AN EMPIRICAL ANALYSIS OF HEDGING AND DIVERSIFICATION ROLE OF COMMODITY FUTURES AS A RISK MANAGEMENT TOOL

Thesis

Submitted in partial fulfilment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

by

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Declaration

I hereby declare that the Research Thesis entitled **An Empirical Analysis of Hedging and Diversification Role of Commodity Futures as a Risk Management Tool** which is being submitted to the National Institute of Technology Karnataka, Surathkal in partial fulfilment of the requirements for the award of the degree of Doctor of Philosophy in Management is a bonafide report of the research work carried out by me. The material contained in this Research Thesis has not been submitted to any University or Institution for the award of any degree.

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This is to certify that the Research Thesis entitled **An Empirical Analysis of Hedging and Diversification Role of Commodity Futures as a Risk Management Tool** submitted by Ritika Jaiswal, (Register Number: HM13F07) as the record of the research work carried out by her, is accepted as the Research Thesis submission in partial fulfilment of the requirements for the award of degree of Doctor of Philosophy.

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ABSTRACT

Commodity futures have resurged as an excellent portfolio diversifier and hedge against inflation over the last decade. Traditional and alternative asset managers are using commodity futures as an investment vehicle for strategic and tactical allocations. Strategic allocation of commodity futures is highly valued due to the benefits of long-term equity-like returns, diversification benefits due to low correlation with other asset classes and inflation hedging potential. Numerous studies have been conducted to examine the inflation hedging and diversification benefits of commodity futures. These studies have examined the commodity futures as an investment tool for the passive allocation in a portfolio of traditional asset mix such as stocks and bonds. However, they have not focussed on the assessment of regime-dependent inflation hedging and diversification role of commodity futures. In addition to the passive asset allocation, commodity futures are used for the tactical asset allocation by designing the active strategies which use the signals of momentum, hedging pressure and idiosyncratic volatility. With the review of the literature, it is found that there is a lack of study which examines the existence of time-varying conditional profitability of these strategies for the commodity futures market in the Indian context. In order to address these issues, primarily, this thesis aims to evaluate the inflation hedging and diversification benefits of individual commodity futures by using the time-varying dynamics under the regime-switching approach. Subsequently, it analyses the time-varying conditional profitability of individual and combined strategies which are designed by using the momentum, term structure and idiosyncratic volatility signals for the Indian commodity futures market.

The study uses a sample of 13 highly traded commodity futures contracts (gold, silver, copper, zinc, aluminium, nickel, lead, cardamom, mentha oil, cotton, crude palm oil, crude oil and natural gas) and three commodity indices (MCXMETAL, MCXENERGY and MCXAGRI) for the study period of June 2006 to April 2016. It uses the time-varying regime-switching approach of Markov Switching-Vector Error Correction Model (MS-VECM) to assess the inflation hedging potential of these commodity futures and commodity indices. The study results confirm the partial inflation hedging ability of gold, silver, lead and CPO futures and marginal hedging potential of copper and cotton futures. In addition, the hedging and diversification role of these

commodity futures and indices are analysed using the regime-switching approach of Markov Switching-Vector Autoregression (MS-VAR) model. The results signify that commodity futures are an excellent tool for diversification of the portfolios of traditional assets mix such as stocks and bonds.

In addition, the study analyses the time-varying conditional profitability of momentum, term structure and idiosyncratic volatility strategies in the Indian commodity futures market. The average monthly mean returns, Sharpe ratio, transaction costs and time-varying risk-based performance evaluation confirm that strategies based on risk i.e idiosyncratic volatility are more profitable compared to strategies based on momentum returns and term structure yield. In addition, the study designs a combined strategy-MomTS which incorporates the methodology of both momentum and term structure strategies and combined strategy-MomIVol which uses the methodology of both momentum and idiosyncratic volatility strategies. The performance evaluation of these strategies confirms that MomIVol strategy gives the highest monthly average return of 25.57 percent compared to momentum, term structure, idiosyncratic volatility and MomTS strategies which yield the average monthly returns of 7.17, 9.54, 11.59 and 16.68 percent, respectively.

The major contribution of the study to the existing literature and to the real time practitioner is the design of a combined strategy, MomIVol which gives a better risk-adjusted return compared to other strategies. In addition, the design of this kind of active strategies plays an important role in the investment decision of institutional investors and professional money managers such as hedge funds and commodity pool operators. The findings of this study provide significant guidance to the investors in the tactical allocation of commodity futures in their portfolio, not only to diversify their portfolio but also to earn an exceptionally high abnormal returns.

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LIST OF ABBREVIATIONS

ACE	Ahmedabad Commodity Exchange
AMEX	American Stock Exchange
AIC	Akaike Information Criterion
ADF	Augmented Dickey Fuller
ARMA	Autoregressive Moving Average
BDS	Brock, Dechert and Scheinkman
BRICS	Brazil, Russia, India, China, South Africa
CBOT	Chicago Board of Trade
CFMA	Commodity Futures Modernization Act
CFTC	Commodity Futures Trading Commission
CPO	Crude Palm Oil
CPI	Consumer Price Index
CRB	Commodity Research Bureau
CPCI	Chase Physical Commodity Index
CCI	Continuous Commodity Index
CCIL	Clearing Corporation of India Ltd.
COMEX	New York Commodity Exchange
CRSP	Center for Research in Security Prices
DJAIGCI	Dow Jones AIG Commodity Index
DBCI	Deutsche Bank Commodity Index
DJUBSCI	Dow Jones UBS Commodity Index
EGARCH	Exponential Generalized Autoregressive Conditional Heteroscedastic
FCRA	Forward Contracts Regulation Act
FMC	Forward Market Commission
GDP	Gross Domestic Product
GSCI	Goldman Sachs Commodity Index
GARCH-DCC	Generalised Autoregressive Conditional Heteroscedastic - Dynamic Conditional Correlation
GARCH	Generalised Autoregressive Conditional Heteroscedastic

GJR-GARCH	Glosten-Jagannathan-Runkle-GARCH
HQ	Hannan-Quinn Information Criterion
ICEX	Indian Commodity Exchange
ICE	Intercontinental Exchange
IID	Independent and Identically Distributed
IVol	Idiosyncratic Volatility
JPMCCI	JP Morgan Commodity Curve Index
KPSS	Kwiatkowski-Phillips-Schmidt Shin
LME	London Metal Exchange
OLS	Ordinary Least Squares
MCX	Multi Commodity Exchange
MS-VECM	Markov Switching-Vector Error Correction Model
MS-VAR	Markov Switching-Vector Autoregression
MLM	Mount Lucas Management
MSIAH	Markov-Switching-Intercept-Autoregressive-Heteroscedastic
MSIA	Markov-Switching-Intercept-Autoregressive
MomTS	Momentum and Term Structure
MomIVol	Momentum and Idiosyncratic Volatility
NMCE	National Multi Commodity Exchange
NCDEX	National Commodity and Derivative Exchange
NARDL	Nonlinear Autoregressive Distributed Lags
NYSE	New York Stock Exchange
NYMEX	New York Mercantile Exchange
NASDAQ	National Association of Securities Dealers Automated Quotations
OTC	Over-the-Counter
OPEC	Organisation of the Petroleum Exporting Countries
PISTA	India Pepper and Spices Trade Association
RICI	Rogers' International Commodity Index
RBI	Reserve Bank of India
RCM	Regime Classification Measure

SEBI	Securities and Exchange Board of India
SPCI	Standard & Poor’s Commodity Index
S&P 500	Standard & Poor’s 500
STR	Smooth Transition Regression
SIC	Schwarz Information Criterion
TS	Term Structure
UCX	Universal Commodity Exchange
US	United States
UK	United Kingdom
VECM	Vector Error Correction Model
VAR-GARCH	Vector Autoregression - Generalized Autoregressive Conditional Heteroscedastic
WPI	Wholesale Price Index
WTI	West Texas Crude

CHAPTER 1
INTRODUCTION

1.1 INTRODUCTION

The market globalization, liberalization and deregulations have relaxed the social, political and economic policies, which resulted in the dynamic interaction of different economies (Bagchi, 2009; Onour, 2009). It increased the prospect of investment avenues for investors, resulted in increased interaction and complexity of these investment channels, disseminated in different regions and countries. The growth in a complex grid of financial markets and instruments worldwide has given more diversification benefits to investors (Baur and Lucey, 2010). But on the other hand, it also propagated financial crisis through contagion effect. During the subprime and European crises periods, volatility and negative shocks had increased and dispersed from these crisis-originating countries to other economies resulting in banking and economic plunges (Kassim et al., 2011; Rannou, 2011; Bagchi and Ryu, 2011). Banking downturn ended with liquidity and credit crunch, whereas economic plunge collapsed the Gross Domestic Product (GDP) growth rate and the recessionary situation in many countries. Sensex[1] and other crisis-affected stock markets reported major stock market plunges due to increased volatility (Rastogi, 2014). Similarly, the economic crisis of China had a significant impact on the entire global economy. The reason for such a contagion effect is that China is the biggest economy in the world which contributes about 50 percent to global GDP growth rate and has a link with other economies (EconomicTimes.com, 2015). These unfavourable developments in global economy enhance investors' bearish sentiment and result in dampening of faith in the stock market. In addition, the current environment of historically low interest rates, increased downward trends in economies such as the US, European countries, China and reduced risk premium for traditional asset classes such as stocks and bonds, have enhanced the demand for alternative investments from institutional investors, private investors and investment fund managers (Fabozzi et al., 2008).

To mitigate the risk arising out of negative shocks of financial crises, investors require the strategic inclusion of alternative assets as a hedge and diversifier in their portfolio (Baur and Lucey, 2010). The inclusion of a strong diversifier in a portfolio strengthen the stability of the capital market and reduces the harshness of financial distress by enhancing the risk-adjusted return of a portfolio (Baur and McDermott, 2010). To construct a well-diversified portfolio, it is a prime requirement to investigate the return and volatility spillover among the traditional and alternative asset classes. A traditional portfolio consists of risky and risk-free assets such as stocks, bonds and cash. The inclusion of a diversifier in this traditional portfolio is justified if it improves the risk-adjusted return performance of the portfolio (Sharma et al., 2014). Many alternative asset classes are available such as hedge funds, commodity futures, private equity, credit derivative and corporate governance (Anson, 2003).

Commodity futures are one such risk management instruments that have been devised to achieve price risk management, in addition, to be used as an alternative asset class for hedging and diversification benefits (Lokare, 2007). It is considered that commodities have a negative correlation with stocks and bonds, and positive correlation with unexpected inflation, which qualifies them as a good diversifier (Gorton and Rouwenhorst, 2006; Erb and Harvey, 2006). The business cycle analysis performed by Anson (2003) showed that increase in inflation causes a decrease in value of stocks and bonds while the commodity futures value increases. Conversely, decrease in inflation results in an increase in the value of stocks and bonds and is associated with a decrease in value of commodity futures. It indicates that commodity futures prices are positively correlated with inflation and value of stocks and bonds are negatively correlated with inflation. In addition, Anson (2003) showed that commodity futures prices and prices of stocks and bonds react very differently during different time periods of the business cycle. For instance, during a period of a booming economy, prices of stocks and bonds decline due to fear of increased inflation, which indicates a long-term expectation. On the contrary, prices of commodity futures increase due to a high demand for raw materials which reflect the short-term expectation.

Commodity futures are one of the alternative ways to invest in commodities. Other different ways of getting exposure to commodity are through investment in physical goods, stocks of Natural Resource Company, commodity-linked notes, commodity mutual funds and commodity futures indices (Fabozzi et al., 2008). Commodity futures are the legal agreement between two parties to buy or sell a commodity at a specified date in the future at a fixed price (Amadeo[a], 2016). Commodity futures prices are the forecast of expected spot prices, which is basically the reflection of market condition, sentiments of the traders and fundamentals of underlying commodities (Amadeo[a], 2016). Investment in commodity futures can be done by passive investment in commodity futures index or as an active investment by using tactical asset allocation techniques. Based on risk appetite, traders in the commodity market are divided into hedgers, speculators and arbitrageurs (Fabozzi et al., 2008). Hedgers enter the commodity market with a motive to hedge their spot market position while speculators participate in the commodity market with the intention of making money by investing in the market. Generally, they liquidate their position in the market before the expiry date of the futures contract instead of taking physical delivery. Arbitrageurs also enter the commodity market to earn a profit by taking advantage of price differential across different markets.

Investment in commodity futures is considered as one of the easiest ways to get exposure to commodity market as it provides several advantages over trading in physical commodities. First, through commodity futures, investors can get direct exposure to commodities without considering the logistics and storage requirements as the purchase of commodity futures contracts do not require the delivery of underlying commodity. Hence, investors can maintain their exposure to the commodity market by rolling the contract to the nearest maturity contract (Sharma et al., 2014). Second, these contracts are traded on an exchange which provides the benefits of a central marketplace, transparent pricing, clearinghouse security and daily liquidity. Third, commodity futures contracts are traded on initial margin hence, it does not require the payment of full price at the time of purchasing the contract (Anson, 2003). In addition, commodity futures' trading is characterized by low transaction costs (Locke and Venkatesh, 1997; Shen et al., 2007; Marshall et al., 2012). Hence, investment in commodity futures requires low capital due to the high leverage attached with the investment in commodity futures contracts (Fabozzi et al., 2008). On the contrary, investment in commodity futures is risky also, due to the high volatility of commodity prices which causes the enhancement in the profit and loss of the market participants compared to the money they invested (Sharma et al. 2014).

The origin of modern trade in commodity future can be traced to the 17th century in Osaka, Japan. In China, a form of futures trading in commodities existed 6000 years earlier. However, the establishment of Chicago Board of Trade (CBOT), puts the milestone for organized trading in the commodity on an exchange. In 2000, Commodity Futures Modernization Act (CFMA) deregulated the commodity market from the control of Commodity Futures Trading Commission (CFTC), a regulatory body in the US. This opened the door for all kinds of investors such as hedge funds, pension funds, investment fund managers and institutional and private investors (Sharma et al. 2014). In addition, from the year 2000-2004, with the issuance of several notifications in India, the government has removed all prohibition on future trading in a large number of commodities in the country. These developments in commodity futures trading worldwide, cause the sharp increase of investment intensity in commodity futures market during last decade and the start of a new era in commodity futures trading. Hence, the academicians and policy-makers shifted their attention towards studying the inflation hedging and diversification benefits of trading in commodity futures which are used by hedgers and speculators to hedge their positions and to make a profit.

1.1.1 Inception of Commodity Market in India

The derivative market of the commodity is instituted to provide a hedge against the risk of adverse movements in prices. Various financial instruments are available to trade in these markets such as futures and forward contracts, option and swaps. Commodity futures are exchange-traded standardized contracts for purchase/sale of a specific commodity at an agreed price for delivery on a specified date (Menzel and Heidorn, 2007). Commodity exchange is an association, which organizes the future trading in commodities. Commodity futures exchanges provide a trading platform to the participants of the contract and standardize the contract in terms of quality, quantity and place of delivery. It provides essential facilities to the participants in the trading of the futures contract and discovery of prices (Sharma, 2015). Commodity futures trading and the commodity exchanges are governed by the Forward Contracts Regulation Act (FCRA), 1952 in India. Forward Markets Commission (FMC) was acting as a regulatory body which was under the purview of Ministry of Consumer Affairs, Food and Public Distribution. However, on September 28, 2015, Securities and Exchange Board of India (SEBI) took over the regulation of the commodity derivative trading due to the merger of FMC with SEBI.

