprising since the market is believed to be dominated by less-informed individual investors. In the relatively longer investment horizons of 6 and 12 months, WRSS portfolios produce momentum profits. Further classification of stocks based on market value and volume of trade reveals that larger-size and high-volume stocks are correctly priced whereas medium- and small-size and medium- and low-volume stocks are not correctly priced, resulting in overall contrarian profits for the market. Decomposition of contrarian and momentum profits suggests that the firm-specific component does not contribute that much to the abnormal returns of large firms. However, the firm-specific component explains a large portion of contrarian returns for medium- and small-size and medium- and low-volume of trade firms. The encouraging phenomenon is the finding that the impact of the firm-specific component has been decreasing since the year 1999.

The results also show that small- and medium-size firms in the Indian stock market contribute to contrarian returns, which indicates the mispricing of these firms and overall market inefficiency. This finding implies that regulatory bodies like SEBI and policymakers should work hard to implement or modify regulations to help small- and medium-size firms perform better so that information is better reflected in their stock prices. Policymakers and regulators should adopt policies such as imposition of stringent accounting rules, more frequent and transparent disclosure of accounts, persuasion of or incentives to local and foreign institutional investors to invest in small- and medium-size firms to improve overall market efficiency.

CHAPTER FOUR

Lead-Lag Relationships between Stock Returns in the Indian Stock Market

4.1 Introduction

The purpose of this study is to investigate the price adjustment and lead-lag relations between size and volume based portfolio returns in the Indian stock market where the market microstructures are considerably different from most developed markets. A lead-lag relationship refers to a situation where the contemporaneous values of a variable are correlated with the lagged values of another variable. Lo and MacKinlay (1988, 1990) argue the contrarian profits result mainly from the existence of asymmetric cross-autocorrelation of stock returns. The authors, introducing the lead-lag relations, discover that lagged returns on the U.S. large stock portfolios are correlated with the current returns on the U.S. small stock portfolios, but the lagged returns on small stock portfolios are not correlated with the current returns on large stock portfolios.

This type of asymmetric cross-autocorrelation suggests a strong leading role of large stock returns over small stock returns that cannot be fully explained by non-synchronous trading. This example illustrates the finding that large-firm stocks may reflect the arrival of new information faster than small-firm stocks. Boudoukh et al. (1994) explain the arrival of new information and categorize their results into three groups. The first is called "Loyalists." This group attributes the arrival of new information to nonsynchronous trading and upholds market efficiency. The second group is the

"Revisionists." Revisionists attribute the predictability of small stock returns to time-varying risk premiums (for example, Conrad and Kaul, 1988). The last group is the "Heretics." This group attributes the predictability of small stock returns to bubbles such as overreactions, underreactions, and other behavioral attributes that may result in the violation of market efficiency (for example, Lo and MacKinlay, 1990b).

In large stock markets, firms are highly differentiated in terms of risk factors or attributes such as size, volume of trade, and market-to-book value (MV/BV) ratio. An issue of interest is how portfolios of firms constructed using these attributes may behave with respect to changes in common market information. Do large firms lead small firms when new common information arrives? For example, Brennan et al. (1993) show that returns on small or low-coverage firms tend to follow the returns on large or high-coverage firms. Similarly, Chordia and Swaminathan (2000) show that returns on firms with high volume of trade lead firms with low volume of trade. They interpret this observation as the outcome of more opportunity for high volume of trade firms to assimilate or impound new information quickly into stock prices through frequent trading.

Since the discovery of the lead-lag effects between stock returns are a relatively recent phenomenon, there are only a few studies that have examined this relationship for firms in emerging markets. For the Indian stock market, this study is a novel attempt to examine the price adjustment and the presence of the lead-lag relationships between stock returns by controlling for other factors that may confound the results.[1] More specifically,

[1] Poshakwale and Theobald (2004), and Karmakar (2010) investigate lead-lag structure on the Indian stock market. However, they do not neutralize other intervening factors in cross-correlation of returns of firms.

this study investigates the presence of lead-lag relationships between stock returns of firms categorized by size, volume of trade, and MV/BV on the Indian stock market. The study's main objective is to provide academicians, investors, and policymakers with insights into the presence of lead-lag relationship and the speed of stock price adjustments to new information on the Indian stock market. The evidence obtained on the lead-lag relationships extends previous research on the Indian stock market.

The rest of the paper is structured as follows. Section 2 provides the literature on the presence of lead-lag relationships between stock returns in developed and emerging stock markets. Section 3 describes the data and methodology used in the study. Section 4 presents the empirical results. Section 5 concludes the paper.

4.2 Literature Review

The relationship between returns and volume of trade of stocks has been studied by academicians and practitioners for more than 40 years (Granger and Morgenstern, 1963). The primary focus of these studies is on how information is disseminated in financial markets. Since a "trade" provides the mechanism by which information incorporated into a stock price, volume of trade is regarded as an important indicator of the process of price adjustment to equilibrium level. This is also supported by two Wall Street adages: (i) Volume of trade is relatively higher in bull markets and lower in bear markets; (ii) volume drives stock prices. Thus early examination of lead-lag effect primarily focuses on the return-volume relationship.

Sinha and Sharma (2008), Debasish (2009), and Mahajan and Singh (2009) find lead-lag relation between an index and its derivatives.

Rogalski (1978) and Epps (1975, 1977) find a positive contemporaneous correlation between volume and returns. Smirlock and Starks (1988) document a strong positive lagged relationship between volume and absolute price changes. Moosa and Al-Loughani (1995) document bi-directional causal relationships between volume of trade and stock returns. However, after examining the direction of causality of the price-volume relationship, Bhagat and Bhatia (1996) find that price changes lead volume but find no evidence that volume leads price changes.

