Testing Financial Market Anomalies in Karachi Stock Exchange

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In Partial fulfillment of the requirement for the degree of

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Dedication

To my Parents (Arshad Mehmood & Shaheen Kausar)

My Supervisor (Dr. Abdul Rashid)

&

My Siblings (Zeeshan, Arslan, Asma and Kainat)

Declaration

I hereby solemnly declare that all the literature presented in following dissertation is entirely based on research work carried out in defense of my thesis topic. This publication is pioneer in its context and has neither similarity to any previously submitted thesis nor any copied material in its contents from any source except where due reference is clearly mentioned. All of the published data is result of my own efforts, research and analysis with support of those mentioned in acknowledgement, in specific my supervisor. If at some later stage plagiarism is detected in the submitted research based literature, I will be fully responsible for all the consequences as per the prevailing rules and law of approval committee.

Saba Kausar

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Abstract

Market anomalies are one of the earliest identified challenges against market efficiency but to a large extent yet, remain unsolved. We have studied major three financial market anomalies, namely, the month anomaly, momentum anomaly, and equity premium puzzle in Pakistan Stock Market (PSX). The study uses simulation based KS type test of Barrett and Donald (2003) based on stochastic dominance approach using time period from January 2000 to December 2014. We test the month anomaly in all listed firms, KSE-100 Index as a proxy for PSX, and the beta based portfolios. We examine the January anomaly exists in both listed firms and KSE-100 Index returns. In order to investigate month anomaly, we have constructed monthly beta based portfolios, namely, Low-Beta, High-Beta, and Medium-Beta portfolios. We find that the January month outperforms in Low-Beta and High-Beta based portfolios and the December month dominates in Medium-Beta based portfolio. Indeed, the existence of the January and December effect give indication of another anomaly the turn-of-the-year effect in PSX. Tax loss selling hypothesis and small firm effect might be the main reasons for these results. We have also examined reverse equity premium puzzle in PSX. As our results suggest that 3-month Treasury bill rate stochastically dominates over the KSE-100 Index returns. Our results potentially reflect that insufficient compensation to investors for bearing the risk associated with volatility of stock market. Furthermore, the lack of depth and breadth of equity market can also be a possible explanation for the existence of reverse equity premium puzzle.

Additionally, we also find the momentum reversal effect in PSX that implies that the loser stocks outperform over the winner stocks and abnormal profit can be driven by adopting the contrarian strategy. Specifically, in order to test the momentum anomaly, we have constructed the winner and loser portfolios by using a 36 months holding period. Overall, the loser portfolio is stochastically dominates over the winner portfolio. Our results are endorsed that most people tend to "overreact" to unexpected and dramatic news events. Overall, the results confirm the presence of the financial market anomalies in PSX. These findings may have useful implications for trading strategies and investment decisions. Investors may look to gain from managing the risk of their portfolios due to time varying volatility documented. Furthermore, the results of this study have interesting implications for our understanding of abnormality in stock returns and volatility in the Pakistani Stock Market.

Key Words: Behavioral Finance, Stochastic dominance approach, Month anomaly, Momentum effect, Equity premium puzzle.

Chapter 1
Introduction

The core purpose of this thesis is to investigate three major financial market anomalies namely; month effect, momentum effect, and equity premium puzzle in Pakistan Stock Exchange (PSX), by using stochastic dominance (SD) Approach. The thesis also emphasizes existing empirical role on, some psychological and behavioral factors which drive these anomalies. The agenda of this chapter is to first present background of the study, problem statement, and the gap in the literature on financial market anomalies. Next, the chapter presents the objectives of the thesis. Finally, the chapter presents the significance of the study and the structure of the thesis.

1.1. Background

Efficient market hypothesis (EMH) is a back-breaker for forecasters. In its crudest form, it is stated stock returns which we likely to forecast are unforecastable. Millions of people around the world are associated with the trading activities of stocks. As, their bread and butter are associated with stock markets, so a lot of literature is available to identify the problems related to stock markets and their respective measures. The most complementary and important issue is that earning of average stock returns are now earning of abnormal returns. These abnormal returns show some trends/patterns that are believed as anomalies as they cannot be rationalized with the aid of one-factor Capital Asset Pricing Model (CAPM), which is proposed by Treynor (1961), Sharpe (1964), Lintner (1965), and Mossin (1966) independently.

In general, according to Lim and Brooks (2011), stock returns show some observable patterns that violate EMH. The EMH[1] explains that abnormal returns can't be earned by using information about past stock prices, all publically available information, trading rules based on fundamental analysis, and even insider information (Fama, 1970).

However, in the last few decades, several studies have been documented that EMH has been confronted and stock prices can be partially predictable. Hence, stock market is often behaving irrational way and follow some observable pattern/trend (Fama & French, 1992). Investors try to ascertain these stocks' trends and on the basis of their shrill analysis get abnormal returns, which creates falsification in financial market that called an anomaly.[2] Thus, market anomaly does lead to abnormal returns. It also indicates that fundamental analysis does have some worth for stockholders/investors (Flifel, 2012; Lim & Brooks, 2011; Shiller, 2006). Thaler (1999) contends that five areas, volume, dividends, volatility, equity premium puzzle, and predictability are the factors, in which behavior of stock prices seem most at adds with the theory of market efficiency.

From an investor's side, there are many psychological and behavioral aspects that may cause market inefficiency and mispricing of stocks. The list of these behavioral aspects is fairly large enough. However, the most well-known aspects include herding behavior, bubbles, and irrational exuberance in stock prices, and cognitive biases (Shiller, 2006; Smith, 2008; Statman, 2010). In the field of cognitive neuroscience,

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[1] Market efficiency has three forms. First weak-form efficiency is stated that investors can't earn abnormal returns by fostering trading rules based on historical stock prices. Second, semistrong-form of market efficiency, explains that no investor can earn abnormal returns with the help of publically available information. Third form stated that abnormal returns can't be earn by investor, using any information either publically available or not, is called strong-form of market efficiency, (Copeland, Weston, Shastri, & Education, 2005).

[2] Size effect, value effect, weekend effect, Monday effect, January effect, December effect, momentum effect and equity premium puzzle etc.

Sapra and Zak (2010) stated that there are major eight factors namely, anticipating rewards, balancing risk, following the herd, wait for it, the new new things, checking preferences, rational rationality, and portfolio love that explain behavioral aspects are significant in affecting the stock prices and investment decisions of investors. The financial theory related to random walk hypothesis states that past movements of stock prices can't be used in order to predict the future movements of stock prices. This is also consistent with the EMH. However, Dupernex (2007) has given arguments which are against random walk model. Specifically, he pointed out that due to the short-run and the long-run serial correlation, stock prices follow trends, rather than random walk. He also stated that mean reversion factors, seasonal trend, and size effect in stock prices can follow momentum patterns and in the long run, it would be reverse. Similarly, according to Fama (1998), under and overreaction behavior of investors exploit random walk pattern of stock prices.

Shiller (2006) stated that continues price increase, in the same direction leads to irrational exuberance. Specifically, he pointed out four main factors (precipitating, amplification, cultural, and psychological) that cause fluctuation in stock prices, conferring to bubble theories. The term irrational exuberance is referring to asset bubbles. In bubble theory, there are large overvaluations of assets which can persist for many years, but eventually burst, causing impulsive decrease before returning to rational stock prices. Amorously, Allen, Larson, and Sloan (2013) demonstrated that around extreme events, short sellers do alteration of their trading, in a way which supports price sighting.

Standard finance states that a rational investor is taking into account of all available information. He/she considers possible costs and benefits in decisive preferences and likelihoods of events and to act constantly in choosing the best optimal. On the flip, behavioral finance states that investors should not necessary are rational. Rather, they may overact or underact when new information is elevated in stock market. Therefore, due to such patterns or regularities in stock prices, investors may have an opportunity to get abnormal returns and thus, they cause anomalies.

Nowadays, financial market anomalies become striking for researcher as well as for investors. They can be analyzed that stock returns are to be systematically higher or lower. Further, in empirical finance, this phenomenon now has become paradox. Existence of financial market anomalies casts doubt on the validity of CAPM model. Hence, financial market anomalies challenge the belief in stock market efficiency as well. Although, there is a substantial work has been done, regarding financial market anomalies on developed stock markets. We need more empirical evidence from emerging and developing stock markets for full and in-depth understanding of the anomalies.

1.2. Problem Statement

Market anomalies are one of the earliest identified changes against market efficiency but to a large extend yet, remain unsolved. This rises that the anomalies are real or simply product of data snooping. Now, anomalies are observed consequences, which seem to be inconsistent with standard finance theories of asset-pricing behavior. They stipulate either inefficiency of market (profit opportunities) or shortfalls in the underlying asset-pricing model. Despite various studies in stock markets related to financial market anomalies, few researchers address this contemporary issue, in asset pricing contexts. Traditional asset pricing models like CAPM and three factor Fama-French model do not consider the behavioral biases of investor. As behavioral biases play an important role in investors' decisions, incorporating these biases into model

Ariss, Rezvanian, & Mehdian, 2011; Haugen & Jorion, 1996; Ke et al., 2014; Sum, 2013; Tangjitprom, 2011; Yuan & Gupta, 2014). There is no study conducted to test these three market anomalies (month effect, equity premium puzzle, and momentum effect) at the same time, on same dataset by using same methodology. Mostly, the studies are done to identify the determinants of stock returns using CAPM model, (Guo, Kassa, & Ferguson, 2014; Richardson & Tuna, 2014; Sun & Wang, 2014).

A handful of research is conducted to test market anomalies from the prospective of Pakistan (Ali & Akbar, 2009; Habib-Ur-Rahman & Mohsin, 2012; Khan & Khan, 2014; Zafar, Urooj, Chughtai, & Amjad, 2012). Furthermore, the previous studies on Pakistan have used fragile econometric techniques. Most of the studies used OLS dummy regression, ARIMA, ARCH, and GARCH models for testing anomalies in stock returns. The main drawbacks of these techniques are that they follow normal distribution assumption for the stock returns. However, the previous studies like, Rashid and Ahmad (2008) documented that increase in stock returns associated with increase in variance of returns (risk). Beedles (1979), Schwert (1991) scrutinized stock returns can be positively or negatively skewed.

Our study not only adds to the literature, about the market efficiency in Pakistan but also fill the gap in following aspects. First, according to our best knowledge, at international level, there is no study done about testing these anomalies at the same time, with same dataset, through stochastic dominance Approach (SD). There is very limited and insufficient work done on testing month and momentum effect (Iqbal, Kouser, & Azeem, 2013; Khan & Khan, 2014; Mohsin, 2012) and no study is done on equity premium puzzle in Pakistan. There is one of the first study which examine all three anomalies in one investigation on same data. Third, in Pakistan, no research has been conducted about testing these market anomalies using sophisticated econometrics techniques, like stochastic dominance Approach. The main advantage of the stochastic dominance approach is that it makes trivial assumptions about investor risk preference or the distribution of stock return. Also, SD rules contemplate the entire distribution of returns, not just the two parameter criteria, as in mean-variance analysis. Furthermore, we are analyzing all firms listed on Pakistan Stock Exchange and by considering longer period carry robustness to our research findings.

1.4. Objectives of the Study

Pakistan Stock Exchange is an emerging market. An investigation in the market anomalies can prove institutive and insightful. The main objective of the study is to identify the presence of financial market anomalies viz. month effect, equity premium puzzle, and momentum effect in Pakistan Stock Exchange. This objective is divided into following three sub-objectives.

1. To investigate the existence of month effect. Specifically, we aim to explore which month of the year dominates on the basis of stock returns.
2. To analysis the persistence of momentum effect and which momentum strategy is profitable in Pakistan Stock Exchange.
3. To compare the return patterns of KSE-100 Index and Treasury rate and using these two return series ascertain the existence of equity premium puzzle.

1.5. Significance of the Study

Due to steadily changings in the investment patterns of stockholders and participant expectations of investors vary extensively. Investors try to make economically beneficial strategies. In order to get more returns they are intended in investing/withdrawing on particular months, stocks or portfolios. According to EMH since, everyone has almost identical information in efficient market, it is hard to beat market and get abnormal returns. On the other hand, this market efficiency is analyzed in the light of the behavioral finance theories. In behavioral finance, there are psychological behavior and cognitive biases, which are very important for investors to comprehend their financial personalities. We can say that the attitude of stockholders/stakeholders is absolutely important to understand why they make sure financial choices or how they are probably to react in common state of uncertainty (Sapra & Zak, 2010). Behavioral finance suggests that an investor's decision is inclined in a large proportion by psychosomatic and emotive factors. These emotional factors include, satisfaction, fear, feelings, envy, euphoria, panic, anxiety, greed, ambition or vanity (Smith, 2008).

Apart from stock returns, there are other enticements (firm value, firm size, and selection biases) in which investors invest their desired stocks. Therefore, any inaccuracy in decisions of their investment would cause serious consciences. Past researches are publicized that stock returns are too much affected by financial market anomalies especially, calendar and fundamental anomalies. Such anomalies in stock returns are influenced by the investor's behavior. Therefore, there is need to investigate the causes as well as the effects on stock returns which help individual and portfolio managers to correctly identify stocks for their investment.

Examination of market anomalies has inquisitive implications for our understanding of the dynamics of volatility in financial markets. In inefficient markets, it is suggesting that arbitrage opportunities may exist; investors may look to gain from managing the risk of their portfolios due to time varying volatility and according to patterns/trends of stock returns.

Evidence on anomalies can also be helpful for such a way that if in stock markets there exist some patterns, then it seems unwise that investors trade against those trading patterns. So, investors can get advantage if they analyze correctly. This study helps local and foreign investors for their asset allocation through portfolio management and by analyzing these anomalies they may get abnormal profit as well. Pettengill, Sundaram, and Mathur (1995) are described that small cap stock with high beta do better perform as compared to large cap, from the context of stock returns. They grow faster. So, investment can be fruitful if investors take into consideration.

Evidence of the existence of stock market anomalies also helps to government as well as security regulations for implementation of their policies. They forbid insider and specialist to have access to private information. After detection of the market anomalies, companies would be well advised to follow rules of security exchange commission and give indication of anomalies in their financial reporting.

In precise, the knowledge of financial market anomalies is important for investors to maximize investment returns as well as for hedging purpose. Most but not all market anomalies are probably to generate abnormal profit. Even if abnormal profit is not possible, knowledge about market anomalies can helps the investor about mispricing and modify the timing of investment to avoid being hurt by it. This is the one basic initiative to probe the most important/significant financial market anomalies in Pakistan Stock Exchange namely; month effect, momentum effect, equity premium puzzle.

1.6. Thesis Outline

The objective of this chapter is to familiarize the topic of the thesis in the introduction section. It aims to shed light on the emphasis of the research; financial market anomalies and major three anomalies which, we have taken, month effect, equity premium puzzle, and momentum effect. Consequently, the research objective and gap are discussed. The rest of the thesis is organized as follows.

Chapter 2, Theoretical Framework, highlights the difference between standard and behavioral finance. Type of financial anomalies and considered anomalies (month effect, equity premium puzzle, and momentum effect) are described in details with their causes. These contextual details related to behavioral finance and market anomalies are needed to help the reader to understand the findings/results.

In Chapter 3, we provide a comprehensive review of the literature on the market anomalies. Empirically, we divide this chapter into three sub-sections. Section 3.1, presents the existing empirical literature on month anomaly. Section 3.2 and 3.3 review the previous existing studies on equity premium puzzle and momentum anomaly, respectively. Finally, we present summary of the literature review and explain how our study differ from the prior exertion and fill the gap on existing literature.

Details explanations of methodology and portfolios construction are given in Chapter 4, Empirical Framework. The chapter starts by describing stochastic dominance Approach (SD) and their orders of stochastic dominance. Then, the SD test is explained. Furthermore, to investigate month anomaly and momentum effect, procedure of portfolio construction is explained.

Chapter 5, presents our empirical results. This chapter is divided into three sub-sections. Each sub-section presents the empirical results related to each examined market anomaly. First sub-section we discuss our finding related to month anomaly. Second and third sub-section results of equity premium puzzle and momentum anomaly are presented.

The final chapter, Chapter 6, concludes the thesis. This chapter provides the main findings from our empirical analysis. Furthermore, it discusses the contributions to the study and policy implications. Finally, some suggestions for future research about capital market are also given in this chapter.

Chapter 2

Theoretical Framework

Approximately, three decades ago numerous respectable financial economists started to work in the field called "Behavioral Finance". Behavioral finance is basically, a moderate agnostic approach to examining the financial markets. It studies the effects of cognitive, emotional and psychological factors which, effect on economic decisions. The core issue in behavioral finance is that why investors make irrational decisions contrary to the assumption of rationality in an efficient market. This irrationality affects the stock prices and resulting market inefficiency. It also explores, that how market participants get advantage through abnormal returns (Thaler, 1999). Behavioral finance integrates insights from microeconomics, neuroscience, and psychology theory. Bounds of rationality are the main concerned in this area. The concept of bounded rationality is that an individual makes decisions based on the available information. Bounded rationality includes investor's submissiveness of the decision problems, cognitive limitations of his mind, and the limited amount of time, he has to make a decision (Sapra & Zak, 2010).

In behavioral finance, cognitive biases combines with standard finance give the ins and outs for why people make absurd investment choices. Cognitive biases include heuristics, market inefficiency, and faulty framing are three main aspects. Behavioral finance provides a link between an investor's psychology and finance. Unlike, from neoclassical finance theory, in behavioral finance there are impediments in investor's decision process, which leads anomalies (De Bondt, Muradoglu, Shefrin, & Staikouras, 2008). Following are the foremost incongruity between standard and behavioral finance.

2.1. Standard Finance Paradigm and its Imperfections

Standard finance introduced in the late 1950s and early 1960s. It was preceded by behavioral finance, beginning in the early 1980s. Standard finance provides four building blocks about capital market.

1. Investors are rational.
2. Market is efficient.
3. Investors take decision on the basis of mean variance portfolio theory.
4. Risk is the only factor that determines stock returns.

Standard finance is peopled by rational investors. They prefer more wealth over less and not tangled by the form of wealth. Efficient market states that stock price is always equal to its fundamental price and investors make their decision of investment based on two-parameter criteria risk and return only. For determination of stock returns, one-factor (CAPM) and three-factor models (Fama and French model) are used.

2.2. Behavioral Finance Theory

Preceding four paradigms are rejected when behavioral finance emanates to begin. From the context of overhead given building blocks, Statman (2010) presented four alternative blocks in behavioral finance. He argued that,

1. Investors are not rational rather, they are normal.
2. Market is inefficient.

3. Investors make investment decisions on the basis of mental accounting portfolio theory.
4. In market, book-to-market, market cap and cognitive biases are the factors which determine the stock returns.

Behavioral finance is peopled by normal investors and they are confused by the form of wealth and affected by biases such as emotions and cognitive biases. They sometimes, want more prestige and social responsibility over wealth. Contrary to the argument of efficient market, stock prices regularly deviate from their fundamental prices. For making investment decisions, investors divide their money into mantel accounting layers of portfolio (Statman, 2010).

2.2.1. Stock Price Determination in Behavioral Finance

According to the standard finance, investors make their investments decisions rationally. They are making logically sound decisions, without doing any error in investment. Behavioral finance's supporter Thaler (1999) argued that mispricing in asset prices are due to cognitive biases. He stated that asset prices are set by marginal investors; as the role of individual investors can't be denied. However, in standard finance, we assume that the marginal investor is well-diversified and only the non-diversifiable risk matters. By considering institution investor, as marginal investor, then this assumption is likely to be true. On the other hand, if the marginal investor is the insider then, this assumption may be dangerous as most insiders are not well-diversified.

Fama (1970) argued that standard finance theory stated that efficient market reflects all relevant information for stock prices. In standard finance, the strong assumption is that investor quickly reacts about investment decisions. The stock prices are determined by simply interaction of demand and supply curves.

Figure 1: Standard Finance Theory of EMH

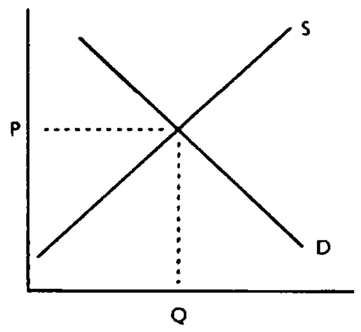
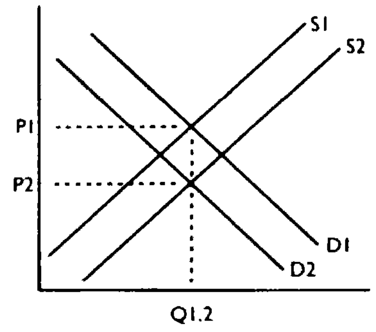


Figure 2: Behavioral Finance Approach



Note: Reported from (Smith, 2008)

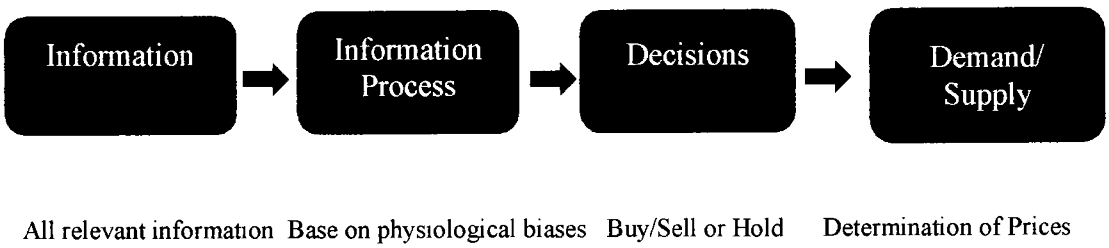
Type of information available   Sell/Buy or hold   Determination of Stock Prices

In behavioral finance, prices determination process is different from above scenario. According to behavioral finance, investment decisions are affected by many psychological biases. These are hindsight biases[3] and faulty framing[4] etc. due to these impediments in processing of information effect investor's decisions. The determined market price in behavioral finance, could be different from that price

[3] A psychological bias, in which past events seem to be more prominent than they appeared while they were occurring. Hindsight bias can lead an individual to believe that an event was more predictable than it actually was, and can result in an oversimplification in cause and effect.

[4] Faulty Framing bias refers to the inclination of decision maker to be influenced by the way that the situation is presented. For example, it is easier for purchaser, to get discount as opposed to have surcharged with the same amount.

which investor may perceive through traditional finance (Roese & Vohs, 2012; Tversky & Kahneman, 1986).



Note: Reported from (Smith, 2008)

A stock price is determined in above diagram, from the context of behavioral fiancé. Extra block is appeared to show those cognitive and physiological biases through which investor's decisions are affected while doing investment decisions (Smith, 2008)

2.3. Types of Financial Market Anomalies

Investment behavior is one of the most complex financial market phenomenon that has highlighted in recent research. As generally, impact of fluctuation of stock prices, on individual and institutional investors differently, similarly, domestic and foreign investors may respond differently in stock market due to behavioral biases (cognitive, hindsight etc.). Such behavioral biases carry popularity in market anomalies.

Some anomalies accrued at once. Others happen often to frustrate the investor, while some other accrued frequently on specific pattern. The important thing is that whether to get abnormal profit by exploitation of anomalies could be worthwhile or not (Tversky & Kahneman, 1986). For the sake of convenience market anomalies are divided into three types as specified by Latif, Arshad, Fatima, and Farooq (2012).

1. Calendar or Seasonal Anomaly
2. Fundamental Anomaly
3. Technical Anomaly

2.3.1. Calendar Anomaly

In calendar anomaly, existence of particular time period is involved in stock returns like daily, monthly, yearly etc. Examples of calendar anomalies are month effect, (turn of month effect, turn of the week effect, weekend effect, January effect, and February effect), turn of year effect etc. (Angelovska, 2014; Annuar, 1987; Haug & Hirschey, 2006; Haugen & Jorion, 1996; Ke et al., 2014; Lean, Smyth, & Wong, 2007; Lee, Hsu, & Ke, 2013; Li & Gong, 2015; Tangjitprom, 2011). In month effect, specific month, week, or day is dominated like January effect is may be due to large liquidity or it may be tax treatment, window dressing, and inventory adjustment by institutions and pension funds, on previous year (Agrawal & Tandon, 1994). Latif et al. (2012) pointed out that mantle behavior of investors causing turn of month effect, at the end of month they sell and repurchase at the start of new month. Abbas and Javid (2015) found significant day of the week effect in major four SAARC countries, Pakistan, India, Bangladesh and Sri Lanka due to investors overreaction and underraction on the specific day of the week.

2.3.2. Technical Anomaly

In technical analysis, we use different econometric techniques to predict future stock prices on the basis of past information and prices for example moving averages, trading range break etc. Through moving averages, investor can get abnormal return through signals of stock prices. For example, buying stocks when short period averages raise over long period averages, and selling of share when, short averages fall below the long period averages. Trading range break analysis is based on support and resistance level. When the stock prices reach at resistance level, then buying signal is created. A selling signal is created when, prices reach the support level which is the minimum price level of given stock (Brock, Lakonishok, & LeBaron, 1992)

2.3.3. Fundamental Anomaly

Such types of anomalies are related to fundamental value of stock price. It includes value anomaly, low price to earnings, low price to book ratio, and high dividend yield, low price to earnings ratio (P/E) and neglected stocks (momentum effect) etc. Momentum effect and equity premium puzzle are included in this type. Value anomaly happens due to false prognostication of investors. Investor overestimates future growth stocks but actual future growth is less as compared to that they perceived (Lakonishok, Shleifer, & Vishny, 1994). Extremely low P/E ratio (lowest docile) earns larger risk-adjusted returns than high P/E stock. Causes of low price to earnings ratio are that mostly, such companies are undervalued, so due to hedging these companies have risk adjusted returns. Overreaction behavior of investors is mainly due to disposition effect (Bondt & Thaler, 1985).

On the basis of time pattern, financial market anomalies are divided into following two categories. Time series anomalies and cross sectional anomalies. Time series anomalies mostly include calendar anomalies and some fundamental type of anomalies. In time series anomalies, stock returns encompass a usual chronological ordering. This quality makes time series anomalies discrete from cross-sectional anomalies. These anomalies generally include daily, weekly, monthly effect, turn of year, earning to price ratio, book to price, momentum, equity premium effect, etc. Cross section anomalies, include mostly technical type of anomalies that don't have similarity like calendar or specific time pattern rather their occurrence mostly depends on characteristics of stocks for example, low cap stocks, high beta stock etc. (Keim, 1983).

2.4. Other Financial Market Anomalies

Despite of above major categories of financial market anomalies following are other market anomalies. Presence of these anomalies in stock market are not has to be neglected. These anomalies include, accrual anomaly, effect of new announcement on stock prices, neglect firms effect, insider trading effect, disposition effect, value effect, size effect, survivorship biases, Ramzan effect, Muharram effect, data mining, data snooping, weather anomaly, event month effect, problem with the validation of asset pricing models, etc.

2.5. Major Financial Market Anomalies

Among different anomalies, we are taking major three market anomalies. Specifically we take month effect from calendar anomaly, and momentum and equity premium puzzle from fundamental anomaly. These major anomalies play crucial role for getting abnormal profit in stock markets. Analysis of these anomalies, for a country such as Pakistan, may offer interesting intuitions. Findings from Pakistan may be different from the findings which have been documented for developed countries. Below we discuss these anomalies in details. This would provide contextual details against which the findings of the current thesis can be assessed.

1. Month Effect
2. Momentum Effect
3. Equity Premium Puzzle

2.5.1. Month Effect

The month effect has been revealed to be a tenacious anomaly in both developed and emerging markets throughout the world. Researchers have renowned that the returns in some months are higher than in others. Although there is a great covenant of support for presence of a monthly pattern/trend, the international evidence is mixed about which month effect is contemporaneous. Different researchers have obtained different outcome while studying various time periods and using different models of expected returns. In calendar anomalies, first anomaly is discovered by Wachtel (1942) that was January effect. Specifically, he observed that strong tendencies exist in stock prices during 1924 to 1939 for US Stock Market. Regarding month effect, mix results have been documented in the empirical literature.

Annuar (1987) stated that January effect, whereas, Wang and Hefner (2014) found that April effect is dominated in US stock market. On the other hand, January effect is dominated also in Asian markets (Lean et al., 2007). Ke et al. (2014) provided evidence on the existing of February effect in Taiwan Stock Market. On the flip side, in GCC[5] (Golf Corporation Council) countries, December effect is discovered, instead of January or February effect (Ariss et al., 2011).

The major causes that lead month effect are yet not known completely. However, some academics have tried to sort out this intricacy. For example, Alagidede (2013) pointed out that January effect may be due to liquidity constraint, tax loss selling pressure, and other omitted risk factors. Fama and French (1993) pointed out that window dressing, book to market, and momentum factors are major reasons for month effect. Similarly, Wang and Hefner (2014) indicated that returns of event months[6] are higher due to annual general meetings. Festivals, portfolio rebalancing, inventory adjustment of traders, and role of exchange specialists are also considered as significant drivers of month effect anomaly.