Trading in commodity futures in India was introduced 125 years ago (Kotak Commodities, 2017). Constitution of the Bombay Cotton Trade Association in the year

1875, was the first milestone for the evolution of organized trading in commodities in India (Ahuja, 2006; Bose, 2008; Agnihotri and Sharma, 2011). Futures trading in oilseeds, ground nuts, castor seeds and cotton was started with the setting up of Gujarati Vyapari Mandali in 1900. The Calcutta Hessian Exchange Ltd. and the East India Jute Association Ltd. were set up in the years 1919 and 1927, respectively for futures trading in raw jute. In 1920, futures markets in bullion started in Mumbai and after that several markets were instituted in Rajkot, Jaipur, Jamnagar, Kanpur, Delhi and Calcutta. In due course, various other exchanges were established in the country, to start trading in commodities viz pepper, turmeric, potato, sugar and jaggery. India Pepper and Spices Trade Association (IPSTA) in Cochin had first organized the futures trade in spices in 1957 (Mishra, 2008).

In India, commodity futures market is working under several institutional constraints. In spite of the country's long history, commodity future markets remain underdeveloped compared to the US and UK due to extensive government intervention (Vashishtha and Kumar, 2010). Regulators viewed this market as a source of rising inflation due to the actions of speculators in the market. In the mid-1960s, prices of many commodities such as major oils, and oilseeds rose due to the sharp fall in production (Raizada and Sahi, 2006). Futures trade was discontinued by the government in 1966 due to war, natural calamities and shortages and to observe the price movements of various agricultural and essential commodities. Based on the Khusro Committee report, a ban on the futures trading of few commodities was removed in 1980. However, the advent of economic liberalization has influenced the government to restart the futures trading on commodities like cotton, jute, potatoes etc. Based on the Kabra Committee recommendation, all the commodities which were banned in 1966 were reintroduced for futures trading as well as many others are added in 1994. In 2000, National Agricultural Policy allowed the widespread use of futures contract in agricultural commodities. However, 2003-04 was considered as a significant year for the development of commodity futures market in India due to the establishment of many nationwide multi-commodity exchanges (Gupta, 2011).

With the notification issued by the government on April 1, 2003, all prohibitions were removed on futures trading in a large number of commodities in the country. The government has also revoked the prohibition on non-transferable specific delivery forward contracts in May 2003. On the recommendation of Forward Market Commission

(FMC), the government of India, granted recognition to National Multi Commodity Exchange, Ahmedabad (NMCE), Multi Commodity Exchange, Mumbai (MCX), National Commodity and Derivative Exchange, Mumbai (NCDEX) as a national commodity exchange. Trading started at MCX in November 2003 and at NCDEX in December 2003 (Mahalik et al. 2009).

However, it is presumed by the regulators that trading in commodity futures causes higher inflation as they increase the volatility in the commodity market. Hence, futures trading on many commodities has been suspended regularly at a certain interval after 2003 (Rajvanshi, 2015). Table 1.1 provides the list of commodities which were suspended from 2003 to 2014. Table 1.2 provides the traded volume on yearly basis for Indian commodity market.

Table 1.1: List of Commodities Suspended from 2003 to 2014

Commodities	Date of Trading Suspended	Date of Trading Revoked
Tur, Urad	23rd January, 2007	Suspension continues
Rice	27th Februray, 2007	Suspension continues
Wheat	27th Februray, 2007	14th May, 2009
Chana Soya Oil	7th May, 2008	30th November, 2008
Rubber, Potato, Sugar	26th May, 2009	30th September, 2010
Guar Seed Guar Gum	27th March, 2012	10th May, 2013

*(**Source:** Rajvanshi, 2015)*

Table 1.2: Total Traded Volume (Value of the contracts in Lakh crore)

Year	Value (Lakh crore in INR)
2003-2004	1.29
2004-2005	5.7
2005-2006	21.6
2006-2007	36.8
2007-2008	40.7
2008-2009	52.5
2009-2010	77.7
2010-2011	119.5
2011-2012	181.3
2012-2013	170.5
2013-2014	101.4
2014-2015	61.7

*(**Source:** FMC, 2014)*

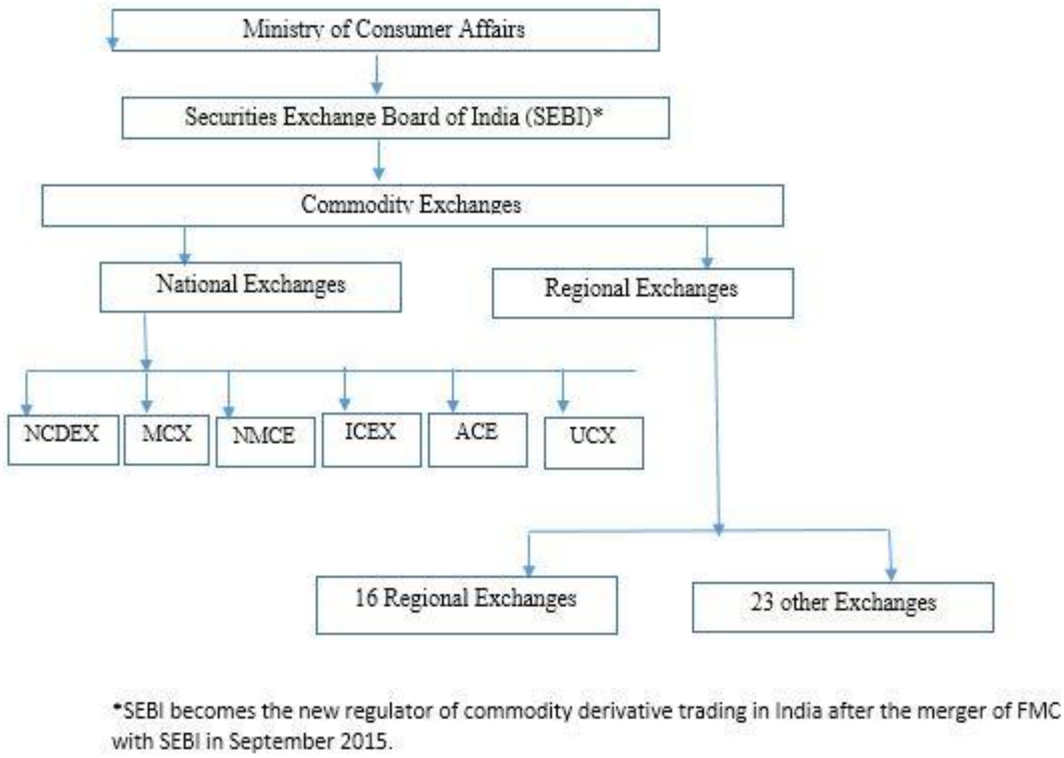
Despite the suspension of trading on many commodities, turnover of the Indian commodity derivative market is increasing continuously. The value of traded commodity futures was Rs. 1.29 lakh crore in 2003-04, it was up by 342 percent in 2004-05 and 277 percent in 2005-06 to Rs. 21.34 lakh crore (Bose, 2008). In 2013-14, the total volume of trade for all the exchanges was 8832.76 lakh MT at a value of Rs. 1.01 lakh crores (FMC, 2014).

1.1.2. Structure of the Commodity Futures Market in India

Commodity market in India has two distinct forms: Over-the-Counter (OTC) Market and Exchange-Based Market. OTC market is essentially for spot market transactions where people such as farmers, processors, wholesalers etc. are directly involved with the transaction of commodities (Culp, 2010; Birthal et al., 2007). Conversely, the exchange-based market is basically for derivative trading where standardized contracts and the settlement process completes. For instance, exchange-based commodity derivative is standardized contracts where a person can purchase a contract by paying only a percentage of the contract amount. Investors can take the benefit of active investment due to a feature of rolling and squaring off before the expiry of derivative contracts (Mishra, 2008).

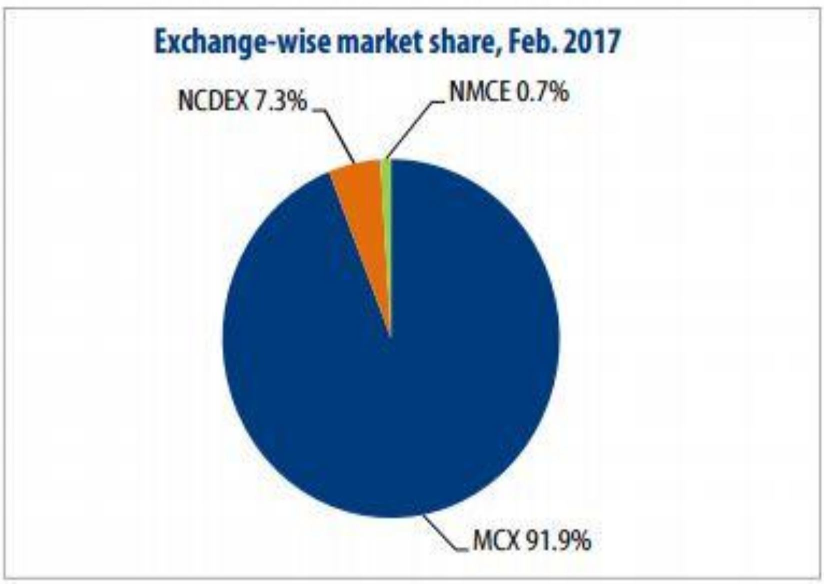
At present, there are six national exchanges viz. MCX, NCDEX, NMCE, Indian Commodity Exchange (ICEX) Ltd., Mumbai, ACE (Ahmedabad Commodity Exchange) Derivatives and Commodity Exchange, Mumbai and Universal Commodity Exchange (UCX) Ltd., Navi Mumbai. They regulate forward trading in 146 commodities covering edible oil seeds, food grains, metals, spices, fibers, sugar, rubber and energy sector. Besides, FMC has given recognition to 11 commodity specific exchanges which regulate trading in various commodities under the FCRA, 1952. In December 2006, 94 commodities were traded in commodity futures market compared to 59 commodities in January 2005 which moved to 113 commodities in 2015 (Masood and Chary, 2016). The typical structure of commodity futures market in India is depicted in Figure 1.1. Market shares of different exchanges for the year 2017 are shown in Figure 1.2.

Amid 2013-14, out of 17 recognized commodity exchanges, only the six major exchanges such as MCX, NCDEX, NMCE, ICEX, ACE and UCX, contributed 99% of the total value of the traded commodities (FMC, 2014). Figure 1.3 shows the market shares of individual segments viz. agricultural, bullion, energy and metal across the exchanges.



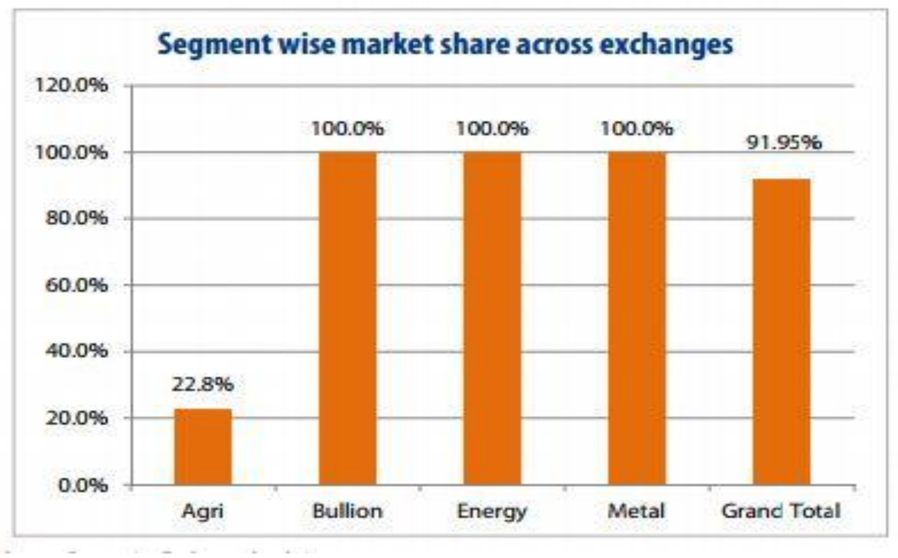
(***Source:*** *FMC, 2014)*

Figure 1.1: Structure of Commodity Futures Market in India



(***Source:*** *Multi Commodity Exchange, 2010)*

Figure 1.2: Exchange-wise Market Share



*(**Source:** Multi Commodity Exchange, 2010)*

Figure 1.3: Market share across Exchanges based on different Segments

1.1.3 Economic Characteristics of Commodities

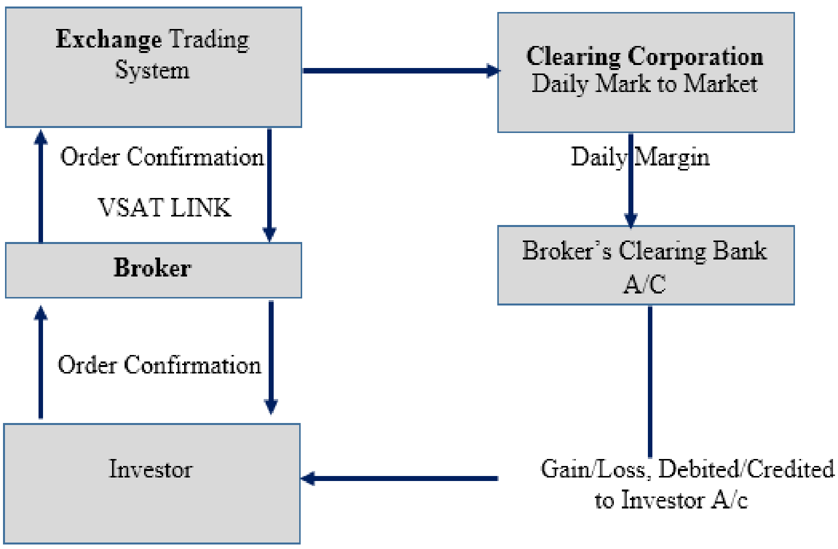
To understand the economic characteristics of commodities, it is essential to analyze the demand and supply dynamics which affect the commodity prices. Like other asset classes, movement in commodity prices impacts the global market due to interdependent global macroeconomic phenomena (Mathur, 2013). According to Baur and McDermott (2010) and Beckmann and Czudaj (2013), the supply of commodities which reflects the production constraints is relatively inelastic for commodities such as energy, precious metals and base metals owing to their difficult extraction process[2]. However, the demand for these commodities due to business cycle fluctuates frequently in response to the global economic events. For example, during the period from 2001-2006, China's demand for copper, aluminium and iron increased by 78, 85 and 92 percent, respectively due to the stimulated growth in China (Fabozzi et al., 2008). Conversely, the economic crisis of China caused a sharp fall in the prices of crude oil, copper and gold owing to sluggish growth in demand from China and many European countries (Egan, 2015). This clearly indicates the significant impact of China on commodity prices. In addition, Organisation of Petroleum Exporting Countries' (OPEC) supply of crude, US inventories of crude, changing scenario of expected demand for crude from emerging and developing countries and geopolitical instability play a crucial role in determining the prices of crude oil. For instance, US shale oil production created a situation of oversupply and boom in domestic crude oil production. This oversupply situation caused a steep fall in crude oil prices. West Texas Crude (WTI) prices fell from $106/barrel in June 2014 to $32.10/barrel in January 2016 (Amadeo[(b)], 2016). Similarly, the natural gas prices are highly influenced by the crude oil prices and international demand and supply dynamics of natural gas. According to Baur and Lucey(2010) and Baur and McDermott (2010), the demand for gold and silver is counter-cyclical due to its demand as a hedge and safe haven during economic and financial turbulence. In addition, exchange rate fluctuation has a significant impact on commodity prices. (Capie et al., 2005; Sjaastad, 2008; Wang and Lee, 2011). According to Ghosh et al. (2004), demand for gold and silver is separated into two categories: the 'use demand' which combines the demand for jewellery, industrial and dental products. The second category is for 'asset demand' where gold is used by governments, fund managers and investors as an investment asset due to its ability to hedge inflation and other uncertainties.