Weigand (1996) uses volume of trade as the process of adjustment to information and suggests that transmission of information between large and small firms is symmetric, suggesting a bi-directional spillover of information. Saatcioglu and Starks (1998) show that for Latin American markets, there is no strong evidence that stock price has an impact on volume. Chen et al. (2001) show strong causality from stock returns to volume of trade but not the other way around. Lee and Rui (2002) find that volume of trade does not Granger-cause stock returns on the New York, Tokyo, and London markets. In addition, they also show a positive feedback relationship between volume of trade and return volatility in all these markets.

The study of lead-lag relationships between stock returns on large and small firms is of relatively recent interest to academicians and practitioners. While examining the contrarian profits in stock returns, Lo and MacKinlay (1990a, 1990b) discover the cross-correlation between the stock returns of large and small stocks. They conclude that nonsynchronous trading is not the cause of this relationship. Brennan et al. (1993) also show that returns on small or low-coverage stocks tend to follow the returns on large or high-coverage firms. Grinblatt et al. (1995) attribute the adjustment asymmetry to the behavior of institutional investors. McQueen et al. (1996) show that such cross-autocorrelation creeps up because of the tendency of the small firms to adjust to new information more slowly than the large ones.

Chordia and Swaminathan (2000) show that returns on firms with high volume of trade lead returns on firms with low volume of trade and interpret this finding as the outcome of opportunity of high trade firms' ability to adjust to new information more quickly. Safvenblad (2000) concludes that autocorrelation patterns are related to trading patterns of individual investors, not to cross-security information processing of the market. Mills and Jordanov (2000) find lead-lag relationship between small and large firms on the London Stock Exchange. Atlay (2003) investigates cross-autocorrelation structure on the German and Turkish stock markets by using daily data. His results indicate that the speed of adjustment of small firms to common market-wide information is slower than for large firms. Chordia et al. (2005) report strong evidence of return and liquidity transmission from large to small firms. Choi and Zhao (2007) find some evidence of cross-autocorrelation for both size and volume portfolios. In addition, they show that lagged returns of large volume firms may not always lead current returns of small volume firms.

Unfortunately, the literature on lead-lag relationships between stock returns for emerging markets is limited. Chang et al. (1999) evaluate six Asian markets and find evidence of cross-autocorrelation in all six Asian markets. In all the markets, returns on the portfolio of large firms lead returns on the portfolio of small firms. Gebka (2008) reports both size- and volume-related cross-autocorrelation on the Warsaw Stock Exchange. He also reports that slower price adjustment of the small portfolios to market-wide information depends on the state (up or down) of the market. Pisedtasalasai (2009) provides evidence of a one-directional relationship between returns and volume of trade of large firms on the New Zealand stock market.

Chui and Kwok (1998) report that for the Chinese stock market, the direction of information flow is mainly from more informed B shares to less informed A shares.[2] Such lead-lag relationship between A shares and B shares persists even after considering serial correlation and volume of trade. Sjoo and Zhang (2000) show that information flow from foreign to domestic investors in large and highly-liquid Shanghai stock exchange, whereas information flow in opposite direction in the small and less-liquid Shenzhen stock exchange.

Few papers have examined the lead-lag relationship on the Indian stock market. Moreover, most of them do focus not on the cross-autocorrelation between stock returns. Poshakwale and Theobald (2004) provide evidence of cross-correlation between the returns of large and small firms in the Indian stock market and find that large caps tend to lead small caps. Sinha and Sharma (2008) study the lead-lag relationship between returns in the Indian spot and futures market and find that new shock is simultaneously absorbed in both the markets, suggesting the absence of any lead-lag relationship. Karmakar (2010) investigates the return and volatility transmission between large and small Indian stocks and finds significant return spillover from portfolio of large stocks to that of small stocks. For volatility transmission, he finds a bidirectional relationship between small and large firms. Debasish (2009) studies the lead-lag relationship between India's NSE Nifty and

[2] There are two classes of shares in the Chinese stock market: class A and class B. Class A shares are available only to Chinese citizens whereas class B shares are available to both Chinese and foreign investors.

its derivative contracts and finds that the derivatives market tends to lead the underlying stock index. Mahajan and Singh (2009) examine the empirical relationship between stock returns and trading volume for the period from October 1996 through March 2006. Their results show significant positive relationship between return and volume.

This study extends the work of Poshakwale and Theobald (2004) by examining additional attributes such as size, volume of trade, and MV/BV ratio and by controlling for intervening factors that may confound the lead-lag results. The study is the first to address microstructure issues related to the Indian stock market using a methodology that considers firm attributes and the speed of adjustment stock prices to new information. Finally, it uses a different time frame and data source.

4.3 Data and Methodology

4.3.1 *Data*

I use weekly data on the Indian stock market collected from Thomson Datastream over the period January 1991 through December 2006. The original sample size consists of 312 firms. To arrive at a usable sample, I include only firms that have data on returns, volume of trade, and number of common shares outstanding for the whole period. To avoid the nonsynchronous trading problem, I drop those firms that are not traded for an extended period of time (eight weeks) from the sample. The final sample consists of 261 firms. For the MV/BV ratio, only annual data are available. Portfolios are rebalanced annually (described below). Moreover, MV/BV ratio for many firms is not available for the initial weeks of the study period and even in the later period the data are reported irregularly resulting in the omission of many firms from the final sample. The final sample that involves the MV/BV ratio consists of 174 firms.

4.3.2 *Causality between returns of large and small firms*

I use the methodology developed by Chordia and Swaminathan (2000) to investigate the presence of lead-lag relationships on the Indian stock market. Although Chordia and Swaminathan concentrate on the lead-lag effect of high- and low-volume firms, I investigate the lead-lag effects between firms of different sizes and volume of trade. In doing so, I control for intervening factors such as firm size, volume of trade, and MV/BV ratio. Thus, it is possible to obtain the effect of firm size on lead-lag relationship by isolating other effects. For example, it is plausible that both large size and higher volume of trade firms may lead smaller size and lower volume of trade firms. To address the effect of firm size on lead-lag relationship, I need to control for volume of trade effects. To accomplish this, I first sort firms by volume of trade and then within each volume of trade category I sort the firms by their size.[3] This process shows the lead-lag relationship between size portfolios for a given level of volume of trade. That is, it disaggregates the lead-lag relationship between size portfolios from the possible presence of volume of trade effects. This portfolio is called volume-size portfolio.