2.5.2. Equity Premium Puzzle

Equity premium puzzle is discovered by Mehra and Prescott (1985). They found that over the period of 1889 to 1978, there is large difference in equity stock returns and risk free rate of returns in US Equity Market. Equity premium puzzle is also known as equity risk premium, market risk premium, and risk premium. This term "equity premium" is used for four different concepts for example, historical equity premium, expected equity premium, required equity premium, and implied equity premium. In this research, we use historical equity premium which is calculated through historical stock prices and risk free rate.

[5] There are six Middle East countries in GCC, Saudi Arabia, Kuwait, the United Arab Emirates, Oman, Bahrain and Qatar.
[6] Event months are those months which are before that month in which AGM held.

1. Explanation of Equity Premium Puzzle through Traditional Economic Aspect

Constantinides (1990) demonstrated that habit persistence is affected to equity premium. Because investors are more subtle to short term variation in consumption level therefore, demand high premium. Similarly, Campbell and J. Y. Campbell, & Cochrane, J. H. (1999) found equity premium puzzle for US Stock Market. He figured out that one of the major reason for higher premium demanded from investors' side, is frequent premium puzzle or bad performance of stock prices in recession. Survivorship bias is another reason for frequent premium puzzle, which was given by Brown, Goetzmann, and Ross (1995).

2. Explanation of Equity Premium Puzzle through Behavioral Economic Aspect

Benartzi and Thaler (1993) investigated causes of equity premium puzzle (EPP) in behavioral aspect. They have documented that, myopic loss aversion combines with loss aversion, affect more to investors. Thus, Investor has to demand high premium to recompense this unevenness. They have tested whether EPP is caused by myopic loss aversion and concluded that investors are short-sighted and myopic risk averse. Another, study by Ang, Bekaert, and Liu (2005) supported the arguments of Benartzi and Thaler (1993) that sometime, investors do not invest even if premium is high. Because their expectations are more than that they perceived due to disappointment aversion. Ambiguity aversion is another evidence to reveal EPP. Investors are ambiguous about profit distribution. As a consequence, in order to compensate this ambiguity, they demand higher returns (Olsen & Troughton, 2000).

2.5.3. Momentum Anomaly

Momentum anomaly is basically found by Jegadeesh and Titman (1993). Momentum effect is a phenomenon which articulates that the pattern of returns was strongly going in the past will be probably a chance to continue in the near future. For example, those stocks which perform well in past 3 to 12 months tend to perform well in the near future as well.

Studies conducted on both in developed and emerging stock markets quantify that momentum effect works more in small cap stocks as compared to large cap. In momentum effect, different profitable strategies are considered like, 3month, 6month, 9month, 1year, 3years. Among different contrarian strategies, 6month strategy is more beneficial as compared to others (Jegadeesh & Titman, 1993). Fundamental reasons for momentum anomaly are behavioral biases like under-reaction and overreaction, investment styles, contrarian strategies, herding behavior, etc. Investors' sentiments are major reasons on stock market turnover rate and cause short-term momentum. This is due to irrational trading behavior of investors. Habib-Ur-Rahman and Mohsin (2012) are found weak but significant momentum effect in Pakistan Stock Exchange. Doukas and McKnight (2005) check momentum effect in 13 European stock markets. They have stated that momentum effect is due to gradual diffusion of private information and psychological conservatism.

Table 2.1: Anomalies and Descriptions

Anomalies	Descriptions	Articles
Month Anomaly		
January Effect	The phenomenon, in which stock returns are high, in first 2, 3 weeks of January.	(Annuar, 1987; Haug & Hirschey, 2006; Haugen & Jorion, 1996; Keim, 1983; Lean et al., 2007; Wachtel, 1942; H. B. Wang, 2011)
February Effect	Due to spring festival money movement stock returns are outperform in the month of February.	(Ke et al., 2014)
April Effect	The stock prices are likely, to increase in the month of April due to Ann ual general meetings.	(Wang & Hefner, 2014)
December Effect	During the last weeks of December, stock returns are high.	(Ariss et al., 2011; Tangjitprom, 2011)
Equity Premium Puzzle		
Positive EPP	EPP refers to the phenomenon, that the stock returns over the past century, are higher than on government bonds.	(Damodaran, 2011; Donadelli & Persha, 2014; Mehra, 2003; Mehra & Prescott, 1985; Neely, Rapach, Tu, & Zhou, 2014; Salomons & Grootveld, 2003; Siegel, 1992)
Reverse EPP	Returns of government bonds are high than stock returns.	(Jagannathan, McGrattan, & Scherbina, 2001; Lim, Maasoumi, & Martin, 2006; Zafar et al., 2012)
Momentum Anomaly		
Momentum effect	Past winner stocks continous to become winner. This tactic looks to capture gains by riding hot stocks and selling cold stocks. This is due to underreaction effect.	(Abraham, 2014; Asness, Moskowitz, & Pedersen, 2013; Birru, 2015; Doukas & McKnight, 2005; Fong, Wong, & Lean, 2005; Hon & Tonks, 2003; Jegadeesh & Titman, 2001; Mohsin, 2012; Sakr, Ragheb, Ragab, & Abdou, 2014; Siganos, 2013)
Momentum reversal effect	Past loser stocks generate positve and high returns as compared to winner . This is due to overreaction effect	(Antoniou, Galariotis, & Spyrou, 2011; Bondt & Thaler, 1985; Wang, Burton, & Power, 2004)

Chapter 3

Literature Review

This chapter reviews the previous empirical studies on market anomalies. A number of researches have scrutinized, whether the EMH hold by applying both statistical and non-statistical tests. Specifically, they have investigated whether stock prices changes are independent that is whether stock prices changes are unpredictable on the basis of historic information. More recent evidence has terrified several abnormalities known as market "anomalies", which cast doubt on efficient market theory, (Jensen, 1978). Whereas, early discoveries were compassionate the hypothesis of market efficiency (Kendall & Hill, 1953).

The focus of this thesis is on three well-known market anomalies, namely, month effect, momentum effect, and equity premium puzzle. The existing empirical evidence suggests that for different stock markets different months dominate. Similarly, the existing empirical findings on momentum effect are also mix at the best. Some studies have provided evidence of the existence of momentum effect, while the other have been failed to suggest the momentum effect phenomenon. According to momentum effect, stock prices depicts observed tendency; rising stock prices rise further, while falling stock prices keep falling further. The third anomaly that we explore in this thesis, equity premium puzzle (EPP) refers to the phenomenon that observed stock returns are high than returns on government bonds. The existing empirical studies on EPP have also provided mix results.

Many academic investigators have focused on these anomalies when investigating the EMH. However, most of the researchers have tested these anomalies for developed countries. Little attention has been given about the presence of these anomalies for developing stock markets. Literature review is divided into three portions according to three considered anomalies.

3.1. Empirical Evidence on Month Anomaly

When we review the empirical literature, we find that several researches have attempted to examine month anomaly in stock markets. They use different terms for it. For example, it is termed as month effect, calendar effect, seasonal effect, turn-of-month effect, event-month effect, or lunar month effect. Researchers have documented different psychological and methodical justification, for observing abnormal returns for some specific month(s).

The previous empirical studies related to month anomaly give mingling results. For example, in some countries, January effect is dominated like, in Japanese Stock Market (Li & Gong, 2015), Egypt, Nigeria, and Zimbabwe Stock Market (Alagidede, 2013), Thailand Stock Market (Tangjitprom, 2011), Singapore Stock Market (Lean et al., 2007), US stock market (Annuar, 1987; Haugen & Jorion, 1996). However, in some other countries, other months are dominated. For example, February is dominated in Taiwan Stock Market (Ke et al., 2014), April is dominated in US stock market (Wang & Hefner, 2014), stock returns are high in the month of August in Macedonian Stock Market (Angelovska, 2014), in Thailand and GCC countries, investors are likely to observe high returns in December (Ariss et al., 2011; Tangjitprom, 2011).

Gu (2015) has found June phenomenon and month-of-year effect in US stock indexes, DJIA, NASDAQ, and S&P 500, from 2001 - 2013 by using *t*-statistics. He identified that April returns are high in S&P 500 and DJIA while, the returns are high in October in case of NASDAQ. He also pointed out that June is the worst month in US stock market. He states that window dressing, tax-loss selling can justify good performance in April, and poor performance of stock returns in the month of June. Li and Gong (2015) have discovered January effect in Japanese Stock Market. They used GARCH model in order to examine the January effect and stated that during the period of 1975 - 1984, January effect is more evident. However, they have also documented that during the 1990s, January effect has been declined. They gave the rationalization of January effect is that high stock volatility in January is not only the cause rather January effect, is due to risk compensation in January can explained high returns in January.

Ke et al. (2014) explores February month outperforms as compared to other months in Taiwan Stock Exchange. They have used stochastic dominance Approach (SD) by taking monthly for the period 1980 - 2009. Linton, Mausaomi, and Whang test (LMW test) is used to check the stochastic dominance relationship among various portfolios and months returns. They made the portfolios based on market capitalization and concluded that small cap stock returns dominate as compared to large cap stock. Among small cap stocks returns of February months dominate. They explained that spring festival money movement hypothesis is the main reason to explain the findings of February effect.

In the US stock market, discovered a new anomaly by Wang and Hefner (2014). They take S&P 1500 firm's shareholders annual general meetings for the period 1992 - 2012 and scrutinize that event months are dominated and returns of these months are high. Prior 40 days to AGM stock prices begin to increase upward and due to such upward trend of stock prices, result large return around April. They have shown that returns of the month of April are outperformed as compared to other months. Annual General Meetings (AGM) are the main reasons of April dominancy.

years' time for the period 1992 - 2011. They reveal that, there is negative Monday and positive Friday effect, significant half-month effect, and turn-of-the-month and the Month-of-the-Year effect, and the Ramadan effect in Pakistan Stock Exchange. They have observed positive stock returns in the month of December. So, in the light of these findings we may conclude that Pakistan Stock Exchange is having anomalous behavior regarding stock prices.

Ariss et al. (2011) find very interesting results for GCC indices (Gulf Cooperation Council). They used the daily closing values of all GCC market indices from inception until June 2008. They study on calendar anomaly, day-of-the-week effect and month effect by using OLS technique. They explore that in GCC countries there is Wednesday effect exist and positive, high, and significant returns are obtained in the month of December. Therefore, there is tenacious of December effect and Wednesday effect in GCC countries.

Ali and Akbar (2009) are conducted the research on calendar anomaly in Pakistan Stock Market. Under calendar anomaly, they use auto-regressive modeling to test daily, weekly and month effect by using data from November 1991 through October 2006. The study concludes that there is no weekly and monthly effect in Pakistan Stock Exchange. However, there is daily effect exist where the fourth and fifth days of a week show higher stock returns. The existence of daily effect endangers the assumption of EMH and concludes that in short-run, Pakistan Stock Exchange market is inefficient.

Another study related to month effect, which is chaperoned on Thailand Stock Market. The stock returns are calculated from SET index from time the time 1988 - 2009 by using GARCH model. Stock returns are high in the first week of January and last week of December, which further leads turn-of-the-year effect although, there is existence of calendar anomaly, but people may not be able to exploit this opportunity, to make abnormal profit because of high transaction cost, (roundtrip commission fees and average bid-ask spread), (Tangjitprom, 2011).

Moreover, Haugen and Jorion (1996) show the existence of January effect in New York Stock Market for the period 1926 – 1993 using OLS regression. January effect is due to the year-end disturbance in the prices of small stocks. It is doubtfully the most renowned of the many stock market anomalies discovered during the past two decades. Evidence directs, however, that the January effect is still going strong 17 years after its detection. Because the anomaly can be inexpensively oppressed, its persistence has implications for the theory of efficient markets.

On the other hand, Wong, Neoh, Lee, and Thong (1990) examine calendar anomaly in Malaysia Stock Market. This study scrutinizes the presence of seasonality in the Gregorian, Chinese and Muslim calendars months. Monthly returns are considered and calculated according to different kinds of calendar. Evidence in support of seasonality is present in Malaysia. The main findings are January effect, Chinese New Year effect, and an Aidilfitri effect. Chinese New Year and January effect is more significant as compared to the Muslim calendar effect. Both economic and non-economic reasons are suggested for the existence of these types of seasonality.

Like Gregorian months, some Islamic months are also dominated as compared to other Islamic months. Mustafa (2011) identified strong Ramadan effect and weak Muharrum effect in Pakistan Stock Exchange. He used OLS technique by using daily data for the period 1991-2010. He has incorporated five regression models including unconditional risk factor and conditional risk factor and institute that Pakistan Stock Exchange is relatively risky in the month of Ramadan.

3.2. Empirical Evidence on Equity Premium Puzzle Anomaly

Equity premium puzzle (EPP) appears to be evidence in stock return patterns for developed as well as embryonic stock markets. Donadelli and Persha (2014) examined EPP in Asian, East European, and Latin American stock markets. Over the time, the difference between share returns and risk free rate is increasing in US stock markets (Mehra, 2003; Neely et al., 2014; Siegel, 1992). EPP also inspected in developed market, G7 countries and emerging markets Asian, Africa and Middle East, Eastern Europe, and Latin America by Salomons and Grootveld (2003). On the contrary, there is revers puzzle is examined in S&P500 by Lim et al. (2006). Following literature exhibits the divergent patterns of EPP.

Donadelli and Persha (2014) have investigated EPP. They imply DCC-GARCH by using industrial level data of 19 countries data period from 1995 - 2012. In Asian Stock Market basic material and healthcare industries mostly paid to extra premium. On the contrary, in East European and Latin American Stock Markets utilities and consumer services industries contributed extra premium but the key reason for this phenomenon remains blur. They grasp on an interesting results first, EPP is higher in emerging stock markets than developed one.

Neely et al. (2014) use technical and macroeconomic variable in order to forecast US equity risk premium. PC-ECON model is used for time period 1950-2011, and results suggest that technical indicator worked better in order to detect the EPP. Typically, EPP when, decline in near throngs (business-cycle peaks) on par with that of macroeconomic variables, which are typically well-known in literature.

Damodaran (2011) examine the presence of EPP in different countries and highlight the issue related to the existence of country risk premium. Survey approach is used to assess the risk premium from investors and managers for the period annual 1926-

and Grootveld (2003). Equity risk premium is higher in emerging markets[7] as compared to developed markets[8]. Monthly total returns dominated in US$ from January 1976 to December 2001 is considered by using *z* and *t*-statistics. They have explained that structural and cyclical factors are driving forces, for equity risk premium and conclude that equity risk premium fallow cyclical pattern so that's why it is higher in emerging markets from the time period they are assumed.

Jagannathan et al. (2001) have observed fascinating result that over the passage of time equity premium is decreasing. They examine the trend of equity premium by considering three indexes BOG[9], S&P500[10] and CRSP[11] stock portfolios. They consider time period from 1926 to 1999 and calculated equity premium by using formulas in classic Gordon stock valuation model. They point out that during 1980s equity premium is negative, but after 1990s it closes to zero for two stock portfolios S&P500 and CRSP. In short, last three decades there is an evidence of reduction of equity premium and from 1926 to 1970, average premium was 7% but after that it was only 0.7%.

Siegel (1992) has found the EPP in US stock market by taking 1802 to 1990 time period. Stocks have provided higher returns as compared to fixed income investment, Treasury bond etc. In order to check the trend of equity returns, he has calculated the total return, capital appreciation, nominal capital appreciation, and real capital appreciation. He has presented that the magnitude of excess returns on equity has

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[7] Emerging markets include Asia, India, Indonesia, Korea, China, Malaysia, Pakistan, Philippines, Thailand, Taiwan, Argentina, Brazil, Chile, Latin America, Colombia, Mexico, Peru, , Africa, Middle East, Venezuela, Egypt, Israel, Eastern Europe, Czech Republic, Hungary, , South Africa, Poland, Turkey and Russia,.

[8] Developed markets include G7, Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States.

[9] BOG: Stocks which are held by residents of US, according to Board of Governors of the Federal Reserve System.

[10] S&P: Standard and Poor's composite index.

[11] CRSP: This value weighted index is constructed by center for research in security prices.

been dramatically increased as compared to fixed income asset like Treasury bill rate. But still, investment in equity is the best way for wealth accumulation in long run.

3.3. Empirical Evidence Related on Momentum Anomaly

Several studies give evidences of momentum anomaly, on the basis of relationship between momentum profit and characteristic of stocks, (Jegadeesh & Titman, 1993). On the other hand, many behavioral aspects are given for explanations of momentum anomaly. For example, Birru (2015) found momentum anomaly in US market, due to disposition effect. Asness et al. (2013) inspected positive momentum effect in four diverse markets, (The USA, UK, Japan, and The Europe) due to liquidity risk factor. Dhankar and Maheshwari (2015) and Bondt and Thaler (1985) examined contrarian strategy (negative momentum) in Indian Stock Market and US stock market, respectively, due to underreaction effect.

Birru (2015) examine momentum effect, NYSE and AMEX stock splits sample period 1967 – 2011 by using Fama-MacBeth weekly cross-sectional regressions. A number of behavioral theories are given to explain the momentum effect for last fifteen years but the disposition effect is the most intense behavioral aspect to explain momentum effect. Although disposition effect is not only the factor which cause stock splits but still can't deny the disposition effect which plays an important role in driving the momentum effect.

Dhankar and Maheshwari (2015) find the existence of momentum and momentum reversal effect in Indian Stock Market. They have followed Jegadeesh and Titman (1993) for momentum and Bondt and Thaler (1985) for contrarian strategies. They have used monthly stock prices traded on National Stock Exchange period from January 1997 to March 2013. Their findings are documented that the existence of statistically significant the short-term momentum and the long-term overreaction effect in India. The study also appraises that the predictions of several behavioral models that suggest, momentum profit eventually reversed in long-term.

Another study related to momentum and momentum reversal effect is done on Egyptian Stock Market (ESM) by Hassan (2014). He make loser and winner portfolios based on cumulative average return for 1month, 3month, 12month, 48month formation period sampled period cover 2000 to 2013 and examined short run momentum effect and log run momentum reversal effect exist in ESM. This implies in short run winner portfolio continued to be the winner over loser portfolio due to underreaction effect. On the other hand, mean reversion pattern or momentum reversal effect exist in long term holding period.

Research is conducted to investigate whether disposition effect drive the momentum anomaly in Egypt Stock Market. They have used the Fama Mecbeth cross sectional regression using the sample period of 48 companies of Egypt, time period from 2004 – 2010. There is no significant momentum anomaly exist. The foremost reason is that retail investors are dominated than institutional investors. Egypt Stock Exchange faces a considerable lack of different trading mechanisms like short selling etc. (Sakr, Ragheb, Ragab, & Abdou, 2014).

Abraham (2014) investigates momentum anomaly between Australian Resource Stock and Chinese Shanghai Composite Index. Partial Adjustment Model is used for data sample contains of weekly, 533 and 33 observations from January 2003 through March 2013 of the Chinese Shanghai Composite Index and Australian Resource stocks, respectively. He customs two momentum strategies Enhanced Indexing, and Index Tracking. He clinches that existence of momentum anomaly in small cap stock and index strategy is more profitable as compared to second.

compound returns of 24 countries and claimed that in each strategy, winner portfolios are stochastically dominate at second and third order.

Wang et al. (2004) investigate momentum in stock returns through overreaction effect in Chinese stock market (Shenzhen and Shanghai). This study reports that the results for a sample of more than 300 Chinese shares over a six-year period beginning in August 1994 by testing overreaction hypothesis. They check the momentum effect in loser and winner stock of domestic-own A shares and foreign-own stocks B shares, in China. They discover overreaction effect is more distinct in domestic-own stock. Contrarian strategy (buying loser and selling winner stocks) is beneficial and loser stocks have high and positive returns as compared to winner.

Richards (1997) find winner-loser reversals in 16 countries for time period 1970 to 1995, using contrarian strategy. No signals are found that loser portfolio is more risky than winner. At horizons of more than one year, loser portfolio outperform than winner portfolio. For 3 and 4 year time horizons show the highest returns strategy in buying losers and selling winner stocks.

Jegadeesh and Titman (1993) are the first to analyze the momentum effect and found the momentum anomaly in US stock market. In order to examine momentum effect, by taking sample period from 1965 to 1989. Different strategies are made like, 3months, 4months, 6months, 8months, 12months, and 16months; portfolios are constructed based on *J*-month lagged returns and held for *K* months. They inspected that 6months strategy outperformed as compared to other strategies. These strategies are based on transaction intensive.

Jegadeesh and Titman (2001) examined the momentum anomaly by sample taking all stock traded on New York Stock Exchange, and reported that momentum is due to delayed overreaction and these are ultimately reversed and momentum profit

(Winner-Loser) is negative. Chui, Wei, and Titman (2000) discover momentum effect in Asian Stock Market from 1976 to 2000 and made 6-6 month strategy reported that very low momentum effect in Asian Markets (only in Hong Kong) and a strong reversal effect is observed.

Bondt and Thaler (1985) have analyzed the overreaction effect due to news events. Their study about market inefficiency shows that investors overreact to unexpected or dramatic news for the time period 1932 - 1980. Results based on CRSP monthly returns, are according to overreaction hypothesis and found that loser portfolios have greater returns as compared to winner portfolios. Another interesting result which further point outs January phenomenon in loser stocks have large abnormal returns in January while, comparing with remaining calendar months.

3.4. Conclusion of Literature Review

This chapter is documented the prior studies about considered market anomalies which lead inefficiency in developed and emerging stock markets. In general, there is extensively less analysis on these anomalies on emerging markets like Pakistan specially, momentums effect and EPP anomaly. Mostly studies are conducted to test the calendar anomalies and plaid overall behavior of stock returns, by considering mostly manufacturing firms and market indexes.

Evidences from prior studies about these anomalies, convey conflicting results. The existence of abnormal returns suggesting there are patterns/trends exist in stock prices. Several researchers have documented different findings. Probable reasons for these different outcomes may be different time span and usage of different empirical models. Current thesis fills the following gaps about these market anomalies. In our research, we examine portfolio vice, behavior of stock returns by testing a large number of firms and investigating a longer period of share price data on Pakistan Stock Exchange, would be a valuable study and fill the gap on existing literature related to this concern. Our study also fills the gap highlighted in methodology side. Prior studies on Pakistan Stock Exchange had used fragile and imperfect statistical analysis to ascertain the market anomalies and stock return irregularities. Therefore, current study extends the existing literature in the methodology side by using stochastic dominance approach and adds to our acquaintance about stock market and its anomalies.

Chapter 4

Empirical Framework

4.1. Introduction

In this chapter, we present empirical framework. Specifically, we first present our baseline model "stochastic dominance" to examine the financial market anomalies in explaining the market inefficiency in Pakistan Stock Exchange. We then, explain stochastic dominance test of Barrett and Donald (2003). In order to examine month and momentum anomaly, we have constructed portfolios based on "Ranked beta" and "Winner and Loser" portfolios, respectively. After that data presentation and its sample characteristics are presented. Developments of hypotheses are given at the last of Chapter.

4.2. Stochastic Dominance Approach

For the past two decades, the standard finance literature has been subjugated by mean variance portfolio selection model, in spite of its well-known theoretical deficiencies. A theory conferring to Roll's critique states that CAPM model can't be completely accurate, and all the asset in the world would be included into fully diversified portfolio (Roll, 1977). Suggesting that, it is terrible to create or identify a truly diversified market portfolio. In recent years, such defects have directed to a reexamination of choice under uncertainty and emphasis the development of a class of models that are consistent with the expected utility hypothesis. The models are called stochastic dominance (SD) models. The SD models are more complicated to use for making choice between investment alternatives (Helms, Jean, & Tehranian, 1986).

Stochastic dominance based on the foundation of utility are mostly coined by (Hanoch & Levy, 1969; Rothschild & Stiglitz, 1970, 1971; Whitmore, 1970). The SD theory provides a general foundation for ranking risky prospects; investor can rank risky prospects/outcomes on the basis of utility theory. The results from stochastic dominance are indeed and powerful. The main advantage for using SD is that it does not take presumption about the shape of investors' utility functions based on their preference. It eradicates the need to clearly specify a firm's utility function. It applies to any function of probability distribution (Copeland et al., 2005). For this study, general mathematical statement about, wealth preference, ruin aversion, and risk aversion criteria are used to select the best between investments.

4.3. Properties of Utility Function

Since stochastic dominance is the generalization of utility theory, we start with the discussion of utility theory. Utility is chastely an ordinal measure. In other words, it can be used to form the rank ordering of consequences but can't be used to define the degree to which one is preferred over the other. According to classical utility theory, rational investors are seeking to maximize their expected utility and choose their investment alternatives accordingly. In mathematical notation, it is expressed as follow. *A* is preferred over *B*, if and only if the terminal wealth satisfies following, with at least one strict inequality $U(w_A) - U(w_B) \geq 0$.

$$E_w[U(w_A)] - E_w\,[U(w_B)] \;\geq 0 \tag{1}$$

This mathematical feature of utility function "*U*" reveals the risk/reward stimuli of investors. These same features also determine what stochastic characteristics, the terminal wealth distribution must possess, if one alternate is to be favored over another. Evaluation of these characteristics is the basis of Stochastic dominance analysis (Heyer, 2001).

4.2.1. Increasing Wealth Preference

Increasing wealth preference custodies the "more wealth is better", philosophy of investors' behavior and is commonly considered a universal feature of utility function. More wealth is preferred over less: so, the utility function must be monotonically increasing (Copeland et al., 2005). Mathematically, it is expressed as:

"A utility function possesses increasing wealth preferences if and only if $U'(w) \geq 0$ *for all w with at least one strict inequality"*(Heyer, 2001). (1.1)

4.2.2. Risk Aversion

Risk aversion states that the willingness of investor to purchase insurance when he/she exposes to risk. It is the subset of increasing wealth preference (Helms et al., 1986). Mathematically expresses as:

"A utility function possesses risk aversion if and only if it satisfies the conditions for increasing wealth preference and $U''(w) \leq 0$ *for all w with at least one strict inequality"*(Heyer, 2001). (1.2)

Under risk aversion, having concave utility function, the expected utility of risky asset is less than the utility of expected outcome. This can be expressed as follows:

$$E_w[U(w)] \leq U(E_w[w])$$

4.2.3. Ruin Aversion (Skewness Preference)

Ruin aversion is typically presented as individual's willingness to play the lottery: to take a small, nearly definite loss in exchange for the remote likelihood of huge returns. An investors' concern, however is with the opposite circumstance, unwillingness to accept small, almost certain gain, in exchange for the remote possibility of ruin. Specifically, the ruin aversion is the subset of risk aversion, an investor having risk aversion with or without exhibiting ruin aversion (Whitmore, 1970). Mathematically, it is expressed as:

"A utility function possesses ruin aversion if and only if it satisfies the conditions for risk aversion and $U'''(w) \geq 0$ for all w with at least one strict inequality"

(Heyer, 2001) (1.3)

4.3. Stochastic Dominance Orders

Few investors have the disposition or means, to select and parameterize their particular utility functions. The problem is that, how we use features like increasing wealth preference, risk aversion and ruin aversion, in order to select investment alternatives without having any specific utility function. Following are the stochastic dominance orders which are helpful in making optimal decision for investors. In order to test financial market anomalies, we use sophisticated technique called stochastic dominance (SD) approach. SD rules are pertinent for well-defined Von Neumann and Morgenstern (1944) set of utility functions. Common stochastic dominance rules based on utility functions are First-order, Second-order, and Third-order stochastic dominance, FSD, SSD, and TSD, respectively (Hadar & Russell, 1969).

In order to explain these rules of SD, let consider two investment alternatives F and G with stochastic outcome "x" which is bounded in range (0,1). The cumulative probability distribution of these two alternative is denoted by F(x) and G(x), respectively.

4.3.1. First-Order Stochastic Dominance

Any investor regardless of whether he/she is risk averse or not seeks to maximize expected utility of his/her wealth. Mathematically, asset x, with CDF $F_x(W)$ stochastically dominates over asset y with CDF: $G_y(W)$ for set of all non-decreasing utility functions if,

$$F_x(W) \leq G_y(W) \qquad \text{for all } W,$$

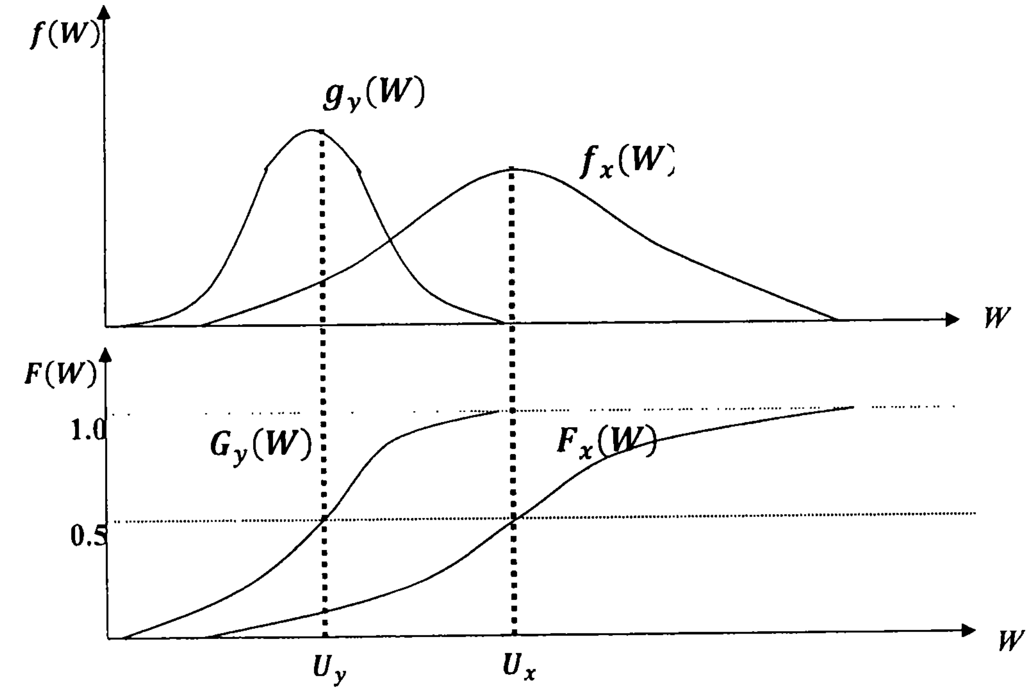
$$F_x(W) < G_y(W) \qquad \text{for some } W_i$$

With the beginning of definition of preference, in equation (1) and the most common constraint on the utility function given in equation (1.1) "Increasing wealth preference". By equation (1.1), $U'(w) \geq 0$

"X is uniformly preferred to Y under increasing wealth preference or X dominates over Y by first order if and only if $[G_y(w) - F_x(w)] \geq 0$ *for all w with at least one strict inequality"*, (Heyer, 2001).