With respect to the agricultural commodities such as Crude Palm Oil (CPO) and mentha oil, demand and supply fundamentals play a crucial role in determining the prices of these commodities (Mathur, 2013). Exchange rate fluctuation also has a significant impact on the prices of these commodities as India is the major exporter of mentha oil and one of the major importers of CPO (Multi Commodity Exchange, 2010). Similarly, in the case of the cotton prices, in addition to domestic demand and supply scenario, global trade plays an important role in determining the prices of cotton yarn. India's cotton prices show the correlation of above 90 percent with cotton fibre prices in different markets across the country (Multi Commodity Exchange, 2010). With respect to cardamom, India holds the second position in world production and consumption of cardamom after Guatemala, which is the largest exporter in the world. The domestic demand and supply constraint, as well as the production in the competing country such as Guatemala, plays a crucial role in influencing the price of cardamom. On the contrary, the demand for base metals such as copper, aluminium, zinc, lead and nickel comes from manufacturing sectors compared to mentha oil and CPO which are part of the edible vegetable oil and used for consumption.

1.1.4 Trading and Settlement of Commodity Futures

The delivery and settlement procedures in the commodity futures trading are defined by the exchange which involves norms of trading, settlement, surveillance and best practices for risk management. It differs for each commodity in terms of quality, place of delivery, penalties and margins (Kotak Commodities, 2017). Futures trading in commodities provides an effective price risk management on account of the participation of different segments of players such as producers, traders, processors, exporters/importers and the end users of the commodity. The process flow diagram for commodity futures trading is shown in Figure 1.4.

The dealer transfers the order placed by the investor at the dealing desk to the exchange trading system. Price is set and initial margin is deposited in the account, once the trade is initiated. Sellers and buyers need to maintain a certain amount as initial margin for the futures contract, they have transacted in the exchange. These margins vary for each commodity and for different contract months. Margins are determined by exchange in which the contracts are transacted and settled by clearing house of the exchange. Margin accounts of all the exchange members are marked daily to the market and at the end of the day, a settlement price is determined by the clearing house.



(***Source:*** *Kotak Commodities, 2017*)

Figure 1.4: Process Flow Diagram in Commodity Futures Trading

On the basis of movements of the market, funds are either withdrawn or added to the clients' account. The settlement price is used as the base price and at end of the day, the settlement price is determined on the basis of spot price fluctuation. The client's account is adjusted to the difference in new settlement price and previous day's price in an appropriate manner. Outstanding contracts at end of the last trading day of contract month are closed out at the rate specified by contract and settled either in cash or in physical delivery. Seller is entitled to offer the delivery at the exchange, determined by the delivery centers (Kotak Commodities, 2017, Mishra 2008).

1.1.5 Sources of Returns in Commodities

Investors can get exposure to commodity futures either by investing in long-only commodity indices or by investing in managed futures products which take both long and short position in different commodities. Sources of returns for long-only commodity indices are as follows (Till, 2015; Menzel and Heidorn, 2007; Fabozzi et al.; 2008):

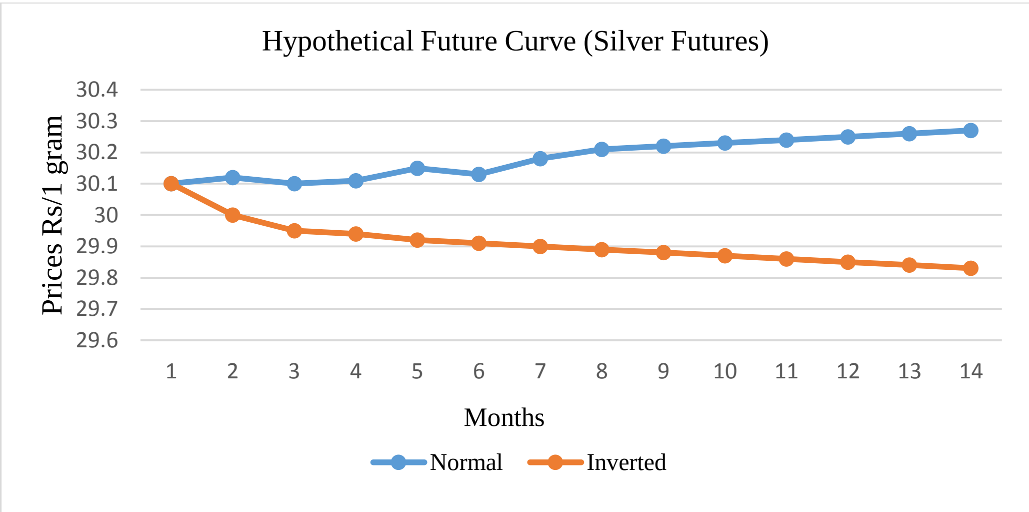
- Collateral Yield: It is a yield on investing the cash in short-term treasuries to collateralize positions in the long-only commodity index. It is basically the return earned on the margin money which acts as a collateral.
- Rebalancing Yield: It is the yield by rebalancing the commodities in an index on a regular basis. Through rebalancing, one can earn benefit due to the fact that commodities do not rise and fall together because the prices of each commodity are affected by varying factors.
- Roll Yield: It is the gain due to change in the price of the underlying commodities and the futures contract on those commodities. It gains due to “roll over” to new contracts on the commodity as the previous contract is near expiration.
- Risk Premium: Market participants like producers and manufacturers can earn risk premium due to the price risk-absorbing capacity of commodity futures by taking a long position in it.

In addition to the above mentioned yield, commodity futures contract can be used to generate abnormal returns by implementing the dynamic asset allocation technique using the different states of the commodity futures market such as backwardation and contango.

1.1.6 Backwardation and Contango State of Commodity Futures Market

The movements of commodity prices give rise to the two states in the future market i.e. backwardation and contango, seen frequently in commodity markets. These two states are used by investors and asset managers for implementing active strategies using tactical and dynamic asset allocation techniques. These two states are the result of a price discrepancy between expected future spot prices and the price of futures contracts.

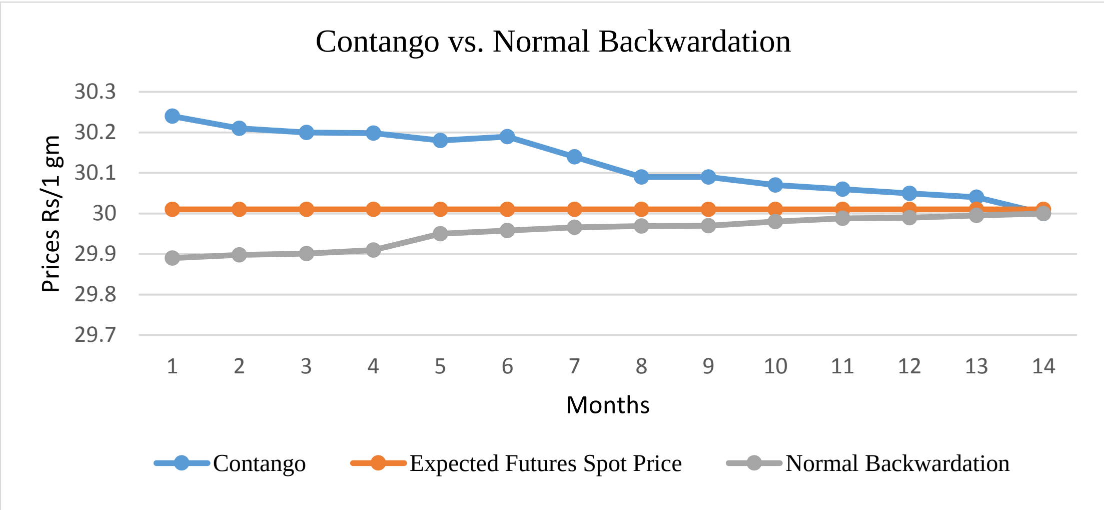
Hedgers and speculators both are concerned to check if the commodity futures markets are a contangoed market or normal backwardation market which can be observed from the shape of the future curve. The future curve for any instrument depicts the futures prices of the corresponding contract expiration date. The future curve can take the form of a normal future curve or inverted curve. The normal curve shows upward sloping trend where price increases as time move forward. The upward slope of a normal curve is due to increase in the 'cost of carry' with a longer expiration. Thus, contract prices are high for the more distant contract month. Inverted curve is the opposite of normal curve and shows downward sloping trend. Inverted curve is the result of a decrease in supply due to weather, natural disaster or any geopolitical events. Thus, prices for distant contracts are less than the current spot prices in the inverted curve. The curve for normal futures and inverted futures are shown in Figure 1.5.



*(**Source:** Folger, 2013)*

Figure 1.5: Chart for Normal Future Curve and Inverted Future Curve

Based on the futures price movements, futures market can take the form of contango or backwardation. The difference between the futures price and the spot price is known as "basis" which is one of the causes for contango and normal backwardation state of the futures market. As the time expires, the futures price will converge to the spot price which is called as convergence. When the futures prices are more than expected future spot prices then it is called contango state in the market. Contango reflects the prices plus cost-of-carry which compensates the holder for the cost of buying and carrying the inventories. On the contrary, when futures prices are less than expected future spot prices then the market is said to be in backwardation. Backwardation basically reflects the tightness of supply which is common in agricultural commodities due to seasonal factors. A hypothetical example of a contango and normal backwardation in silver futures is depicted in Figure 1.6.



*(**Source:** Folger, 2013)*

Figure 1.6: Chart for Contango and Normal Backwardation State of Futures Market

Backwardation and contango are normal and very frequent state of the futures market. To construct a well-diversified portfolio of conventional stock/bond and commodity futures, it is necessary that traders should opt for strategies for tactical allocation of commodity futures to exploit these two market states. Erb and Harvey (2006), Miffre and Rallis (2007), Fuertes et al. (2010), Basu & Miffre (2013), Gorton and Rouwenhorst (2006), Gorton et al. (2013), Miffre et al. (2012) have shown that by adopting active strategies for commodity futures investment, one can generate above average return and lower risk than a long-only commodity futures exposure.

1.1.7 Role of Commodity Futures

Roles of commodity futures can be classified based on their market-specific and investors-specific functions. One of the basic functions of commodity futures is the price risk management and price discovery which justify their market-specific role. Conversely, their inflation hedging potential, ability to hedge stock and bond markets risk and to generate an abnormal return, basically justify the investor-specific roles. These roles of commodity futures are discussed in the following sections.

1.1.7.1 Commodity Futures as a Hedge against Price Risk

Commodity futures perform various economic functions such as hedging, price discovery, liquidity and price stabilization. Prices of commodities, shares and currencies have a nonlinear movement which increases the risk arising from unforeseen price changes. The frequent fluctuation in prices of assets leads to more price risk. Futures contract performs a major economic function of price risk management and price discovery, used by producer and consumer to mitigate the price risk (Wang and Ke, 2005; Lokare, 2007; Bose, 2008; Iyer and Pillai, 2010).

1.1.7.2 Commodity Futures as a Hedge against Inflation

Investment in hard assets such as metals, energy and agricultural commodities is considered as a decent approach to hedge against inflation, as they tend to maintain their values in times of inflation (Worthington and Pahlavani, 2007). From a theoretical aspect, it is considered that one of the fundamental reasons to invest in a commodity is its capability to provide a natural hedge against inflation (Conover et al., 2010). Normally, it is observed that the prices of the commodities move with the inflation as the commodities are the essential components for consumption by individuals and industries. Investors expand their investments in commodities to protect their purchasing power due to decline in money value. Alternatively, they buy a commodity as a consumer and producer to be on a safer side, due to an expectation of a rise in the prices of commodities (Beckmann and Czudaj, 2013). These exercises expand the demand for the commodities and yield to an increase in price also. On the contrary, the stock and bond markets fail to keep their values during a period of unexpected inflation as investors closed their positions in stock and bond markets due to the fear of a rise in commodity prices (Jaiswal and Uchil, 2015). Hence, commodity futures can be used to hedge future inflation risk and consequently to hedge stock and bond market plunges (Beckmann and Czudaj, 2013).

1.1.7.3 Commodity Futures as a Diversifier

To mitigate risk and to earn a stable return, it is necessary for portfolio managers and investors to diversify their portfolios by including an alternative asset in the portfolio. Commodity futures have resurged as an excellent portfolio diversifier and hedge against inflation over the last decade. Commodities provide the benefits of alternative asset classes due to their negative correlation with stock and bond markets (Gorton and Rouwenhorst, 2006). Traditional and alternative asset managers use commodity futures as an investment vehicle for strategic and tactical allocations. Strategic allocation of commodity futures is highly valued due to the benefits of long-term equity-like returns, diversification benefits due to low correlation with other asset classes and inflation hedging potential (Bodie and Rosansky, 1980; Jensen et al., 2002; Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006; Mensi et al., 2013).

1.1.7.4 Commodity Futures as a Source of Abnormal Return

In addition to the strategic asset allocation, commodity futures are used for tactical asset allocation to generate the abnormal alpha as shown by previous studies (Erb and Harvey, 2006; Miffre and Rallies, 2007). The active strategies, used for tactical asset allocation, are designed based on the momentum, term structure and idiosyncratic volatility signals available in the market. The active strategy based on momentum signal is designed by taking a long position in commodity futures that outperform the market with the highest historical return and a short position in commodity futures that underperform the market with the lowest returns. In addition, an active strategy can be designed based on hedging pressure hypothesis to earn an abnormal return called as term structure strategy. The term structure strategy can be implemented by taking a long position in the backwardated contract and short position in the contangoed contract as designed by Erb and Harvey (2006) and Fuertes et al. (2010). Similarly, an active strategy based on idiosyncratic volatility can be designed by exploiting the negative pattern between idiosyncratic volatility and expected return of an asset as shown by Ang et al. (2009) and Miffre et al. (2012). The idiosyncratic volatility strategy can be implemented by taking a long position in the commodity futures with low idiosyncratic volatility and a short position in the commodities with high idiosyncratic volatility.

1.2 RESEARCH GAP IDENTIFICATION

On an analysis of the existing literature, it is evident that very few studies have been conducted to examine the equilibrium relationship between individual commodity futures and inflation by incorporating the nonlinear relationship. Similarly, it is found that studies have focussed less on the assessment of regime-dependent hedge and safe haven roles of individual commodity futures. In addition, with the review of the literature, it is found that there is a lack of study which examines the existence of time-varying conditional profitability of momentum, term structure and idiosyncratic volatility strategies for the commodity futures market in the Indian context. Moreover, there is a lack of study which combines the theoretical concept of both momentum returns and idiosyncratic volatility to design a combined strategy. These research gaps are more prominent in the Indian scenario since the number of studies in this realm is minimal.

1.3 PROBLEM DEFINITION

In order to address these research gaps, the research problem is defined as: "To investigate hedging and diversification roles of commodity indices and commodity futures contracts in the conventional portfolio of stocks and bonds. It defines strategic and tactical strategies with the allocation of commodity futures in a portfolio."

1.4 RESEARCH QUESTIONS

The research questions are framed after analysing the research gaps which are identified based on the extensive literature review.

1. How are the commodity futures and commodity indices related to inflation?
2. How can commodity futures and commodity indices hedge and diversify a portfolio against equity and bond risk?
3. What are the influences of the business cycle and monetary cycle on the role of commodity futures as a risk management tool?
4. How do the signals of momentum, term structure and idiosyncratic volatility of commodity futures market help to increase the risk-adjusted returns of a portfolio?

1.5 RESEARCH OBJECTIVES

Based on the research gaps and research questions, the following research objectives have been formulated.

1. To assess the role of commodity futures and commodity indices as a hedge against inflation.
2. To investigate the hedging and diversification role of commodity futures and commodity indices against equity and bond risk.

3. To assess the time-varying conditional profitability of momentum, term structure and idiosyncratic volatility strategies in the commodity futures market.
4. To design the combined strategies using momentum, term structure, idiosyncratic volatility and evaluate their time-varying conditional profitability.