To construct the size-volume portfolios, I first sort the firms into three categories; small, medium, and large – based on size. Then for each size category, I sort firms into

[3] There are several definitions of volume of trade. In this study, volume of trade is defined as the number of shares traded divided by the number of shares outstanding. I use weekly data of number of shares traded.

high, medium, and low categories based on volume of trade.[4] Thus size-volume portfolios control for size effects. I construct the volume-size portfolios in the same manner. Since there are 261 firms in the sample, each size-volume or volume-size portfolio consists of 29 (261/9 = 29) firms.[5] By constructing MV/BV-size and MV/BV-volume portfolios I also control for MV/BV to investigate the size and volume effects. Since MV/BV data are available for 174 firms, I sort the MV/BV portfolios into three categories - high, medium, and low, but only two categories for size (large and small) and volume (high and low) portfolios.[6] Thus each portfolio has also 29 (174/6 = 29) firms. Portfolios are rebalanced annually.

After sorting the firms, I apply the Vector Autoregression (VAR) method to investigate how one category of firms leads or lags another. To do so, I first construct portfolios A (for example, portfolio of large size-low volume of trade firms) and B (portfolio of large size-high volume of trade firms). I then test for the lead-lag effect between portfolio B and portfolio A using the following VAR framework: [7]

$$r_{A,t} = a_0 + \sum_{k=1}^{K} a_k \, r_{A,t-k} + \sum_{k=1}^{K} b_k \, r_{B,t-k} + u_t, \qquad (1)$$

---

[4] "Volume" and "volume of trade" are used interchangeably throughout the paper. In the context of this paper, they have same meaning.

[5] The total number of firms is divided by nine because there are three types of firms based on volume (size) and then for each volume (size) category there are three types of size (volume), resulting in 3x3 = 9 portfolios.

[6] Highest one-third firms in terms of MV/BV are high MV/BV firms, while next one-third firms are medium firms. Likewise, lowest one-third are low firms.

[7] Chordia and Swaminathan (2000) point out that "since the regressors are the same for both regressions, the VAR can be efficiently estimated by running ordinary least squares (OLS) on each equation individually."

$$r_{B,t} = c_0 + \sum_{k=1}^{K} c_k\, r_{A,t-k} + \sum_{k=1}^{K} d_k\, r_{B,t-k} + v_t, \tag{2}$$

where in equation (1), $r_{A,t}$ is the return of portfolio *A* at time *t*, $r_{A,t-k}$ and $r_{B,t-k}$ are the returns of portfolio *A* and *B* at lag *k* = 1, 2, 3, and 4, respectively. Likewise, in equation (2), $r_{B,t}$ is the return of portfolio *B* at time *t*, $r_{A,t-k}$ and $r_{B,t-k}$ are the returns of portfolio *A* and *B* at lag *k* = 1, 2, 3, and 4, respectively.[8] Moreover, in equation (1), $a_k$and $b_k$are the coefficients of lagged returns of portfolio *A* and portfolio *B*, respectively, and in equation (2), $c_k$and $d_k$are the coefficients of lagged returns of portfolio *A* and portfolio *B*, respectively. a_0 and c_0 are the constant terms of equation (1) and (2), respectively. Finally, u_t and $v_t$are the error terms of equation (1) and (2), respectively. I consider portfolio *B* and *A* as the portfolios of large size (high volume of trade) and small size (low volume) stocks, respectively.

In equation (1), if the lagged returns of portfolio *B* can be used to predict the returns of portfolio *A*, then the sum of coefficients of returns on portfolio *B* ($\sum_{k=1}^{K} b_k$) must be significantly greater than zero. Likewise, in equation (2), if the lagged returns of portfolio *A* can be used to predict those of portfolio *B*, then the sum of coefficients of returns on portfolio *A* ($\sum_{k=1}^{K} c_k$) must be significantly greater than zero. In this VAR framework, I use a lag of four weeks. A related issue of interest in this econometric analysis is which of the two portfolio returns have more power and impact on the other. For example, if

[8] I use four lags. The reason for using four lags is somewhat arbitrary. However, I assume that the market is efficient enough to incorporate information into stock prices in four weeks.

$\sum_{k=1}^{K} b_k$ in equation (1) is significantly greater than $\sum_{k=1}^{K} c_k$ in equation (2), then the effect of the lagged returns of portfolio *B* on portfolio *A* is larger than that of lagged returns of portfolio *A* on portfolio *B*. Thus, it is possible to investigate the relative effects of these two portfolios on each other.

4.3.3 *Speed of adjustment from Dimson Beta Regression*

To investigate the speed of price adjustment, I use Dimson Beta estimates. To do so, I use a framework where firms are sorted and then invested so that a zero-investment portfolio is created. Similar to the VAR test described above, I control for size differences by making three size portfolios. Under each size portfolio, I construct three portfolios based on volume of trade. This type of sorting allows me to find the lead-lag relationship between high and low volume of trade firms and to control for the possible size effects. Then I use the Dimson (1979) beta regression to measure the speed of price adjustment of different size-volume portfolios. In the model, the speed of price adjustment to information for various categories of firms depends on both contemporaneous and lagged betas.

To use the Dimson beta regression, I construct a zero net investment portfolio *O*. I construct this portfolio by buying portfolio *B* and selling (shorting) portfolio *A*. Portfolio A and B (based on various firm attributes) have already been constructed in section 4.3.2. I then regress the returns of the zero-investment portfolio on the leads and lags of the market portfolio returns as given by the following model:

$$r_{O,t} = \alpha_O + \sum_{k=-K}^{K} \beta_{O,k}\, r_{m,t-k} + u_{O,t}, \tag{3}$$

where $r_{O,t}$ is the return of zero net investment portfolio, $\beta_{O,k} = \beta_{B,k} - \beta_{A,k}$, which is also the coefficients of lead and lagged returns of the market, and $\beta_{B,k}$ and $\beta_{A,k}$ are the coefficients of returns of portfolio B and A, respectively (they have already been constructed in the previous section). Since I am using four lags and leads, $\sum_{k=-K}^{K} r_{m,t-k}$ includes returns, which can be disaggregated as $\sum_{k=-4}^{-1} r_{m,t-k}$, $r_{m,t=0}$, and $\sum_{k=1}^{4} r_{m,t-k}$, representing lead, contemporaneous, and lagged returns of the market portfolio, respectively. Finally, α_O and $u_{O,t}$ are the constant and error terms, respectively.