The CDF for asset y always lies to the left of CDF for x If it is true then x is said to be dominated over y. First-order stochastic dominance (FSD) is stochastic ordering in which an investor ranks assets based on his preferences regarding outcomes. FSD states that investor prefers more wealth over less or investor is non-satiated.

Figure 4.1: First-order Stochastic Dominance



Source: Copeland et al. (2005).

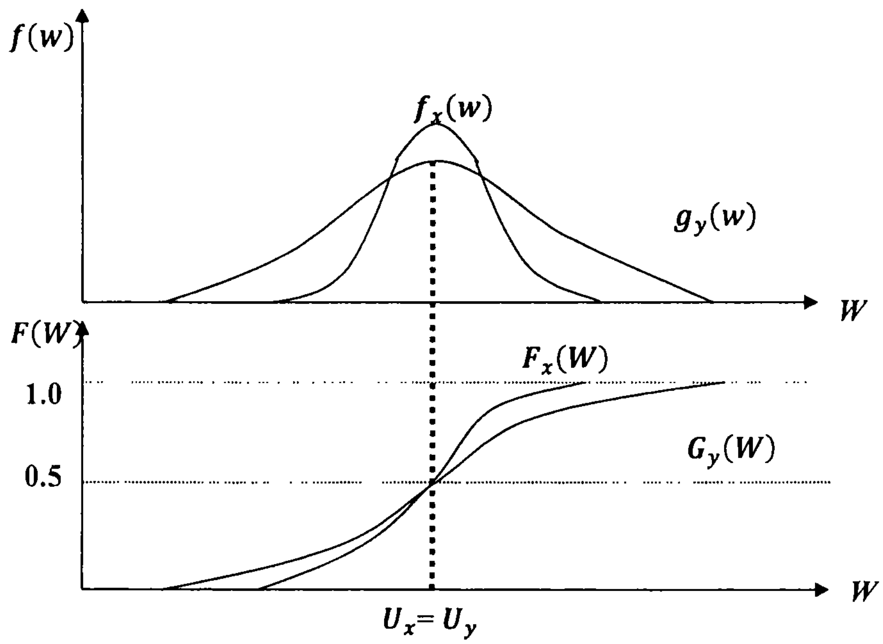
If an asset has high expected utility than the other asset then, every expected utility maximizer with increasing utility function should prefer the first asset over the second one (Hadar & Russell, 1969; Levy & Levy, 2001; Schmid & Trede, 1998).

4.3.2. Second-Order Stochastic Dominance

Since risk aversion is the subset of increasing wealth preference, second-order stochastic dominance (SSD) assumes that utility functions not only, marginal wealth is positive, but also totals utility increase at decreasing rate. By equation (1.2) we know $U''(w) \leq 0$:

"x is uniformly preferred over y under risk aversion or x dominates over y by second order if and only if $\int_{\infty}^{w}[F_y(W) - F_x(W)]du \geq 0$ *for all w with at least one strict inequality"* (Heyer, 2001). The second-order SD is shown in the following figure.

Figure 4.2: Second-order Stochastic Dominance



Note: SSD is presented reproduce from, (Copeland et al., 2005).

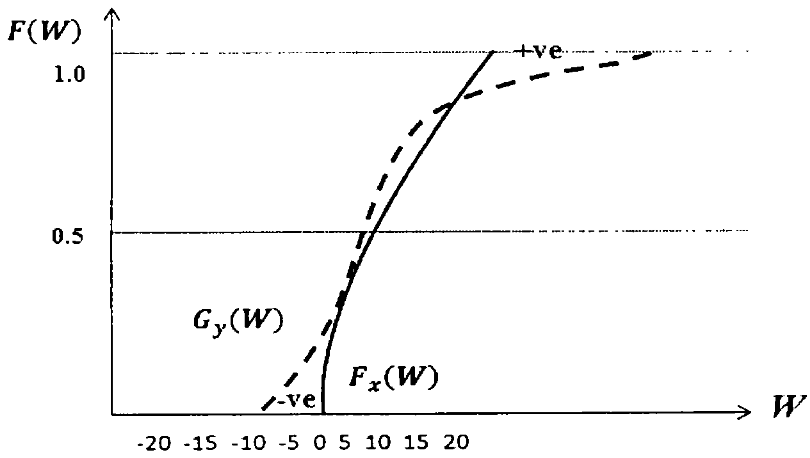
We can observe from the Figure 4.2 that according to SSD asset x said to be dominate over asset y for all risk averse investors, if the accumulated area under CDF of y must be greater than the accumulated area for x. This implies that unlike FSD, CDFs can cross. That is if first asset "x" is having less risk or at least high mean as compared to other asset "y" then an investor with increasing and concave utility function prefer first asset over second. SSD states that investor does not only prefer more wealth over less but he is risk averse also (Hadar & Russell, 1969; Levy & Levy, 2001; Schmid & Trede, 1998).

4.3.3. Third-Order Stochastic Dominance

Third-order SD (TSD) has assumption that investor prefers more over less is risk averse and having decreasing absolute risk aversion. There are sufficient and necessary conditions for TSD. Specifically for TSD, SSD is sufficient condition and the necessary condition is that expected mean of first asset "x" should be greater than or equal to the other asset "y" (Hadar & Russell, 1969; Levy & Levy, 2001; Schmid & Trede, 1998). By using the definition of preference and ruin aversion, given in equation (1.1) and (1.3) respectively, we define Third-order stochastic dominance as follows:

"x is uniformly preferred to y under ruin aversion or x dominates y by TSD if and only if $\int_{\infty}^{W}\int_{\infty}^{1}[F_y(u) - F_x(u)]\, dudt \geq 0$ *for all W with at least one strict inequality"* (Heyer, 2001). The following figure presents TSD graphically,

Figure 4.3: Third-order Stochastic Dominance



Note: TSD is presented and reproduced from Heyer (2001)

The above figure presents the CDF for two asset x and y that satisfy the equation (1.3). It is obvious that the CDFs intersect and FSD does not apply. Similarly, although not keenly apparent from the graph the negative area between CDFs is greater than the positive area so, SSD also does not apply. However, asset x has less negative skewness.

4.4. Stochastic Dominance Tests

In order to check the stochastic dominance, there are many tests that have been used in econometrics literature. For example, DD test, LMW test, LSW test and KS type test that are presented by Davidson and Duclos (2000), Linton, Maasoumi, and Whang (2005), Improved Bootstrap stochastic dominance test (Linton, Song, & Whang, 2010) and Barrett and Donald (2003), respectively. KS type (Kolmogorov-Smirnov) test is different from K-S normality test. In order to check the stochastic dominance for FSD, SSD and TSD, we have used KS type test. As concerned to check the stock returns' normality we have used KS normality test

We use KS type test (Kolmogorov-Smirnov) by Barrett and Donald (2003). In very initial, Kolmogorov-Smirnov type test was developed by McFadden (1989) for fist order stochastic dominance for independent samples with equal number of observations. The asymptotic distribution of the test statistics for $s \geq 2$ is analytically intractable. Afterward, that KS type test developed by Barrett and Donald (2003). The advantage of this test is that it is applied for stochastic dominance of any pre-specified orders and use to independent distributions and unequal sample sizes as well. As, this test is relatively new we provide a brief description of the test as well as the null and alternative hypotheses. Let $\{X_i\}$, $i= 1,2,....,N$ be an identical independent distribution (i.i.d) sample of returns to dominate distribution of population with cumulative distribution function (CDF), F_X(r).

Without loss of generality, assume that all CDFs have common support [0, r] where r > 0 and are continuous in [0, r]. From the give the assumption mentioned above, we define $D_X^s(r)$ as the function that integrates F_X(r) to order s-1 as follows,

$D_X^1(\mathrm{r}) = F_X(r)$ First-Order Stochastic dominance (FSD)

$D_X^2(\mathrm{r}) = \int_0^r F_X(u)du = \int_0^r D_X^1(u)du$ Second-Order Stochastic dominance (SSD)

$D_X^3(\mathrm{r}) = \iint_0^r F_X(v)dvdu = \int_0^r D_X^2(u)du$ Third-Order Stochastic dominance (TSD)

Similarly, $\{Y_i\}$, $i = 1,2\ldots\ldots,N$, be i.i.d sample of returns to non-dominate distribution with CDF $F_Y(\mathrm{r})$. For the distribution, $D_Y^s(r)$ defined analogously as for $D_X^s(\mathrm{r})$. The null and alternative hypotheses for KS type test is as follows,

$H_0^s : D_X^s(\mathrm{r}) \leq D_Y^s(\mathrm{r})$ for all r (stock returns)

$H_1^s : D_X^s(\mathrm{r}) > D_Y^s(\mathrm{r})$ for some r (stock returns)

The null hypothesis is that target output *(say X)* dominates over other output *(say Y)*, while alternative hypothesis implies that distribution *Y* dominates over *X* distribution. In order to test H_0^s following test statistic is applied.

$$K_s = \left(\frac{N^2}{2N}\right)^{1/2} \sup_r \left[D_X^{-s}(r) - D_Y^{-s}(r)\right] \quad (2)$$

So, this test can be applied for s=2 or s>2 , (second or higher orders of stochastic dominance), it is analytically intractable to derive critical values of the test statistic because the limiting distribution of K_s depends on the underlying CDFs. We estimate suprema of K_s with the help of p-values through simulation method is proposed by Barrett and Donald (2003).

4.5. Portfolio Construction

In the literature there are various studies that have examined the behavior of stock returns by constructing the different portfolio structures. Stock investors constantly hear the wisdom of diversification. The concept is to simply not put all of your eggs in one basket, which in turn helps mitigate risk, and generally leads to better performance or return on investment. There are different ways of diversifying and constructing of portfolios. It is also helpful to change tactics or strategy in investment style. To test month anomaly portfolios are formed on the basis of ranked betas (Ritter & Chopra, 1989). In order to test momentum anomaly we have constructed portfolios based on "Winner" and "Loser" which is the actual empirical procedure proposed by Bondt and Thaler (1985).

4.5.1. Portfolio Formulation for Month Effect

In empirical literature, portfolios are constructed on different way to test the month anomaly. For instance, market capitalization portfolios (Ke et al., 2014), based on compound returns (Fong et al., 2005), In our study we construct the portfolios based on beta the risk factor (Ritter & Chopra, 1989). We have calculated daily stock returns and KSE-100 Index returns. Then, with the help of these daily returns we have calculated monthly ranked betas for all listed firm. As over the time, the beta of each firm is changing so, we calculate the beta of each firm over the subsequent months. After the construction of monthly betas, we rank beta based portfolios in High-Beta, Medium-Beta and Low-Beta based portfolios.

In finance literature quartile approach can be used to divide the data set into four parts. Boundaries of data set are three quartile segments. The 25th percentile, 50th percentile, and 75th percentile are Q_1 (lower quartile), Q_2 (median value), and Q_3 (upper quartile) respectively. Then, sample data is divided into High-Beta, Medium-Beta, and Low-Beta portfolios. Since, over the month firms' betas are not remained constant number of firms in each portfolio and in each month vary due to change in the value of their betas. We use following formula for beta calculation.

$$\beta_i = \frac{\sigma_{im}}{\sigma_m^2} = \frac{COV(R_{it}, R_{mt})}{VAR(R_{mt})} \tag{3}$$

where

$COV(R_{it}, R_{mt})$	Covariance between i^{th} stock return and market return at t month
$VAR(R_{mt})$	Variance of market return at t month

4.5.2. Portfolio Construction for Momentum Anomaly

We construct contrarian strategy (Loser-Winner) of Bondt and Thaler (1985). We expedient contrarian strategy on all the listed firms of Pakistan Stock Exchange using sample period January 2000 to December 2014 with certain modification according to our data feasibility. Winner and loser portfolios are constructed based upon past excess returns of stocks

Residuals or excess returns are estimated as $\hat{u}_{jt} = R_{jt} - R_{mt}$. In order to get excess return, for every period t KSE-100 Index return (market return) R_{mt} is subtracted from all R_{jt}'s raw returns of stocks for respective periods. Loser and winner portfolios are then constructed on the basis of market adjusted excess returns. In order to test overreaction hypothesis, following procedure is explained to construct winner and loser portfolios.

1. For every stock j on the tape with at least 36 months of stock returns data (months 1 to 36 months), without missing values in between and starting from 1st month (January 2000) to the next 36 monthly (December 2002) excess

returns/residual returns $\hat{u}_{jt}$ are calculated. If any raw return of stock is missing beyond the 36 month, the excess returns are calculated up to that point. This procedure is repeated four times starting in January 2003, January 2006, January 2009, and January 2012. As time goes on and new securities appear on the tape, more and more stocks qualify for this for this step.

2. For every stock j, starting in December 2002 (month 36; the portfolio formation date") t = 0, (comprising 36 months, formulation period), we compute cumulative excess returns $CU_j = \Sigma_{t=-35}^{t=0} u_{jt}$ for prior 36 months (the "portfolio formation" period, months 1 month to 36 months). This procedure is repeated four times for remaining non-overlapping three-year period dated between January 2000 to December 2014. On each four relevant three-year periods formation dates (December 2002, December 2005, December 2008 and December 2011) CU_j are ranked from low to high and portfolios are formed. Top 50 firms are identified as loser and bottom 50 firms are identified as winner. Thus, both portfolios (winner and loser) are formed conditional upon excess past returns behavior prior to t = 0 the portfolio formation date. The initial for three-year period in which winner and loser portfolio are classified at n = 0 known as rank period/formulation period. The succeeding three-year periods in which the performance of these stocks is evaluated are identified as test periods or holding periods. Loser and winner portfolios' setup are equally weighted.
3. For both portfolios in each of four non-overlapping test periods, starting in January 2003 and up to December 2014, we now compute the cumulative average residual returns for all securities in the portfolio (winner and loser) for next 36 months (January 2003 to December 2005) i.e., from t =1 through t

Since, $s_t/\sqrt{N}$ represents the sample estimate of the standard error of $AR_{w,t}$, the t-statistics :

$$T_t = AR_{W,t}/(s_t/\sqrt{N}) \tag{7}$$

Similar procedure applies for the loser portfolios. Using the above formula for t-statistics, we calculate 36 t-values for each 36 test periods.

4.6. Development of Hypotheses

In order to check the efficiency of Pakistan Stock Exchange, we test the market anomalies. As from the counter argument of market efficiency investors can beat the stock market in order to get abnormal return which leads anomalies. Therefore, the core objective of the thesis is to examine the presence of anomalies in Pakistan Stock Exchange viz. month effect, equity premium puzzle, and momentum effect. Following three hypotheses could be tested according to our sub-objectives by using stochastic dominance KS type test.

> H_{01}: Target month stochastically dominates over non-target month at the s^{th} order.
>
> H_{02}: Loser stocks dominate over winner stocks.
>
> H_{03}: Risk-free rate dominates over the equity returns.

4.7. Data and Sample Characteristics

Daily stock prices of all listed firms at Pakistan Stock Exchange, and monthly KSE-100 Index prices are taken from the official website of Pakistan Stock Exchange. 3-

month Treasury bill rate is taken from the official website of State Bank of Pakistan. The study covers a 15-years period ranging from January 2000 to December 2014. Free entry and exit for firms are allowed in the data. We write codes to construct beta-based and winner and loser portfolios for month anomaly and momentum anomaly.[13] The idea of calculating the stock returns are taken from the study of Annuar (1987), Fong et al. (2005), and Tangjitprom (2011).

$$SR_{it} = ln(P_{it}/P_{it-1}) \tag{7}$$

where

SR_{it} is stock return of i^{th} stock at month t

P_{it} is current price of i^{th} stock at month t

P_{it-1} is i^{th} lag value of stock price

[13] All data handling, figures and coding is done through "STATA 12" software. For month anomaly, to make Beta-Based portfolios, and for momentum anomaly, to make "Winner" and "Loser" portfolios, by using three year (36 months) strategy, we have made all codes in "STATA 12". For estimation purpose, we have used "GAUSS" software. References and citation are done through "EndNote X5" software. ReferenceChecker_Wd2003 software is used to check the citation and references. Apart from this estimation (KS Type test), we have employed one additional test for momentum anomaly that is, to test the overreaction hypothesis. In order to check momentum through overreaction hypothesis, we have used the t-statistic with the help of pooled estimate of population variance.

Chapter 5
Empirical Results

5.1. Introduction

The previous chapter describes the empirical framework, estimation techniques, portfolios construction, data sample, and hypotheses. This chapter presents the empirical results. In particular, according to our considered three market anomalies we divide this chapter into three sections. First section documents the findings of month anomaly. Specifically, it presents the results for the "winner month" based on high returns in listed firms, the beta based portfolios, and KSE-100 Index. The results of equity premium puzzle are presents in second section. Specifically, we first present the return behavior of equity and the risk-free rate and then compare these two return distributions in order to identify which one is dominated based on stochastic dominance approach. Third section presents the results about momentum anomaly. Specifically, we document the stochastic dominance of loser portfolios over winner by observing the contrarian strategy.

5.1.1. Results for Month Anomaly

This section examines month anomaly. For this purpose we divide the section into three sub-sections. In first sub-section, the descriptive statistics about returns of all listed firms, the beta based portfolios, and KSE-100 Index are presented to examine the month effect based on high returns. The second sub-section, presents the results based on normality test of stock returns. Finally, we investigate the month effect and presents the stochastic dominance results for returns of all listed stock in Pakistan Stock Exchange, beta based portfolios, and KSE-100 Index.

5.1.2. Descriptive Statistics of Month Anomaly

Before testing the existence of month anomaly, we present month vice descriptive statistics for all listed firms, beta based portfolios, and KSE-100 Index returns. Table 5.1 shows the summary statistics of calendar months returns for the period from January 2000 to December 2014. The table provides several notable information, specifically, the table shows that majority of months have positive mean returns, which shows upward trend in stock returns over the examined period. It is also clear from the table that the highest mean returns are in the month of January (4.668%).

On the other hand, the lowest mean return is in the month of August with the magnitude of -1.891%. These observations are consistent with the result for developed market. In particular, several existing empirical studies have documented that the returns of January are positive and high as compared to other calendar months (Agrawal & Tandon, 1994; Boudreaux, 1995; Gultekin & Gultekin, 1983; Haugen & Jorion, 1996). Median value (3.849%) is also high for the month of January. Looking at the value of standard deviation presented in the table, we observe that the standard deviation value of returns for the month of January is 26.3%, which is high as compared to other months. Thus, the table provides evidence that in January not only the stock returns are high, as compared to other months, but their standard deviation is also high. This observation is consisted with the standard finance that states that high returns should also be associated with the high level of risk (Ghysels, Santa-Clara, & Valkanov, 2005).

Table 5.1: Months vice Returns for all listed Firms

Months	January	February	March	April	May	June	July	August	September	October	November	December
Mean	4.668	3.060	-1.598	3.199	-0.842	-1.101	0.720	-1.891	0.347	0.021	0.986	3.077
Median	3.849	1.393	-1.806	2.356	-2.329	-1.632	0.540	-1.553	-0.694	0.170	0.091	3.006
Standard Deviation	26.3	20.8	19.9	20.8	20.9	20.0	18.1	19.3	19.5	18.9	19.4	22.9
Kurtosis	18.972	87.288	21.956	15.200	12.344	13.915	26.109	58.612	37.553	12.854	18.357	13.422
Skewness	-0.143	4.850	0.866	-0.289	0.691	0.735	0.522	-2.726	2.103	-0.101	1.287	0.251
No of Observation	4473	4348	4462	4728	4587	4653	4658	4047	4496	4536	3445	4639

Analogously, the lowest standard deviation occurs in the month of July with the magnitude of 18.1%. One should note that on average, the returns of July are lower as compared to the other months as well.

The table also suggests that the stock returns may not be normally distributed. Specifically, we observe that returns are negatively skewed in 4 out of 12 months. In addition, the statistics of kurtosis for all the calendar months are much higher than the critical value of 3, which is required for a normal distribution. In sum, the skewness and kurtosis values suggest non-normality in the return distributions.

As it is explained in the methodology chapter, to test the month anomaly, we construct the portfolios based on risk (beta). Specifically, we construct High-Beta, Medium-Beta, and Low-Beta based portfolios. Table 5.2 presents mean returns and standard deviation of beta based portfolios and KSE-100 Index. The table is divided into four panels: High-Bets, Medium-Beta, Low-Beta based portfolios, and Market Index.

In High-Beta portfolio, Low-Beta portfolio, and Market Index portfolio, on average, returns are relatively high in the month of January having value 11.6%, 5.7%, and 5%. respectively. Hence, January month may outperforms in High-Beta portfolio, Low-Beta portfolio and Market Index portfolios as compared to the other calendar months. On the other hand, we observe that in Medium-Beta portfolio the mean returns of December (2.8%) is high as compared to other calendar months. Thus, December month may outperform in Medium-Beta portfolio. The mean values of beta based portfolios returns provide preliminarily evidence for existing January and December effect in Pakistan Stock Exchange.

Table 5.2: Monthly Return for Beta-Based Portfolios and Market Index

	Beta-Based Portfolios											
	High-Beta Portfolio			Medium-Beta Portfolio			Low-Beta Portfolio			Market Index		
Months	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.
January	11.6	(31.7)	1135	0.5	(20.2)	2225	5.7	(29.2)	1113	5.0	(8.5)	15
February	5.7	(30.7)	1048	1.5	(15.3)	2215	3.4	(18.3)	1085	3.6	(7.8)	15
March	-0.8	(23.5)	1112	-2.5	(15.3)	2248	-0.3	(23.6)	1102	3.9	(6.6)	15
April	4.9	(24.4)	1168	2.5	(17.4)	2388	2.7	(22.9)	1172	2.3	(4.7)	15
May	3.2	(24.1)	1142	-3.7	(15.0)	2311	0.9	(26.0)	1134	-3.1	(9.9)	15
June	-1.3	(25.1)	1157	-2.5	(13.9)	2341	2.1	(23.9)	1155	2.0	(4.2)	15
July	0.8	(22.0)	1158	1.1	(13.6)	2335	-0.3	(21.2)	1165	1.9	(7.6)	15
August	-1.4	(26.2)	1005	-1.5	(14.7)	2031	-2.9	(18.9)	1011	-0.2	(8.6)	15
September	-0.2	(21.2)	1115	0.6	(13.9)	2266	0.3	(26.1)	1115	1.4	(5.6)	15
October	1.0	(21.7)	1127	0.1	(15.9)	2278	-1.1	(21.3)	1131	3.8	(7.4)	15
November	2.9	(24.1)	858	-0.3	(14.8)	1722	1.6	(21.9)	865	0.8	(6.1)	15
December	1.6	(29.0)	1156	2.8	(17.2)	2330	5.0	(25.4)	1153	2.1	(12.8)	15

In principle, high returns should associate with high risk. We observe this scenario in some cases. However, in some cases, we do not observe the high risk – high return relationship. For example, in both High-Beta and Low-Beta portfolio, not only the returns but also the standard deviations are high in the month of January as compared to the other months. However, in Medium-Beta based portfolio, the returns are high in the month of December (2.8%) whereas, the standard deviation of return is high in the month of January (20.2%). Similarly, in case of market portfolio, average returns are high in January (5%). Yet, the returns are more volatile in the month of December as compared to the other months.

5.1.3. Normality Test Results

We start our empirical investigation by checking normality of stock returns. For this purpose, we apply Kolmogorov-Smirnov (K-S) normality test proposed by Justel, Peña, and Zamar (1997). This test is designed to test whether the underlying sample comes from a specific distribution. In particular, this test is used to explore whether the sample comes from a population which is normally distributed. By considering the mean and variance of the distribution, the K-S normality test tests the following hypothesis.

H_o : Distribution is normal

H_1 : Distributions is not normal

Table 5.3 presents the results for Kolmogorov-Simonov normality test. We apply this test to check whether month vice returns of beta based portfolios are normally distributed. We also test whether month vice returns of all stocks are normally distributed or not. The table is divided into five panels. First panel is for all month vice returns distribution of data sample. These months vice returns are than further divided into High-Beta, Medium-Beta, and Low-Beta based portfolios. Fourth panel shows month vice normality statistics for Market Index. In each panel, two columns are presented, one for the K-S absolute difference between the empirical CDFs and the CDFs of standard normal distribution and the other column presents the p-values. In full sample panel, the month vice K-S difference and p-values are also presented. In the table, July (0.247), August (0.238), and February (0.235) months have high values of K-S differences as compared to remaining months. The p-value associated with these statistics indicates that for all month, the null hypothesis of normal distribution is rejected. Thus, we conclude that in full sample, month vice returns are not normally distributed.

We also apply K-S normality test on portfolio vice stock returns. We find almost similar results for High-Beta, Medium-Beta, and Low-Beta based portfolios. For all three panels of portfolio the K-S difference values are non-zero and p-values are almost zero in all cases. The K-S normality test statistics provides evidence that the month vice returns of beta based portfolios are also not normally distribution. These results are consistent with the prior studies of Khilji and Nabi (1993), Harvey (1995), Husain and Uppal (1998), Iqbal and Brooks (2007), and Javid (2009). Khilji and Nabi (1993) documented that stock returns on the Pakistan Stock Exchange are leptokurtic and positively skewed. Harvey (1995) also examined the non-normality of stock returns and stated that emerging markets are characterized with non-normal leptokurtic and skewed returns distribution. Husain and Uppal (1998) found that in Pakistan the returns on equity are non-normal with high peaks and flat tails. Iqbal and Brooks (2007) also analyzed that investors demand high premium for negative

Table 5.3: Kolmogorov-Simonov (K-S) Normality Test Results

	Kolmogorov-Simonov Normality Tests									
	Full Sample		High-Beta Portfolio		Medium-Beta Portfolio		Low-Beta Portfolio		KSE-100 Index	
Months	K-S Differenc e	P-Values	K-S Differenc e	P-Values	K-S Difference	P-Values	K-S Difference	P-Values	K-S Difference	P-Values
January	0.229	0.000	0.118	0.000	0.172	0.000	0.111	0.000	0.146	0.527
February	0.235	0.000	0.173	0.000	0.096	0.000	0.091	0.000	0.180	0.375
March	0.221	0.000	0.113	0.000	0.098	0.000	0.108	0.000	0.196	0.315
April	0.096	0.000	0.109	0.016	0.087	0.000	0.092	0.000	0.106	0.714
May	0.226	0.000	0.107	0.000	0.080	0.000	0.087	0.000	0.105	0.716
June	0.230	0.000	0.091	0.000	0.085	0.000	0.101	0.000	0.139	0.558
July	0.247	0.000	0.120	0.000	0.097	0.000	0.109	0.000	0.082	0.815
August	0.238	0.000	0.145	0.000	0.101	0.000	0.101	0.000	0.140	0.552
September	0.231	0.000	0.103	0.000	0.109	0.000	0.145	0.000	0.109	0.698
October	0.200	0.000	0.115	0.000	0.103	0.000	0.115	0.000	0.166	0.437
November	0.213	0.000	0.115	0.000	0.085	0.000	0.088	0.000	0.081	0.820
December	0.207	0.000	0.137	0.000	0.122	0.000	0.109	0.000	0.104	0.720

Note: Kolmogorov-Simonov K-S normality test is used to check month vice normality in all months for whole data sample, beta based portfolios (High-Beta, Medium-Beta,and Low Beta-Based portfolios) , and Market Index returns, in respective months as well.