1.6 RESEARCH HYPOTHESIS

Based on literature review, following research hypotheses are designed.

H_1 There is a positive correlation between commodity futures return and inflation.

H_2 There is a positive correlation between commodity index return and inflation.

H_3 There is a negative and significant correlation between commodity futures return and equity return.

H_4 There is a negative and significant correlation between commodity index return and equity return.

H_5 There is a negative and significant correlation between commodity futures return and bond return.

H_6 There is a negative and significant correlation between commodity index return and bond return.

1.7 MOTIVATION

Two extreme sides of inflation, in terms of hyperinflation and deflation always create a havoc for the economy. To maintain inflation at an acceptable rate becomes the cornerstone of a policy framework for an economy which is suffering from a long-run erosive effect of unstable inflation on assets' return and overall growth of the economy (Pettinger, 2014)[3]. In addition, the complexity of investment channels worldwide is eased due to deregulation and liberal policies enacted in different regions and countries (Bagchi, 2009; Onour, 2009). This worldwide growth disseminates the financial crises by contagion effect, in addition, to provide an expanded list of investment assets which can be used to get more diversification benefits. Further, it increases the volatility and uncertainty in the equity and bond markets returns. It becomes necessary for portfolio managers and investors to diversify their portfolios by including the alternative asset in their portfolios due to a reduced risk premium for traditional asset classes such as stocks and bonds (Fabozzi et al., 2008). It increases the demand for alternative investments from institutional investors, private investors and investment fund managers.

Many previous studies have justified the role of commodity futures as a risk management instrument to achieve price risk management, in addition, to its hedging and diversification benefits. According to Gorton and Rouwenhorst (2006), commodities provide benefits of alternative asset classes due to their negative correlation with the stock and bond markets which is stronger in long-term diversification strategy. However, post 2007-2009 financial crisis, the correlation between commodity and stock returns has increased and breaks the common notion that commodities serve as a hedge (Lombardi and Ravazzolo, 2016; Hansen and Overaae, 2015). In addition, the economic crisis of China gives evidence that the impact of global macroeconomic environment on both the stock and commodity markets is more prominent compared to market-specific and idiosyncratic risk. These facts have raised questions on the role of a commodity as an alternative asset class. On the contrary, studies such as Jensen et al. (2002), Gorton and Rouwenhorst (2006), Chong and Miffre (2010), Conover et al. (2010) and Creti et al. (2013) confirmed that the inclusion of commodity futures in a portfolio of traditional asset classes gives benefits of portfolio diversification. In addition, conventional wisdom related to commodities indicates that commodities are physical assets, hence, they can be used to hedge future inflation risk. This, in turn, reduces the returns of financial assets like stocks and bonds (Worthington and Pahlavani, 2007). Normally, it is observed that the prices of an asset which move with inflation can be used as a hedge against stock and bond markets plunge. This is due to the fact that stock and bond markets fail to keep their values during periods of unexpected inflation due to Fisher Effect postulated by Fisher (1930). Hence, commodities can be used to hedge future inflation risk and consequently to hedge stock and bond market plunges (Beckmann and Czudaj, 2013).

In addition, conventional wisdom indicates that commodity futures can be a natural hedge against inflation due to its ability to accommodate expected commodity price changes (Bhardwaj et al., 2011). The rationale of using commodity futures as an inflation hedge is its ability to incorporate future trends in commodity prices and to foresee the expected deviation in inflation (Gorton and Rouwenhorst, 2006). However, sensitivity in returns of commodity futures to the changes in the inflation rate does not remain constant over time and varies from one commodity future to another (Erb and

Harvey, 2006). These studies show the contradictory findings and time-varying pattern of diversification and inflation hedging potential of commodity futures.

It is the prime concern of an investor, traditional and alternative asset manager to earn a stable and abnormal return, in addition, to get the inflation hedging and diversification benefits from their investments. Hence, many previous studies have designed the active strategies in commodity futures market to earn an abnormal return such as Erb and Harvey (2006), Gorton et al. (2013), Shen et al. (2007), Miffre and Rallis (2007), Fuertes et al. (2010) and Zaremba (2016).

However, in the Indian context, it is necessary to justify the role of commodity futures as an alternative asset class to reap the benefits of diversification, in addition, to earn abnormal returns. Hence, it provides a strong motivation to the researcher to explore the feasible implications of conventional wisdom related to commodity futures, as an inflation hedge and diversifier against the stock and bond market movements in the Indian scenario. In addition, this study is an attempt to design active strategies for tactical asset allocation by using the momentum, term structure and idiosyncratic volatility signals, available in the commodity futures market.

1.8 SIGNIFICANCE OF STUDY

In the current environment of a global downward trend, it becomes a prime concern of individual and institutional investors to identify an appropriate risk management tool in order to mitigate the risk and earn abnormal returns. This study is an attempt to identify the role of commodity futures as a risk management tool. The current study uses the nonlinear regime-switching approach to investigate the inflation hedging and diversification benefits of commodity futures in the latent regimes. These latent regimes arise due to the uncertainty in the global financial market. The findings of the study provide guidance to the investors in designing their investment strategy in terms of astute selection of appropriate commodity futures and their proper allocation in the portfolio based on the respective regimes. In addition, the current study implements active strategies based on momentum, term structure and idiosyncratic volatility signals present in the commodity futures market. These findings guide the investors with respect to dynamic asset allocation of commodity futures in the portfolio for implementing the active strategies. These strategies give exceptionally high abnormal returns. Hence, this study is relevant in the current scenario of global financial meltdown because it addresses the issues of strategic and dynamic asset allocation of commodity futures in a portfolio to get the benefit of diversification, in addition, to earn abnormal returns.

1.9 SCOPE OF THE STUDY

In India, 17 national and 16 regional exchanges are operating with 146 commodities. The scope of the research is limited to MCX which is the largest commodity exchange in India where 91.90 percent of the commodity trading happens. This study is conducted on three sub-indices- MCXAGRI, MCXMETALS and MCXENERGY and 13 commodity futures. These commodity futures are the highly traded contracts in MCX based on their average daily turnover, volume and open interest. In addition, these commodity futures are the constituents of above mentioned commodity sub-indices which are the part of a composite commodity index MCXCOMDEX.

1.10 OPERATIONAL DEFINITIONS

Operational definitions used in the study, which give a clear, concise and detailed definition of different measures are discussed below.

Inflation Hedging: The inflation hedging potential of an asset refers to the long-run equilibrium relationship of the asset with the inflation index.

Hedge against stock and bond markets movements: An asset is qualified to be a hedge if it is uncorrelated or negatively correlated with other assets on an average.

Safe Haven: The safe haven role of an asset is justified if it is uncorrelated or negatively correlated with other assets during extreme market movements and financial crisis.

Diversifier: An asset becomes a diversifier if it is positively and imperfectly correlated with other assets on an average.

Strong /weak hedge: An asset is qualified to be a strong (weak) hedge if it is negatively correlated (uncorrelated) with another asset or portfolio on an average.

Strong/weak safe haven: An asset is justified to be a strong (weak) safe haven if it is negatively correlated (uncorrelated) with another asset or portfolio during the extreme market movements.

LIMITATIONS OF THE STUDY

The limitations of the study are as follows:

1. The prime limitation of the study is the inconsistency in data, as futures trading on different commodities began at different time periods. In addition, the weights of the components of composite commodity index MCXCOMDEX is determined annually or as required by index committee which sometimes causes a change in the composition of this index.
2. Availability of data with a higher frequency can give a better analysis of linearity and nonlinearity in the movements of commodity futures and their inflation hedging and diversification benefits.
3. Years 2003-04 are considered as a significant year for the development of commodity futures market in India due to the establishment of many nationwide multi-commodity exchanges (Gupta, 2011). However, the prices of commodities considered for the study are taken from June 2006, due to the inconsistency in the availability of data for all the months from the year 2003 to the year 2005. Hence, the study period is short to give a firm conclusion[4].

1.12 THESIS OUTLINE

The remaining chapters of this thesis are organized as follows:

Chapter 2 presents the existing studies with respect to inflation hedging and diversification benefits of commodity futures. In addition, it highlights the literature review on performance evaluation of active strategies, designed to earn abnormal returns by using the momentum, term structure and idiosyncratic volatility signals of the commodity futures market. Based on literature outcome, the research gaps are identified.

Chapter 3 discusses the methodology used to analyse the time-varying inflation hedging and diversification benefits of commodity futures. In addition, it specifies the methodology used to design the active strategies. Basically, it explains the methodology to capture the market signals of momentum, term structure and idiosyncratic volatility signals for designing the active strategies. Moreover, it describes the process to combine the methodology of momentum, term structure and idiosyncratic volatility strategies to implement the combined strategies.

Chapter 4 analyses the time-varying dynamics of inflation hedging potential of individual commodity futures and commodity indices using linear Vector Error Correction Model (VECM) and nonlinear Markov Switching-Vector Error Correction Model (MS-VECM). It assesses the hedge and safe haven properties of individual commodity futures and commodity indices against stock and bond markets movements using a nonlinear regime-switching framework of Markov Switching-Vector Autoregression (MS-VAR) model. In addition, active strategies are designed by using the momentum, term structure and idiosyncratic volatility signals available in the commodity market. The time-varying risk-return trade off performance of these active strategies is also evaluated in this Chapter. Moreover, the combined strategies are designed in this Chapter and their time-varying profitability is assessed.

Finally, Chapter 5 summarizes the entire thesis work. It elaborates the findings, recommendations, conclusions, theoretical and policy implications of the study. It ends with the direction for future research.

1.13 SUMMARY

This chapter introduces commodity trading, economic characteristics of commodities including the inception, structure and participants of the commodity futures market in India. In addition, it describes the backwardation and contango state of the commodity futures market which is basically used to design active strategies for tactical allocation of commodity futures. This chapter also outlines the research questions, research objectives, the relevance of the study, limitations and scope of the study.

Notes:

[1]Sensex is also called as S&P BSE Sensex, a leading stock market index in India.

[2]However, increased supply of crude oil triggered by rising US shale oil exploration causes the fall in the prices of crude oil from their 2014 peak.

[3] It is apparent from the deflationary situation in European countries and the US due to Eurozone and financial crises. In addition, the ruinous case of hyperinflation in Russia during 1992 and 1994, in Zimbabwe during 1999-2009 and highest inflation rate in Venezuela in 2015 are few cases which confirm that price stability should be the primary goal of monetary policy-makers (Pilling and England, 2016; Hanke, 2015).

[4]However, during this period commodity market has experienced many ups and downs such as industrialization of China which has given the boost to the global economy, the sub-prime crisis in the US, European crisis and a recent economic slowdown in China. Hence, the period is rich enough to give a better regime-specific analysis of inflation hedging and diversification benefits of commodity futures.

CHAPTER 2
LITERATURE REVIEW

2.1 CHAPTER OVERVIEW

This chapter highlights the previous work with respect to inflation hedging and diversification benefits of commodity futures. It also highlights the implementation of active strategies by using the market signals of momentum, term structure and idiosyncratic volatility. Sections 2.2 and 2.3 review the studies related to inflation hedging potential and diversification benefits of commodity futures. Section 2.4 discusses the studies which have created the active strategies by using momentum, term structure and idiosyncratic volatility signals of commodity futures market. In addition, it deals with the discussion of studies which have combined the methodology of momentum, term structure and idiosyncratic volatility and created the combined strategies. Section 2.5 discusses the outcomes of the literature review with the help of literature map. The chapter ends with a chapter summary in Section 2.6.

2.2. COMMODITY FUTURES AS A HEDGE AGAINST INFLATION

This section discusses the related work with respect to inflation hedging potential of stocks and commodities. The summary of the discussion is given in Table 2.1.

The intricate relationship between inflation and stocks has been addressed extensively in the literature which is discussed as follows. Ely and Robinson (1997) used Vector Error Correction Model (VECM) to identify the long-run and short-run dynamics between output, money, stock prices and goods prices. According to them, stock prices are considered to be a good hedge against inflation if, in response to a real or monetary shock in inflation, stock prices adjust their values relative to the goods prices. Anari and Kolari (2001) identified that long-run Fisher elasticity of stock prices with respect to goods prices ranged from 1.04 to 1.06 which reveals that stock prices have a long-run equilibrium relationship with inflation. It justified the significant long-run and short-run dynamics between stock return and inflation which affirm the inflation hedging ability of stocks. On the contrary, Bekaert and Wang (2010) found that standard securities such as nominal government bonds and equities are a poor hedge against inflation. Other standard assets such as treasury bills, foreign bonds, real estate and gold improved the relationship where foreign bonds and gold performed better than other assets. However, it is difficult for these assets also to hedge the inflation risk.

Numerous studies are available which have examined the long and short-run relationship between gold and inflation. The outcomes of the study performed by Mahdavi and Zhou (1997) suggested that the short-term movements in the gold prices are very volatile to forecast the gradual changes in the general price level. In addition, the inflation hedging potential of gold diminished over time which undermined the role of gold as an indicator of inflation. On the contrary, Levin et al. (2006) found significant cointegration between inflation index and gold which demonstrates the long-run one-for-one relationship among these variables. However, there was a presence of slow reversion towards long-run equilibrium from any deviation caused by shocks in short-run. Their conclusions are in line with the outcomes of Laurent (1994), Harmston (1998), Adrangi et al. (2003) and Ghosh et al. (2004) which confirmed the reliability of gold as an inflation hedge both in long and short-run in the US, UK, France, Germany and Japan. Harmston (1998) showed that gold performs the role of a long-term store of value. He suggested that during a period of price fluctuation, gold had maintained its real purchasing power in the long-run for US, Britain, France, Germany and Japan. Similarly, Adrangi et al. (2003) showed that there is an insignificant relationship of gold and silver returns with unexpected inflation. However, gold and silver prices have a positive correlation with expected inflation. Hence, both gold and silver function as a reliable hedge against inflation in the short and long-run. However, Ghosh et al. (2004) found that long-run relationship between the nominal price of gold and US retail price index is dominated by short-run influences such as gold lease rate, gold's beta and US/world exchange rate. Tkacz (2007) performed the study on 14 countries and confirmed that gold price movements provide a direction to the future movements of inflation. In addition, Worthington and Pahlavani (2007) provided confirmation of cointegration between gold and inflation amidst post-war period and post 1970s. They adopted the Zivot and Andrews (1992) unit root test to identify the most convincing endogenous structural breaks which modified the cointegration strategy by integrating these breaks. Their modified cointegration method using these breaks suggested a strong cointegrating relationship between gold and inflation which confirmed gold as an effective inflation hedge. Tiwari (2011) used cointegration analysis and consolidated most significant structural breaks and seasonal adjustments to investigate the inflation hedging ability of gold in the Indian context. His results provided evidence of cointegration between gold prices and inflation which legitimize gold as an effective inflation hedge.

Wang et al. (2011), Beckmann and Czudaj (2013) and Van Hoang et al. (2016) have examined the long and short-run inflation hedging potential of gold by using a nonlinear approach. The findings of Wang et al. (2011) suggested that gold returns cannot be used as a hedge against inflation in both US and Japan during low momentum regimes. In the case of high momentum regimes, gold has shown its inflation hedging potential only in the US while it has not been able to fully hedge inflation in Japan during short-run. Beckmann and Czudaj (2013) found that gold is a partial hedge against inflation in the long-run in the US and the UK rather than in the Euro area and Japan. In addition, inflation hedging potential of gold crucially depended on the time horizon of investment. Conversely, Van Hoang et al. (2016) analysed the inflation hedging potential of gold which was denominated in the local monthly prices of China, India, Japan, France, UK and US. Their results confirmed that gold was not a hedge against inflation in the long-run for any of the countries. However, gold was an inflation hedge in the short-run only in the UK, US and India. In addition, they found that there was a lack of long-run equilibrium relationship between gold prices and the CPI in China, India and France.