Chordia and Swaminathan (2000) suggest that the adjustment of portfolio B is faster than that of portfolio A if and only if the contemporaneous coefficient of portfolio B is greater than the contemporaneous coefficient of portfolio A and the sum of lagged betas of portfolio B ($\sum_{k=1}^{K} \beta_{B,k}$) is less than the sum of lagged betas of portfolio A ($\sum_{k=1}^{K} \beta_{A,k}$). This result suggests that portfolio B responds to market-wide information faster than portfolio A (or the former leads the latter). This technique is used for large versus small and high versus low volume of trade firms by controlling for the effects of size, volume of trade, and MV/BV ratio. The evidence obtained from these tests supplements and extends the previous research on the lead-lag issue on the Indian stock market.

4.4 Analyses of Empirical Results

Table 4.1 provides the cross-autocorrelations results of weekly returns for size-volume, volume-size, MV/BV-size and MV/BV-volume portfolios. Panel A presents the cross-autocorrelations for size-volume portfolio returns. For every size category, the results suggest that the correlation between lagged high volume portfolio returns and current low volume portfolio returns is greater than the correlation between lagged small volume portfolio returns and current high volume portfolio returns. For example, in the small size category, the correlation between lagged high volume portfolio returns, $P_{small,high,t-1}$ and the contemporaneous low volume portfolio returns, $P_{small,low,t}$ is 0.1779, while the correlation between the lagged low volume portfolio returns, $P_{small,low,t-1}$ and the contemporaneous high volume portfolio returns, $P_{small,high,t}$ is 0.1636. This finding suggests that lagged returns of high volume portfolios have an impact on the contemporaneous returns of low volume portfolios for a given level of firm size. However, the difference in the correlations is small, suggesting that nonsynchronous trading may be the only source of these lead-lag relationships and that the lead-lag effect arising from cross-autocorrelation may not exist in the Indian stock market.

Panel B provides the cross-autocorrelation between large and small size portfolio returns when volume of trade effect is controlled for. The correlation between lagged large portfolio returns and current small portfolio returns is greater than the correlation between current large portfolio returns and lagged small portfolio returns for every level of volume of trade. For example, for high volume category, the correlation between lagged large portfolio returns, $P_{high,large,t-1}$ and contemporaneous small portfolio returns,

$P_{high, small,t}$ is 0.1168, while the correlation between the lagged small portfolio returns, $P_{high,small,t-1}$ and the contemporaneous large portfolio returns, $P_{high,large,t}$ is 0.0840. This result also shows that the difference between the portfolio correlations is small suggesting that any relationship is probably weak. I obtain similar results in panels C and D. All the results show a weak lead-lag relationship.

I also use the portfolios' own autocorrelations to investigate the lead-lag relationship and cross-autocorrelation between large (high) and small (low) size (volume) portfolio returns. For example, if corr($P_{large,high,t-1}$, $P_{large,low,t}$) > corr($P_{large,low,t-1}$, $P_{large,low,t}$), then the lagged returns of high volume firms have additional impact on current returns of low volume firms given that the firms are large. That is, low volume firm's own autocorrelation does not fully explain the cross-autocorrelation between high and low volume firms' returns and the former may be able to explain part of the latter. In Panel A, Table 4.1, the values of corr($P_{large,high,t-1}$, $P_{large,low,t}$) and corr($P_{large,low,t-1}$, $P_{large,low,t}$) are 0.1249 and 0.1330, respectively. Because the difference in these values is small, the results suggest that the lead-lag effect is not likely to have any impact on the returns of low volume firms and that the cross-autocorrelation probably arises due to own autocorrelation. The corr($P_{med,high,t-1}$, $P_{med,low,t}$) and corr($P_{med,low,t-1}$, $P_{med,low,t}$) give similar results. Panel B shows similar results to those of Panel A for all volume-size portfolio returns. Panels C and D also show that if MV/BV is held constant, volume and size portfolio returns do not show lead-lag effects.

Table 4.1
Cross-Autocorrelations between Portfolio Returns

Panel A: Size-Volume Portfolios

	$P_{large,high,t}$	$P_{large,low,t}$	$P_{med,high,t}$	$P_{med,low,t}$	$P_{small,high,t}$	$P_{small,low,t}$
$P_{large,high,t-1}$	0.0817	0.1249	0.1131	0.1318	0.1144	0.1339
$P_{large,low,t-1}$	0.0864	0.1330	0.1236	0.1485	0.1321	0.1430
$P_{med,high,t-1}$	0.0774	0.1200	0.1088	0.1492	0.1412	0.1610
$P_{med,low,t-1}$	0.1058	0.1514	0.1456	0.1541	0.1634	0.1829
$P_{small,high,t-1}$	0.0916	0.1409	0.1270	0.1599	0.1445	0.1779
$P_{small,low,t-1}$	0.0963	0.1404	0.1218	0.1572	0.1636	0.1512

Panel B: Volume-Size Portfolios

	$P_{high,large,t}$	$P_{high,small,t}$	$P_{med,large,t}$	$P_{med,small,t}$	$P_{low,large,t}$	$P_{low,small,t}$
$P_{high,large,t-1}$	0.0625	0.1168	0.1109	0.1159	0.1205	0.1243
$P_{high,small,t-1}$	0.0840	0.1482	0.1178	0.1681	0.1441	0.1852
$P_{med,large,t-1}$	0.0719	0.1480	0.1183	0.1415	0.1454	0.1532
$P_{med,small,t-1}$	0.0688	0.1450	0.0970	0.1477	0.1256	0.1695
$P_{low,large,t-1}$	0.0892	0.1597	0.1292	0.1582	0.1462	0.1769
$P_{low,small,t-1}$	0.0946	0.1729	0.1259	0.1758	0.1539	0.1584