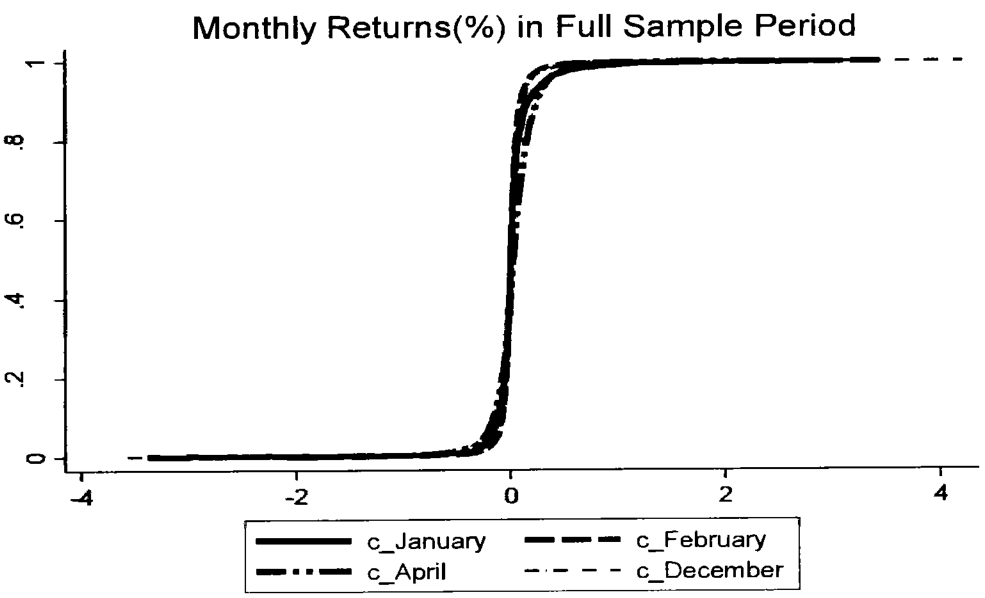
skewness under the examined period. Javid (2009) extended the mean-variance CAPM by incorporating higher order moments in conditional and unconditional framework and found that the co-skewness risk is rewarded in the Pakistan Stock Exchange. Thus, we can conclude that stock returns are not normally distributed. This evidence suggests that the stochastic dominance (SD) approach is the appropriate technique to test the said anomalies in Pakistan Stock Exchange. Now, we present the results of stochastic dominance approach to test the existence of month anomaly, equity premium puzzle, and momentum anomaly in Pakistan Stock Exchange. However, the normality statistics about Market Index shows that month vice Market Index return distributions are normally distributed.

5.1.4. January Effect in Pakistan Stock Exchange

In this section, we test the January effect in all listed firms. For this purpose, we examine stochastic dominance relationship among January returns and other calendar months. As Table 5.1 exhibits, on average, the returns of January month are high as compared to other months. So, we concern the stochastic dominance of January over all remaining calendar months. Before applying the formal test to check the stochastic dominance, cumulative density function is used to examine the visual dominancy. The best way to visualize stochastic dominance of any asset is to draw the graph of the corresponding cumulative distribution. It is the direct comparison between two distributions. Inspection of the graph can give a clue of stochastic dominance order.

Figure 5.1 shows the cumulative density functions (CDFs) of four months which have high returns. As in Table 5.1 we examine that top four month on the basis of their returns are January (4.668.%), April (3.199%), December (3.077%), and February (3.060%). Therefore, we present the CDFs of these four months. The remaining months' CDFs are omitted to reduce clutter. On the whole, the CDF of January and April month lie to the right side of the other CDFs, implying that returns in the month of January or April appear to outperform the remaining calendar months. However, these CDFs cross each other this implies that there is no first order stochastic dominance among these months. The formal test of stochastic dominance is used to examine which month dominates based on stochastic dominance analysis.

Figure 5.1: The CDFs of the Monthly Returns of all Listed Firms



Note: The CDFs of monthly returns of all listed firms are presented for January, February, April, and December months. We present the CDFs of top four months which have high returns. The CDFs of January and April are the most right side as compared to the other months' CDFs.

In Table 5.4, we present the stochastic dominance test results of January with respect to other months. The table is divided into two panels. In first panel, namely January versus other months, we present p-values for testing the null hypothesis that is $H_0: X >_s Y$, the target month stochastically dominates over non-target months at s^{th} order. The second panel shows the p-values for reverse hypothesis, that is, $H_1: Y >_s X$, the non-target month stochastically dominates over target month. If we accept H_0, then we infer that the target month outperforms over the non-target month.

The SD1, SD2, and SD3 denote the stochastic dominance order first, second, and third, respectively. The p-values presented in first panel of the table show that there is no first and second order stochastic dominance of January over other calendar months. Said differently, we reject the null hypothesis that target month dominates over the non-target months as for all cases the p-values for first and second order are nearly zero. On the other hand, the results of third order show that January month strongly dominates over other calendar months with third order except for the month of April and October. For the month of April, the results indicate that April month outperforms over January month at third order of stochastic dominance with the p-value of 0.682. In contrast, the p-value for January *versus* April is zero.

Table 5.4: Stochastic Dominance of January Month in all Listed Firms

	January *versus* Other Months			**Other Month *versus* January**		
	KS P-value					
Months	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**
January		Winner				
February	0.000	0.000	0.240	0.000	0.000	0.000
March	0.028	0.001	0.198	0.000	0.000	0.000
April	0.000	0.000	0.000	0.000	0.005	0.682
May	0.004	0.007	0.397	0.000	0.000	0.000
June	0.000	0.001	0.201	0.000	0.000	0.000
July	0.000	0.000	0.167	0.000	0.000	0.000
August	0.000	0.000	0.207	0.000	0.000	0.000
September	0.000	0.000	0.396	0.000	0.000	0.000
October	0.000	0.000	0.033	0.000	0.002	0.096
November	0.000	0.000	0.192	0.000	0.000	0.000
December	0.000	0.001	0.206	0.000	0.035	0.159

Note: This table presents stochastic dominance of January month in all listed firms. The first panel namely January versus other months tests the null hypothesis that is January month dominates over other calendar months. The SD1, SD2, and SD3 are the stochastic dominance orders. The p-values are calculated through described simulation method.

Similarly, the p-value for October *versus* January (0.096) also indicate that October strongly dominates over January at third order of stochastic dominance. Overall, January month strongly dominates over calendar months and weakly dominates over the month of October at third order of stochastic dominance. The p-value of January *versus* October is 0.033, while the p-value for October *versus* January is 0.093, which shows the strong dominancy of October month over the month of January.

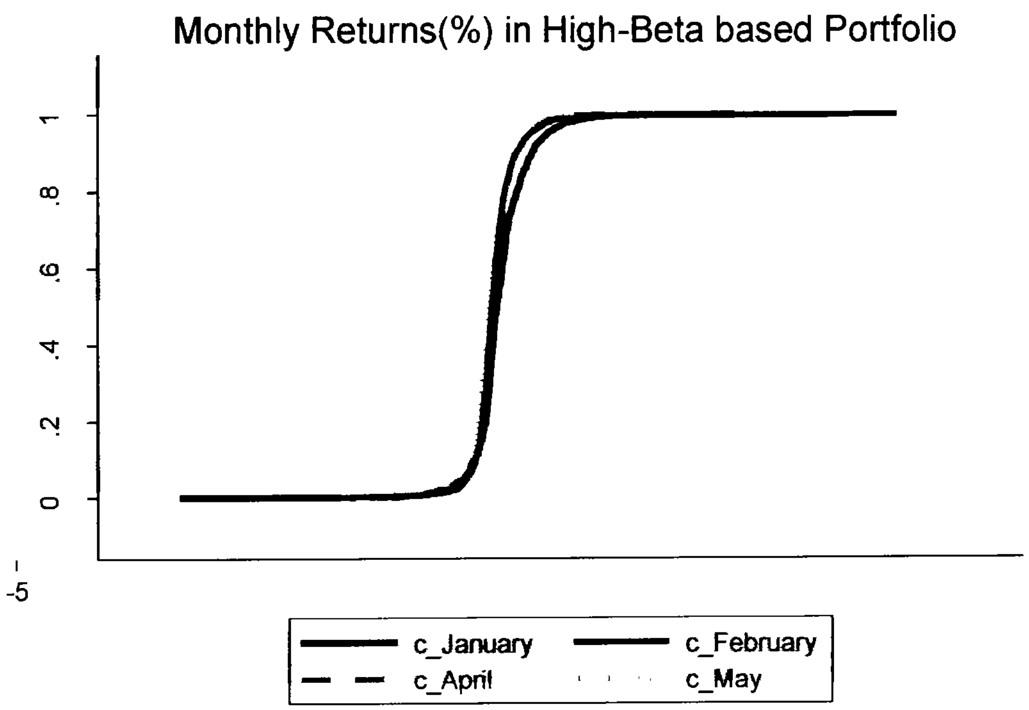
5.1.5. January Effect in High-Beta and Low-Beta Portfolio

In this section, we specifically examine the January effect in High-Beta and Low-Beta portfolios. We do so, because the descriptive statistics presented in Table 5.2 suggest that on average, the return of the month of January are high as compared to other months for High-Beta and Low-Beta portfolios. The cumulative density function (CDF) is the graphical representation which is helpful to check the performance based on the probability of returns. Figure 5.2 and Figure 5.3 demonstrate the cumulative density functions (CDFs) of returns for those months which have high returns in High-Beta and Low-Beta portfolios.

In particular, the CDFs of January, February, April, and May are presented and remaining months' returns are not included due to space consideration or clutter. Table 5.2 shows that on average the highest returns are for the month of January (11.6%). The returns of February (5.7%), April (4.9%), and May (3.2%) are at second, third, and forth position, respectively. The CDFs of January (black solid line) and February months (red solid line) are the most to the right side imply that the returns of January and February seem to outperform than the other months' returns.

On the other hand, the CDFs of April (magenta long dash dot line) and May (purple dotted line) are left side of theirs. In short, from Figure 5.2, we observe that January or February returns may dominate over all remaining months' returns at certain stochastic dominance orders in High-Beta Portfolio. To confirm this perception, we apply the formal test of stochastic dominance by considering January as a "winner" month and the results are presented in Table 5.5.

Figure 5.2: The CDFs of the Monthly Returns of High-Beta Based Portfolio

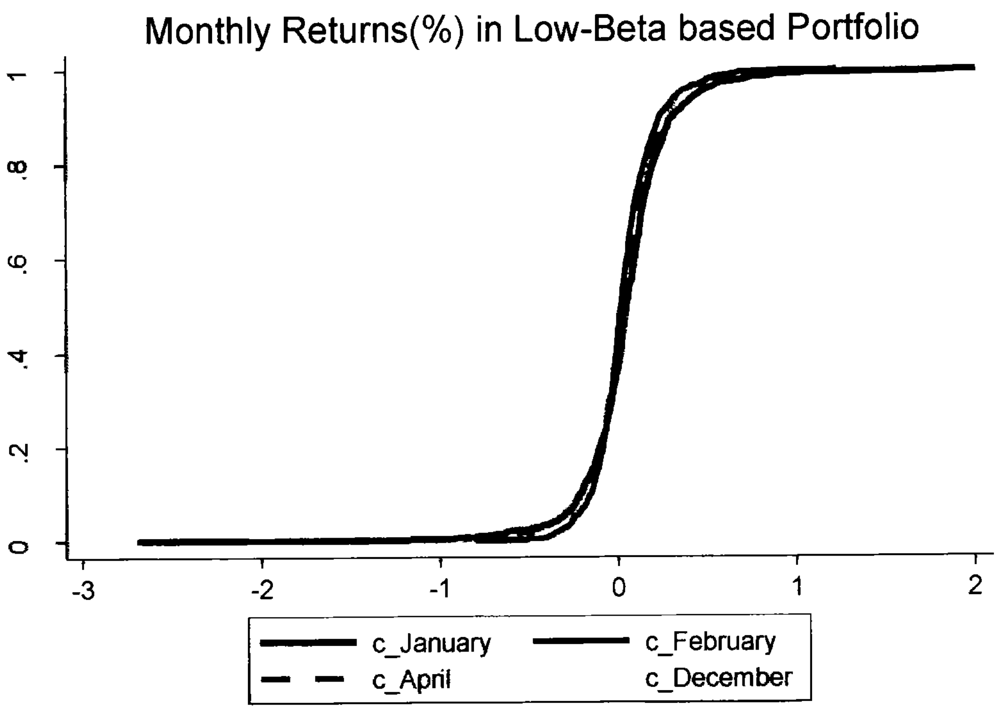


Note: The CDFs of high month the returns are showed for High Beta-Base Portfolio. As January month returns are the highest so, CDF of January month return (Black line) is most to the right side as compared to other months CDFs.

Figure 5.3 displays the CDFs of top four months' returns of Low Beta-Base portfolio. The four month are January (5.7%), December (5%), February (3.4%), and April (2.7%). We can observe from the figure that the CDFs curve of January (black solid line) and December (purple dotted line) are most likely to right side as compared to the CDFs of other months in the figure. Thus, we may do the prediction of January or December anomaly in Low-Beta based portfolio. Therefore, similar to the case of High-Beta based portfolio, we consider January as a "winner" month in Low-Beta based portfolio and formally test the dominance of January by applying stochastic dominance approach.

In sum, Figure 5.2 and Figure 5.3 exhibit the dominance of January or February months over calendar months in High-Beta base portfolio and January or December month in Low-Beta and. We now formally test to examine the presence of the month anomaly in beta based portfolios. As we mentioned earlier, to do this, we apply KS type test. Specifically, given the preliminary evidence presented in Figure 5.2, we test the stochastic dominance in January month with respect to other months. The results are presented in Table 5.4

Figure 5.3: The CDFs of the Monthly Returns of Low-Beta Based Portfolio



Note: The CDFs of High monthly returns are presented for Low-Beta base portfolio January, December, February and April are the position on the basis of their months' returns. The CDF of January month returns are the most to the right side as compared to other months' CDFs

Full sample data is divided into High-Beta, Medium-Beta, and Low-Beta based portfolios. Therefore, the table is also divided into three major panels High-Beta, Medium-Beta, and Low-Beta based portfolios and then each panel is further divided into two sub-panels (1) January *versus* others months and (2) other months *versus* January. We present KS type p-values of SD1, SD2, and SD3 representing stochastic order first, second, and third, respectively. The sub-panel labeled as January *versus* other months is stated the null hypothesis that is the January month stochastically dominates over other month. On the other hand, the second sub-panel labeled as other month *versus* January test the opposite hypothesis that is, the underlying month stochastically dominates over January. For High-Beta and Low-Beta based portfolios, the p-values given in the panel January *versus* other month provides strong evidence in favor of not rejecting the null hypothesis for all three stochastic dominance orders. These imply that the January month dominates over other months in both High-Beta and Low-Beta based portfolios at first, second, and third order of stochastic dominance orders. The p-values presented in panel other months *versus* January confirm the dominance of January month in High-Beta and Low-Beta portfolios. In particular, the p-values indicate the rejection of the null hypothesis.

To observe whether the January effect strongly or weakly exists, we compare the p-values for the null hypothesis with the p-values of the reverse null hypothesis. Comparing the p-value for the case of High-Beta based portfolios, we examine that the January month strongly dominates over other calendar months at all three examined orders of stochastic dominance.

On the other hand, the p-values suggest that in Low-Beta based portfolio, January month strongly outperforms at all three examined orders over all other calendar months except December, where it weakly dominates over the December month. Specifically, the January weakly dominates over December at first and third stochastic order.

Table 5.5: Stochastic Dominance in January Month with respect to other Months

	High Beta Portfolio						Medium Beta Portfolio						Low Beta Portfolio					
	January *versus* Other Months			Other months *versus* January			January *versus* Other Months			Other Months *versus* January			January *versus* Other Months			Other Months *versus* January		
	KS P-value																	
Months	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**
January		**Winner**												**Winner**				
February	0.637	0.269	0.426	0.000	0.000	0.000	0.019	0.000	0.000	0.000	0.675	0.641	0.076	0.003	0.154	0.000	0.000	0.067
March	0.961	0.522	0.446	0.000	0.000	0.000	0.136	0.000	0.047	0.000	0.000	0.000	0.970	0.525	0.434	0.000	0.000	0.000
April	0.587	0.433	0.419	0.000	0.000	0.000	0.018	0.000	0.000	0.058	0.719	0.677	0.789	0.288	0.410	0.000	0.001	0.001
May	0.815	0.380	0.426	0.000	0.000	0.000	0.062	0.000	0.001	0.000	0.000	0.000	0.891	0.348	0.379	0.000	0.000	0.000
June	0.974	0.513	0.442	0.000	0.000	0.000	0.022	0.000	0.001	0.000	0.000	0.000	0.847	0.398	0.415	0.000	0.000	0.000
July	0.904	0.344	0.390	0.000	0.000	0.000	0.006	0.000	0.000	0.000	0.714	0.676	0.667	0.215	0.360	0.000	0.000	0.000
August	0.997	0.713	0.671	0.000	0.000	0.000	0.071	0.000	0.000	0.000	0.000	0.000	0.843	0.258	0.356	0.000	0.000	0.000
September	0.845	0.304	0.370	0.000	0.000	0.000	0.002	0.000	0.023	0.000	0.460	0.676	0.617	0.410	0.492	0.000	0.000	0.000
October	0.946	0.491	0.426	0.000	0.000	0.000	0.101	0.000	0.050	0.000	0.028	0.397	0.974	0.477	0.386	0.000	0.000	0.000
November	0.943	0.502	0.433	0.000	0.000	0.000	0.058	0.000	0.030	0.000	0.000	0.113	0.750	0.178	0.306	0.000	0.000	0.000
December	0.999	0.564	0.477	0.000	0.000	0.000	0.005	0.000	0.000	0.361	0.711	0.666	0.361	0.420	0.379	0.615	0.204	0.407

Note: Three Beta-Base Portfolios are showed. The number of comparison between any two calendar months in each portfolio is C(12,2)=66. January months' results (Winner month) present only. SD1, SD2 and SD3 and the KS type P-values for stochastic order first, second and third respectively

The p-values for two pair of assets are calculated through simulation method of Barrett and Donald (2003) .Yet, January strongly dominates over December as the p-values for January is 0.402, whereas, the corresponding figure for December is 0.204. In short, we can say that in Low-Beta based portfolio, January strongly dominates over other months at all three examined stochastic dominance orders and weakly dominates over December at the first and third order of stochastic dominance.

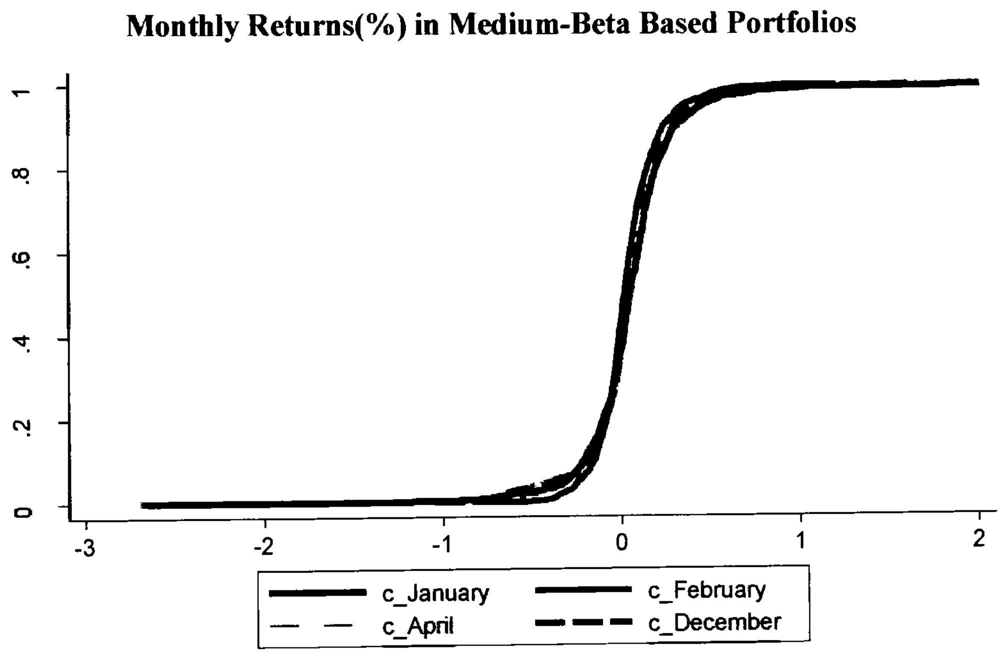
Our results are consistent with many previous studies on this issue. For instance, Li and Gong (2015) found the January effect in Japanese Stock Market. Our results are in favor of Haugen and Jorion (1996) and Wong et al. (1990). Haugen and Jorion (1996) January effect in New York Stock Market from the period 1926 to 1993.Wong et al. (1990) also examine calendar anomaly in Malaysia Stock Market and examined January phenomenon. Our results are also in favor of Keim (1983). He documented that the January effect is larger for small firms as compared to large firms. He explained that the relative larger effect for small firms is because of more information costs for small firms and they suffer relatively more from asymmetric information problems. In other study of Sum (2010) reported the empirical evidence of January and size effect in USA. Specifically, he found that January effect is high particularly, in the small-cap portfolio.

Turning to the result for Medium-Beta based portfolio, we observe that January does not stochastically dominates over other calendar months at either stochastic dominance order. The reported p-values are either zero or less than the acceptable level of significance, suggesting the rejection of the null hypothesis that the target month, January outperforms over other calendar months. When we look at the p-values for the reverse null hypothesis that the non-target month (the underlying calendar month) stochastically dominates over the target month we find that the null hypothesis is rejected for most of the cases. For the first order of stochastic dominance, the null hypothesis is rejected for all months except December. For the second order of stochastic dominance, the null hypothesis is rejected for 6 out of 11 months, while, for the third order, the null hypothesis is rejected for 4 months. One should note that the null hypothesis that December stochastically dominates over January is not rejected at either examined stochastic dominance order. This implies that December stochastically outperform over January in Medium-Beta portfolio. This evidence is consistent with the information provided by the CDFs presented in Figure 5.3. This evidence also motivates as to test the stochastic dominance of December over other calendar months. Indeed, we do so in the next sub-section.

5.1.6. December Effect in Medium-Beta Portfolio

In this section, we examine the December effect in Medium-Beta based portfolio. The descriptive statistics presented in Table 5.2 suggest that in Medium-Beta based portfolio, on average, the returns of the month of December (2.8%) are high as compared to other calendar months. Before apply the formal test for testing the stochastic dominance of December month, we present the CDFs of top four month based on their average returns over the examined period. Figure 5.4 shows the CDFs of monthly returns of Medium-Beta based portfolio. The CDFs of top four months are showed on the basis of their monthly returns. These four months are January, February, April, and December. By doing the precarious assessment of the CDFs, we observe that the CDF of December (green dash line) having the highest monthly returns (2.8%) and April month (magenta long dash dot line) has the second position with (2.5%) monthly returns are shifted most to the right as compared to the CDFs of remaining months. Thus, the CDFs suggest the likelihood of the presence of either the December or April month effect in Medium-Beta based portfolio.

Figure 5.4: The CDFs of the Monthly Returns of Medium-Beta Portfolio



Note: The CDFs of High month returns are showed for Medium-Beta based portfolio. The CDFs of top four months are December, April, February and January are presented So, in with the critical view of positive returns, the CDF of April and December months' returns are the most to the right side as compared to other months CDFs.

We now formally test the dominance of December month in Medium-Beta based portfolio by apply the KS type test of stochastic dominance. The p-values of the KS type test statistics are presented in Table 5.6 for the December month. Note that the remaining characteristic and attributes are similar to Table 5.5. As for concern for Medium-Beta based portfolio, we find an interesting result. Specifically, we find that the December returns outperform over all other calendar months' returns in all three examined stochastic dominance orders. The p-values for the null hypothesis that is December *versus* other months are considerably greater than the acceptable level of significance, suggesting that we are not able to reject the null hypothesis. On the opposite side, the p-values for null hypothesis of other months *versus* December are nearly zero in all calendar months except for April. Thus, we can conclude that the December month stochastically dominates over the calendar months at all three examined stochastic dominance order in Medium-Beta based portfolio. However, we also find that April month weakly dominate over December at third order with p-value is 0.172. On the other hand, the p-value for December is 0.484, which clearly, shows a strong dominancy of December over April.

Turning to the results for High-Beta based and Low-Beta based portfolios, we also observe some fascinating evidence. For example, in case of High-Beta portfolio the reported p-values for null hypothesis of December *versus* other month provide evidence in favor of rejection of null hypothesis. This implies that the December month does not stochastically dominates over other calendar months at either examined stochastic dominance order. In general, these results are confirmed by the p-values reported for the reverse null hypothesis of that other month stochastically dominates over December. Yet, one should note that in some cases December month stochastically dominates over the other months. For example, the December month stochastically dominates over June, in particular, at the first and the third stochastic order. Similarly, the December month stochastically dominates over March and July at the third stochastic dominance order. It can also be observe from p-values that in High-Beta based portfolio the month of January, February, May, July and November stochastically dominates over December month.

Table 5.6: Stochastic Dominance in December Month with respect to other Months

	High Beta Portfolio						Medium Beta Portfolio						Low Beta Portfolio					
	December *versus* Other months			Other months *versus* December			December *versus* Other months			Other months *versus* December			December *versus* Other months			Other months *versus* December		
	KS P-Value																	
Months	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**
January	0.000	0.000	0.000	0.999	0.564	0.477	0.360	0.711	0.666	0.005	0.000	0.000	0.615	0.204	0.407	0.361	0.420	0.379
February	0.000	0.000	0.000	0.054	0.745	0.703	0.941	0.565	0.473	0.001	0.008	0.004	0.109	0.001	0.138	0.000	0.017	0.145
March	0.017	0.000	0.303	0.000	0.000	0.000	0.998	0.582	0.504	0.000	0.000	0.000	0.833	0.516	0.686	0.000	0.000	0.000
April	0.000	0.000	0.000	0.241	0.707	0.643	0.998	0.542	0.484	0.001	0.002	0.172	0.512	0.216	0.552	0.000	0.000	0.000
May	0.000	0.000	0.000	0.000	0.648	0.547	0.989	0.509	0.449	0.000	0.000	0.000	0.498	0.273	0.503	0.000	0.000	0.000
June	0.200	0.020	0.316	0.000	0.000	0.000	0.929	0.280	0.422	0.000	0.000	0.000	0.630	0.324	0.500	0.000	0.000	0.000
July	0.005	0.000	0.184	0.000	0.134	0.432	0.824	0.286	0.431	0.000	0.000	0.000	0.450	0.156	0.461	0.000	0.000	0.000
August	0.016	0.008	0.668	0.000	0.000	0.000	0.958	0.480	0.667	0.000	0.000	0.000	0.528	0.154	0.396	0.000	0.000	0.000
September	0.007	0.000	0.121	0.000	0.001	0.02	0.616	0.088	0.356	0.000	0.000	0.000	0.595	0.352	0.686	0.000	0.000	0.000
October	0.008	0.000	0.067	0.000	0.171	0.545	0.996	0.524	0.471	0.000	0.000	0.000	0.724	0.372	0.569	0.000	0.000	0.000
November	0.003	0.000	0.005	0.002	0.741	0.709	0.979	0.517	0.466	0.000	0.000	0.000	0.341	0.104	0.377	0.000	0.000	0.000
December	Winner																	

Note: Three betas based Portfolios are showed. The number of comparison between any two calendar months in each portfolio is C(12,2)=66. December months results (Winner month) present only. SD1, SD2 and SD3 and the KS type P-values for stochastic order first, second and third, respectively

When we look at the p-values reported for Low-Beta portfolio, we observe that the December month stochastically dominates over all calendar months except the month of January. This evidence holds for all three examined stochastic dominance orders. Taking together, the results presented in Table 5.5 and 5.6, we come to the conclusion that both January and December stochastically dominate over all other calendar months. The stochastic dominance of both January and December month suggest the existence of the turn-of-the-year effect[14]. This evidence is consistent with several previous existing studies. Example of these are Sikes (2014) Tangjitprom (2011), Ritter and Chopra (1989), and Lakonishok and Smidt (1984).

Based on the reported p-values, we conclude that in Medium-Beta based portfolio, the month of December is dominated over all the calendar months. These results are consistent with the study of Sum (2013). He also documented that the highest returns are in the month of December (2.91%) in Pakistan Stock Exchange during examined period.

For month effect we document the results consistent with the earlier international studies. For instance, Lean et al. (2007) documented the evidence of the January effect in Singapore Stock Market. Our results are also consistent with Haug and Hirschey (2006). They studied for US market and found that the January anomaly exists in large cap stock (low beta firms) and small cap stock (high beta firms). However, Ariss et al. (2011) have documented evidence in favor of the December effect rather the January effect in GCC indices.

[14] Turn-of-the-year effect implies that the stock returns are high during the last weeks of December and starting weeks of January month.