With respect to inflation hedging potential of commodity futures, Bodie (1983), Ankrim and Hensel (1993), Lummer and Siegel (1993), Froot (1995), Kaplan and Lummer (1997), Anson (1998), Becker and Finnerty (2000) and Menzel and Heidorn (2007) found that commodity futures are valuable portfolio components as they perform better during high inflationary periods. Bodie (1983) found that risk and return performance of a portfolio consisting of stocks, bonds and Treasury bills improved with the inclusion of commodity futures. This ability of commodity futures is stronger during an inflationary environment. Similarly, Kaplan and Lummer (1997) suggested that Goldman Sachs Commodity Index (GSCI) collateralized futures can be used by risk-averse investors to hedge the returns of stocks and bonds against the risk of rising inflation. Hence, it can be used as an efficient tool for diversification which provides a protection against the poor performance of other asset classes. Becker and Finnerty (2000) suggested that inclusion of Commodity Research Bureau (CRB) and GSCI indices in a portfolio enhances the performance of a portfolio. They found that the risk-adjusted return performance of a portfolio is stronger for the decades of seventies rather than in eighties. The reason for such time-varying performance is that the years of seventies were characterised by high inflation which justified the role of commodity futures as an inflation hedge. According to Menzel and Heidorn (2007), commodities contribute to enhance the risk-return ratio of a portfolio only in selected periods such as the periods of the inflationary environment and restrictive monetary policy. Hence, the best time of investment in commodities is the period of high expected and unexpected inflation rate. Gorton and Rouwenhorst (2006) have conducted a study on an equally-weighted index of commodity futures and substantiated a positive correlation between commodity futures and inflation. They found that commodity futures are more effective in providing diversification benefits during periods of unexpected inflation. This is because commodity futures are positively correlated with unexpected inflation and changes in expected inflation. Similarly, Anson (2003) found that inflation has a positive effect on commodity prices compared to stocks and bonds. A conflicting view was given by Erb and Harvey (2006) who suggested that individual commodity futures show varying exposures to inflation. On the contrary, they found that inflation hedging ability of a portfolio of commodity futures relies on the composition of the portfolio. Similarly, Kat and Oomen (2006) showed that commodity futures' returns are positively correlated with inflation. However, this ability varies among different commodities such as energy, metals, cattle and sugar offer the best inflation hedge compared to other commodities.

Spierdijk and Umar (2014) and Zhou (2014) considered the nonlinear relationship between commodity futures and inflation. Spierdijk and Umar (2014) assessed the hedging properties of commodity futures by using Vector Autoregression (VAR) model. To incorporate structural changes in the inflation rate and commodity futures price, they have employed rolling window and sub-sample analysis. Their empirical evidence suggested that commodity futures have a noteworthy capacity to hedge the US inflation, especially for a one-year investment horizon. Similarly, Zhou (2014) analysed the inflation hedging property of Standard & Poor-Goldman Sachs Commodity Index (S&P-GSCI) against the seasonally adjusted Consumer Price Index (CPI) of US. He adopted the regime-specific analysis of Markov Switching-Vector Error Correction Model (MS-VECM). His findings confirmed the significant hedging ability of the sub-indices of energy, industrial and precious metals. However, the hedging capacity exhibited substantial variation over time. Zaremba (2015) suggested that commodities can be used as an inflation hedge in the financialised market. Hence, portfolio returns can be hedged against inflation using commodity futures.

In the Indian context, Joshi (2013), Thota and Bandi (2015) and Sharma (2015) have investigated inflation hedging potential of commodity futures. Joshi (2013) used the standard statistical method to provide a strategy to hedge the equity returns against inflation by including commodity futures in a portfolio. His work includes pepper, steel, mustard seed and wheat futures and found that these commodity futures provide a hedge against fall in the equity prices in an inflationary environment. Similarly, Thota and Bandi (2015) found that all the commodity futures under the base metals and agricultural sectors are a perfect hedge against inflation, expected and unexpected inflation. Conversely, turmeric and nickel are perfect hedge against inflation and unexpected inflation only. In addition, Sharma (2015) created the inflation tracking portfolio and analysed the performance of a conventional portfolio with and without inflation tracking portfolios. They found that conventional portfolio gives a higher Sharpe ratio during the high inflationary period due to the presence of inflation tracking portfolio. Hence, his results indicated that commodity futures possess inflation hedging properties except for the agricultural commodities.

Table 2.1: Summary of Studies Related to Inflation Hedging Potential of Commodity Futures

Authors' Name	Study Period	Data	Methodology	Results	Research Gap
Anari and Kolari (2001)	1953-1998	Stock index (US, Canada, UK, France, Germany and Japan)	VECM	Confirms inflation hedging potential of stocks.	
Bekaert and Wang (2010)	1970-2010	Stock bonds, Treasury bills, real estate and gold for 45 countries	Estimation of inflation beta using a simple regression	Confirms inability of stocks, bonds, treasury bills real estate and gold to hedge inflation risk.	
Mahdavi and Zhou (1997)	1958-1994	Gold (UK)	VECM	Confirms inability of gold to hedge inflation risk.	
Levin et al. (2006)	1976-2005	Gold (US, India, China, Turkey, Saudi Arabia and Indonesia)	Cointegration regression technique	Confirms inflation hedging potential of gold.	

Laurent (1994)	1968-1993	Gold (US)	Simple regression model	Confirms inflation hedging potential of gold.	
Harmston (1998)	1968-1996	Gold (US, UK, France, Germany and Japan)	Risk-return analysis using simple regression model	Confirms inflation hedging potential of gold.	
Ghosh et al. (2004)	1975-1999	Gold (US, UK, Germany, France and Japan)	Cointegration regression technique	Confirms inflation hedging potential of gold.	
Worthington and Pahlavani (2007)	1945-2006	Gold (US)	Zivot and Andrews unit root test with endogenous structural breaks	Confirms inflation hedging potential of gold.	
Tiwari (2011)	1990-2010	Gold (Indian prices)	Cointegration analysis with structural breaks and seasonal adjustment	Confirms inflation hedging potential of gold.	
Wang et al. (2011)	1971-2010	Gold (US and Japan)	Nonlinear model and impulse response function	Confirms regime-specific inflation hedging potential of gold.	
Beckmann and Czudaj (2013)	1970-2011	Gold (US, UK, Euro and Japan)	MS-VECM	Confirms regime-specific inflation hedging potential of gold.	Research Gap 1
Van Hoang et al. (2016)	1955-2015	Gold (China, India, Japan, France, UK and US)	NARDL	Confirms inability of gold to hedge inflation risk.	
Froot (1995)	1970-1993	Commodity Futures (GSCI, CRB, gold and crude oil)	Regression	Confirms inflation hedging potential of commodity futures.	
Kaplan and Lummer (1997)	1970-1996	Commodity futures index (GSCI)	Risk-return and correlation estimation.	Confirms inflation hedging potential of commodity futures.	
Becker and Finnerty (2000)	1970-1990	Commodity futures index (CRB, GSCI)	Risk-return estimation	Confirms inflation hedging potential of commodity futures.	
Menzel and Heidorn (2007)	1976-2006	Commodity futures index (CRB, GSCI, DJAIGCI , RICI , DBCI and SPCI)	Markowitz's portfolio selection model	Confirms inflation hedging potential of commodity futures.	
Gorton and Rouwenhorst (2006)	1959-2004	Commodity futures index (Equally-weighted commodity	Sharpe ratio and correlation	Confirms inflation hedging potential of commodity futures.	

		futures total return index)			
Anson (2006)	1990-2000	Commodity futures index (GSCI, DJAIGCI, CPCI, MLM)	Correlation	Confirms inflation hedging potential of commodity futures.	
Erb and Harvey (2006)	1969-2004	Commodity futures index (GSCI, DJAIGCI and CRB)	Fama and French five-factor model	Confirms varying exposure of different commodity futures to inflation risk.	
Kat and Oomen (2006)	1965-2005	Commodity futures index (GSCI)	GARCH (1,1)-DCC (1,1)	Confirms varying exposure of different commodity futures to inflation risk.	
Spierdijk and Umar (2014)	1970-2011	Commodity futures index (GSCI)	VAR	Confirms time-varying inflation hedging potential of gold.	
Zhou (2014)	1983-2012	Commodity futures index (GSCI)	MS-VECM	Confirms regime-specific inflation hedging potential of gold.	Research Gap 1
Zaremba (2015)	1970-2013	Commodity futures index (GSCI, JPMCCI and DJUBSCI)	Fama and Schwert (1977)	Confirms inflation hedging potential of commodity futures.	
Joshi (2013)	10 June 2011-20 October 2011	Pepper, wheat, steel and mustard seed (Indian prices)	Standard statistical method	Confirms inflation hedging potential of pepper, wheat, steel and mustard seed.	Research Gap 1
Thota and Bandi (2015)	2004-2014	Base metals and agricultural commodities (Indian prices)	Simple regression model	Confirms inflation hedging potential of base metals and agricultural commodities.	Research Gap 1
Sharma (2015)	2005-2012	Individual commodity futures (Indian prices)	Inflation Tracking Portfolio	Confirms inflation hedging potential of commodity futures except for agricultural commodities.	Research Gap 1

*(**Source:** Literature Review)*

2.3. COMMODITY FUTURES AS A DIVERSIFIER

This section discusses hedge and safe haven role of gold and commodity futures against the stock and bond market movements which is summarized in Table 2.2.

Studies conducted to provide an insight into the diversification role of commodities, especially gold, are discussed below. Baur and Lucey (2010) studied the three major financial markets viz. the US, UK and Germany. Their empirical results confirmed that gold is a hedge and safe haven in extreme stock market movements. However, gold acts as a safe haven only for 15 trading days. The findings of Baur and McDermott (2010) suggested that gold is a strong hedge and safe haven for the European and the US market. Conversely, gold does not act as a hedge and safe haven in Brazil, Russia, India, China and South Africa (BRICS) countries, Australia, Canada and Japan. Beckmann et al. (2015) studied hedge and safe haven property of gold for 18 individual markets and five regional indices over a study period from 1970 to 2012. Their findings confirmed that hedge and safe haven properties of gold depend on market-specific behaviour.

The following literature discusses the diversification property of commodity futures. Jensen et al. (2002) have shown that performance of a portfolio is enhanced with an addition of commodity futures. However, this benefit accrued exclusively during periods when the restrictive monetary policy was given by the Federal Reserve. Gorton and Rouwenhorst (2006) found that diversifying a portfolio using an equally-weighted index of commodity futures gives an excess return and reduces the risk as measured by the standard deviation. The findings of Laws and Thompson (2007) and Buyuksahin et al. (2008) are in line with the perception that inclusion of commodities in a portfolio provides benefits of portfolio diversification. According to Buyuksahin et al. (2008), commodities provide benefits of portfolio diversification to equity investors as there is a lack of evidence of an increase in co-movement between commodities and traditional asset classes. Chong and Miffre (2010) found that conditional correlation between commodity futures and S&P 500 return fell during a period of high volatility in the stock market. Similarly, the correlation of commodity futures with treasury bills fell during a period of high volatility in the short-term interest rates. Conover et al. (2010) suggested that investors can make substantial benefit by investing five percent and more in commodities. However, the addition of commodity futures enhances the portfolio returns only during those periods when the Federal Reserve increased the interest rates. Furthermore, Cheung and Miu (2010) assessed diversification benefits of commodity futures in different economic regimes such as bull and bear state of commodity and stock markets. Their results confirmed that commodities enhance the risk-adjusted performance of portfolio during a bullish environment of commodity and stock markets in contrast to a bearish environment. Moreover, the addition of commodity futures to a portfolio produces a better risk-adjusted return for risk-averse investors rather than for other investors. Mensi et al. (2013) found a high conditional correlation of S&P 500 with gold and West Texas Intermediate index. Moreover, optimal weights and hedge ratio showed that including commodities in a portfolio increases the risk-adjusted return performance. According to Creti et al. (2013), the correlation between commodity and stock returns is highly volatile during the period of financial crisis of 2007 to 2008. It basically confirms the time-varying pattern of correlation between these asset classes. In addition, the 2007-2008 crisis played an important role in emphasising the relationship between commodity and stock markets which highlighted the financialisation of commodity markets. In addition, out-of-sample analysis of Bessler and Dominik (2015) confirmed that commodity index improves the risk-return performance of a stock-bond portfolio which shows a time-varying pattern. This ability of commodity index is stronger for base metals, energy and precious metals compared to livestock and agricultural commodities.

In the Indian context, Bansal et al. (2014) examined the diversification role of commodity futures in a traditional portfolio mix of stock and bond. They used mean-variance optimization technique for the study period from the year 2005 to year 2011. Their findings are in line with the findings of Mishra (2008) which confirmed that adding commodity futures in a portfolio of equities enhances the risk-adjusted return of a portfolio.

Contrarian views were given by Erb and Harvey (2006), Daskalaki and Skiadopoulos (2011), Batavia et al. (2012), Lombardi and Ravazzolo (2016) and Hansen and Overaae (2015). Erb and Harvey (2006) suggested that the average returns of the individual commodity futures are almost equal to zero. The “equity–like” returns of a portfolio of commodity futures is due to portfolio rebalancing. Daskalaki and Skiadopoulos (2011) found that benefits of diversification are not available in the out-of-sample analysis with an exception during the years of 2005 to 2008, a period of the commodity boom. It implies that benefits of including commodities in a traditional portfolio can only be the exception, not the rule. Batavia et al. (2012) showed that addition of commodities in a portfolio of stocks does not provide any improvement to Sharpe ratio which is more evident in an extreme environment. In addition, Lombardi and Ravazzolo (2013) suggested that the portfolio which consisted of commodities produces substantially higher volatility and it does not always produce higher Sharpe ratios. Hansen and Overaae (2015) found that addition of commodities to a portfolio gives reduced returns and increased volatility for all the strategies during the period of 2000-2014. In addition, the sub-periods analysis indicates that diversification benefits of commodity futures depend on the allocation strategy and the period studied.

Table 2.2: Summary of Studies Related to Diversification Benefits of Commodity Futures

Authors' Name	Study Period	Data	Methodology	Results	Research Gap
Baur and Lucey (2010)	1995-2005	Gold (US, UK Germany)	GARCH-constant and time-varying approach	Confirms hedge and safe haven role of gold	
Baur and McDermott (2010)	1979-2009	Gold (G7 and BRICS countries, Australia and Switzerland	Regression, GARCH-constant and time-varying approach	Confirms country-specific hedge and safe haven role of gold.	
Beckmann et al. (2015)	1970-2012	Gold (18 individual markets and five regional indices)	STR	Confirms market-specific hedge and safe haven role of gold	Research Gap 2
Jensen et al. (2002)	1973-1999	Commodity Futures Index (GSCI)	Mean-Variance optimization technique	Confirms diversification benefits of commodity futures.	
Gorton and Rouwenhorst (2006)	1959-2004	Commodity Futures index	Sharpe ratio estimation of portfolio	Confirms diversification benefits of commodity futures.	
Laws and Thompson (2007)	1994-2007	Commodity Futures Index (CCI)	Markowitz approach of portfolio construction	Confirms diversification benefits of commodity futures.	
Buyuksahin et al. (2008)	1991-2008	Commodity Future Indices (DJAIG and GSCI)	Dynamic correlation and recursive cointegration techniques	Confirms diversification benefits of commodity futures.	
Chong and Miffre (2010)	1980-2006	25 individual commodity futures contracts (US, UK, Europe, Asia pacific, Latin America	GARCH- DCC	Confirms diversification benefits of commodity futures.	Research Gap 2
Conover et al. (2010)	1970-2007	Commodity Futures Index (GSCI)	Fama and French (1993) three-factor model	Confirms diversification benefits of commodity futures.	