Panel C: MV/BV-Volume Portfolios

	$P_{high,high,t}$	$P_{high,low,t}$	$P_{med,high,t}$	$P_{med,low,t}$	$P_{low,high,t}$	$P_{low,low,t}$
$P_{high,high,t-1}$	0.1003	0.1292	0.1140	0.1468	0.0951	0.1221
$P_{high,low,t-1}$	0.0904	0.1213	0.1115	0.1406	0.0813	0.1174
$P_{med,high,t-1}$	0.1006	0.1310	0.1095	0.1571	0.1005	0.1265
$P_{med,low,t-1}$	0.0958	0.1332	0.1241	0.1418	0.0992	0.1322
$P_{low,high,t-1}$	0.0891	0.1223	0.1256	0.1520	0.0973	0.1369
$P_{low,low,t-1}$	0.1140	0.1355	0.1360	0.1670	0.1239	0.1527

Panel D: MV/BV-Size Portfolios

	$P_{high,large,t}$	$P_{high,small,t}$	$P_{med,large,t}$	$P_{med,small,t}$	$P_{low,large,t}$	$P_{low,small,t}$
$P_{high,large,t-1}$	0.0775	0.1321	0.1145	0.1234	0.0796	0.0922
$P_{high,small,t-1}$	0.0859	0.1291	0.1151	0.1414	0.1046	0.1256
$P_{med,large,t-1}$	0.0837	0.1354	0.1299	0.1383	0.1059	0.1203
$P_{med,small,t-1}$	0.0860	0.1363	0.1130	0.1323	0.0945	0.1247
$P_{low,large,t-1}$	0.0876	0.1415	0.1278	0.1567	0.1007	0.1402
$P_{low,small,t-1}$	0.0817	0.1333	0.1199	0.1575	0.1099	0.1461

Table 4.2 presents the results obtained from VARs of all pair-wise combinations of portfolios. In Panel A, the left hand side (LHS) of VAR is comprised of extreme volume portfolios for a given firm size.[9] Panel B presents VAR results for extreme size portfolios for a given volume of trade. Likewise, Panel C and D give VAR results for extreme size and volume portfolios for given level of MV/BV ratios, respectively. Since data are weekly, I use four lags for VAR. In Table 4.2, the columns, "Low/Small" and "High/Large" provide the sum of coefficients of own and other variable's lags, depending on the pair of dependent variables used in the VAR. "Low" and "High" indicate low and high volume portfolios for a given level of size and MV/BV, respectively. "Small" and "Large" indicate small and large size portfolios for a given level of volume and MV/BV, respectively. The results in Panel A, Table 4.2 support the findings presented in Table 4.1. In the first regression, LHS is comprised of the portfolio of large size-high volume firms denoted by $P_{large,high}$ and the portfolio of large size-low volume firms denoted by $P_{large,low}$. Given that firms are large, the lagged returns of the portfolio of low volume firms explain current returns of portfolio of high volume firms while returns of own lags of the former significantly explain own current returns.

[9] Extreme portfolios consist of either large (high) or small (low) size (volume) portfolios. Thus, medium size (volume) portfolios are not considered as extreme portfolio.

Table 4.2
Vector Autoregression for Size and Volume Portfolio Returns

LHS	Low/Small	*t*-stat.	High/Large	*t*-stat.	r-squared	*t*-stat.
Panel A: Size-Volume Portfolios						
$P_{large,high}$	0.3724	2.16*	-0.0967	-0.62	0.0225	-1.38
$P_{large,low}$	0.3178	1.91**	-0.0628	-0.41	0.0337	
$P_{med,high}$	0.2480	1.46	-0.0057	-0.04	0.0362	-0.83
$P_{med,low}$	0.2625	1.59	-0.0068	-0.04	0.0392	
$P_{small,high}$	0.0390	0.27	0.2032	1.44	0.0427	0.52
$P_{small,low}$	0.1101	0.77	0.1800	1.29	0.0461	
$P_{large,high}$	-0.0512	-0.63	0.2557	2.64*	0.0234	-1.42
$P_{small,low}$	0.0661	0.77	0.1866	1.85**	0.0312	
Panel B: Volume-Size Portfolios						
$P_{high,large}$	0.0408	0.46	0.1535	1.35	0.0298	0.58
$P_{high,small}$	0.0389	0.41	0.1550	1.29	0.0393	
$P_{med,large}$	-0.1054	-1.25	0.3606	3.23*	0.0295	2.64*
$P_{med,small}$	-0.1427	-1.53	0.4106	3.34*	0.0357	
$P_{low,large}$	-0.1429	-1.69**	0.4572	4.15*	0.0523	2.95*
$P_{low,small}$	-0.1109	-1.20	0.4300	3.56*	0.0463	
$P_{high,large}$	-0.0002	0.00	0.1945	2.05*	0.0202	0.98
$P_{low,small}$	0.0350	0.44	0.1570	1.57	0.0332	
Panel C: MV/BV-Volume Portfolio						
$P_{high,high}$	0.2996	1.91**	-0.0244	-0.15	0.0368	-0.94
$P_{high,low}$	0.2595	1.67	0.0167	0.11	0.0395	
$P_{med,high}$	0.2187	1.19	0.0327	0.19	0.0369	-0.56
$P_{med,low}$	0.2468	1.37	0.0275	0.17	0.0441	
$P_{low,high}$	0.3477	2.00*	-0.1598	-0.93	0.0247	-1.64
$P_{low,low}$	0.3981	2.33*	-0.1985	-1.17	0.0345	
$P_{high,high}$	-0.0311	-0.35	0.2750	2.45*	0.0332	-1.15
$P_{low,low}$	0.0266	0.28	0.1949	1.62	0.0379	
Panel D: MV/BV-size Portfolio						
$P_{high,large}$	-0.0290	-0.25	0.2880	2.06*	0.0253	1.06
$P_{high,small}$	-0.0150	-0.12	0.2404	1.66	0.0431	
$P_{med,large}$	-0.2044	-1.77**	0.4631	3.80*	0.0396	2.53*
$P_{med,small}$	-0.1205	-1.02	0.3758	3.01*	0.0376	
$P_{low,large}$	-0.1645	-1.24	0.3679	2.55*	0.0293	2.01*
$P_{low,small}$	-0.1657	-1.22	0.3815	2.59*	0.0360	
$P_{high,large}$	-0.0929	-1.44	0.3601	3.81*	0.0346	2.57*
$P_{low,small}$	-0.0774	-1.04	0.3137	2.90*	0.0359	