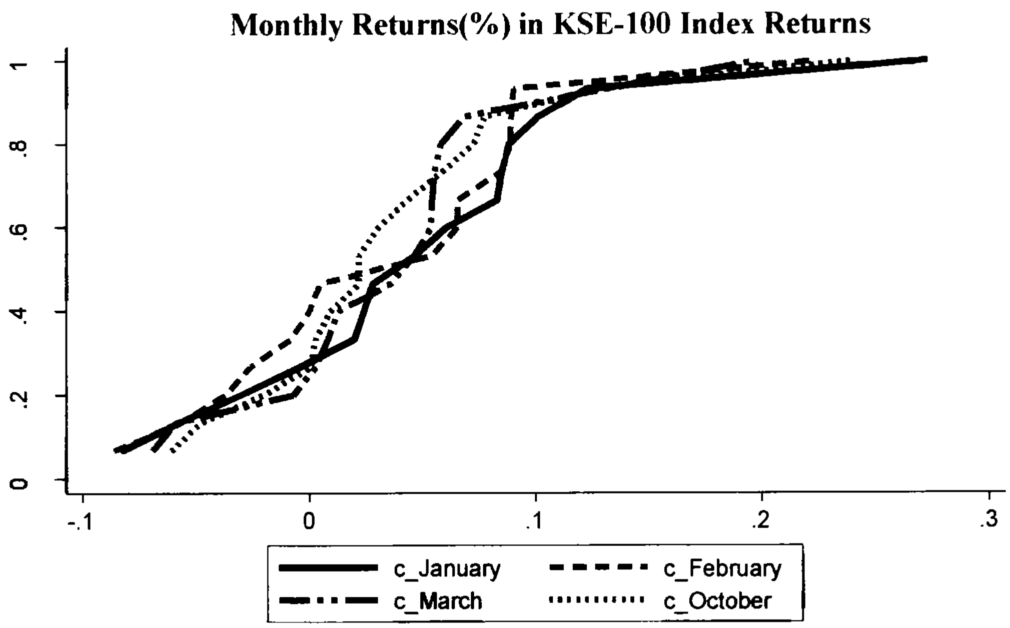
5.1.7. January Effect in KSE-100 Index Returns

The results in Table 5.4 confirm the existence of the January effect in returns of all listed firm included in the sample. Similarly, the results presented in Table 5.5 and Table 5.6 provide evidence of existence of the January effect in High-Beta and Low-Beta based portfolios and the December effect in Medium-Beta based portfolio. In this section, we present results for the month effect in overall Pakistan Stock Exchange using KSE-100 Index as a proxy for overall market returns. We do so, as one of the objective of our study is also to examine month anomaly in overall Pakistan equity market. We used the market index namely, the KSE-100 Index as a proxy for overall market as the several existing studies have also used market indexes as proxy for overall stock market performance. For example these studies are Agrawal and Tandon (1994) and Ariss et al. (2011).

Similar to previous sections, we start the empirical investigation by presenting the CDFs to get preliminary evidence of the dominate month and then apply stochastic dominance test to formally test the dominance of that month. We make the CDFs of top four months' returns based on descriptive statistics presented in Table 5.2. Figure 5.5 shows the CDFs of the top four months' returns, namely January (5%), March (3.9%), October (3.8%), and February (3.6%). The figure shows that the CDF of January and March returns are the most to the right side as compared to other months' CDFs. The figure clearly gives the indication of the January or March effect in Pakistan Stock Market.

Table 5.7 presents the p-values of KS type test monthly returns of KSE-100 Index. Specifically, we apply the test on month vice KSE-100 Index returns. The table is divided into two panels. First panel is titled as January *versus* other months while, the second panel is titled as other months *versus* January. In the fists panel the p-values for the null hypothesis that January stochastically dominated over other months at the first order (SD1), the second order (SD2), and the third stochastic order (SD3) are presented. Similarly, in the second panel the p-values for the reverse null hypothesis that is other underlying month stochastically dominates over the January month are presented for all three examined stochastic dominance orders.

Figure 5.5: The CDFs of the Monthly Returns of KSE-100 Index



Note: The CDFs of KSE-100 Index are showed for January, February, March and October. The critical view of positive returns, the CDF of January and March are the most to the right side as compared to other months CDFs

Comparing the p-values of January with other months, we observe that the January month strongly dominates over all other calendar months. In particular, the p-values reported in the first panel of the table are considerably greater than the acceptable level of significance for all the examined stochastic dominance orders. This implies that we are not able to reject the null hypothesis that the January month stochastically dominates over the other calendar months. The dominance of the January over other months is generally, confirmed by the p-values in the second panel of the table for testing the reverse null hypothesis.

Nevertheless, we find some months weakly dominate over January. For instance, by comparing the p-values across both panels of the table, we find that the February, March, April, and October weakly dominate in all three examined stochastic dominance orders. For instance, the p-values for January *versus* February for first, second, and third SD orders are 0.831, 0.380, and 0.393, respectively. On the other hand, the p-values for February *versus* January are 0.264, 0.199, and 0.330, respectively, which show strong dominance of January over February month and weak dominance of February over January. One should note that the January strongly dominates over October month at the first, second, but weakly dominate at third order of stochastic dominance with p-value 0.180, while the corresponding p-value is 0.105.

Table 5.7: Stochastic Dominance of January Month in KSE-100 Index Returns

	January *versus* Other Months			Other Month *versus* January		
	KS P-value					
Months	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**
January		Winner				
February	0.831	0.380	0.393	0.264	0.199	0.330
March	0.785	0.577	0.524	0.203	0.162	0.081
April	0.631	0.388	0.421	0.152	0.023	0.051
May	0.987	0.691	0.648	0.003	0.000	0.000
June	0.946	0.718	0.676	0.019	0.014	0.002
July	0.317	0.084	0.225	0.005	0.001	0.052
August	0.887	0.474	0.468	0.011	0.000	0.000
September	0.674	0.168	0.254	0.004	0.001	0.019
October	0.609	0.180	0.253	0.077	0.105	0.356
November	0.779	0.317	0.311	0.006	0.001	0.010
December	0.526	0.716	0.685	0.017	0.000	0.000

Note: January months results (Winner month) present only. SD1, SD2 and SD3 and the KS type P-values for stochastic order.January month significantly outperforms on other calendar months. The number of comparison between any two calendar months in KSE-100 Index is C(12,2)=66.

The results given in Table 5.7 are consistent with the studies of Boudreaux (1995) Haugen and Jorion (1996), Annuar (1987), Fountas and Segredakis (2002), Haug and Hirschey (2006), , Lean et al. (2007), and Li and Gong (2015). Boudreaux (1995) found the January phenomenon in Denmark, Germany, and Norway Stock Markets.

Haugen and Jorion (1996) also found the January effect in US stock market. They pointed out that the January effect specifically exists in small firms. Kuala Lumper Stock Market also experienced January anomaly found by Annuar (1987). The main reasons of the January effect can be liquidity constraint, tax loss selling, and omitted risk factor. Fountas and Segredakis (2002) examined the January effect in eighteen[15] from 1987 to 1995, emerging stock market including Pakistan. They have documented that the January effect is due to tax-loss selling hypothesis. Wachtel (1942) and Branch (1977) formulate an explanation for disproportionately large January returns based on the year-end tax loss selling of shares that have declined in value over the previous year. The most common theory which explain January phenomenon is that individual investors, who are income tax-sensitive and who disproportionately hold small stocks, sell stocks for tax reasons at year end (such as to claim a capital loss) and reinvest after the first of the year. Li and Gong (2015) have also discovered January anomaly in Japanese Stock Market during the period from 1975 to 1984 They gave the rationalization of January effect is that high stock volatility in January is not only the cause rather the January effect, is due to risk compensation in January can explained high returns in January.

However, our results on the existence of the January effect are inconsistent with the studies of Gu (2015). He has found June phenomenon and in US stock indexes, DJIA, NASDAQ, and S&P 500, from 2001 to 2013. Ke et al. (2014) documented the February effect instead of the January effect in Taiwan Stock Market and stated that spring festival follow February phenomenon. In the USA the April anomaly exists due to the event month effect that explains stock prices are increasing prior 40 days of annual general meetings (Wang and Hefner, 2014). On the other hand, Ariss et al.

[15] Pakistan, Argentina, Chile, Colombia, Greece, India, Jorden, Korea, Malaysia, Mexico, Nigeria, Philippines, Portugal, Thailand, Taiwan, Turkey, Venezuela, Zimbabwe,

(2011) documented the December effect in GCC countries. In Indian Stock Market, the returns of Novemeber month is dominating over other calendar months (Chakrabarti & Sen, 2008). However, Ali and Akbar (2009) found weekly the fourth and the fifth day effect and no month effect in PSX during their study period.

5.1.8. Conclusion of Month Anomaly

This section has examined the month anomaly for Pakistan Stock Market (PSX). In particular, we test the month anomaly in overall listed firms, beta based portfolios, and KSE-100 Index returns. Initially, descriptive statistics was presented to see whether any calendar anomaly is presented in the market. Then, we apply the K-S normality test and provide significance evidence that month vice and beta based portfolios' returns are not normally distributed. After confirming that stock returns are not normally distributed we test the existence of the month effect in beta based portfolios as well as in overall market. The stochastic dominance test (KS type test) then confirmed that the stochastic dominance of January and December month. This suggests that the returns discrepancies remain in the market and could be exploited by developing specific investment strategies to gain abnormal returns. Overall, the January effect is found in return of all listed firms included in the sample. We also found that in High-Beta and Low-Beta based portfolios there is the strong dominancy of January month, while for Medium-Beta portfolio, the December effect exists.

We also observe that in Low-Beta portfolio, the December month is dominating over January at the first and third stochastic orders, while, January dominates over December at the second order of stochastic dominance. In case of KSE-100 Index returns, the January month is outperformed over all other calendar months at the first, second, and third order of stochastic rules. Therefore, abnormally high returns for

January month and December month give the indication of another anomaly in Pakistan Stock Exchange that is called the turn-of-the-year effect.

Many researchers have found turn-of-the-year effect by examining abnormal stock returns in the month of January and December. For instance, Tangjitprom (2011) found that returns are high in the last week of December and first week of January in Thailand. Similarly, Sikes (2014) and Lakonishok and Smidt (1984) studied the calendar anomalies for USA stock market and found that the existence of the turn-of-the-year effect is more likely in small firms. They explain that small cap stocks earn usually high returns in early days of January due to the tax loss selling by individual investors and last week of December due to window dressing by institutional investors.

In sum, the results regarding the month anomaly that we presented in this study also suggest the turn-of-the-year effect. A possible explanation for these results is that the individual investors, who are income tax-sensitive and who disproportionately hold small stocks, sell stocks for tax reasons at year end (such as to claim a capital loss) and reinvest after the first month of the year. Another cause is the payment of year-end bonuses in January. Some of this bonus money is used to purchase stocks, driving up prices. We have presented the resulted tables for only dominated months (January and December). The remaining tables and KS type tests results for beta based portfolios and KSE-100 Index returns are showed in the appendix.

5.2. Equity Premium Puzzle Anomaly

Equity premium puzzle (EPP) is the difference between equity returns and government bond/Treasury bill rates. The term equity premium puzzle is coined by Mehra and Prescott (1985). In their seminal work, they compared the equity returns and Treasury rate for the United States and found the difference between the equity returns and Treasury bill rate 7.9% for the examined period. The puzzle has directed to an extensive exploration in both finance and macroeconomics. Indeed, there are several studies existed in the empirical literature and found the EPP anomaly for different developed and developing countries. For instance, Donadelli and Persha (2014) examined the EPP anomaly for Asian, East European, and Latin American Stock Markets. They found significance evidence in favor of the existence of the EPP anomaly. Neely et al. (2014) and Mehra (2003) worked on US stock markets and investigated the EPP anomaly.

However, Lim et al. (2006) and Jagannathan et al. (2001) investigated reverse equity premium puzzle for US stock market during their study period. Revising the previous literature we come to know that previous studies have given a range of useful theoretical tool and statistical plausible description for the existence of equity premium puzzle anomaly. Yet, no one solution is generally accepted by the economist. In principal, the EPP anomaly is examined by the following two ways. The first method to examine the EPP anomaly is simply based on descriptive statistics. Specifically, in this method, one compares the return distributions of equity returns and the risk-free rate. The second method, involve estimating the risk aversion factor for the chosen theoretical model (Mehra & Prescott, 1985). In this section, we examine the EPP anomaly based on the first method. Specifically, we first calculate the EPP by find the difference between equity returns and the risk-free rate and then, we check the existence of the EPP anomaly by applying stochastic dominance approach. We use 3-month Treasury bill rate as a proxy for the risk-free rate and the returns of KSE-100 Index are used as a proxy for equity market returns.

This section is divided into three sub-sections. In the first sub-section, we first present descriptive statistics of equity returns and the risk-free rate. The graph of KSE-100 Index returns, risk-free rate, and the calculated equity premium is also presented to show the trend of these three return distributions. Then, in the second sub-section, we apply formal test of stochastic dominance namely, KS type test to examine the stochastic dominance relationship between of 3-month Treasury bill rate over equity returns. In the last sub-section, we conclude the equity premium puzzle anomaly and give some possible justifications for the obtained findings.

5.2.1. Empirical Results of Equity Premium Puzzle

Before applying the formal test for equity premium puzzle we first present summary statistics in Table 5.8. Sample mean of KSE-100 Index returns and 3-month Treasury bill rate are 1.974% and 9.039%, respectively. This implies that on average, 3-month Treasury bill rate are higher as compared to the equity returns. Similarly, the median value of the return is also higher for 3-month Treasury bill rate as compared to the KSE-100 Index returns. In particular, the median value of returns for KSE-100 Index is 2.1%, where the corresponding figure for 3-month Treasury bill rate is 9.4%.

Yet, one should note that the median value of returns is significantly higher than the mean value in case of both KSE-100 Index returns as well as 3-month Treasury bill rate. This indicates that both returns distributions are negatively skewed. These observations are also verified by the skewness values reported in the table, which is negative for both returns distributions.

By comparing the standard deviation of returns, we find that the KSE-100 Index is more volatile than the 3-month Treasury bill rate. The estimate value of kurtosis is 3.34 for the KSE-100 Index returns while, the corresponding figure for the 3-month

Treasury bill rate is 0.049. Further evidence of the higher risk from investing in equities is highlighted by observing that the extreme returns in equities are much high than the extreme returns experienced by 3-month Treasury bill rate. These statistics provide preliminary evidence on the existing difference between both returns distributions.

Further, the estimated values of the skewness and kurtosis suggest that both the returns distributions are not normally distributed. However, we apply the K-S normality test to examine whether the underlying returns distribution is normally distributed. The p-values for K-S normality test are also reported in Table 5.8. The estimated p-values provide evidence that the KSE-100 Index returns are normally distributed, whereas the 3-month Treasury bill rate is not normally distributed. The size of equity premium between equities and 3-month Treasury bill rate is (1.974% - 9.039% = -7.065%). This negative value of equity premium puzzle is termed as "reverse puzzle".

Table 5.8: Descriptive Statistics of Equity Premium Puzzle

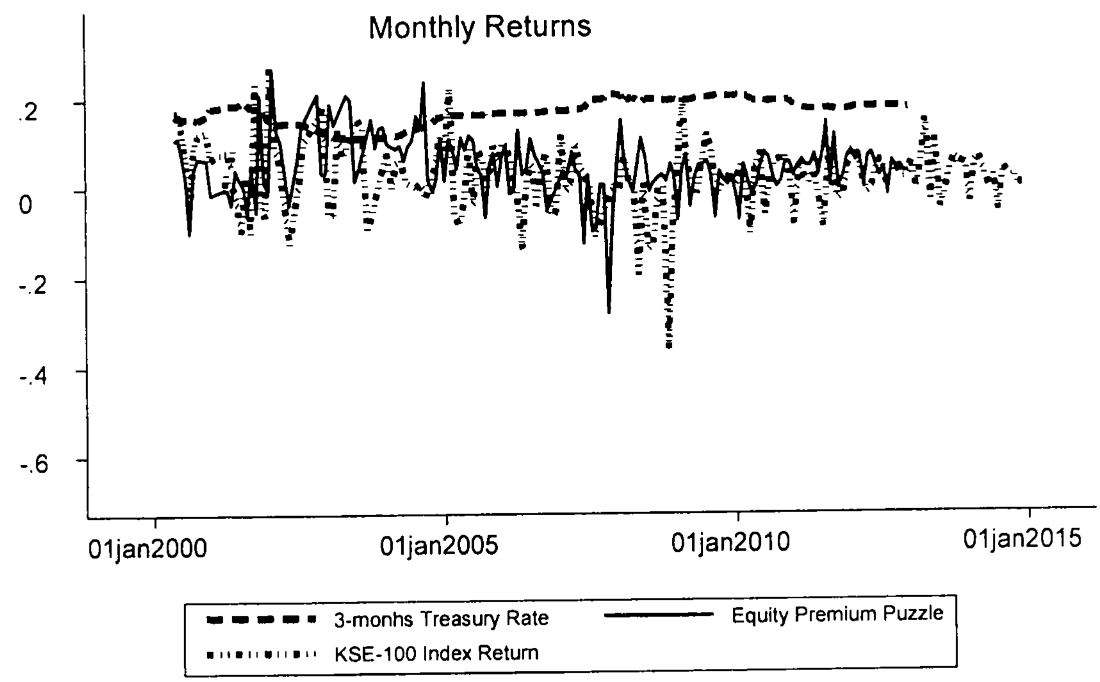
	KSE-100 Index	*3-month Treasury bill rate*
Mean	1.974	9.039
Median	2.143	9.448
Standard Deviation	7.924	3.393
Kurtosis	3.348	0.049
Skewness	-0.512	-0.834
Minimum	-36.20	1.000
Maximum	27.30	13.80
K-S Normality test P-value	0.192	0.015
Count	180	165

Note: Descriptive Statistics of KSE-100 Index and 3-month Treasury rate are reported. Mean values of return of KSE-100 Index and 3-month Treasury bill are 9.039% and 1.974% respectively.

The reverse puzzle is also reported by Lim et al. (2006) for US stock market over the period 1989 – 2003. Another study by Jagannathan et al. (2001) has also reported the declining EPP, suggesting that the EPP is decreasing over the time. To get idea about trend in return distributions of 3-month Treasury bill rate and KSE-100 Index, we present the trends in both return distributions along with the calculated equity premium over the time in Figure 5.6.

Dash line represents 3-month Treasury bill rate and dotted line shows return of KSE-100 Index. Solid line shows EPP series which is the difference of KSE-100 Index returns and 3-month Treasury bill rate returns. It can be observe from the figure the KSE-100 Index returns are more volatile as compared to 3-month Treasury bill rate.

Figure 5.6: Returns of KSE-100 Index, 3-months Treasury Rate, and Equity Premium Puzzle



Note: Returns of KSE-100 Index, Treasury Rate and EPP time period from January 2000 to December 2014.

We can also observe from the figure equity returns are positive for some period while they are negative for other periods. On the flip, 3-month Treasury bill rate remain positive throughout the examined period.

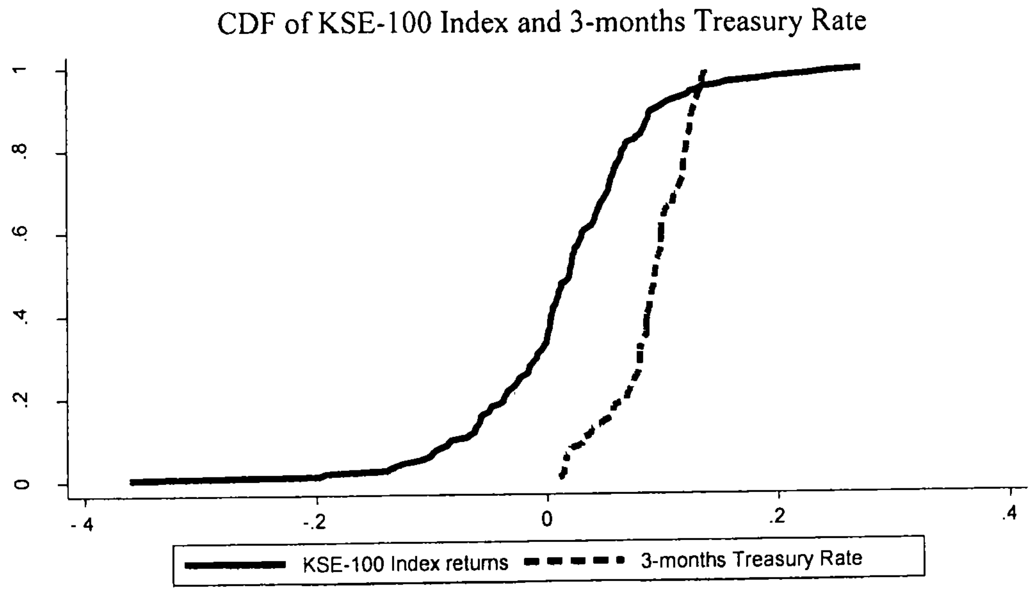
The curve of EPP suggests that the estimated EPP is relatively more volatile throughout the examined period. However, it is relatively stable during to the last years of sample as compared to the early years of sample. Overall, the equity premium remains negative. However, for some periods it becomes positive.

5.2.2. Stochastic Dominance of the Risk-Free Rate over Equity Returns

In this section, we formally test the stochastic dominance relationship between the risk-free rate and equity returns. First, we predict the stochastic dominance through graphically by drawing cumulative density functions (CDFs) graph of these two return distributions. Figure 5.7 presents the CDFs of returns distributions of KSE-100 Index and 3-month Treasury bill rate. The summary statistics presented in Table 5.8 shows that mean returns of 3-month Treasury bill rate is high (9.039%) as compared to the KSE-100 Index (1.974%) while, the standard deviation of the 3-month Treasury bill rate (3.393%) is less than half of KSE-100 Index standard deviation (7.924%).

We can also observe from the figure that the CDF of 3-month Treasury bill rate is below and lies right side of the CDF of KSE-100 Index returns. This implies that it is very likely that the 3-month Treasury bill rate would stochastically dominates over the KSE-100 Index returns. What follows below we test the stochastic dominance of the 3-month Treasury bill rate by applying KS type test.

Figure 5.7: The CDFs of KSE-100 Index Return and 3-month Treasury Rate



Note: The CDFs of KSE-100 Index returns and 3-month Treasury bill are presented. Solid line represents returns of KSE-100 Index series and square dotted line shows the CDF of 3-month Treasury bill. The CDF of 3-month Treasury bill rate is right side as compared to the CDF of KSE-100 Index returns distribution.

We apply the stochastic dominance test namely, KS type test, on these two return distributions. Table 5.9 provides the p-values for KS type test to test the null hypothesis of 3-month Treasury bill rate stochastically dominate over the KSE-100 Index returns and reverse null hypothesis that the KSE-100 Index returns stochastically dominates over the 3-month Treasury bill rate over the examined period. The first and second panel of the table reports the null hypothesis that is, 3-month Treasury bill rate *versus* KSE-100 Index returns and the reverse null hypothesis KSE-100 Index returns *versus* 3-month Treasury bill rate, respectively.

The p-values reported in the first panel indicating that we unable to reject the null hypothesis, as the p-values for all three examined stochastic dominance orders are considerably higher than the acceptable level of significance. This implies that 3-month Treasury bill rate are stochastically dominate over the KSE-100 Index returns at the first, second, and third stochastic dominance order.

Table 5.9: Stochastic Dominance of 3-month Treasury Rate *versus* KSE-100 Index

	3-month Treasury Rate *versus* KSE-100 Index	KSE-100 Index *versus* 3-month Treasury Rate
SD Orders	**KS P-value**	
SD1	0.711	0.000
SD2	0.738	0.000
SD3	0.694	0.000

Note: Stochastic dominance of two pair of assets is revealed. KS P-values are calculated through simulation and SD1, SD2, SD3 are three p-values of stochastic orders first, second and third.

The p-values presented in second panel of the table confirmed the stochastic dominance of 3-month Treasury bill rate. In particular, the reported p-values are zero, indicating the rejection of null hypothesis that the KSE-100 Index returns stochastically dominates over the 3-month Treasury bill rate. These finding suggest that there exists reverse puzzle in Pakistan equity market. That is the risk-free rate dominates over the equity returns during the examined period.

The results on reverse equity premium puzzle are consistent with the studies of Lim et al. (2006) and Jagannathan et al. (2001). Lim et al. (2006) found "reverse puzzle" and examined that 3-month Treasury bill rate dominates over S&P500 Index at third and higher stochastic dominance orders. Jagannathan et al. (2001) examined equity premium (EPP) is decreasing over the time in US stock market from 7% to 0.7% during the examined period (1926 – 1999). They found that during the1980s the EPP is negative and after 1990s it even become close to zero.

However, results are inconsistent with the studies of Siegel (1992), Mehra (2003), Salomons and Grootveld (2003), Damodaran (2011) and Donadelli and Persha (2014). Siegel (1992) has found the EPP in US stock market time period from 1802 to 1990 and examined that stocks have higher returns as compared to fixed income investment, Treasury bill rate. Mehra (2003) also worked on the data of the UK, USA, France, Germany, and Japan and found positive equity premium puzzle. They stated that taxes, borrowing constraits and bearing risk are the main reasons of high equity premium. Salomons and Grootveld (2003) investigated the equity risk premium in both developed and emerging markets during the study period from January 1976 to December 2001. They have explained that structural and cyclical factors are driving forces high equity risk premium and concluded that equity risk premium fallow cyclical pattern so that's why it is higher in emerging markets. Similarly, Damodaran (2011) and Donadelli and Persha (2014) examined the equity premium puzzle for different emerging and developed markets and concluded that the EPP is high in emering markets as compared to developed markets but the key reason still remains blur.

5.2.3. Conclusion of Equity Premium Puzzle Anomaly

In previous section, we have investigated the second anomaly namely, equity premium puzzle (EPP) in Pakistan Stock Market. We found the EPP anomaly in reverse direction. 3-month Treasury rate dominate over KSE-100 Index returns at all three examined orders of stochastic dominance. This implies that investors prefer risk-free assets over risky assets, when making their investment decisions. In fact, returns of risky assets might not be enough to compensate the investors for bearing risk related with their risky prospects or outcomes.

Another possible reason for the existence of reverse equity premium puzzle is that Pakistan equity market is more volatile and dominated by only big investors who generally, invest in stock based on their speculations rather than based on fundamentals. Political law and orders, macro-economic uncertainty in the country may be other reasons behind the reverse equity premium puzzle. Further, the existence of reverse equity premium puzzle in Pakistan can also be attributed to the behavior of investors.

The investors' country like Pakistan prefers to invest in fixed returns securities rather than equity. Furthermore, the lack of depth and breadth of equity market can be a possible explanation for the existence of reverse equity premium puzzle. Finally, in Pakistan the debt market dominates over the equity market because of large public sector debt. The dominance of debt market over equity market definitely results in reverse equity premium puzzle.

5.3. Momentum Anomaly

The focus of this section is to examine the momentum anomaly. From the context of momentum anomaly, the notion of market efficiency has been challenged by overreaction and underreaction effect from investors' side Bondt and Thaler (1985) and Jegadeesh and Titman (1993) respectively. An important issue in the predictability of stock returns is the existence of negative or positive serial correlations. Indeed, strong correlation observed in the historical returns (Ball & Kothari, 1989; J. Y. Campbell, Grossman, & Wang, 1992; Islam & Sultana, 2015).The observed correlation lead academician and researcher to take up the two main directions in theoretical finance and present challenge the traditional view of security prices.

In particular, positive serial correlations stock returns imply that stocks having positive returns in the past are also likely to have positive returns in the future. This rising trend in stock returns is termed as momentum effect or underreaction effect in the behavioral finance literature (Jegadeesh & Titman, 1993). In particular, if the momentum effect exists, then the momentum strategy is beneficial for investors to get abnormal returns. On the other hand, the existence of negative serial correlations in stock returns implies that stocks those exhibit positive returns in the past are prone to have negative returns in the future. Said differently, winner stocks become loser in the future. This revers pattern in the stock returns is known as momentum reversal effect or overreaction effect (Bondt & Thaler, 1985). The theoretical literature is suggested that investors may earn abnormal returns by adopting contrarian strategy in case of momentum reversal effect.

As we mentioned earlier, Bondt and Thaler (1985) and Jegadeesh and Titman (1993) found the "overreaction" and the "momentum" effects respectively. Bondt and Thaler (1985) investigated a reversal phenomenon in the US stock market where in the long run, past loser stocks outperformed the past winner stocks over a subsequent period of three to five years. The investment strategy based on such reversal that is to buy past loser stocks and to sell past winner stocks is known as contrarian strategy (Mun, Vasconcellos, & Kish, 1999).

In contrast, the momentum strategy entails the purchase of winner stocks and sale of loser stocks. This is the exact opposite of what the contrarian strategy recommends. Jegadeesh and Titman (1993) documented the profitable momentum strategies using monthly data of the US stock market. They found the existence of continuation pattern in stock returns over a short term period say 3 to 12 months, wherein past winners continue to outperform past losers. Looking at the recent literature we find several recent studies that have also examined the momentum effect and the momentum reversal effect in different countries across the globe. The worth mentioned studies are Birru (2015), Dhankar and Maheshwari (2015), Hassan (2014), Asness et al. (2013), Siganos (2013), and Antoniou et al. (2011).

In this section, we apply stochastic dominance test, namely, KS type test to examine stochastic dominance relationship among loser and winner portfolios. We also apply additional *t*-test on the returns of winner and loser portfolio in order to get conformity of our results. To start empirical investigation, we construct winner and loser portfolios in the spirit of Bondt and Thaler (1985). First, we present summary statistics of returns for winner and loser portfolios. Next, we present the p-values of KS type test to examine which portfolio has dominance over other. In last sub-section we present the statistics of *t*-test to examine either there is an existence of the momentum effect or the momentum reversal effect (overreaction effect). Then, we conclude the momentum anomaly and explain what type of investment strategy should be followed in Pakistan Stock Exchange (PSX).