Cheung and Miu (2010)	1970-2005	Commodity Futures index (Canada, US and Non-North America)	Sharpe ratio estimation of portfolio (Regime-based analysis)	Confirms diversification benefits of commodity futures.	Research Gap2
Mensi et al. (2013)	2000-2011	Commodity future indices for energy, food, gold and beverages (US)	VAR-GARCH	Confirms diversification benefits of commodity futures.	
Creti et al. (2013)	2001-2011	Individual commodity futures and commodity indices (CRB)	GARCH-DCC	Confirms time-varying diversification benefits of commodity futures.	Research Gap 2
Bessler and Dominik (2015)	1983-2012	Commodity futures index (US)	Markowitz Mean-Variance strategy of portfolio construction	Confirms time-varying diversification benefits of commodity futures.	
Bansal et al. (2014)	2005-2011	Commodity futures index (India)	Mean-Variance optimisation technique	Confirms diversification benefits of commodity futures.	Research Gap 2
Mishra (2008)	2005-2007	Commodity futures index (India)	Mean-Variance optimisation technique	Confirms diversification benefits of commodity futures.	Research Gap 2
Erb and Harvey (2006)	1969-2004	Commodity futures index (GSCI, DJAIG and CRB)	Fama and French five-factor model	Confirms inability of commodity futures to diversify the portfolio.	
Daskalaki and Skiadopoulos (2011)	1989-2009	Individual commodity futures and commodity indices (GSCI, DJUBS)	Mean-Variance and Non-Mean-Variance spanning tests	Confirms inability of commodity futures to diversify the portfolio.	
Batavia et al. (2012)	1999-2010	Commodity future indices (GSCI, RICI DJUBS) and individual commodity futures (gold)	Correlation, Sharpe Ratio	Confirms inability of commodity futures to diversify the portfolio.	

Lombardi and Ravazzolo (2013)	1980-2012	Commodity Futures index (GSCI)	Bayesian Dynamic Conditional Correlation	Confirms inability of commodity futures to diversify the portfolio.	
Hansen and Overaae (2015)	1995-2014	Commodity Futures index (GSCI)	Risk parity approach such as standard deviation, covariance, semi-deviation, and expected-tail-loss in addition to traditional allocation model	Confirms inability of commodity futures to diversify the portfolio.	

*(**Source:** Literature Review)*

2.4 COMMODITY FUTURES AS A SOURCE OF ABNORMAL RETURN

Many previous studies have been conducted which designed active strategies using momentum, term structure and idiosyncratic volatility signals available in the market. These studies are discussed as follows.

2.4.1 Active Strategies Based on Momentum Signal

This section discusses the available literature with respect to the creation of active strategies based on momentum signals. The summary of the discussion is given in Table 2.3.

The fundamental rule of momentum strategy is to buy past winners and sell past losers which cause the prices to overreact due to the temporary price reversal from their long-run values. Numerous studies have been conducted to examine the momentum strategies in the international equity market. Jegadeesh and Titman (1993) found that the strategies that buy past winner stocks and sell past loser stocks during the period from 1965 to 1989 earn significant abnormal returns. The strategy was based on six months ranking and six months holding periods, which provided a compounded excess return of 12.01 percent per year and lasted on an average for about one year. Similar results were found by Rouwenhorst (1998) for the sample of 12 European countries. He found that internationally diversified portfolio of past winners outperforms the past losers by more than one percent per month. This returns continuation lasted for about one year after accounting for risk and was negatively related to firm size and market.

The findings of Jegadeesh and Titman (1993) are not limited to the market of United States only, but similar results have been found by other researchers for different markets. Chui et al. (2000) have shown that momentum strategies are highly profitable for Asian stock markets with the exception of Japan. In addition, momentum profits are stronger for firms with small size, lower book-to-market ratios and higher turnover ratios. Van et al. (2003) found that momentum strategies generated significant excess returns in 32 emerging markets over the period from 1985 to 1999. Fama and French (2012) found that momentum profitability is present in North America, Europe and Asia-Pacific countries with the exception of Japan. In addition, average momentum returns decrease with the increase in size. Chaves (2012) found that momentum based on idiosyncratic returns reduces the volatility of momentum strategies and generates abnormal alpha. Moreover, these strategies perform well in 21 countries including Japan also. Asness et al. (2013) found significant momentum returns premia across eight diverse markets and posed a challenge for asset pricing theories that basically concentrates on US equities. Lobão and Lopes (2014) also found that momentum strategies generate significant positive returns for three to twelve months holding periods in the Portuguese stock market.

A growing body of research has supported the presence of momentum returns in diverse equity markets. Several causes of momentum profitability have been found in the literature. However, there is a lack of clear consensus on the source of its existence in the equity market. There is a possibility that momentum profits are merely a compensation for risk. Grundy and Martin (2001) and Korajczyk and Sadka (2004) found that returns of momentum strategies are not merely a compensation for different market risk factors. Grundy and Martin (2001) have shown that Fama and French (1993) three-factor model cannot explain the mean returns of winner or loser portfolios. According to them, the profitability of momentum strategies is not the compensation for cross-sectional variability in required returns or for bearing industry risk. Conrad and Kaul (1998) suggested that the cross-sectional variation in the mean returns of individual securities are the main cause of momentum profitability rather than any time series variation in stock returns. However, Jegadeesh and Titman (2001) nullified this argument and confirmed that momentum profits are positive only during the first 12 months of portfolio formation which show that winner and loser portfolios do not give a consistently superior performance in futures. Daniel et al. (1998) and Barberis et al. (1998) have shown that momentum returns in the equity market are the result of investor cognitive biases related to underreaction and overreaction to a news. Chan et al. (1996) found that momentum profitability cannot be explained by size and book-to-market effects. Moreover, market risk, size and book-to market effects do not explain the large drift in future returns. Moskowitz and Grinblatt (1999) found that the profitability of momentum strategies is reduced after considering industry momentum. Conversely, industry momentum strategy which takes a long position in stocks of past winning industries and short position in stocks of past losing industries gives high profitability. This profitability is intact even after taking into account the factors of size, book-to-market and individual stock momentum. Lee and Swaminathan (2000) found that momentum strategies based on past trading volume which represents the demand for the stock can predict the magnitude and persistence of future price momentum. A strategy which buys past high volume winners and sells past low volume losers outperforms the price momentum strategy by two percent to seven percent. Hong et al. (2000) have reported that momentum strategies perform better for stocks with low analyst coverage and decline sharply with firm size. On the contrary, Johnson (2002) suggested that momentum profitability in the equity market is due to the time-varying risk factors such as dividend growth rate. Similarly, Chordia and Shivakumar (2002) have shown that time-varying expected returns play an important role in defining the momentum payoffs. According to them, momentum profit is the compensation for lagged macroeconomic variables. Hence, momentum profits are reduced when stock returns are adjusted due to these macroeconomic variables. Similarly, Li et al. (2008) suggested that momentum profits are merely a compensation for time-varying unsystematic risks. In addition, time-varying volatility pattern of the winner is different from the loser as the volatility of winner is more sensitive to recent news and less persistent, while the volatility of losers is sensitive to distant news and more persistent. In addition, Chui et al. (2010) suggested that the magnitude of momentum profits is positively related to individualism, analyst forecast dispersion, transaction costs and familiarity of foreigners with the market. Conversely, it is negatively related to firm size and volatility. On the contrary, Keim (2003) reported that most of the momentum returns are eroded by the cost of implementing the momentum strategies. Contrarian view was given by Griffin and Martin (2003) who have shown that momentum profits cannot be explained by macroeconomic variables. Hence, momentum profits are independent of negative and positive economic growth both in the US and other countries.

Limited studies have been conducted to examine the existence of momentum profitability in commodity futures market. However, there are several benefits involved which justify the implementation of momentum strategies in commodity futures market more strongly rather than in equity markets. First, implementation of momentum strategy in commodity futures market requires low transaction costs (0.0004 to 0.033 percent) as reported by Locke and Venkatesh (1997) and recently by Marshall et al. (2012), compared to the equity markets. Based on the estimates of bid-ask spreads by Locke and Venkatesh (1997), Shen et al. (2007) considered additional transaction costs of $10 per contract and estimated the transaction costs which ranges from a low of 0.044 percent to a high of 0.146 percent. On the contrary, according to Lesmond et al. (2004), trading costs related to implementing the momentum strategies in the stock market is much higher as the composition of momentum portfolio is skewed towards trading in high transaction cost stocks. Second, momentum strategies trade on most liquid nearby contracts. In addition, taking a short position in the commodity market is as easier as taking a long position (Miffre and Rallies, 2007; Shen et al., 2007). In contrast, short sale restriction in the stock market has a significant impact on the momentum strategy implementation (Lesmond et al., 2004).

The following studies confirm the presence of momentum profitability in commodity futures market. Erb and Harvey (2006) created relative strength portfolios by taking long positions in winner portfolios with positive returns in the year preceding the study and taking a short position in loser portfolios with the negative returns. This portfolio generated the highest excess return of 10.8 percent and highest Sharpe ratio of 0.55 contrast to 0.25 generated by long-only GSCI. Gorton et al. (2013) supported the existence of momentum profitability in commodity futures market. However, they suggested that this momentum return is merely the compensation for risk which arises due to inventory level. Shen et al. (2007) found that significant positive returns are given by momentum strategies for short and intermediate time horizons and magnitude of these returns are close to the returns reported in stocks. In addition, the excess returns of momentum strategies can easily accommodate the transaction costs of implementing these strategies. Moreover, they found that momentum payoffs are not merely the compensation for systematic risk exposure. In addition, Miffre and Rallis (2007), Fuertes et al. (2010) and Narayan et al. (2015) have confirmed that momentum strategies in commodity futures market give a significant abnormal alpha. Miffre and Rallis (2007) found that momentum strategies in commodity futures market generate an average return of 9.38 percent a year while long-only investment in an equally-weighted portfolio of the same 31 commodities gives a negative return of 2.64 percent a year. In addition, momentum portfolios have low correlation with traditional asset classes which makes them good candidates for inclusion in well-diversified portfolios. Moreover, momentum returns are not a compensation for time-varying risk. Similarly, Fuertes et al. (2010) have shown that profitable momentum strategy earns an average return of 10.53 percent or an alpha of 10.1 percent while long-only investment in a portfolio of commodity futures earns a return of 3.40 percent and GSCI gives a return of 3.62 percent. Narayan et al. (2015) suggested that significant momentum profits are present in the commodity futures market with oil to be the most profitable commodity and gold is the least profitable commodity. In addition, trading strategies which allow short-selling, give greater profits compared to strategies which do not allow for short-selling in the commodity market.

Moskowitz et al. (2012) found significant time series momentum in equity, currency, bond and commodity futures which are consistent with the sentiment theories of initial under-reaction and delayed over-reaction. Blitz and Groot (2014) confirmed the presence of momentum factor premium in the commodity futures market. Moreover, diversified commodity factor premiums add significant value to the conventional portfolio of stock and bond. In addition, Bianchi et al. (2015) suggested that 'microscopic momentum' which decomposes the intermediate returns momentum into single-month momentum components, generates persistent economic profits. Zaremba (2016) provided fresh evidence for the existence of momentum profitability in commodity futures markets. However, he has shown that level of momentum profitability is lower in the market of high financialisation. In the Indian context, Sharma et al. (2014) analysed the profitability of only one momentum strategy of ranking and holding period of one month using Markowitz mean-variance optimization technique for the study period from the year 2004 to the year 2012. Their results confirmed that allocation of commodity futures to a traditional portfolio using momentum and term structure strategies gives better risk-adjusted returns. However, they have not analysed the time-varying risk-adjusted return performance of momentum strategies.

Table 2.3: Summary of Studies Related to Active Strategy Based on Momentum Signals

Authors' Name	Study Period	Data	Methodology	Results	Research Gap
Jegadeesh and Titman (1993)	1965-1989	Stock market (NYSE , AMEX)	Formation of relative strength portfolio which buys past winners and sells past loser portfolios	Confirms abnormal profitability of momentum strategies in stock market.	
Rouwenhorst (1998)	1978-1995	Stock market (2190 firms from 12 European countries)	Formation of relative strength portfolio which buys past winners and sells past loser portfolios	Confirms abnormal profitability of momentum strategies in stock market for all 12 countries.	
Chui et al. (2000)	1975-1997	Stock market (stocks listed on eight Asian stock markets)	Formation of relative strength portfolio which buys past winners and sells past loser portfolios	Confirms abnormal profitability of momentum strategies for Asian stock markets with the exception of Japan.	
Chui et al. (2010)	1980-2003	Stock market (20,000 stocks for 41 countries)	Formation of relative strength portfolio which buys past winners and sells past loser portfolios	Confirms abnormal profitability of momentum strategies in stock markets.	
Van et al. (2003)	1985-1999	Stock markets (2851 stocks from 32 emerging markets)	Strategies designed based on value, momentum, earnings, size, liquidity and mean reversion	Confirms abnormal profitability of strategies which are designed based on momentum and value for all the 32 emerging markets.	
Fama and French (2012)	1989-2011	Stock market (Stocks from 23 developed markets)	Fama and French (1993) three-factor model and Carhart (1997) four-factor model	Confirms abnormal profitability of momentum strategies for all the countries of sample except for Japan.	
Asness et al. (2013)	1972-2011	Stock market (Stocks from US, UK, Europe and Japan)	Fama and French (1993) three-factor model	Confirms abnormal profitability of value and momentum strategies across eight diverse markets.	
Lobão and Lopes (2014)	1988-2012	Stock market (data of Portuguese Stock Market)	Formation of momentum portfolio which buys past winners and sells past loser portfolios	Confirms abnormal profitability of momentum strategies for Portuguese stock markets.	