* and ** indicate significance at 5% and 10%, respectively.

However, as shown in the last column, the difference in cross-equation sums of betas is insignificant (*t*-statistic = -1.38). That is, the ability of the lagged returns of high (low) volume firms to predict current returns of low (high) volume firms is not significantly better than the ability of lagged returns of low (high) volume firms to predict returns of high (low) volume firms. For both medium size and small size firm categories, the relationship between the portfolio of high volume firms and portfolio of low volume firms is insignificant. The last pair in Panel A is comprised of two portfolios – portfolios of large size-high volume firms and small size-low volume firms. For this pair, the current returns of $P_{large,high}$ and $P_{small,low}$ are explained by their own lags and high volume firms, respectively. The results show that the difference between the sums of lagged coefficients of low volume portfolio returns in the first equation and that of the lagged coefficients of high volume returns in the second equation is insignificant.

Table 4.2, Panel B presents results of volume-size portfolios where I control for volume effects in examining the effects of size on the lead-lag effects between portfolio returns. In the VAR model, I only use the extreme size firms (i.e., large and small firms) for every volume category. The results show that $P_{high,large}$ and $P_{high,small}$ are not related (individual *t*-statistic of all four lagged returns and cross-equation difference are insignificant).

The second pair, $P_{med,large}$ and $P_{med,small}$ show that returns of large and small firms are related for medium volume firms. For this pair of medium volume firms, large portfolio returns are explained only by their own lagged returns whereas small portfolio returns are significantly explained by lagged large portfolio returns (*t*-statistic = 3.34). Thus, the lagged returns of small firms do not seem to possess any informational content that affect the contemporaneous returns of large firms whereas the lagged returns of large firms do possess informational content that affect the contemporaneous returns of small firms. Moreover, as shown in the last column, the difference in cross-equation sums of betas is significant (*t*-statistic = 2.64), suggesting that the effect of lagged large firm returns on current small firm returns is greater than that of lagged small firm returns on current large firm returns. In market inefficiency literature, finance theory predicts that large firms lead small firms in the adjustment of information into stock prices. However, in an efficient stock market, there should be no existence of a lead-lag relationship between firms as every stock should reflect information correctly no matter its size, volume or MV/BV. The existence of a lead-lag effect for large firms suggests that large firms are more efficient than small firms in terms of the stock price adjustments to new information.

For low volume portfolios, the results show that large firm returns are significantly explained by their own returns and weakly by the returns of small firms. On the other hand, small portfolio returns are significantly explained by lagged large portfolio returns only. The results are similar to the high volume portfolios case above where the cross-equation difference between sums of lagged coefficients is significant (*t*-statistic = 2.95) suggesting that lagged returns of large portfolios have greater impact on small portfolio returns than the other way around. For the pair $P_{high,large}$ and $P_{low,small}$, the returns of the former is explained by its own lagged returns and there is no lead-lag relationship.

Table 4.2, Panel C presents the results of VAR for MV/BV-volume portfolios. The results show that for low MV/BV firms, the sum of lagged coefficients of small volume firms significantly explains the returns of large volume firms. On the other hand, only own lagged returns explain low volume firm returns. However, the difference between the cross-equation lagged beta coefficients is insignificant.

Table 4.2, Panel D presents the results of VAR for MV/BV-size portfolios. The results show that there is no evidence of correlation between the returns of large and small portfolios for high MV/BV category. In both the medium and low MV/BV categories, own lagged returns and lagged large firm returns significantly explain the returns of large and small portfolios, respectively. The cross-equation difference between the sums of lagged coefficients is also significant at 5% level (*t*-statistic = 2.53 and = 2.01, for medium and low MV/BV portfolios, respectively). Thus, lagged large size portfolio returns explain contemporaneous small portfolio returns but not the other way around. When $P_{high,large}$ and $P_{low,small}$, which are most different both in terms of volume and size, are considered, the lagged returns of the former significantly explains the returns of the latter.

Table 4.3 presents evidence of the speed of information adjustment into zero beta portfolio returns. I construct zero beta portfolio returns by subtracting one extreme portfolio return from the other. That is, for a given level of size, I construct a zero beta portfolio by subtracting the returns of low volume portfolios from that of high volume portfolios. Chordia and Swaminathan (2000) show that if the high volume portfolio adjusts faster than the low volume portfolio, the contemporaneous betas should be positive and the sum of lagged betas should be negative. In Table 4.3, columns $\sum_{k=-1}^{-4} \beta_{O,k}$ and $\sum_{k=1}^{4} \beta_{O,k}$ provide the sums of lead and lagged betas, respectively.

Table 4.3, Panel A presents the results for size-volume portfolios. For every size portfolios, the zero investment portfolio return sum of lagged betas is negative but insignificant. However, relevant contemporaneous beta is positive and significant at 5%. Thus, there is weak evidence that high volume firms react to common market information faster than low volume firms.