5.3.1. Descriptive Statistics of Winner and Loser Portfolio

To test momentum anomaly, we follow the procedure adopted by Bondt and Thaler (1985). Starting in December 2002 the stocks are ranked in descending order on the basis of their cumulative continuous returns over the previous 36 months. This procedure is iterated 5 times for all non-overlapping 3-year periods between January 2000 and December 2014. In order to construct winner and loser portfolios, on each of the relevant portfolio formation dates, (December 2002, December 2005, December 2008, and December 2011), the cumulative average returns are ranked low to high and portfolios are constructed.

Specifically, two portfolios winner and loser are formed. The winner portfolio includes top 50 stocks based on the cumulative average returns (*CAR*) over the prior 36 months. The loser portfolio contains the bottom 50 stocks based on cumulative average return over the prior 36 months. Both portfolios are held for next 36 months or a 3-year holding period. Then, the average of these cumulative average returns ($ACAR$) is calculated for both portfolios between test periods. Doing so, we get the two return distributions for winner and loser portfolios named as $ACAR_W$ and $ACAR_L$, respectively.

Table 5.10 reports descriptive statistics of $ACAR_W$ and $ACAR_L$ over 36 test periods (t = 1 to t = 36). The table also presents the difference between $ACAR_W$ and $ACAR_L$. The mean of $ACAR_L$ is higher as compared to mean of $ACAR_W$. This implies that on average, the mean of $ACAR_L$is higher the mean of $ACAR_W$ over all test periods. . The average risk exposure for the test periods returns states support to our hypothesis that the returns of loser stock dominate over winner. The values of standard deviation indicate $ACAR_L$are more volatile as compared to the $ACAR_W$. On average, over the test period the difference between the $ACAR_W$ and $ACAR_L$ is 39.8%. This observation suggests that investor may earn abnormal returns by adopting contrarian strategy.

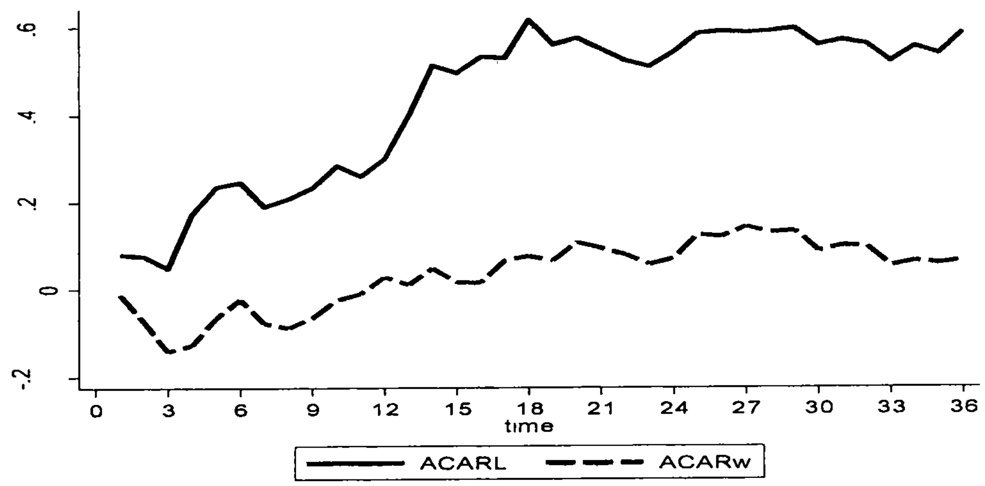
Table 5.10: Descriptive Statistics of the Mean of $ACAR_L$, $ACAR_W$, and $ACAR_L - ACAR_W$

	$ACAR_L$	$ACAR_W$,	$ACAR_L - ACAR_W$
Mean	43.2%	3.40%	39.8%
SD	18.0%	7.6%	11.4%
Test Period	36	36	36

Note: The mean of Average of cumulative access returns (ACAR) of loser and winner portfolios of 36 test period (t =1 to t =36).Overall, mean and standard deviation of loser Portfolio are 39.8% (0.114), more than winner portfolio.

In Figure 5.8 we show the trend of $ACAR_W$ and $ACAR_L$ over the test periods. Inspection of the figure reveals that the spread between the $ACAR_W$ and $ACAR_L$ (loser and winner) is increasing over the time. Further the $ACAR_L$ of loser portfolio has upward trend, suggesting long position for loser portfolio and short position for winner portfolio. This dominance performance of loser stocks may be attributed to small firm effect. Richards (1997) has defined the small firm as a "losing firm" around the turn-of-the-year. He also explained that the losing firms have experienced positive and high returns in the month of January as compared to the other calendar months. To check whether loser portfolio really dominates over the winner portfolio in the month of January, we show Table 5.11, the mean of cumulative average returns of loser and winner portfolio for the January month only.

Figure 5.8: *ACARs* of Loser and Winner Portfolios for 36 Test Periods



Note: Average cumulative average returns of top 50 winners and bottom 50 loser stocks in 36 test periods.

We find that on average, the cumulative average returns of loser portfolio are higher than that of winner portfolio in the month of January over the test periods. In particular, the mean of cumulative average returns and the standard deviation for the loser portfolio across all the month of January is 35.6% and 44.5%, respectively. On the other hand, very dejected performance is appeared for the winner portfolio in the month of January. The mean value of winner portfolio (4.1%) is relatively less with high standard deviation (56.8%). This indicates a clear-cut dominance of loser portfolio over the winner portfolio in the month of January. This observation also provides evidence of small firm effect. In addition, the t-statistics also show that the results are significant.

Table 5.11: Descriptive Statistics of the Mean of $ACAR_L$ and $ACAR_W$ for January Month

	January Month			
	$ACAR_L$	$ACAR_W$,	*t-test*	
Mean	35.6%	4.1%	t-statistics	2.860
SD	44.5%	56.8%	Mean(diff)>0	0.0077
N	12	12		

Note: The mean of average of cumulative access returns of loser and winner portfolios for the months of January is reported. Average of excess return of Loser portfolio in January month is high and standard deviation is less as compared to contestant.

These observations compliment for the previous work about the January effect due to the small firm effect. Keim (1983) and Reinganum (1981) have studied small firms and the January effect and the January effect further affected by the Price/Earning (P/E) ratio effect and the dividend yield effect. January phenomenon is typically explicated by tax-loss selling (Roll, 1983). Fry, Keim, and Meiners (1982) documented that high P/E stocks are "overvalued" whereas low P/E ratio are "undervalued".

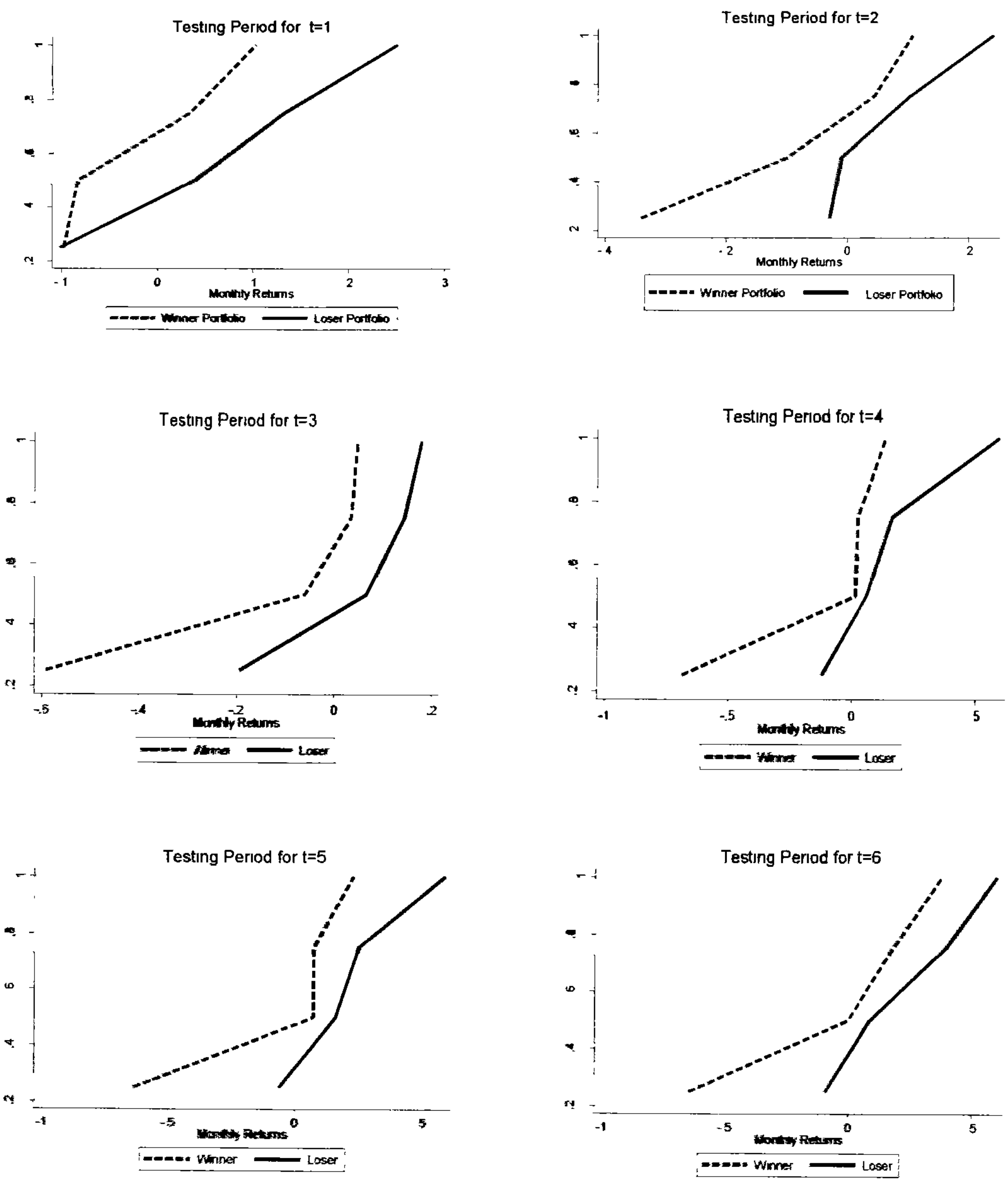
This argument implies that the P/E effect is also for the most part a January phenomenon. Another explanation to support this argument is that the persistent positive relationship between divided yield (a variable that is correlated with P/E ratio) and the January month excess returns. However to formally test the small firm effect there is need to investigate further by constructing winner and loser portfolios based on firm size. We do not expend on these line as this is beyond the scope of the study. However, we recommend this for the future research on this issue.

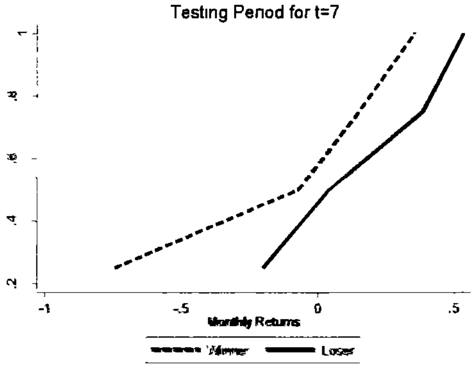
5.3.2. Empirical Results for Momentum Portfolio

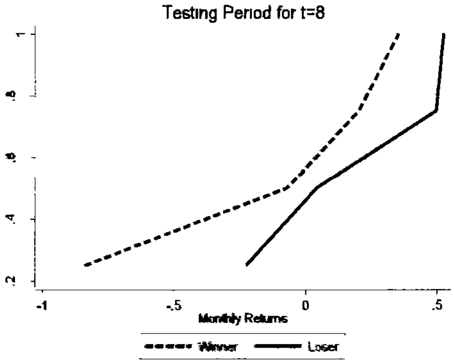
Descriptive statistics shown in Table 5.9 and Figure 5.8 provide preliminary evidence on the dominance of loser portfolio over the winner portfolio. To proceed further, we now present the CDFs of both portfolios for each test period through (t = 1 through t = 36). One can inspect from Figure 5.9 the curves of loser portfolio (solid black line) are most likely lies to the right to the CDF of winner one (dash black line) in all test periods. We can see the paired vice performance of $ACAR_W$ and $ACAR_L$ of winner and visual dominancy and then apply formal test of KS type test on loser and winner portfolio. loser stocks for each test period from, t =1, to t =36. In order to examine the momentum effect, we first have drawn the cumulative density function to check the

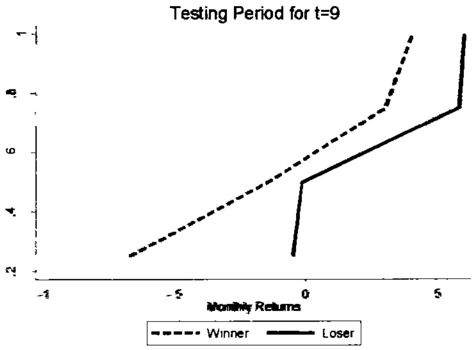
After the initial evidence on the dominance of loser portfolio over the winner portfolio through the CDFs. we now formally test the stochastic dominance of loser over winner portfolio. Similar to the previous two examined anomalies, we apply KS type test to check the stochastic dominance relationship between loser and winner portfolio. The p-values of the test statistics are presented in Table 5.12. The table is divided into two panels. In the first panel labeled as Loser *versus* Winner, we have given the p-values for null hypothesis that is loser portfolio stochastically dominates over winner portfolio at s^{th} order of Stochastic dominance ($L >_s W$). The second penal named as Winner *versus* Loser shows the p-values for alternative hypothesis ($W >_s L$). The first column of the table shows the test period from t = 1 to t = 36 for loser and winner portfolio. Specifically, the p-values for all examined stochastic dominance orders are considerably higher than the any acceptable level of significance. In fact, the p-values for the first order stochastic dominance appear 1. This implies that we are unable to reject the null hypothesis that is loser portfolio stochastically dominates over winner portfolio.

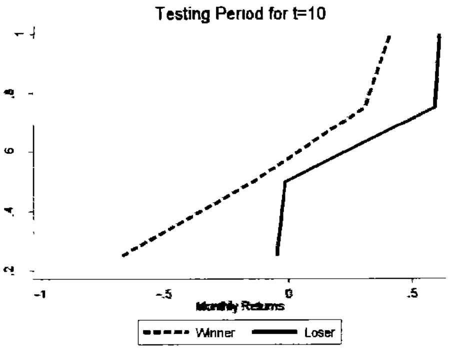
Figure 5.9: The CDFs of $ACAR_W$ and $ACAR_L$ from Test Periods t =1 to t = 36

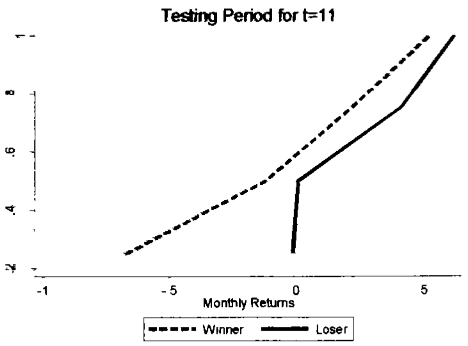


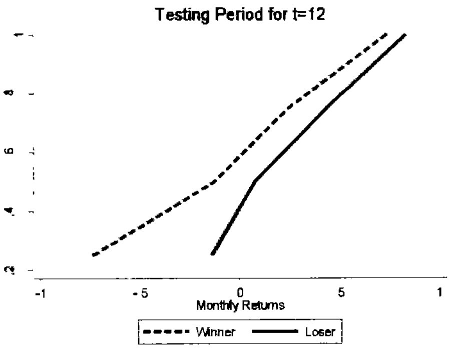

Testing Period for t=7
Monthly Returns
Winner
Loser

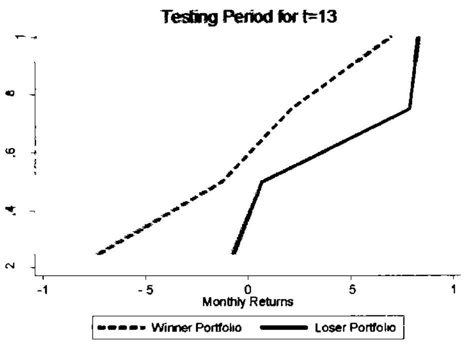

Testing Period for t=8
Monthly Returns
Winner
Loser


Testing Period for t=9
Monthly Returns
Winner
Loser


Testing Period for t=10
Monthly Returns
Winner
Loser


Testing Period for t=11
Monthly Returns
Winner
Loser


Testing Period for t=12
Monthly Returns
Winner
Loser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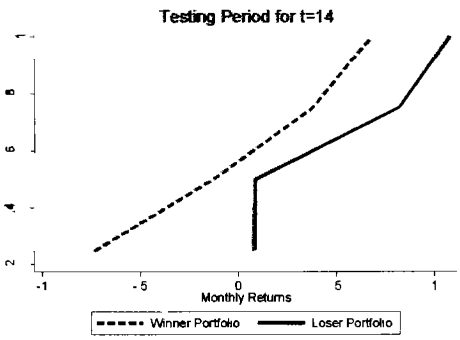
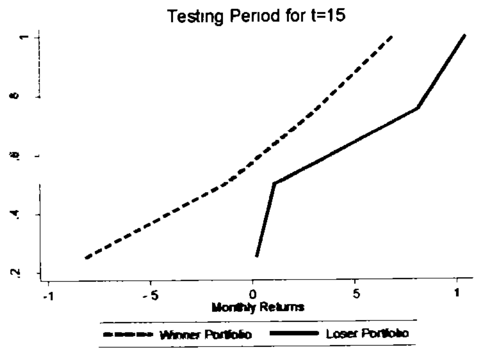
Monthly Returns
Winner Portfolio
Loser Portfolio


Testing Period for t=14
Monthly Returns
Winner Portfolio
Loser Portfolio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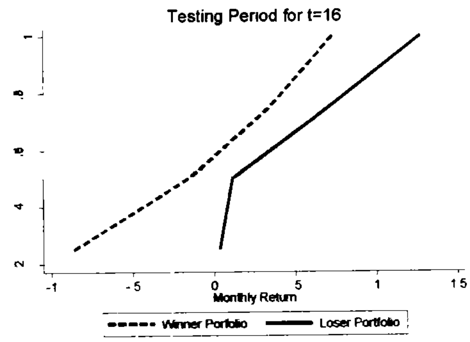
Monthly Returns
Winner Portfolio
Loser Portfolio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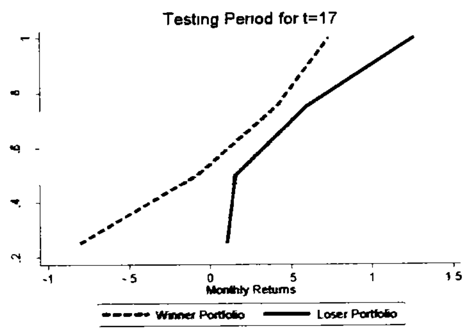
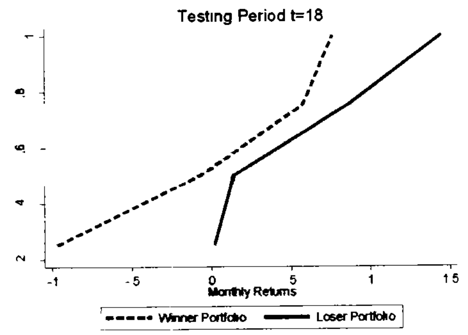
Monthly Return
Winner Portfolio
Loser Portfolio


Testing Period for t=17
Monthly Returns
Winner Portfolio
Loser Portfolio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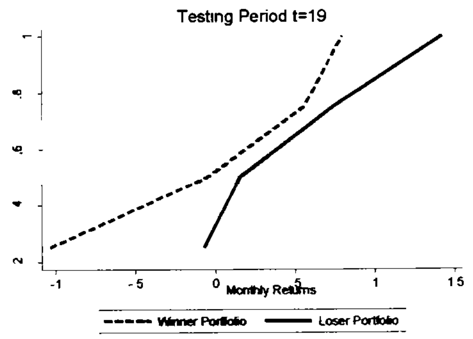
Monthly Returns
Winner Portfolio
Loser Portfolio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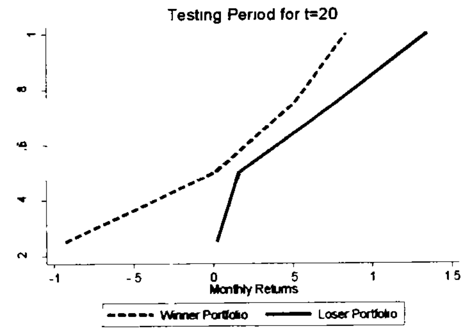
Monthly Returns
Winner Portfolio
Loser Portfolio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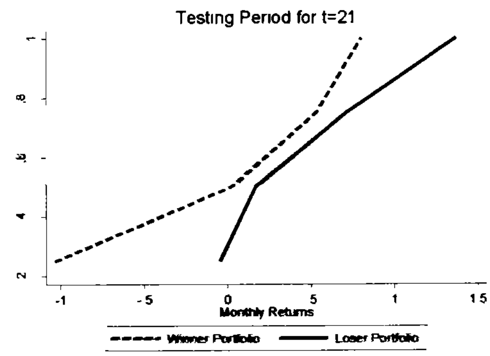
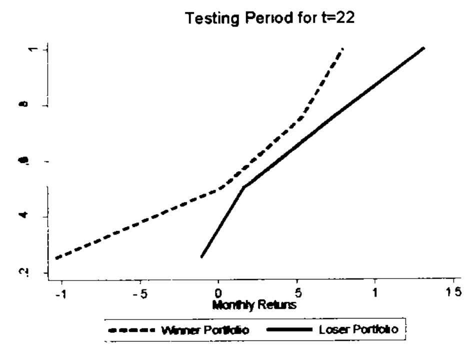
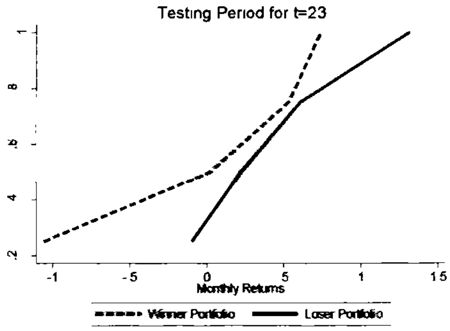
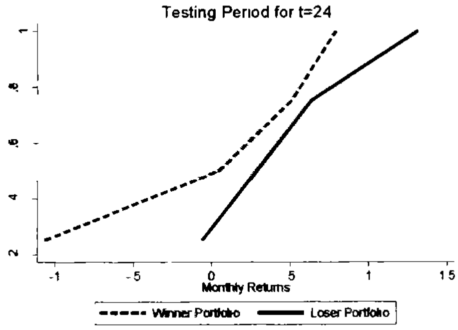
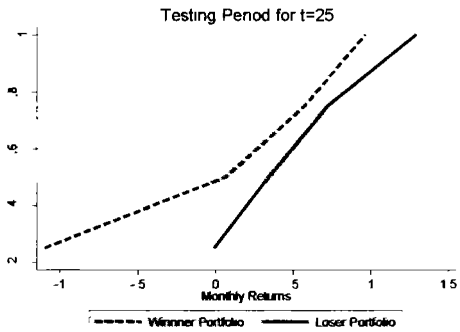
Monthly Returns
Winner Portfolio
Loser Portfolio

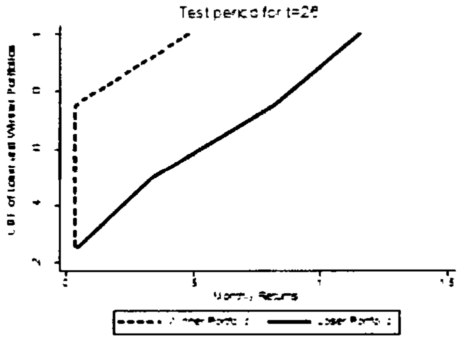

Testing Period for t=21
Monthly Returns
Winner Portfolio
Loser Portfolio

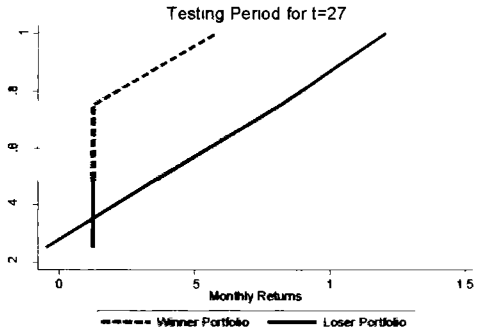

Testing Period for t=22
Monthly Returns
Winner Portfolio
Loser Portfolio

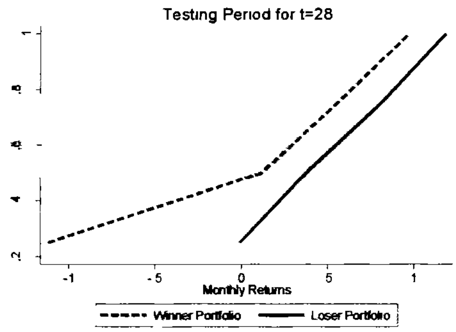

Testing Period for t=23
Monthly Returns
Winner Portfolio
Loser Portfolio

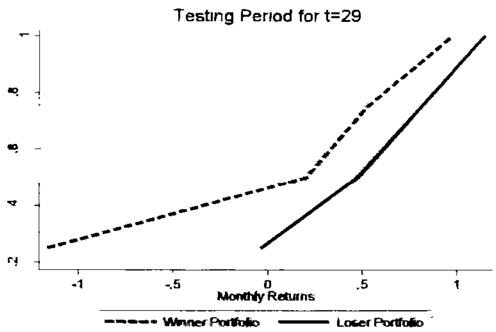

Testing Period for t=24
Monthly Returns
Winner Portfolio
Loser Portfolio

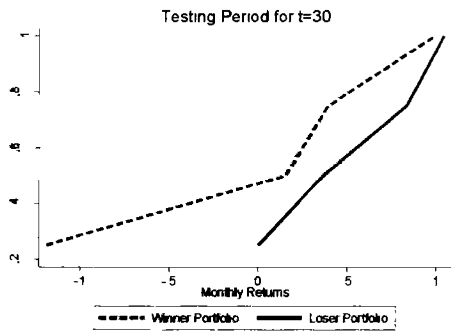

Testing Period for t=25
Monthly Returns
Winner Portfolio
Loser Portfolio

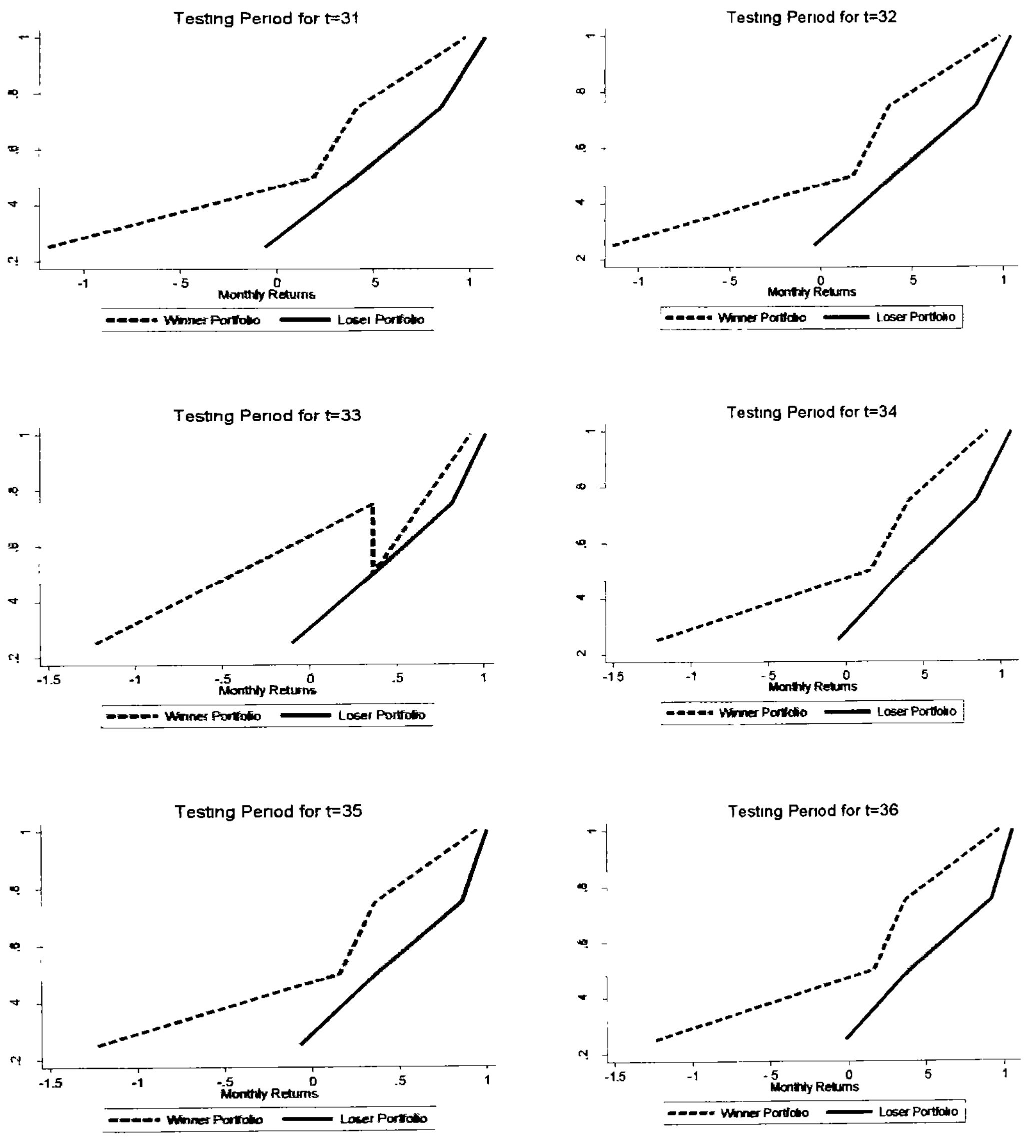



Testing Period for t=27
Monthly Returns
Winner Portfolio
Loser Portfolio


Testing Period for t=28
Monthly Returns
Winner Portfolio
Loser Portfolio


Testing Period for t=29
Monthly Returns
Winner Portfolio
Loser Portfolio


Testing Period for t=30
Monthly Returns
Winner Portfolio
Loser Portfolio



Note: The CDFs $ACAR_W$ and $ACAR_L$ loser and winner portfolios are presented from test period $t = 1$ to $t = 36$. Dashed line represents CDF for winner portfolio and solid line shows the CDF of loser portfolios. The CDF of loser portfolio is more right sides as compared to the CDF of winner Portfolios