Jegadeesh and Titman (2001)	1965-1997	Stock market (NYSE, AMEX)	Formation of momentum portfolio and use of Fama and French (1993) three-factor model	Confirms that the cause of momentum profits is the time-series properties of stock returns rather than the cross-sectional variation in returns.	
Chan et al. (1996)	1977-1993	Stock market (NYSE, AMEX)	Formation of momentum portfolio and use of Fama and French (1993) three-factor model	Confirms that momentum profitability is not a compensation for different risk factors.	
Moskowitz and Grinblatt (1999)	1963-1995	Stock market (NYSE, AMEX and NASDAQ)	Formation of momentum portfolio and use of multifactor model	Confirms the profitability of momentum strategies which are based on industry factor.	
Lee and Swaminathan (2000)	1965-1995	Stock market (NYSE, AMEX)	Formation of momentum portfolio and use of Fama and French (1993) three-factor model	Confirms profitability of momentum strategy which is based on past trading volume.	
Hong et al. (2000)	1980-1996	Stock market (NYSE, AMEX and NASDAQ)	Formation of momentum portfolio and use of cross sectional-regression and gradual – information-diffusion model	Confirms the profitability of momentum strategies which declines with firm size.	
Johnson (2002)	1977-1995	Stock market (NYSE)	Formation of momentum portfolio and use of time-varying regime-switching model of Hong and Stein (1999)	Confirms time-varying momentum profitability in the equity market.	
Chordia and Shivakumar (2002)	1926-1994	Stock market (NYSE, AMEX)	Formation of momentum portfolio and use of multifactor regression model	Confirms that the momentum profitability is a compensation for lagged macroeconomic variables.	
Li et al. (2008)	1975-2001	Stock market (data for stocks of 6,155 companies)	GJR-GARCH (1,1)-M and Fama and French (1993) three-factor model	Confirms that the momentum profits as a compensation for time-varying risk.	
Keim (2003)	1996-2000	Stock market (Data for stocks of	Formation of momentum portfolio and	Confirms momentum profitability as a	

		33 firms in the US and 36 other equity markets worldwide)	use of logit model	compensation for trading costs of implementing it.	
Lesmond et al. (2004)	1980-1998	Stock market (NYSE, AMEX and NASDAQ)	Formation of momentum portfolio and use of arbitrageur's model	Confirms the momentum profits as the compensation for costs of implementing these strategies.	
Erb and Harvey (2006)	1969-2004	Commodity market (GSCI, DJAIGCI and CRB)	Formation of momentum portfolio which buys GSCI in case of positive return and sells for the case of negative returns.	Confirms abnormal profitability of momentum strategies in commodity markets.	
Shen et al. (2007)	1959-2003	Commodity market (data for 28 commodity futures from CRB)	Formation of relative strength portfolio in spirit to Jegadeesh and Titman's (1993) approach.	Confirms momentum profitability is not the compensation for transaction costs and systematic risk factors.	
Miffre and Rallis (2007)	1979-2004	Commodity market (data on 31 US commodity futures contract)	Formation of relative strength portfolio in spirit to Jegadeesh and Titman's (1993) approach and use of multifactor model	Confirms momentum profitability is not the compensation for time-varying risk factors.	Research gap 3
Fuertes et al. (2010)	1979-2007	Commodity market (data on 37 commodity contracts)	Formation of relative strength portfolio in spirit to Jegadeesh and Titman's (1993)	Confirms abnormal profitability of momentum strategies in commodity markets.	
Gorton et al. (2013)	1969-2006	Commodity market (data on 33 commodity futures traded in North American exchanges)	Formation of relative strength portfolio and use of an infinite horizon model of intertemporal inventory dynamics	Confirms momentum profitability as a compensation for the level of inventories.	
Moskowitz et al. (2012)	1965-2009	Commodity market (data on futures contracts for 24 futures contract and GSCI	Formation of relative strength portfolio and use of VAR and multivariate regression model	Confirms the momentum profitability in the commodity market.	

		commodity index).			
Narayan et al. (2015)	1986-2010	Commodity market (data on oil, gold, silver and platinum)	Formation of relative strength portfolio based on various combination of moving average.	Confirms the momentum profitability in the commodity market which shows varying exposure to the different commodities.	
Bianchi et al. (2015)	1969-2011	Commodity market (data from LME, COMEX, NYMEX, ICE and CBOT)	Formation of microscopic momentum portfolios.	Confirms the microscopic momentum profitability in the commodity market.	
Zaremba (2016)	1986-2013	Commodity market (data on 26 commodity futures collected from ICE, NYMEX, CBOT and Chicago Mercantile Exchange)	Index Model, Fama and French (1993) three-factor model and fundamental model used by Fuertes et al. (2014)	Confirms the microscopic momentum profitability in the commodity market.	
Sharma et al. (2014)	2003-2012	Commodity market (data on commodity futures traded in MCX and NCDEX)	Formation of relative strength portfolio in spirit to Jegadeesh and Titman's (1993) and use of Markowitz optimization technique	Confirms the momentum profitability in the Indian commodity market.	Research gap 3

*(**Source:** Literature Review)*

2.4.2 Active Strategies Based on Term Structure Signal

This section discusses the studies related to active strategies which are designed by using term structure signals in commodity futures markets which are summarised in Table 2.4.

A major branch of the futures pricing literature have shown that one of the sources of risk premium for commodity futures is the hedging pressure hypothesis advanced by Keynes (1930) and Hicks (1939) where the hedgers transfer the risk of price fluctuation to speculators and speculators bear the risk in a hope to get large positive returns. On the contrary, Kaldor (1939), Working (1949) and Brennan (1958) have given the Theory of Storage in which it is shown that storage costs, interest rates and the convenience yields have a significant impact on the commodity futures prices. These theories were extended by Hirshleifer (1990), who used the general equilibrium framework and have shown that the non-participation by consumers affects the hedging pressure which influences the risk premium. After taking into consideration of trading costs, Hirshleifer (1990) basically linked the backwardation (downward bias) with the hedgers' net short position under inelastic demand and the contango (upward bias) with the hedgers' net long position for elastic demand.

These theories explain the shape of the term structure and source of risk premium. If the number of hedgers taking a short position is more than the number of hedgers taking a long position, then current futures price has to face the downward pressure. This influenced the speculators to take a long position in the futures market. This caused the downward sloping curve which is referred to as normal backwardation where the current futures price is less than the futures price at maturity. On the contrary, the prevalence of long hedgers in the market, causes the current futures price to be more than the futures price at maturity and induced the speculators to take a short position. The upward sloping curve due to a decrease in the futures price at the time of maturity is referred to as contango. Hence, the disequilibrium between the long hedger and short hedgers in the market, causes the speculators to take the opposite positions which give the normal backwardation and contango state of the market.

A hypothetical investor can use this hedging pressure hypothesis to design an active strategy called as term structure strategy to earn an abnormal return which takes a long position in a backwardated contract and a short position in a contangoed contract. Many previous studies have proved the validity of this dynamic active strategy. The study of De Roon et al. (2000) on 20 futures market indicated that individual futures markets hedging pressure and cross-sectional futures markets hedging pressures have a significant impact on futures returns. Erb and Harvey (2006) provided evidence which suggested that active strategies based on the term structure of the futures prices generate an excess return of 8.2 percent a year and a higher Sharpe ratio, compared to returns of 2.68 percent from long-only investment in GSCI. Fuertes et al. (2010) have suggested that the implementation of term structure strategies gives an average annual return of 12.28 percent by consistently taking the long position in the backwardated contracts and a short position in the contangoed contracts. Conversely, passive long-only investment in a portfolio of same commodity futures gives a return of 3.40 percent while GSCI index earns a return of 3.62 percent. Basu and Miffre (2013) have shown that fullycollateralised hedging pressure long-short portfolios generate an average Sharpe ratio of 0.51 compared to the Sharpe ratio of 0.05 given by long-only investment in equally-weighted portfolios of commodity futures. Hence, the active commodity strategies based on hedging pressure hypothesis give better performance rather than the investment in long-only commodity benchmarks. Kim and Kang (2014) suggested that dynamic-slope strategy which takes a long position in commodity futures with dynamic backwardation and shorts the futures with dynamic contango, generates large profits. In fact, these profits remain robust after considering the transaction costs. In addition, Zaremba (2016) provided fresh evidence on the performance evaluation of term structure strategies and suggested that term structure strategies generate better performance in non-financialised markets compared to momentum profits.

Table 2.4: Summary of Studies Related to Active Strategy Based on Term Structure Signals

Authors' Name	Study Period	Data	Methodology	Results	Research Gap
De Roon et al. (2000)	1986-1994	Commodity market (data of 20 futures contracts from financial, agricultural, mineral and currency futures)	Simple models are used to measure its own hedging pressure and hedging pressure from other markets called as cross-sectional hedging pressures.	Confirms the impact of own hedging pressure and cross-sectional hedging pressure on futures risk premium.	
Erb and Harvey (2006)	1969-2004	Commodity market (GSCI, DJAIGCI and CRB)	Formation of relative strength long-short portfolio by going long in backwardated contract and short in contango contract	Confirms the abnormal profitability of term structure strategies in commodity futures market	
Fuertes et. al (2010)	1979-2007	Commodity Market (data on 37 commodities contracts)	Formation of relative strength long-short portfolio by going long in backwardated contract (highest roll returns) and short in contango contract (lowest roll return)	Confirms the abnormal profitability of term structure strategies in commodity futures market.	Research gap 3
Basu and Miffre (2013)	1992-2011	Commodity Market (data on Friday settlement prices for 27 commodity futures)	Formation of relative strength long-short portfolio for hedgers which takes long position in the cross section with the lowest average hedgers' hedging pressure and short position in the cross section with the highest average	Confirms the abnormal profitability of strategy based on hedging pressure.	

			hedgers' hedging pressure.		
Zaremba, (2016)	1986-2013	Commodity market (data on 26 commodity futures collected from ICE, NYMEX, CBOT and Chicago Mercantile Exchange)	Formation of relative strength long-short portfolio by going long in contracts with the highest implied yield and short in contracts with the lowest implied yield	Confirms the abnormal profitability of term structure strategy.	

*(**Source:** Literature Review)*

2.4.3 Active Strategies Based on Idiosyncratic Volatility Signal

This section explores the literature review with respect to the active strategies which are designed based on the idiosyncratic volatility signals. The summary of the discussion is given in Table 2.5.

Various active trading strategies based on the different signals in the market such as momentum (past positive and negative returns), term structures (high and low roll yield) and hedging pressure (net long/short hedgers and net short/long speculators) are designed in previous studies to generate an abnormal return and also to get the benefits of diversification. The design of these active portfolios gives an exceptionally high performance by systematically buying the futures contracts with good past performance, high roll yield, net short hedgers and net long speculators and taking the short position in futures contract with poor past performance, low roll yield, net long hedgers and net short speculators (Erb and Harvey, 2006; Gorton et al., 2013; Shen et al., 2007; Miffre and Rallis, 2007; Fuertes et al.,2010; Zaremba, 2016; De Roon et al., (2000); Basu and Miffre, 2013, Kim and Kang, 2014; Szymanowska, 2014 and Bakshi et al., 2015). These active trading strategies are designed based on the future pricing Theory of Storage propagated by Kaldor (1939), Working (1949) and Brennan (1958), the Theory of Normal Backwardation and hedging pressure hypothesis advanced by Keynes (1930) and Hicks (1939).

Different strands of active strategies examined in the literature use the idiosyncratic volatility and established the relationship between idiosyncratic volatility and expected return. The Market Equilibrium Theory of asset prices given by Sharpe (1964), Litner (1965) and Fama and McBeth (1973), suggested that idiosyncratic volatility is endemic to a particular asset such as stocks which are diversified away and hence this kind of risk is not priced. According to Fama and McBeth (1973), risk-averse investors attempt to hold portfolios which are efficient in terms of value and dispersion of returns. In addition, their results are consistent with the assumption of the efficient capital market where prices of securities fully reflect available information as there are neither transaction costs nor information costs. On the contrary, Merton (1987), Malkiel and Xu (2002), Goyal and Santa-Clara (2003), Spiegel and Wang (2005), Fu (2009) and Brockman et al. (2010) found a positive relation between the estimated idiosyncratic volatility and expected returns as the investors demand compensation for firm-specific risk. Malkiel and Xu (2002) found that idiosyncratic risk affects the assets' returns even after controlling for factors such as size and book-to-market. In addition, Spiegel and Wang (2005) showed that the idiosyncratic risk and liquidity of a stock are negatively related. Conversely, stock returns increase with the level of idiosyncratic risk and decrease with the stock's liquidity. However, Bali et al. (2005), Bali and Cakici (2008), Fink et al. (2010), Huang et al. (2010) and Han and Lesmond (2011) confirmed that there is a lack of robust and significant relation between idiosyncratic risk and expected returns. On the contrary, Ang et al. (2006, 2009) and Guo and Savickas (2006), Jiang et al. (2009) found that value-weighted idiosyncratic volatility is negatively related to the aggregate future stock market return. Ang et al. (2006) found that the portfolio of stocks with the highest idiosyncratic volatility earns negative returns of -0.02 percent per month. In fact, their robustness analysis suggested that stocks with high idiosyncratic volatility are associated with low average returns.

The relationship between idiosyncratic volatility and expected returns in commodity futures market was first introduced by Hirshleifer (1988). He proposed the theoretical framework which suggested that residual risk premium deviates from the market prediction when the fixed cost of participating in a futures market limits the participation of some classes of traders in commodity futures market. Bessembinder (1992) validated the theoretical model given by Hirshleifer (1988) and confirmed that returns in agricultural futures vary with the idiosyncratic volatility based on net holdings of hedgers, after controlling for systematic risk. Miffre et al. (2012) validated the empirical evidence given by Ang et al. (2009) and suggested that idiosyncratic volatility is negatively priced if the traditional pricing models are used. On the contrary, it is not priced if fundamental pricing model is used where backwardation and contango cycle of commodity futures markets are captured. Fernández et al. (2016) have shown that relation between idiosyncratic volatility and expected returns depends on the asset pricing model, used to extract the idiosyncratic volatility. According to them, idiosyncratic volatility is not priced when the phases of backwardation and contango are properly considered in the pricing model. In addition, the profitability of idiosyncratic volatility mimicking portfolio is overstated, if phases of backwardation and contango are not recognized in the pricing model.

Table 2.5: Summary of Studies Related to Active Strategy Based on Idiosyncratic Volatility Signals

Authors' Name	Study Period	Data	Methodology	Results	Research Gap
Fama and McBeth (1973)	1926-1968	Stock Market (stocks traded on the NYSE)	Two-parameter portfolio model and models of market equilibrium	Confirms that idiosyncratic volatility cannot be priced.	
Malkiel and Xu (2002)	1935-2000	Stock market (stocks listed with NYSE, AMEX and NASDAQ)	Capital Asset Pricing Model (CAPM), Framework of Fama and McBeth (1973) and Fama and French (1993) Three-factor model	Confirms positive relation between idiosyncratic volatility and expected returns.	
Goyal and Santa-Clara (2003)	1962-1999	Stock market (data for daily value weighted returns from CRSP)	Measure of the market variance and returns.	Confirms positive relation between idiosyncratic volatility and expected returns.	
Fu (2009)	1963-2006	Stock market (stocks listed with NYSE, AMEX and NASDAQ)	EGARCH	Confirms positive relation between idiosyncratic volatility and expected returns.	
Bali et al. (2005)	1963-2012	Stock market (stocks listed with NYSE, AMEX and NASDAQ)	Measure of the market variance and returns using approach given by French et al. (1987).	Confirms lack of significant relation between idiosyncratic volatility and expected returns	
Spiegel and Wang (2005)	1962-2003	Stock market (stocks listed with NYSE, AMEX and NASDAQ)	Fama and French (1993) three-factor model and EGARCH model	Confirms positive relation between idiosyncratic volatility and expected returns.	
Bali and Cakici (2008)	1958-2004	Stock market (stocks listed with NYSE,	CAPM, Fama and French (1993) three-factor model	Confirms lack of significant relation between idiosyncratic	

		AMEX and NASDAQ)		volatility and expected returns	
Brockman et al. (2010)	1980-2007	Stock market (data contains details of 58,000 stocks from 44 countries).	Fama and French (1993) three-factor model and EGARCH model	Confirms positive relation between idiosyncratic volatility and expected returns.	
Fink et al. (2010)	1963-2008	Stock market (stocks listed with NYSE, AMEX and NASDAQ)	Fama and French (1993) three-factor model, ARMA and EGARCH model	Confirms lack of significant relation between idiosyncratic volatility and expected returns	
Huang et al. (2010)	1963-2004	Stock market (stocks listed with NYSE, AMEX and NASDAQ)	Framework of Fama and McBeth (1973) and Fama and French (1993) three-factor model	Confirms lack of significant and reliable relation between idiosyncratic volatility and expected returns	
Han and Lesmond (2011)	1984-2008	Stock market (stocks listed with NYSE, AMEX and NASDAQ)	Fama and French (1993) three-factor model	Confirms lack of significant and reliable relation between idiosyncratic volatility and expected returns	
Ang et al. (2006)	1986-2000	Stock market (stocks listed with NYSE, AMEX and NASDAQ)	CAPM and Fama and French (1993) three-factor model	Confirms negative relation between idiosyncratic volatility and expected returns.	
Ang et al. (2009)	1980-2003	Stock Market (data on daily returns on firms from 23 developed markets)	Fama and French (1993) three-factor model	Confirms negative relation between idiosyncratic volatility and expected returns.	
Guo and Savickas (2006)	1962-2002	Stock market (data from daily CRSP stock files)	Fama and French (1993) three-factor model	Confirms negative relation between idiosyncratic volatility and expected returns.	
Jiang et al. (2009)	1974-2002	Stock market (data from daily CRSP stock files)	Fama and French (1993) three-factor model, Carhart (1997) four-factor model and Fama and MacBeth (1973)	Confirms negative relation between idiosyncratic volatility and expected returns.	
Miffre et al. (2012)	1979-2011	Commodity market (data on 27 commodity futures)	Fama and MacBeth (1973), cross-section regression by OLS	Confirms the abnormal profitability of active strategy which is designed based on	Research gap 3

				idiosyncratic volatility.	
Fernandez et al. (2016)	1989-2013	Commodity market (Data for 27 commodity futures)	Fama and MacBeth (1973), time-series factor mimicking portfolio approach	Confirms the abnormal profitability of active strategy which is designed based on idiosyncratic volatility.	Research gap 3

*(**Source:** Literature Review)*

2.4.4 Active Strategy by Combining the Methodology of Momentum and Term Structure Strategies

This section reviews the literature related to active strategies designed by combining the methodology of momentum and term structure strategies which are summarized in Table 2.6.