Table 4.3
Dimson Beta Regression Results

LHS	$\sum_{k=1}^{4}\beta_{O,k}$	*t*-stat.	$\beta_{O,0}$	*t*-stat.	$\sum_{k=-1}^{-4}\beta_{O,k}$	*t*-stat.	*r*-sq.
Panel A: Size-Volume Portfolios							
$P_{large,high} - P_{large,low}$	-0.0481	-1.76**	0.1201	7.33*	-0.0377	-1.12	0.0678
$P_{med,high} - P_{med,low}$	-0.0349	-1.07	0.1693	8.64*	-0.0344	-1.05	0.0923
$P_{small,high} - P_{small,low}$	-0.0368	-0.94	0.0438	1.87**	0.0393	1.00	0.0214
Panel B: Volume-Size Portfolios							
$P_{high,large} - P_{high,small}$	-0.0613	-1.52	-0.2307	-9.54*	0.0028	0.07	0.1374
$P_{med,large} - P_{med,small}$	-0.0485	-1.22	-0.2780	-11.64*	0.0853	2.13*	0.1639
$P_{low,large} - P_{low,small}$	-0.0465	-1.10	-0.2226	-8.79*	0.1027	2.43*	0.1117
Panel C: MV/BV-Volume Portfolios							
$P_{high,high} - P_{high,low}$	-0.0328	-1.25	0.0326	2.08*	-0.0179	-0.68	0.0179
$P_{med,high} - P_{med,low}$	-0.0662	-2.33*	0.1292	7.59*	-0.0073	-0.25	0.0783
$P_{low,high} - P_{low,low}$	-0.0640	-2.07*	0.0856	4.60*	-0.0452	-1.45	0.0315
Panel D: MV/BV-Size Portfolios							
$P_{high,large} - P_{high,small}$	-0.0339	-1.14	-0.1668	-9.31*	0.0144	0.48	0.1184
$P_{med,large} - P_{med,small}$	-0.0312	-0.90	-0.1022	-4.92*	0.0702	2.02*	0.0433
$P_{low,large} - P_{low,small}$	-0.0307	-0.86	-0.0794	-3.70*	0.0639	1.78**	0.0327

* and ** indicate significance at 5% and 10%, respectively. $\sum_{k=1}^{4}\beta_{O,k}$ and $\sum_{k=-1}^{-4}\beta_{O,k}$ represent sum of lagged and lead betas, respectively.

Table 4.3, Panel B shows that for high, medium, and low volume portfolios, the difference between extreme (large and small) size portfolio returns (i.e., zero beta portfolio returns) are negative and insignificant. However, every contemporaneous beta is negative and significant. These results suggest that large firms do not react to market information significantly faster than small ones.

Table 4.3, Panel C presents the results for all MV/BV-sorted extreme volume portfolios. Although I obtain results that are similar to those found in Panel A, these results are stronger. The main difference is that results in panel C give stronger evidence of faster adjustment to information for high volume firms. For example, in the medium and low MV/BV portfolios, the zero investment portfolios have significantly negative sum of lagged betas and significantly positive contemporaneous beta at 5% level of significance. This result suggests that high volume firms react to common information faster than low volume firms. This also confirms the notion that trading volume is an important channel through which information adjusts into the stock prices. Panel D also shows that MV/BV-size portfolio returns follow the same pattern as in Panel B and provide no evidence of the speed of information adjustment.

4.5 Conclusion

Several previous papers (for example, Boudoukh et al., 1994; Chordia and Swaminathan, 2000; McQueen et al., 1996) find evidence of lead-lag relationships between large and small firms. However, these studies mainly focus on developed markets. This paper examines the presence of lead-lag relationship between portfolio returns of large (high volume) and small (low volume) firms on the Indian stock market by controlling for the intervening factors such as size, volume, and MV/BV ratios.

The results of the study show that there is weak evidence of lead-lag relationship between large and small firms listed on the Indian stock market. This size-related lead-lag effect exists for medium and low volume firms, but does not exist for high volume firms. The lead-lag relationship between high and low volume firms is almost nonexistent for both size-volume and MV/BV-volume portfolios. Thus, size portfolios rather than volume portfolios exhibit relatively stronger lead-lag relationships between firms.

I find that the effect of lagged returns of large firms on the contemporaneous returns of small firms is significantly stronger than the effect of lagged returns of small firms on the contemporaneous returns of large firms for medium and low volume and MV/BV sorted categories. However, this result is not as strong as that of Chordia and Swaminathan (2000) for the U.S. markets. Using the Dimson beta regression to evaluate how fast different portfolios adjust to common market-wide information, I find that high volume portfolios respond to market-wide relevant information faster than low volume portfolios. This result is obtained for medium and low MV/BV sorted portfolios only, implying that high volume firms are more informationally efficient than low volume ones. This finding is consistent with the established theory that trading volume plays an important role in the speed of information adjustment into stock prices.

Since the lead-lag relationship on the Indian stock market is weak, it indicates reasonable efficiency for the market. The implication of this finding is that I cannot reject the conclusion that the Indian stock market is at least weak-form efficient from the lead-lag point of view. However, it is not possible to make any definite conclusions about the efficiency of the Indian stock market based on the evidence provided in this study. The non-existence of a strong lead-lag relationship may be due to the very nature of the Indian stock market. For example, the influence of institutional investors in the Indian stock market is much smaller than that found in developed markets such as the U.S. Moreover, unlike in the Indian market, large numbers of analysts follow stocks in developed markets.

In the Indian stock market, large and high volume firms get most of the attention from foreign and institutional domestic investors whereas the opposite happens for small and low volume firms. Although in the literature the lead-lag relationship talks about the relationship between different types of firms, e.g. size, volume, and MV/BV, it in fact examines the relationship between firms and their reactions to common market-wide information (Garcia et al., 2006). When new information comes to the market, the stock prices of large firms react to it rationally and faster, but small firms do not react to it in a similar fashion. This may happen because analysts and domestic institutional and foreign investors have more interest in large size or high volume firms. Moreover, large firm stocks are more frequently traded than small ones. This pricing process may cause firms to act independently of volume or size type, which may result in low or no lead-lag relationships. As such, the absence of lead-lag relationship might mean that one of the two firm types (large and small size or high and low volume) is mispriced, indicating the possibility of overall market inefficiency. Future research will be able to answer these issues.