These results suggest that loser portfolio dominates over winner portfolio at $t = 1$ through $t = 36$. The p-values presented in the second panel of the table for testing the reverse hypothesis that is winner portfolio dominates over loser portfolio, confirm the dominance of loser over winner at comparing the p-values across both panels. We find that the loser portfolio dominates over winner portfolio at the all three examined stochastic orders. However, the p-value highlight that the loser portfolio more

Table 5.12: Stochastic Dominance of Loser over Winner Portfolio

	Loser *versus* Winner $L >_s W$			Winner *versus* Loser $W >_s L$		
Test Periods	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**
t=1	0.778	0.655	0.621	0.367	0.044	0.026
t=2	1.000	0.625	0.584	0.367	0.002	0.000
t=3	1.000	0.637	0.577	0.105	0.000	0.000
t=4	1.000	0.748	0.691	0.367	0.002	0.000
t=5	1.000	0.669	0.618	0.367	0.001	0.000
t=6	1.000	0.630	0.592	0.367	0.030	0.000
t=7	1.000	0.631	0.604	0.367	0.027	0.000
t=8	1.000	0.624	0.595	0.367	0.014	0.000
t=9	1.000	0.537	0.509	0.367	0.052	0.000
t=10	1.000	0.540	0.512	0.367	0.037	0.000
t=11	1.000	0.642	0.614	0.367	0.064	0.000
t=12	1.000	0.639	0.604	0.778	0.100	0.003
t=13	1.000	0.628	0.607	0.367	0.053	0.002
t=14	1.000	0.671	0.639	0.367	0.041	0.003
t=15	1.000	0.697	0.673	0.367	0.036	0.003
t=16	1.000	0.705	0.667	0.367	0.039	0.003
t=17	1.000	0.690	0.648	0.367	0.046	0.003
t=18	1.000	0.703	0.659	0.367	0.048	0.004
t=19	1.000	0.633	0.588	0.778	0.062	0.005
t=20	1.000	0.698	0.662	0.367	0.070	0.009
t=21	1.000	0.692	0.661	0.778	0.079	0.008
t=22	1.000	0.691	0.662	0.778	0.078	0.006
t=23	1.000	0.690	0.654	0.778	0.059	0.005
t=24	1.000	0.681	0.642	0.778	0.053	0.005
t=25	1.000	0.668	0.635	0.778	0.071	0.005
t=26	1.000	0.609	0.565	0.105	0.025	0.028
t=27	0.778	0.502	0.536	0.367	0.070	0.117
t=28	1.000	0.651	0.621	0.778	0.062	0.002
t=29	1.000	0.635	0.596	0.778	0.051	0.001
t=30	1.000	0.650	0.609	0.778	0.048	0.000
t=31	1.000	0.640	0.596	0.778	0.047	0.000
t=32	1.000	0.645	0.598	0.367	0.049	0.000
t=33	1.000	0.616	0.570	0.367	0.053	0.000
t=34	1.000	0.650	0.607	0.778	0.034	0.000
t=35	1.000	0.644	0.603	0.367	0.041	0.000
t=36	1.000	0.643	0.600	0.367	0.033	0.000

Note: Test of stochastic dominance shows that loser portfolio dominates over winner portfolio throughout the test period from $t=1$ to $t=36$. KS type p-values are calculated through simulation and SD1, SD2, SD3 are p-values of stochastic orders first, second, and third respectively.

investor who prefer more positive skewness would also have chosen to buy loser and strongly dominates at the third order of stochastic dominance as compared to the other two stochastic orders. This is because the p-values for the reverse hypothesis are almost near to zero for the third order of stochastic dominance. The SD1, SD2, and

SD3 are reported the p-values of KS type test for the first, second, and third, stochastic orders, respectively. These p-values are computed simulation based method which is given in (Barrett & Donald, 2003).

The p-values presented in the table show that the loser portfolio at the second and the third stochastic order throughout the test periods. This implies that the strong dominance of loser portfolio over the winner portfolio at the third order suggests that sell winner stocks and buy loser stocks. These results suggest that in Pakistan equity market investors can be earn abnormal returns by constructing portfolios based contrarian strategies. These findings are consistent with several previous empirical studies. For instance, Bondt and Thaler (1985) have documented that the loser portfolio tends to outperform over winner portfolio by up to 25% during their examined period. He stated that this phenomenon is due to overreaction effect. Our results also reported that that loser portfolio returns are larger than that of the winner portfolio over the subsequent period with the magnitude of 52.2% (t = 36). Similarly, studied by Dhankar and Maheshwari (2015), Hassan (2014), and Asness et al. (2013) also reported the dominance of loser stocks over the winner stocks.

5.3.3. Empirical Results of Momentum Effect from Mean Difference Test

In previous sub-section, we test the momentum anomaly in Pakistan Stock Exchange by applying the KS type test. The results of the test provide evidence of the momentum reversal effect (the overreaction effect or Loser – Winner effect) instead of momentum effect (the underreation effect or Winner – Loser effect). In this sub-section, we use an additional test to assess the robustness of our results presented in the previous sub-section. Specifically, we use t-test to test whether the difference between the mean of loser and winner portfolios is statistically greater than zero. Fong et al. (2005) and Wang et al. (2004) have also used the t-test, to examine the momentum effect in loser and winner portfolios.

Hence, if during test period

$[ACAR_w - ACAR_L] > 0$: then, it shows the signal of Momentum effect

$[ACAR_L - ACAR_W] > 0$: then, it shows the signal of Momentum reversal effect

The results are presented in Table 5.13. The table presents the average of cumulative access returns *(ACAR)* for loser and winner portfolios, the difference between the $ACAR_L$ of loser and the $ACAR_W$ of winner portfolio, t-statistics, and the p-values to test the null hypothesis that the difference is greater than zero. Inspection of the results indicate that the difference between the $ACAR_L - ACAR_W$ is positive throughout the test period. However, by examine carefully, we find the highest difference appears in the month t = 36 (52.2%), whereas, the lowest difference appears in the month t = 1 (9.1%). In particular, in the month t = 1 the winner portfolio is only 1.1%, suggesting 9.1% abnormal returns. In month t = 2, again loser stocks perform well, showing 7.6%, average cumulative returns. On the other hand, during the same period winner stocks show negative returns with the magnitude of -7.2% . The abnormal returns for t = 2 period are 14.8%. This profitable pattern prevail throughout all test period (t =1 to t =36).

However, we can also see form the table that the difference between average cumulative returns of loser and winner is larger for later test periods as compared to the initial test periods. This implies that more the test periods higher the abnormal returns. For example, in month t = 36, the difference between two $ACAR_L - ACAR_W$ is 52.2%. The p-values shown in the table indicates that 14 out of 36 test period the

Table 5.13: Performance of $ACAR_L, ACAR_W,$ and $ACAR_L - ACAR_W$ in Test Period and t-statistics

Test Periods	$ACAR_{L,n,t}$	$ACAR_{W,n,t}$	$ACAR_{L,} - ACAR_{W,}$	t- statistics	Mean(diff) > 0
t=1	8.0	-1.1	9.1	1.676	0.096
t=2	7.6	-7.2	14.8	2.630	0.039
t=3	4.9	-14.2	19.1	2.476	0.045
t=4	17.5	-12.7	30.2	2.398	0.048
t=5	23.6	-6.5	30.0	2.794	0.034
t=6	24.7	-2.2	26.9	2.703	0.037
t=7	19.1	-7.7	26.8	2.803	0.034
t=8	20.9	-8.8	29.7	2.585	0.041
t=9	23.4	-6.5	29.9	3.023	0.028
t=10	28.5	-2.4	30.9	2.510	0.044
t=11	26.0	-1.0	27.0	2.045	0.067
t=12	30.1	2.8	27.3	2.444	0.046
t=13	40.1	1.0	39.1	2.685	0.037
t=14	51.5	4.9	46.6	2.747	0.036
t=15	49.7	1.6	48.1	2.683	0.037
t=16	53.3	1.6	51.8	2.202	0.058
t=17	53.1	6.6	46.5	1.760	0.088
t=18	61.7	7.6	54.1	2.377	0.049
t=19	56.2	6.7	49.5	1.981	0.071
t=20	57.6	10.7	46.9	1.865	0.080
t=21	55.1	9.5	45.6	1.791	0.086
t=22	52.5	8.0	44.5	1.827	0.083
t=23	51.2	5.8	45.4	1.780	0.087
t=24	54.4	7.1	47.3	1.779	0.087
t=25	58.6	12.5	46.1	1.600	0.104
t=26	59.0	12.1	46.9	2.488	0.044
t=27	58.8	14.5	44.3	1.747	0.090
t=28	59.1	13.1	45.9	1.688	0.095
t=29	59.8	13.5	46.3	1.694	0.094
t=30	56.0	8.8	47.3	1.624	0.101
t=31	57.1	10.1	47.0	1.731	0.091
t=32	56.2	9.8	46.5	1.730	0.091
t=33	52.3	5.5	46.8	1.438	0.123
t=34	55.6	6.5	49.1	1.808	0.084
t=35	54.0	6.0	48.0	1.772	0.087
t=36	58.9	6.7	52.2	1.873	0.079

Note: This table presents the average of cumulative returns (ACAR) for loser, winner and loser-winner portfolios. In sampled data there are 36 test periods from $t=1$ to $t=36$. The p-values are calculated based on two sample t-test having null hypothesis is that mean difference for (loser-winner) is zero.

abnormal returns $(ACAR_L - ACAR_W)$ are significantly greater than zero at the 5% level of significance. Similarly, among the remaining test periods, for 20 test periods, the abnormal returns are statistically greater than zero at greater than 5% but less than 10% level of significance.

One should note that, in month $t = 1$, the abnormal returns are statistically greater than zero at 10% level of significance. However, after month $t = 2$ to $t = 15$ the abnormal returns are statistically greater than zero at 5% level of significance. Yet, for the subsequent the test period, again the abnormal returns appear statistically greater than zero at the 10% level of significance with an exception of month $t = 25$, $t = 30$, and $t = 33$. In these three test periods abnormal returns are statistically greater than zero at 11% or 12% level of significance.

The momentum reversal effect entails that for any test period, $ACAR_L > 0$ and $ACAR_W < 0$ so that by inference $[ACAR_L - ACAR_W] > 0$. The momentum reversal effect foretells that the winner portfolio underperform than loser one. We also observe that the average of cumulative returns $(ACAR_L)$ for loser portfolio is high and positive. This implies that the existence of the momentum reversal effect or overreaction effect.

In sum, loser portfolio dominates over winner in all 36 test periods. On average, loser stocks earn 39.8% excess returns as compared to winner stocks. These findings are consistent with the studies of Dhankar and Maheshwari (2015), Hassan (2014), Wang et al. (2004), Richards (1997), and Bondt and Thaler (1985). Dhankar and Maheshwari (2015) examine the presence of statistically significant long term momentum reversal effect (overreaction effect) in India. Hassan (2014) investigated mean reversion pattern exists Egypt Stock Market, this implies that in the long run winner portfolios' returns yield negative returns. Analogously, Bondt and Thaler

(1985) found the overreaction effect for the US stock market that implies that loser stocks earn positive and high returns than winner stocks. They give the reason for such results is that investors overreact to negative/bad news to larger extent than positive/good news. Richards (1997) worked on data for 16 countries and concluded that loser countries are less risky than winner countries and examined the momentum reversal effect in national market indices of the underlying 16 countries. He stated that the main reason for the existence of the momentum reversal effect is market imperfection. Similarly, Wang et al. (2004) also found the momentum reversal effect in Chinese Stock Market and concluded that this effect is more pronounced in domestic owned stocks, as compared to foreign owned stocks.

However, our results are inconsistent with the studies of Birru (2015). He examined the momentum effect in US stock market during the period from 1967 to 2011. Abraham (2014) also investigated momentum anomaly in Australian Resource Stock and Chinese Shanghai Composite Index for time period from January 2003 to March 2013. He concluded that the existence of momentum anomaly is mainly in small cap stock. Fong et al. (2005) also investigated that winner stochastic dominates loser portfolio by using stock index data for 24 countries during the period 1989 – 2001. Jegadeesh and Titman (1993, 2001) investigated the momentum effect over short term (3 month to 12 month) and long term (13 months to 60 months), respectively. Their findings support to the momentum anomaly in US stock market. They gave the argument that the momentum profit is due to delayed overreaction from investor side.

There are a lot of research has been done to understand the mechanism that derive the momentum or momentum reversal effect. The stylized dominancy of the loser portfolio is consistent with many of the reasons postulated. The major reasons that emerge from the empirical analysis are the underreaction effect (Birru, 2015), the role of retail or institutional investor (Sakr et al., 2014), the overreaction effect (Bondt & Thaler, 1985; Wang et al., 2004), and the liquidity risk factor (Asness et al., 2013). Yet, what factors exactly derive the momentum or momentum reversal effect are still an open to debate (Jegadeesh & Titman, 2001).

5.3.3. Conclusion of Momentum Anomaly

Momentum phenomenon exists globally. In this section, we have investigated the momentum effect in Pakistan Stock Exchange. Yet, our results suggest the momentum reversal effect, rather than the momentum effect in Pakistan Stock Exchange during the examined period. In order to test momentum anomaly, we first apply stochastic dominance test namely as the KS type test to examine the dominance relationship between loser and winner portfolios. After that, we also apply *t*-test to check the robustness of our results. Both tests produce similar results that indicate the momentum reversal effect and loser portfolio dominates over winner. Getting similar findings from both tests show the robustness of our results and give us greater confidence to conclude that the momentum reversal effect exists in Pakistan equity market. The presence of reversal effect in equity market is an evidence of violation of the efficient market hypothesis.

Nevertheless, momentum or momentum reversal effect remains an anomaly for the EMH and standard equilibrium asset pricing models. Along with the previous studies that reveal either the momentum or momentum reversal effect suggest that equity market is not an efficient with respect to historical information. The fans of efficient markets may contend that this phenomenon is impulsive and that there must be some yet-to-be-discovered equilibrium asset pricing models that should be capable of rationalizing the momentum phenomenon.

Chapter 6
Conclusions

6.1. Dissertation Snapshot

Behavioral finance designates a revolution in standard finance. The amalgamation of financial theory with other societal sciences resulted arrival of behavioral finance. Our study is also based on behavioral finance. This study has conducted a comprehensive examination of three major financial market anomalies in Pakistan Stock Exchange (PSX) using stochastic dominance approach. In particular, the main objective of the study is to test, month anomaly, equity premium puzzle, and momentum anomaly in Pakistan Stock Exchange. To do so, we use monthly stock returns of all listed firms during the period from January 2000 to December 2014.

We start our empirical investigation by examining whether the stock returns are normally distributed. For this purpose, we apply K-S normality test proposed by Justel et al. (1997). After confirming that the returns are not normally distributed, we plot the CDFs of each return series to get preliminary evidence of the stochastic dominance. Barrett and Donald (2003) proposed the KS type test to examine whether one return series (say x) stochastically dominates over another return series (say y), at different stochastic orders. In this, we examine the stochastic dominance of return series at the first (SD1), second (SD2), and the third (SD3) orders. To test the considered market anomalies in stock returns behavior, we use stochastic dominance (SD) approach.

The main advantage of the stochastic dominance approach is that it makes trivial assumptions about investor risk preference or the distribution of stock returns.

Further, stochastic dominance rules contemplate the entire distribution of returns not just the two parameter criteria, as in the mean-variance analysis. In order to test the month anomaly and the momentum anomaly, we have constructed beta based portfolios and winner and loser portfolios respectively. For month anomaly, we calculate monthly beta for each firm over the subsequent months, and rank the calculated betas into High-Beta, Medium-Beta, and Low-Beta based portfolios. In order to test momentum anomaly, we formed winner and loser portfolios based the procedure given by Barrett and Donald (2003). We divide our sample data (January 2000 to December 2014) into five non-overlapping three-year holding periods (36 months). In each holding period, we have calculated cumulative excess returns prior to 36 months (from -35 to 0 months).

After that, in each holding period we rank loser and winner portfolios on dated December 2002, December 2005, December 2008, and December 2011. Then, we do tracing of from test period $t=1$ to $t=36$ on the starting month of January for each holding period. After that we have calculated *ACAR* of loser and winner portfolios from $t=1$ to $t=36$. We have applied the KS type stochastic dominance test on these two distributions of loser and winner portfolio. We have also used additional t-test to check the robustness of our results. In additions, we also explain the behavioral aspects that cause to such anomalies as well as other anomalies

The remainder of this chapter is divided into three sections. Section 6.2 outlines the key findings that have emerged from this study and documents the major conclusions that have been drawn. The policy implications for this study are discussed in Section 6.3. Finally, Section 6.4 highlights limitations and areas for future research in this topic.

6.2. Key Findings

We find that the financial market anomalies have significant influence on Pakistan Stock Market and stock prices follow trends which should not be happened from the context of efficient market hypothesis. Following are the summary of results according to each examined anomaly.

In month anomaly, we test the month effect in the all listed firms, beta based portfolios, and KSE-100 Index returns by using stochastic dominance (SD) approach. By applying stochastic dominance test namely KS type test, we find significant results in favor of the January month in all listed firms as well as in KSE-100 Index returns.. We find from empirical analyses that January month has outperformed over all other calendar months for all listed firms and KSE-100 Index returns. These results offer a strong support to the previous studies of Haugen and Jorion (1996), Annuar (1987), Fountas and Segredakis (2002), Haug and Hirschey (2006), , Lean et al. (2007), and Li and Gong (2015). The main reasons of the January phenomena is due to the small firm effect, liquidity constraint, tax loss selling, and omitted risk factor.

The empirical results based on beta based portfolios show that the January effect exists in High-Beta and Low-Beta based portfolios. On the other hand, the December effect exists in Low-Beta based portfolio. Taking together, with the findings of the High-Beta, Medium-Beta, and Low-Beta based portfolios, we examined the January and December effect which further gives the indication of another anomaly in Pakistan Stock Exchange that is the turn-of-the-year effect. These results are consistent with the prior studies that have also examined the abnormal stock returns in the month of January and December. For instance, Tangjitprom (2011), Sikes (2014) and Lakonishok and Smidt (1984). The main explanation that drives the turn-of-the-year effect is tax loss selling hypothesis. Individual investor, who are income tax-sensitive and who disproportionately hold small stocks, sell stocks for tax reasons at year end (such as to claim a capital loss) and reinvest after the first of the year. Another cause is the payment of year-end bonuses in January month. Some of this bonus money is used to purchase stocks that driving up prices.

When we turn to investigate equity premium puzzle, we have found the reverse equity puzzle effect in Pakistan Stock Exchange. 3-month Treasury bill rate dominates over KSE-100 Index returns in all three examined orders of stochastic dominance this implies that investors prefer risk-free rate over the risk asset. We find that the size of reverse equity premium puzzle is -7.065% in Pakistan Stock Exchange our the examined period. Our results are consistent with the studies of Lim et al. (2006) and Jagannathan et al. (2001). This mystery of reverse puzzle has directed to an extensive research tussle in both finance and macroeconomics. In fact, returns of risky assets might not be enough to compensate the investors for bearing risk. Other possible reasons for the existence of equity premium puzzle are taxes, borrowing constraints, bearing risk, structural and cyclical business factors are the driving forces that cause the equity premium puzzle

We have examined notable results about momentum anomaly that suggest the existence of the momentum reversal effect rather the momentum effect in Pakistan Stock Exchange. By applying stochastic dominance test namely, the KS type test, the loser portfolio dominates over the winner portfolio at all three examined stochastic dominance orders. We have examined that the both tests give similar results, suggesting that in Pakistan Stock Exchange there is the existence of momentum reversal effect. The results suggest that the contrarian strategies can be adopted to get abnormal returns as loser portfolio stochastically dominates over winner at all three examined stochastic dominance orders. Contrarian strategy is attributed to overreaction effect. Finally, the empirical results show that the by adopting the contrarian strategy investor can be able to generate significantly positive returns 52.2% more than the winners for test period (t = 36). In sum, loser portfolio dominates over winner in all 36 test periods. On average, loser stocks earn 39.8% excess returns as compared to winner stocks.

The momentum effect does not seem to be confined to any particular types of stocks or any sub-periods. However, the returns are, on average, found to be somewhat larger in small cap stocks Richards (1997) has defined the small firm as a "losing firm" around the turn-of-the-year. He also explained that the losing firms have experienced positive and high returns in the month of January as compared to the other calendar months. We also investigated that on average, returns of losing firms have higher than winner in the month of January month

These findings are consistent with the studies of Dhankar and Maheshwari (2015), Hassan (2014), Wang et al. (2004), Richards (1997), and Bondt and Thaler (1985). This formalized dominancy of the loser portfolio is consistent with many of the reasons that derive momentum reversal effect. For instance, the role of retail or institutional investor (Sakr et al., 2014), the overreaction effect (Bondt & Thaler, 1985; Wang et al., 2004), and the liquidity risk factor (Asness et al., 2013).

Finally, the empirical results show that the contrarian strategies are able to generate significantly positive returns. Evidently a significant number of researchers subscribe to the view that contrarian strategies and momentum strategies yield significant profits in the investment horizon. However, the source of the profits is widely debated. Yet, what factors exactly derive the momentum or momentum reversal effect are still an open to debate (Jegadeesh & Titman, 2001).

6.3. Policy Implications

These findings have vital practical implication to different stock market participants such as investors, managers, researchers/academics, and policy makers. Specifically, our findings indicate the portfolio specific characteristics that are significantly important for investors in their investing decisions. Investors can frame their investment tactics and predict stock returns patterns and get abnormal returns by making trading strategies accordingly.

This research is relevant for portfolio managers who indulge in portfolio diversifications as well as for policy makers who are looking for long-term economic cooperation and greater financial integration. Shareholders also seem to be somewhat skeptical of firms that desist from revealing sufficient information or that reveal in a non-salient style. For example, it is a common practice that firm tends to announces good news early and bad news late. Behavior biases have very much affected on such stock prices, internet bubble 1990s is one of the example of this. It is often casually contended that the madness of crowds requires administration intervention in, and regulation of markets. Transaction taxes, circuit breakers, and government stabilization of stock market have been used as devices to lessen risk of financial panics, regularities/trends and speculation in stock market. Security and Exchange Commission Pakistan should also make the firm binding to explicitly report sufficient information in their financial reporting. The reverse puzzle generally attributed to high volatility, political law and order and uncertainty so, government should take to account the necessary measures.

6.4. Limitation and Future Area for Research

This study represents the solid work from our side. Apart from this, we would like to propose more extensive studies to improve and enhance the existing literature related to testing the market anomalies in Pakistan Stock Exchange. In fact, there is prodigious room to improve this study through following ways:

1. This study can be done by using same empirical framework as our study, on South Asian Stock Markets and compare the returns behavior of stocks among South Asian countries.
2. Apart from these three anomalies, it would be worth able to test more market anomalies in Pakistan Stock Exchange, some of these are, the value and size effect, weekend effect, turn-of-month and year effect, Halloween anomaly[16], Mark Twain effect[17] and other seasonality effect.
3. This empirical analysis can be done by considering commodity market on Pakistan Mercantile Exchange
4. One can also do the study, to test market anomalies for manufacturing and non-manufacturing firms separately, and then compare the intensity and behavior of these anomalies would also be the good research study.
5. Or empirical analysis can be done by constructing the portfolios based on market capitalizations and then check the impact of market anomalies on small cap and large cap stock.

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[16] This effect relates to the concept of seasonality. A phrase is famous for this anomaly, "Sell in May and then walk away,". Specifically, stocks perform well in the winter months than in the summer.

[17] The Mark Twain effect is the phenomenon of stock returns in October being lower than in other months. The name comes from a line in Mark Twain's Pudd'nhead Wilson: "October. This is one of the peculiarly dangerous months to speculate in stocks.

6. Momentum anomaly can be testing by considering different holding periods say 6 months, 12 months, 1.5 years, and 2 years etc.