CHAPTER FIVE

Summary, Conclusion, Recommendations, and Future Research

5.1 Summary

In three related essays, the dissertation examines behavioral finance issued related to the Indian stock market. Behavioral finance is a relatively new field that seeks to combine behavioral and cognitive psychological theory with conventional economics and finance to provide explanations for why people (investors) make irrational financial decisions. Investors either overreact or underreact to new information. This irrational behavior provides an opportunity for some investors to realize abnormal returns if they adopt appropriate trading strategies. In finance theory, the presence of abnormal returns suggests market inefficiency.

Essay one investigates the existence of contrarian or momentum profits in the Indian stock market, the relationship between such profits and duration of investment, and the effects of size (market value) and volume of trade on such profits. The major findings of this essay are: (i) In general, there are no observed momentum profits or return reversals on the Indian stock market in the medium- and long-term investment horizon and (ii) there are return reversals in the short-term investment horizon. That is, this month's winner (loser) portfolio consistently becomes loser (winner) portfolio in the next month. Thus, an investor could easily devise an investment strategy that would result in abnormal profit by changing the portfolio every month and holding it for one month.

Essay two focuses on the presence of contrarian or momentum profits, their sources, and robustness of results with regard to various risk factors and changes in the behavior of the sources of such profits over time since 1991. The results of this essay show that (i) there are contrarian profits in the short run, (ii) contrarian profits turn into momentum profits when portfolios are held for medium horizons of 6 to 12 months, (iii) mainly the small- and medium-size firms and low- and medium-volume of trade firms exhibit contrarian phenomena, (iv) firm-specific sources are the main component of contrarian profits, and finally (v) large (high volume of trade) firms are more correctly priced than medium and small (medium and low volume of trade) firms.

Essay three investigates the presence of lead-lag relationships between stock returns of firms categorized by size, volume of trade, and MV/BV in the Indian stock market. The study's main objective is to provide academicians, investors, and policymakers some insight on the lead-lag relationship between firms and the direction and speed of stock price adjustments to new information from a common factor on the Indian stock market. The results of this essay show that (i) there is weak evidence of lead-lag relationship between large and small firms, (ii) this size-related lead-lag effect exists for medium and low volume firms, but does not exist for high volume firms, (iv) lead-lag relationship between high and low volume firms is almost nonexistent for both size-volume and MV/BV-volume portfolios, and finally (v) high volume portfolios respond to market-wide relevant information faster than low volume portfolios.

5.2 Conclusion

Essay one finds that there are no momentum and contrarian profits on the Indian stock markets in the investment horizons of 3 to 24 months. Interestingly, there is evidence of short-term (one month) contrarian profits, which exists even after stocks are sorted by volume of trade and size. This suggests that investors may be able to make abnormal profits in the short investment horizon by forming appropriate strategies. This finding suggests that the market is not weak-form efficient.

Essay two finds that contrarian profits are related to firm attributes such as size and volume of trade. Findings also show that firms-specific component is the most important source of contrarian profits in the Indian stock market. Moreover, contrarian profits are present only for medium (medium volume of trade) and small (low volume of trade) size firms, but not for large size (high volume of trade) firms. The contribution of firm-specific component to contrarian profits has reduced to a large extent in the last six years of the study.

Essay three shows that there is weak evidence of lead-lag relationship between large and small firms in the Indian stock market. This size-related lead-lag effect exists for medium and low volume firms, but does not exist for high volume firms. Size portfolios rather than volume portfolios exhibit relatively stronger lead-lag relationships between firms. The effect of lagged returns of large firms on the contemporaneous returns of small firms is significantly stronger than the effect of lagged returns of small firms on the contemporaneous returns of large firms for medium and low volume and MV/BV sorted categories. I find that high volume portfolios respond to market-wide relevant information faster than low volume portfolios. This result is obtained for medium and low MV/BV sorted portfolios only, implying that high volume firms are more efficient than low volume ones.

5.3 Recommendations

The evidence of the presence of contrarian profits in the Indian stock market is the most important finding of the dissertation. The second most important finding is that contrarian profits are mainly the phenomenon of small (low volume) and medium size (medium volume) firms. The third most important finding is that unlike in the U.S. market, the lead-lag effect is not an important concern in the Indian stock market. These findings have important implications which I summarize below in the form of policy recommendations, which if implemented, will possibly make the market more efficient.

First, SEBI should be more vigilant in enforcing compliance for medium and small size and medium and low volume of trade firms (for example, strict rule for dividend declaration and distribution) because these stocks are the main source of abnormal returns. Second, regulators and policy makers may give incentives to domestic institutional and foreign investors to invest a significant portion of their portfolio in medium and small size and medium and low volume of trade firms. This way, the market will give more attention to these stocks, which will ultimately make these stocks more efficient. Third, SEBI may impose stricter disclosure rules so that investors feel more confident to rely on accounting numbers of these firms. This will also reduce the information asymmetry of the market. Specially, foreign investors will be motivated to invest in these stocks. Fourth, policy may be changed or formulated so that there are more incentives (for example, tax benefits) for the less-informed domestic investors to invest through institutions. This will make the market more homogeneous in terms of processing of available information.

5.4 Future Research

So far, the research on the behavioral issues on the Indian stock market is limited. The path set by this dissertation sheds some light on how future research may follow. Since high frequency data are available now, researchers may test behavioral models in very short-term investment horizons. There may be other intervening factors such as state of the market, which I have not considered. It is possible, for example, that contrarian profits found in this dissertation is an artifact of state (up or down) of the market. Contrarian profits may even be industry-specific. Future research may consider these factors. It is often argued that Indian market is highly related with the influx and exit of foreign investors. Researchers may devise models to account for such phenomenon, which will present a better picture of behavioral aspects in the market. Nonetheless, this market needs more research before academicians come to a solid conclusion on the impact of behavioral finance on this emerging market.

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