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Appendix

Table A.1: Stochastic Dominance in February Month with respect to Other Months

	High Beta Portfolio						**Medium Beta Portfolio**						**Low Beta Portfolio**					
	February *versus* Other Months			Other Months *versus* February			February *versus* Other Months			Other Months *versus* February			February *versus* Other Months			Other Months *versus* February		
	KS P-Value																	
Months	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**
January	0.000	0.000	0.000	0.636	0.269	0.426	0.000	0.675	0.641	0.019	0.000	0.000	0.000	0.000	0.067	0.076	0.003	0.154
March	1.000	0.757	0.711	0.000	0.000	0.000	0.995	0.568	0.494	0.000	0.000	0.000	0.940	0.714	0.676	0.000	0.000	0.000
April	0.213	0.481	0.685	0.894	0.237	0.275	0.000	0.000	0.000	0.071	0.022	0.381	0.117	0.721	0.684	0.195	0.003	0.001
May	0.390	0.739	0.701	0.000	0.008	0.004	0.986	0.440	0.459	0.000	0.000	0.000	0.428	0.733	0.704	0.000	0.000	0.000
June	1.000	0.706	0.666	0.000	0.000	0.000	0.929	0.198	0.370	0.000	0.000	0.000	0.484	0.725	0.686	0.029	0.002	0.000
July	0.989	0.722	0.685	0.000	0.000	0.000	0.522	0.103	0.334	0.004	0.047	0.126	0.999	0.704	0.670	0.000	0.000	0.000
August	1.000	0.724	0.672	0.000	0.000	0.000	0.944	0.412	0.676	0.000	0.000	0.000	1.000	0.727	0.681	0.000	0.000	0.000
September	0.972	0.551	0.532	0.000	0.000	0.000	0.722	0.048	0.329	0.000	0.000	0.000	0.932	0.724	0.673	0.000	0.000	0.000
October	0.998	0.722	0.682	0.002	0.000	0.000	0.966	0.480	0.471	0.004	0.000	0.000	0.998	0.695	0.663	0.000	0.000	0.000
November	0.998	0.743	0.696	0.038	0.002	0.000	0.973	0.426	0.439	0.000	0.000	0.000	0.726	0.714	0.691	0.000	0.000	0.000
December	0.054	0.745	0.703	0.000	0.000	0.000	0.001	0.008	0.004	0.941	0.565	0.473	0.000	0.017	0.145	0.109	0.001	0.138

TableA.2: Stochastic Dominance in March Month with respect to Other Months

	High Beta Portfolio						**Medium Beta Portfolio**						**Low Beta Portfolio**					
	March *versus* Other Months			Other Months *versus* March			March *versus* Other Months			Other Months *versus* March			March *versus* Other Months			Other Months *versus* March		
	KS P-Value																	
Months	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**
January	0.000	0.000	0.000	0.961	0.522	0.446	0.000	0.000	0.000	0.136	0.000	0.047	0.000	0.000	0.000	0.970	0.525	0.434
February	0.000	0.000	0.000	1.000	0.757	0.711	0.000	0.000	0.000	0.995	0.568	0.494	0.000	0.000	0.000	0.940	0.714	0.676
April	0.000	0.000	0.000	0.992	0.578	0.516	0.000	0.000	0.000	0.987	0.603	0.556	0.000	0.000	0.000	0.924	0.519	0.449
May	0.000	0.000	0.000	0.996	0.563	0.491	0.876	0.244	0.420	0.000	0.000	0.000	0.013	0.026	0.027	0.011	0.289	0.616
June	0.284	0.682	0.600	0.058	0.024	0.094	0.659	0.038	0.261	0.073	0.445	0.664	0.000	0.000	0.000	0.908	0.655	0.570
July	0.000	0.004	0.000	0.776	0.712	0.669	0.000	0.000	0.000	0.999	0.623	0.502	0.372	0.093	0.239	0.577	0.526	0.465
August	0.142	0.735	0.685	0.528	0.147	0.039	0.001	0.000	0.000	0.615	0.502	0.414	0.752	0.222	0.432	0.000	0.000	0.000
September	0.364	0.145	0.058	0.785	0.727	0.682	0.000	0.000	0.000	0.996	0.716	0.676	0.208	0.169	0.222	0.434	0.518	0.469
October	0.000	0.000	0.000	0.930	0.593	0.512	0.000	0.000	0.000	0.997	0.718	0.676	0.143	0.333	0.484	0.156	0.074	0.115
November	0.000	0.000	0.000	0.998	0.687	0.620	0.000	0.000	0.000	0.888	0.696	0.656	0.019	0.002	0.000	0.845	0.716	0.686
December	0.000	0.000	0.000	0.017	0.000	0.303	0.000	0.000	0.000	0.998	0.582	0.504	0.000	0.000	0.000	0.833	0.516	0.686

Table A.3: Stochastic Dominance in April Month with respect to Other Months

	High Beta Portfolio						Medium Beta Portfolio						Low Beta Portfolio					
	April *versus* Other Months			Other Months *versus* April			April *versus* Other Months			Other Months *versus* April			April *versus* Other Months			Other Months *versus* April		
	KS P-Value																	
Months	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**
January	0.000	0.000	0.000	0.587	0.433	0.419	0.058	0.719	0.677	0.018	0.000	0.000	0.000	0.001	0.001	0.789	0.288	0.410
February	0.894	0.237	0.275	0.213	0.481	0.685	0.071	0.022	0.381	0.000	0.000	0.000	0.195	0.003	0.001	0.117	0.721	0.684
March	0.992	0.578	0.516	0.000	0.000	0.000	0.987	0.603	0.556	0.000	0.000	0.000	0.924	0.519	0.449	0.000	0.000	0.000
May	0.938	0.466	0.507	0.000	0.002	0.001	0.936	0.337	0.406	0.000	0.000	0.000	0.622	0.536	0.473	0.000	0.000	0.000
June	0.992	0.542	0.490	0.000	0.000	0.000	0.775	0.112	0.321	0.000	0.000	0.000	0.888	0.552	0.457	0.063	0.055	0.078
July	0.960	0.368	0.454	0.000	0.000	0.000	0.074	0.004	0.124	0.000	0.000	0.000	0.928	0.494	0.447	0.000	0.000	0.000
August	0.995	0.729	0.695	0.000	0.000	0.000	0.858	0.267	0.529	0.000	0.000	0.000	0.961	0.425	0.349	0.000	0.000	0.000
September	0.909	0.298	0.419	0.000	0.000	0.000	0.032	0.000	0.257	0.000	0.000	0.000	0.869	0.723	0.675	0.000	0.000	0.000
October	0.974	0.532	0.511	0.000	0.000	0.000	0.880	0.394	0.439	0.000	0.000	0.000	0.996	0.493	0.401	0.000	0.000	0.000
November	0.981	0.500	0.476	0.001	0.001	0.000	0.715	0.138	0.418	0.000	0.000	0.000	0.755	0.308	0.348	0.001	0.005	0.023
December	0.241	0.707	0.643	0.000	0.000	0.000	0.001	0.002	0.172	0.998	0.542	0.484	0.000	0.000	0.000	0.512	0.216	0.552

Table A.4: Stochastic Dominance in May Month with respect to Other Months

	High Beta Portfolio						Medium Beta Portfolio						Low Beta Portfolio					
	May *versus* Other Months			Other Months *versus* May			May *versus* Other Months			Other Months *versus* May			May *versus* Other Months			Other Months *versus* May		
	KS P-Value																	
Months	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**
January	0.000	0.000	0.000	0.815	0.380	0.426	0.000	0.000	0.000	0.062	0.000	0.001	0.000	0.000	0.000	0.892	0.348	0.379
February	0.000	0.008	0.004	0.390	0.739	0.701	0.000	0.000	0.000	0.986	0.440	0.459	0.000	0.000	0.000	0.428	0.733	0.704
March	0.996	0.563	0.491	0.000	0.000	0.000	0.000	0.000	0.000	0.876	0.244	0.420	0.011	0.289	0.616	0.013	0.026	0.027
April	0.000	0.002	0.001	0.938	0.466	0.507	0.000	0.000	0.000	0.936	0.337	0.406	0.000	0.000	0.000	0.622	0.536	0.473
June	0.992	0.549	0.481	0.000	0.000	0.000	0.000	0.000	0.000	0.814	0.707	0.671	0.000	0.002	0.002	0.727	0.503	0.541
July	0.066	0.521	0.481	0.000	0.000	0.000	0.000	0.000	0.000	0.980	0.638	0.549	0.000	0.017	0.375	0.000	0.032	0.093
August	0.820	0.709	0.669	0.000	0.000	0.000	0.000	0.000	0.000	0.866	0.472	0.323	0.076	0.150	0.412	0.000	0.000	0.000
September	0.971	0.382	0.443	0.000	0.000	0.000	0.000	0.000	0.000	0.974	0.705	0.664	0.000	0.050	0.544	0.000	0.129	0.141
October	0.036	0.621	0.546	0.000	0.000	0.000	0.000	0.000	0.000	0.924	0.502	0.661	0.000	0.099	0.475	0.000	0.000	0.000
November	0.070	0.373	0.485	0.269	0.275	0.312	0.000	0.000	0.000	0.870	0.693	0.667	0.013	0.015	0.030	0.379	0.716	0.677
December	0.000	0.648	0.547	0.000	0.000	0.000	0.000	0.000	0.000	0.989	0.509	0.449	0.000	0.000	0.000	0.498	0.273	0.503

Table A.5: Stochastic Dominance in June Month with respect to Other Months

	High Beta Portfolio						Medium Beta Portfolio						Low Beta Portfolio					
	June *versus* Other Months			Other Months *versus* June			June *versus* Other Months			Other Months *versus* June			June *versus* Other Months			Other Months *versus* June		
	KS P-Value																	
Months	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3
January	0.000	0.000	0.000	0.974	0.513	0.442	0.000	0.000	0.000	0.022	0.000	0.001	0.000	0.000	0.000	0.847	0.398	0.415
February	0.000	0.000	0.000	1.000	0.706	0.666	0.000	0.000	0.000	0.929	0.198	0.370	0.029	0.002	0.000	0.484	0.725	0.686
March	0.058	0.024	0.094	0.284	0.682	0.600	0.073	0.445	0.664	0.659	0.038	0.261	0.908	0.655	0.570	0.000	0.000	0.000
April	0.000	0.000	0.000	0.992	0.542	0.490	0.000	0.000	0.000	0.774	0.112	0.321	0.063	0.055	0.078	0.888	0.552	0.457
May	0.000	0.000	0.000	0.992	0.532	0.468	0.814	0.707	0.671	0.000	0.000	0.000	0.727	0.503	0.541	0.000	0.002	0.002
July	0.000	0.000	0.000	0.234	0.694	0.638	0.000	0.000	0.000	0.989	0.523	0.456	0.531	0.293	0.541	0.000	0.000	0.000
August	0.001	0.050	0.674	0.135	0.198	0.240	0.000	0.000	0.000	0.894	0.311	0.271	0.753	0.363	0.466	0.000	0.000	0.000
September	0.004	0.001	0.001	0.258	0.737	0.699	0.000	0.000	0.000	0.993	0.696	0.645	0.618	0.535	0.687	0.000	0.000	0.000
October	0.000	0.000	0.000	0.598	0.560	0.503	0.000	0.000	0.000	0.736	0.159	0.418	0.919	0.609	0.503	0.000	0.000	0.000
November	0.000	0.000	0.000	0.983	0.651	0.564	0.000	0.000	0.000	0.939	0.371	0.468	0.537	0.228	0.395	0.015	0.224	0.288
December	0.000	0.000	0.000	0.200	0.020	0.316	0.000	0.000	0.000	0.929	0.280	0.422	0.000	0.000	0.000	0.630	0.324	0.500

Table A.6: Stochastic Dominance in July Month with respect to Other Months

	High Beta Portfolio						Medium Beta Portfolio						Low Beta Portfolio					
	July *versus* Other Months			Other Months *versus* July			July *versus* Other Months			Other Months *versus* July			July *versus* Other Months			Other Months *versus* July		
	KS P-Value																	
Months	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**
January	0.000	0.000	0.000	0.904	0.344	0.390	0.000	0.714	0.676	0.006	0.000	0.000	0.000	0.000	0.000	0.667	0.215	0.360
February	0.000	0.000	0.000	0.989	0.722	0.685	0.004	0.047	0.126	0.006	0.000	0.000	0.000	0.000	0.000	0.715	0.471	0.713
March	0.776	0.712	0.669	0.000	0.004	0.000	0.999	0.623	0.502	0.000	0.000	0.000	0.577	0.526	0.465	0.372	0.093	0.239
April	0.000	0.000	0.000	0.960	0.368	0.454	0.000	0.000	0.000	0.074	0.004	0.124	0.000	0.000	0.000	0.928	0.494	0.447
May	0.000	0.000	0.000	0.060	0.449	0.428	0.980	0.638	0.549	0.000	0.000	0.000	0.000	0.032	0.093	0.000	0.017	0.375
June	0.234	0.694	0.638	0.000	0.000	0.000	0.989	0.523	0.456	0.000	0.000	0.000	0.000	0.000	0.000	0.531	0.293	0.541
August	0.972	0.727	0.683	0.016	0.000	0.000	0.992	0.679	0.657	0.000	0.000	0.000	0.991	0.473	0.415	0.000	0.000	0.000
September	0.893	0.518	0.513	0.000	0.039	0.015	0.834	0.241	0.410	0.000	0.000	0.000	0.624	0.230	0.440	0.730	0.391	0.377
October	0.264	0.398	0.456	0.738	0.363	0.450	0.592	0.637	0.533	0.001	0.000	0.000	0.495	0.531	0.478	0.328	0.044	0.011
November	0.003	0.007	0.001	0.812	0.502	0.496	0.931	0.562	0.479	0.000	0.000	0.000	0.003	0.000	0.000	0.250	0.700	0.667
December	0.000	0.134	0.432	0.005	0.000	0.184	0.000	0.000	0.000	0.824	0.286	0.431	0.000	0.000	0.000	0.450	0.156	0.461

Table A.7: Stochastic Dominance in August Month with respect to Other Months

	High Beta Portfolio						Medium Beta Portfolio						Low Beta Portfolio					
	August *versus* Other Months			Other Months *versus* August			August *versus* Other Months			Other Months *versus* August			August *versus* Other Months			Other Months *versus* August		
	KS P-Value																	
Months	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3
January	0.000	0.000	0.000	0.998	0.713	0.671	0.000	0.000	0.000	0.071	0.000	0.000	0.000	0.000	0.000	0.843	0.258	0.356
February	0.000	0.000	0.000	1.000	0.724	0.672	0.000	0.000	0.000	0.074	0.000	0.001	0.000	0.000	0.000	0.873	0.443	0.503
March	0.528	0.147	0.039	0.142	0.735	0.685	0.615	0.502	0.414	0.000	0.000	0.000	0.000	0.000	0.000	0.752	0.222	0.432
April	0.000	0.000	0.000	0.995	0.729	0.695	0.000	0.000	0.000	0.858	0.267	0.529	0.000	0.000	0.000	0.961	0.425	0.349
May	0.000	0.000	0.000	0.808	0.694	0.651	0.866	0.472	0.323	0.000	0.000	0.000	0.000	0.000	0.000	0.076	0.150	0.412
June	0.135	0.198	0.240	0.001	0.050	0.674	0.894	0.311	0.271	0.000	0.000	0.000	0.000	0.000	0.000	0.753	0.363	0.466
July	0.016	0.000	0.000	0.972	0.727	0.683	0.000	0.000	0.000	0.992	0.679	0.657	0.000	0.000	0.000	0.991	0.473	0.415
September	0.617	0.017	0.000	0.076	0.736	0.681	0.000	0.000	0.000	0.999	0.697	0.652	0.000	0.000	0.000	0.950	0.326	0.401
October	0.036	0.000	0.000	0.987	0.723	0.682	0.000	0.000	0.000	0.872	0.392	0.684	0.000	0.000	0.000	0.723	0.187	0.340
November	0.000	0.000	0.000	0.999	0.713	0.668	0.002	0.000	0.000	0.966	0.637	0.669	0.000	0.000	0.000	0.992	0.729	0.697
December	0.000	0.000	0.000	0.016	0.008	0.668	0.000	0.000	0.000	0.958	0.480	0.667	0.000	0.000	0.000	0.528	0.154	0.396

Table A.8: Stochastic Dominance in September Month with respect to Other Months

	High Beta Portfolio						Medium Beta Portfolio						Low Beta Portfolio					
	September *versus* Other Months			Other Months *versus* September			September *versus* Other Months			Other Months *versus* September			September *versus* Other Months			Other Months *versus* September		
	KS P-Value																	
Months	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3
January	0.000	0.000	0.000	0.846	0.304	0.370	0.000	0.460	0.676	0.003	0.000	0.023	0.000	0.000	0.000	0.617	0.410	0.492
February	0.000	0.000	0.000	0.972	0.551	0.532	0.000	0.000	0.000	0.002	0.000	0.030	0.000	0.000	0.000	0.680	0.664	0.699
March	0.785	0.727	0.682	0.364	0.145	0.058	0.996	0.716	0.676	0.000	0.000	0.000	0.434	0.518	0.469	0.208	0.169	0.222
April	0.000	0.000	0.000	0.909	0.298	0.419	0.000	0.000	0.000	0.032	0.000	0.257	0.000	0.000	0.000	0.869	0.723	0.675
May	0.000	0.000	0.000	0.970	0.337	0.404	0.974	0.705	0.664	0.000	0.000	0.000	0.000	0.129	0.141	0.000	0.050	0.544
June	0.258	0.737	0.699	0.004	0.001	0.001	0.993	0.696	0.645	0.000	0.000	0.000	0.000	0.000	0.000	0.618	0.535	0.687
July	0.000	0.039	0.015	0.893	0.518	0.513	0.000	0.006	0.008	0.834	0.241	0.410	0.730	0.391	0.377	0.624	0.230	0.440
August	0.076	0.736	0.681	0.617	0.017	0.000	0.999	0.697	0.652	0.000	0.000	0.000	0.950	0.326	0.401	0.000	0.000	0.000
October	0.000	0.017	0.018	0.888	0.316	0.432	0.001	0.731	0.693	0.015	0.000	0.002	0.599	0.465	0.443	0.344	0.009	0.027
November	0.000	0.000	0.000	0.964	0.401	0.462	0.393	0.738	0.700	0.006	0.002	0.000	0.015	0.006	0.000	0.266	0.739	0.690
December	0.000	0.001	0.02	0.007	0.000	0.121	0.000	0.000	0.000	0.616	0.088	0.356	0.000	0.000	0.000	0.595	0.352	0.686

Table A.9: Stochastic Dominance in October Month with respect to Other Months

	High Beta Portfolio						Medium Beta Portfolio						Low Beta Portfolio					
	October *versus* Other Months			Other Months *versus* October			October *versus* Other Months			Other Months *versus* October			October *versus* Other Months			Other Months *versus* October		
	KS P-Value																	
Months	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**
January	0.000	0.000	0.000	0.946	0.491	0.426	0.000	0.028	0.397	0.101	0.000	0.050	0.000	0.000	0.000	0.974	0.477	0.386
February	0.002	0.000	0.000	0.998	0.722	0.682	0.004	0.000	0.000	0.104	0.000	0.054	0.000	0.000	0.000	0.986	0.760	0.731
March	0.930	0.593	0.512	0.000	0.000	0.000	0.997	0.718	0.676	0.000	0.000	0.000	0.156	0.074	0.115	0.143	0.333	0.484
April	0.000	0.000	0.000	0.974	0.532	0.511	0.000	0.000	0.000	0.880	0.394	0.439	0.000	0.000	0.000	0.996	0.493	0.401
May	0.000	0.000	0.000	0.033	0.607	0.527	0.924	0.502	0.661	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.099	0.475
June	0.598	0.560	0.503	0.000	0.000	0.000	0.736	0.159	0.418	0.000	0.000	0.000	0.000	0.000	0.000	0.916	0.616	0.526
July	0.738	0.363	0.450	0.264	0.398	0.456	0.001	0.000	0.000	0.592	0.637	0.533	0.328	0.044	0.011	0.495	0.531	0.478
August	0.987	0.723	0.682	0.036	0.000	0.000	0.880	0.604	0.689	0.000	0.000	0.000	0.723	0.187	0.340	0.000	0.000	0.000
September	0.888	0.316	0.432	0.000	0.017	0.018	0.015	0.000	0.002	0.001	0.731	0.693	0.344	0.009	0.027	0.599	0.465	0.443
November	0.056	0.008	0.005	0.706	0.699	0.666	0.774	0.260	0.452	0.079	0.093	0.097	0.001	0.000	0.000	0.405	0.722	0.690
December	0.000	0.171	0.545	0.008	0.000	0.000	0.000	0.000	0.000	0.996	0.524	0.471	0.000	0.000	0.000	0.724	0.372	0.569

Table A.10: Stochastic Dominance in November Month with respect to Other Month

	High Beta Portfolio						Medium Beta Portfolio						Low Beta Portfolio					
	November *versus* Other Months			Other Months *versus* November			November *versus* Other Months			Other Months *versus* November			November *versus* Other Months			Other Months *versus* November		
	KS P-Value																	
Months	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3
January	0.000	0.000	0.000	0.943	0.502	0.433	0.000	0.000	0.113	0.059	0.000	0.030	0.000	0.000	0.000	0.750	0.178	0.306
February	0.038	0.002	0.000	0.998	0.743	0.696	0.000	0.000	0.000	0.973	0.426	0.439	0.000	0.000	0.000	0.773	0.316	0.445
March	0.998	0.687	0.620	0.000	0.000	0.000	0.888	0.696	0.656	0.000	0.000	0.000	0.845	0.716	0.686	0.019	0.002	0.000
April	0.001	0.001	0.000	0.981	0.500	0.476	0.000	0.000	0.000	0.715	0.138	0.418	0.001	0.005	0.023	0.755	0.308	0.348
May	0.269	0.275	0.312	0.067	0.344	0.467	0.870	0.693	0.667	0.000	0.000	0.000	0.379	0.716	0.677	0.013	0.015	0.030
June	0.983	0.651	0.564	0.000	0.000	0.000	0.939	0.371	0.468	0.000	0.000	0.000	0.015	0.224	0.288	0.537	0.228	0.395
July	0.812	0.502	0.496	0.003	0.007	0.001	0.000	0.000	0.000	0.931	0.562	0.479	0.250	0.700	0.667	0.003	0.000	0.000
August	0.999	0.713	0.668	0.000	0.000	0.000	0.966	0.637	0.669	0.002	0.000	0.000	0.992	0.729	0.697	0.000	0.000	0.000
September	0.964	0.401	0.462	0.000	0.000	0.000	0.006	0.002	0.000	0.393	0.738	0.700	0.266	0.739	0.690	0.015	0.006	0.000
October	0.706	0.699	0.666	0.056	0.008	0.005	0.079	0.093	0.097	0.774	0.260	0.452	0.405	0.722	0.690	0.001	0.000	0.000
December	0.002	0.741	0.709	0.003	0.000	0.005	0.000	0.000	0.000	0.979	0.517	0.466	0.000	0.000	0.000	0.341	0.104	0.377

Table A.11: Stochastic Dominance in February Month with respect to Other Month in KSE-100 Index

	February *versus* Other Months			Other Month *versus* February		
	KS P-Value					
Months	SD1	SD2	SD3	SD1	SD2	SD3
January	0.264	0.199	0.330	0.831	0.380	0.393
March	0.675	0.649	0.614	0.596	0.206	0.147
April	0.661	0.560	0.528	0.335	0.150	0.134
May	0.988	0.704	0.666	0.038	0.000	0.000
June	0.853	0.723	0.688	0.091	0.049	0.018
July	0.315	0.180	0.329	0.066	0.053	0.206
August	0.962	0.561	0.525	0.084	0.004	0.000
September	0.664	0.238	0.352	0.041	0.035	0.104
October	0.477	0.225	0.331	0.378	0.481	0.659
November	0.502	0.409	0.446	0.011	0.015	0.036
December	0.217	0.711	0.662	0.076	0.000	0.000

Table A.12: Stochastic Dominance in March Month with respect to Other Month in KSE-100 Index

	March *versus* Other Months			Other Month *versus* March		
	KS P-Value					
Months	SD1	SD2	SD3	SD1	SD2	SD3
January	0.203	0.162	0.081	0.785	0.577	0.524
February	0.596	0.206	0.147	0.675	0.649	0.614
April	0.469	0.200	0.276	0.180	0.196	0.492
May	0.987	0.691	0.654	0.026	0.000	0.000
June	0.911	0.713	0.678	0.254	0.088	0.063
July	0.179	0.027	0.092	0.080	0.060	0.643
August	0.891	0.513	0.487	0.041	0.001	0.001
September	0.335	0.078	0.155	0.044	0.054	0.467
October	0.325	0.056	0.114	0.227	0.554	0.681
November	0.547	0.102	0.167	0.076	0.019	0.272
December	0.117	0.713	0.665	0.022	0.000	0.000

Table A.13: Stochastic Dominance in April Month with respect to Other Month in KSE-100 Index

	April *versus* Other Months			Other Month *versus* April		
	KS P-Value					
Months	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**
January	0.152	0.023	0.051	0.631	0.388	0.421
February	0.335	0.150	0.134	0.587	0.433	0.419
March	0.180	0.196	0.492	0.469	0.200	0.276
May	0.606	0.709	0.678	0.027	0.000	0.000
June	0.371	0.722	0.688	0.338	0.069	0.108
July	0.748	0.188	0.309	0.161	0.331	0.652
August	0.384	0.654	0.590	0.100	0.003	0.001
September	0.819	0.279	0.347	0.151	0.245	0.402
October	0.386	0.179	0.086	0.615	0.717	0.678
November	0.518	0.341	0.371	0.192	0.111	0.224
December	0.227	0.692	0.646	0.305	0.000	0.000

Table A.14: Stochastic Dominance in May Month with respect to Other Month in KSE-100 Index

	May *versus* Other Months			Other Month *versus* May		
	KS P-Value					
Months	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**
January	0.003	0.000	0.000	0.987	0.691	0.648
February	0.038	0.000	0.000	0.988	0.704	0.666
March	0.026	0.000	0.000	0.987	0.691	0.654
April	0.027	0.000	0.000	0.606	0.709	0.678
June	0.201	0.000	0.000	0.942	0.702	0.666
July	0.002	0.000	0.000	0.474	0.700	0.661
August	0.352	0.009	0.000	0.794	0.713	0.675
September	0.018	0.000	0.000	0.448	0.675	0.645
October	0.008	0.000	0.000	0.933	0.678	0.632
November	0.017	0.000	0.000	0.624	0.707	0.667
December	0.001	0.000	0.000	0.358	0.000	0.000

Table A.15: Stochastic Dominance in June Month with respect to Other Month in KSE-100 Index

	June *versus* Other Months			Other Month *versus* June		
	KS P-Value					
Months	SD1	SD2	SD3	SD1	SD2	SD3
January	0.019	0.014	0.002	0.946	0.718	0.676
February	0.091	0.049	0.018	0.853	0.723	0.688
March	0.254	0.088	0.063	0.911	0.713	0.678
April	0.338	0.069	0.108	0.371	0.722	0.688
May	0.942	0.702	0.666	0.201	0.000	0.000
July	0.131	0.036	0.108	0.224	0.484	0.680
August	0.925	0.441	0.450	0.369	0.050	0.076
September	0.242	0.045	0.136	0.186	0.373	0.648
October	0.279	0.026	0.010	0.691	0.732	0.693
November	0.271	0.068	0.192	0.487	0.248	0.691
December	0.097	0.715	0.670	0.144	0.000	0.000

Table A.16: Stochastic Dominance in July Month with respect to Other Month in KSE-100 Index

	July *versus* Other Months			Other Month *versus* July		
	KS P-Value					
Months	SD1	SD2	SD3	SD1	SD2	SD3
January	0.005	0.001	0.052	0.317	0.084	0.225
February	0.066	0.053	0.206	0.315	0.180	0.329
March	0.080	0.060	0.643	0.179	0.027	0.092
April	0.161	0.331	0.652	0.748	0.188	0.309
May	0.474	0.700	0.661	0.002	0.000	0.000
June	0.224	0.484	0.680	0.131	0.036	0.108
August	0.336	0.655	0.615	0.040	0.002	0.000
September	0.313	0.654	0.642	0.519	0.385	0.292
October	0.076	0.066	0.074	0.721	0.485	0.657
November	0.052	0.489	0.474	0.368	0.185	0.128
December	0.095	0.701	0.669	0.666	0.000	0.000

Table A.17: Stochastic Dominance in August Month with respect to Other Month in KSE-100 Index

	August *versus* Other Months			Other Month *versus* August		
	KS P-Value					
Months	SD1	SD2	SD3	SD1	SD2	SD3
January	0.011	0.000	0.000	0.887	0.474	0.468
February	0.084	0.004	0.000	0.962	0.561	0.525
March	0.041	0.001	0.001	0.891	0.513	0.487
April	0.100	0.003	0.001	0.384	0.654	0.590
May	0.794	0.713	0.675	0.352	0.009	0.000
June	0.369	0.050	0.076	0.925	0.441	0.450
July	0.040	0.002	0.000	0.336	0.655	0.615
September	0.090	0.006	0.000	0.325	0.635	0.586
October	0.031	0.000	0.000	0.772	0.690	0.651
November	0.059	0.012	0.000	0.466	0.687	0.630
December	0.009	0.714	0.669	0.272	0.000	0.000

Table A.18: Stochastic Dominance in September Month with respect to Other Month in KSE-100 Index

	September *versus* Other Months			Other Month *versus* September		
	KS P-Value					
Months	SD1	SD2	SD3	SD1	SD2	SD3
January	0.004	0.001	0.019	0.674	0.168	0.254
February	0.041	0.035	0.104	0.664	0.238	0.352
March	0.044	0.054	0.467	0.335	0.078	0.155
April	0.151	0.245	0.402	0.819	0.279	0.347
May	0.018	0.000	0.000	0.448	0.675	0.645
June	0.186	0.373	0.648	0.242	0.045	0.136
July	0.519	0.385	0.292	0.313	0.654	0.642
August	0.325	0.635	0.586	0.090	0.006	0.000
October	0.319	0.038	0.026	0.927	0.694	0.660
November	0.251	0.491	0.474	0.637	0.307	0.280
December	0.056	0.710	0.668	0.625	0.000	0.000

Table A.19: Stochastic Dominance in October Month with respect to Other Month in KSE-100 Index

	October *versus* Other Months			Other Month *versus* October		
	KS P-Value					
Months	SD1	SD2	SD3	SD1	SD2	SD3
January	0.077	0.105	0.356	0.609	0.180	0.253
February	0.378	0.481	0.659	0.477	0.225	0.331
March	0.227	0.554	0.681	0.325	0.056	0.114
April	0.615	0.717	0.678	0.386	0.179	0.086
May	0.933	0.678	0.632	0.008	0.000	0.000
June	0.691	0.732	0.693	0.279	0.026	0.010
July	0.721	0.485	0.657	0.076	0.066	0.074
August	0.772	0.690	0.651	0.031	0.000	0.000
September	0.927	0.694	0.660	0.319	0.038	0.026
November	0.931	0.580	0.563	0.167	0.005	0.004
December	0.156	0.676	0.637	0.285	0.000	0.000

Table A.20: Stochastic Dominance in November Month with respect to Other Month in KSE-100 Index

	November *versus* Other Months			Other Month *versus* November		
	KS P-Value					
Months	SD1	SD2	SD3	SD1	SD2	SD3
January	0.006	0.001	0.010	0.779	0.317	0.311
February	0.011	0.015	0.036	0.502	0.409	0.446
March	0.076	0.019	0.272	0.547	0.102	0.167
April	0.192	0.111	0.224	0.518	0.341	0.371
May	0.624	0.707	0.667	0.017	0.000	0.000
June	0.487	0.248	0.691	0.271	0.068	0.192
July	0.368	0.185	0.128	0.052	0.489	0.474
August	0.466	0.687	0.630	0.059	0.012	0.000
September	0.637	0.307	0.280	0.251	0.491	0.474
October	0.167	0.005	0.004	0.931	0.580	0.563
December	0.023	0.701	0.660	0.557	0.000	0.000

Table A.21: Stochastic Dominance in December Month with respect to Other Month in KSE-100 Index

	December *versus* Other Months			Other Month *versus* December		
	KS P-Value					
Months	**SD1**	**SD2**	**SD3**	**SD1**	**SD2**	**SD3**
January	0.017	0.000	0.000	0.526	0.716	0.685
February	0.076	0.000	0.000	0.217	0.711	0.662
March	0.022	0.000	0.000	0.117	0.713	0.665
April	0.305	0.000	0.000	0.227	0.692	0.646
May	0.358	0.000	0.000	0.001	0.000	0.000
June	0.144	0.000	0.000	0.097	0.715	0.670
July	0.666	0.000	0.000	0.095	0.701	0.669
August	0.272	0.000	0.000	0.009	0.714	0.669
September	0.625	0.000	0.000	0.056	0.710	0.668
October	0.285	0.000	0.000	0.156	0.676	0.637
November	0.557	0.000	0.000	0.023	0.701	0.660