It is indicated in the previous studies conducted by Erb and Harvey (2006) and Miffre and Rallis (2007) that momentum strategies buy backwardated contracts and sell contangoed contracts. It is based on the fundamental concept of hedging pressure hypothesis and Theory of Backwardation advanced by Keynes (1930), Hicks (1939), Kaldor (1939), Working (1949), Brennan (1958) and Hirshleifer (1990). According to their concept, if hedgers are net short, then futures prices increase as maturity approaches which induce the speculator to take a long position. It causes the term structure curve to be downward sloping. Conversely, if hedgers are net long then futures prices fall as the maturity approaches, which entices the speculator to take a short position and causes the upward sloping term structure curve. The comparison of these hypotheses with the momentum strategies indicates that momentum strategies take a long position in the winner portfolios which basically contains the backwardated contracts and a short position in the loser portfolio which is skewed towards the contangoed contracts (Miffre and Rallis, 2007). Similarly, term structure strategies take a long position in backwardated contracts and a short position in contangoed contracts. This comparison shows that momentum and term structure strategies are similar. However, Fuertes et al. (2010) found that although the correlation between momentum and term structure portfolios are positive and significant, they are very low in magnitude which indicates that these portfolios are not completely overlapping. The correlation between these portfolios induced Fuertes et al. (2010) to design a double sort strategy which combines the methodology of both momentum and term structure strategies. Fuertes et al. (2010) showed that combined strategies earn an average return of 21.32 percent and an alpha of 21.02 percent which is superior to average returns of 10.53 (12.28) percent given by individual momentum (term structures) strategies. In addition, their robustness analysis indicated that the abnormal returns of combined strategies are not the compensation for liquidity risk, data snooping and time-varying risk factors. In line with the analysis of Fuertes et al. (2010), this study estimates the correlation between momentum and term structure portfolios. It shows a positive and insignificant correlation between momentum and term structure portfolios which indicates that winner (loser) portfolios of momentum strategies do not overlap with backwardated (contango) portfolios of term structure strategies. These results provide a strong motivation to design a combined strategy (MomTS) using both momentum and term structure strategies.

2.4.5 Active Strategy by Combining the Methodology of Momentum and Idiosyncratic Volatility Strategies

This section reviews the literature related to active strategies designed by combining the methodology of momentum and idiosyncratic volatility strategies which are summarized in Table 2.6.

The critical analysis of the relation between idiosyncratic volatility and return is always a puzzling anomaly for the academician and practitioner. The classical finance theory, given by Sharpe (1964), Litner (1965) and Fama and McBeth (1973) suggested that investors are mean-variance optimizers and hold fully-diversified portfolios. In these portfolios, idiosyncratic risk is diversified away and hence cannot be priced. On the contrary, Merton (1987) argued that the investors hold the undiversified portfolios due to the costs incurred by investors to acquire the information. The investors demand compensation for firm-specific risk hence, stock returns are positively related to the idiosyncratic risks. This theory is extended by Barberis (2001), Malkiel and Xu (2002), Goyal and Santa-Clara (2003) and Fu (2009). Both the theories are challenged by Ang et al. (2006, 2009). They suggested that average returns of the portfolio with the lowest idiosyncratic volatility is higher compared to the portfolio with the highest idiosyncratic volatility. This result is robust against the value, size, liquidity, volume and momentum effects. Further, Jiang et al. (2009) have shown that stocks with high idiosyncratic return volatility give low future returns which are induced by the information about the future earnings.

The contradiction of the empirical explanation given by the researchers for the above anomalies, induced Frieder and Jiang (2007) to examine the relation between idiosyncratic volatility and futures return from the aspect of mispricing of risk. Their results indicated that the returns of the momentum strategies may be enhanced by the inclusion of stocks "upside" volatility which is associated with positive idiosyncratic returns. In addition, they showed that there is a lack of inverse relation between "downside" risk which is associated with negative idiosyncratic returns and future stock returns which indicated the mispricing of risk. In addition, Arena et al. (2008) found that high idiosyncratic volatility stocks give high returns on momentum investing which shows a positive relation between momentum returns and aggregate idiosyncratic volatility. They showed that the stocks with higher idiosyncratic volatility show higher momentum compared to stocks with lower idiosyncratic volatility. Their robustness analysis indicated that this relationship is consistent with the consideration of firm size, transaction costs, turnover, price delay, different sample periods and holding periods. Furthermore, Sonmez (2013) has shown that there is a negative relation between idiosyncratic volatility and future returns for low and mid-priced stocks compared to high-priced stocks where the relation is opposite. In addition, consideration of momentum does not change the relation between idiosyncratic volatility and future returns for low, mid and high-priced stocks.

Miffre et al. (2012) analysed the relationship between idiosyncratic volatility and commodity futures returns. They found that relative strength portfolio which buys low idiosyncratic volatility commodities and shorts high idiosyncratic volatility commodities gives better mean returns. The outcomes of Fernandez et al. (2016) are in line with the findings of Miffre et al. (2012) which suggested that relation between idiosyncratic volatility and commodity futures returns, depends on the asset pricing model which is used to extract the idiosyncratic volatility. In addition, they found that the strategies which buy low idiosyncratic volatility commodities and sell high idiosyncratic volatility commodities offer exceptionally high abnormal returns if, asset pricing model fails to recognize the backwardated and contangoed state of the market. On the contrary, Miffre and Rallis (2007) designed an active strategy by using the price momentum of commodity futures which allocates the wealth towards the commodity futures with a positive return in the past and take the short position in the commodity futures with the historical negative returns. These active strategies have given the average annual return of 9.38 percent. Based on the empirical evidence given by Erb and Harvey (2006), Fuertes et al. (2010) suggested that the implementation of term structure strategies gives an average annual return of 12.28 percent by consistently taking a long position in the backwardated contracts and a short position in the contangoed contracts.

After showing the abnormal performance of individual active strategies such as momentum, term structure and idiosyncratic volatility strategies, Fuertes et al. (2010) designed a double-sort strategy which combines the methodology of both momentum and term structure strategies. This double-sort strategy has given abnormal returns of 21.02 percent which clearly outperforms the single-sort strategies. In the same vein, Fuertes et al. (2015) designed a triple-screen strategy which buys commodities with high past performance, high average roll yields and low idiosyncratic volatility. On the contrary, it shorts the commodities with low past performance, low average roll yields and high idiosyncratic volatility. It gives an average annual return of 7.39 percent and average Sharpe ratio of 0.69. Conversely, average Sharpe ratio of individual signals is 0.37 and for S&P GSCI, it is only 0.14. In addition, they suggested that triple-screen portfolios are good candidates for portfolio diversification but not to hedge inflation risk.

Based on the above analysis it is found that there is a lack of study which combines the theoretical concept of both momentum returns and idiosyncratic volatility to design a double-sort strategy. Hence, the present study combines the methodology of the winner and loser portfolios creation of momentum strategy and the long and short portfolios construction of idiosyncratic volatility strategy to create a combined strategy (MomIVol).

Table 2.6: Summary of Studies Related to Active Strategy Based on the different combination of momentum, term structure and Idiosyncratic Volatility Strategies

Authors' Name	Study Period	Data	Methodology	Results	Research Gap
Fuertes et al. (2010)	1979-2007	Commodity market (data on daily closing prices of the nearby, second-nearby and distant	Formation of relative strength portfolios which take long position in commodities with the best past performance and the highest roll-	Confirms the abnormal profitability of MomTS strategy.	Research gap 4

		contracts of 37 commodities)	return and short commodities with the worst past performance and the lowest roll-returns.		
Arena et al. (2008)	1965-2002	Stock market (stocks listed with NYSE, AMEX and NASDAQ)	Formation of momentum portfolio in the spirit of Jegadeesh and Titman (2001), estimation of idiosyncratic volatility from the market model residuals and use of Fama and French (1993) three-factor model	Confirms high momentum for stocks which is associated with high idiosyncratic volatility.	
Sonmez (2013)	1963-2008	Stock market (data for US listed stocks derived from CRSP)	Fama and French three-factor model, Carhart (1997) four-factor models and Fama and MacBeth (1973)	Confirms the insignificant impact of momentum on the relation between idiosyncratic volatility and futures returns.	
Fuertes et al. (2015)	1979-2011	Data on daily settlement prices of 27 commodity futures contracts and S&P GSCI	Benchmark model based on the S&P GSCI as a single risk factor	Confirms abnormal profitability of triple-screen strategy.	Research gap 4

*(**Source:** Literature Review)*

2.5 OUTCOMES OF THE LITERATURE REVIEW

Based on discussed literature in Sections 2.2, 2.3 and 2.4, following research gaps are identified which are depicted through literature map in Figure 2.1.

1. Through the literature review of Section 2.2, it is found that inflation hedging potential of gold was analysed by Beckmann and Czudaj (2013) by using the regime-switching approach of MS-VECM. There are very few studies which have adopted the nonlinear approach. Amongst the very few, Zhou (2014) is the only study which adopted a nonlinear MS-VECM method to analyse the inflation hedging potential of commodity futures index. However, he has not considered the individual commodity futures in his study. In addition, a small group of

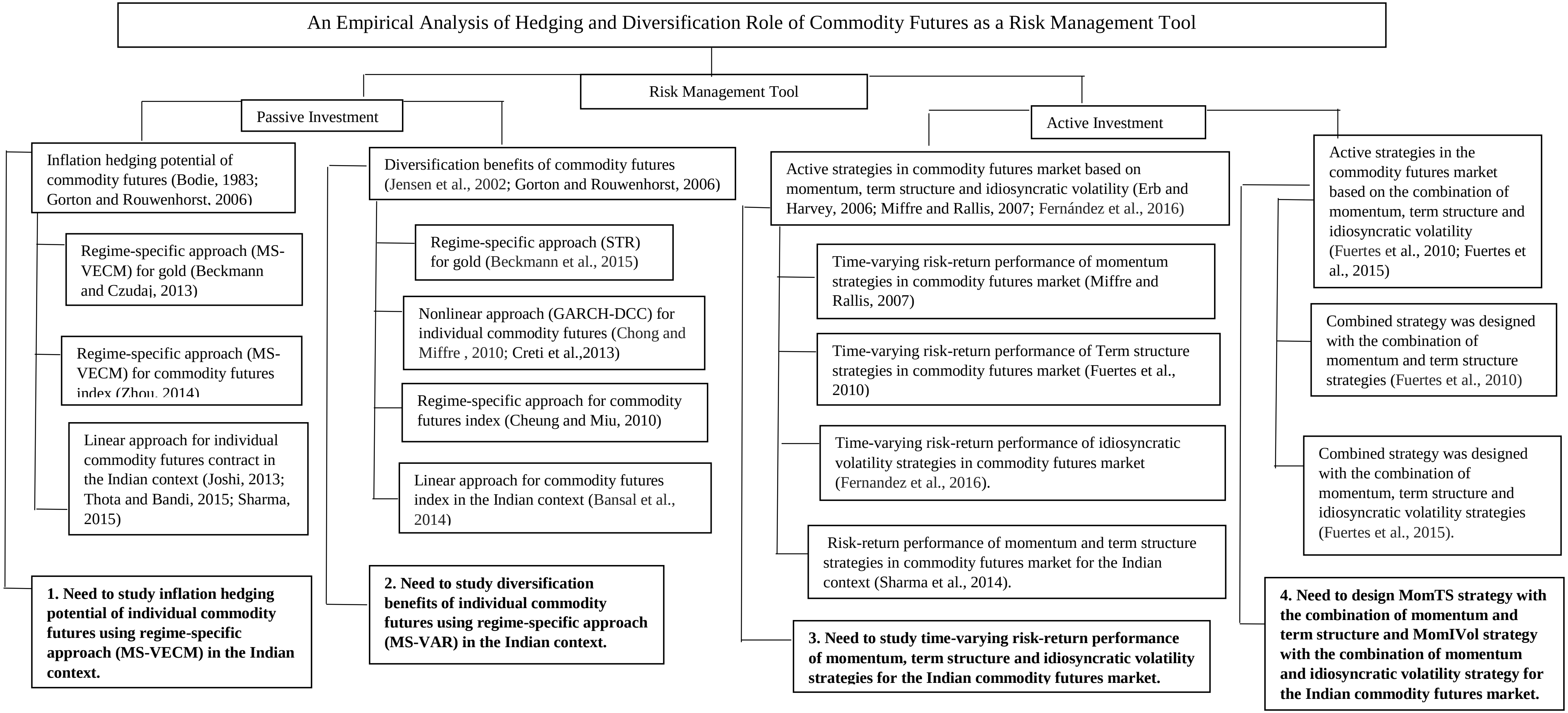
studies is conducted on commodity futures in the Indian context. For instance, Joshi (2013), Thota and Bandi (2015) and Sharma (2015) have analysed the inflation hedging potential of commodity futures in the Indian scenario. In their work, a simple linear regression model is used. Hence, in the Indian scenario, there is a need to analyse the inflation hedging capability of individual commodity futures by using the nonlinear approach of regime-switching framework MS-VECM.

2. The literature discussed in Section 2.3 shows that Beckmann et al. (2015) analysed the hedge and safe haven role of gold by using the regime-specific approach of Smooth Transition Regression (STR). Similarly, Cheung and Miu (2010) used the regime-specific approach to analyse hedging and diversification benefits of commodity futures index. Conversely, Chong and Miffre (2010) and Creti et al. (2013) assessed the diversification benefits of individual commodity futures by using the nonlinear approach of GARCH-DCC. In the Indian context, Bansal et al. (2014) investigated the diversification benefits of commodity futures index by a linear approach of Mean-Variance Optimization Technique. They have not considered the individual commodity futures contracts. Hence, there is a need to analyse the hedge and safe haven role of individual commodity futures by using the nonlinear approach of regime-switching framework MS-VAR.
3. Based on the discussed literature in Sections 2.4.1, 2.4.2 and 2.4.3, it is concluded that active strategies which are designed by using momentum, term structure and idiosyncratic volatility signals generate abnormal profits. Studies such as Miffre and Rallis (2007) and Fuertes et al. (2010) have justified these abnormal returns by using time-varying risk-adjusted performance. In the Indian context, Sharma (2015) assessed the performance of active strategies by using momentum and term structures market signals. However, they have not considered the time-varying approach. Hence, there is a need to analyse the time-varying risk-adjusted return performance of momentum, term structure and idiosyncratic volatility strategies in the Indian context.
4. From literature review in Sections 2.4.4 and 2.4.5, it is observed that very few studies are conducted with respect to active strategies which strategically combine the methodology of momentum, term structure and idiosyncratic volatility. For instance, Fuertes et al. (2010) designed a double-sort strategy which combines the theoretical concepts of momentum and term structure

strategies. Similarly, Fuertes et al. (2015) created a triple-screen strategy which includes the methodology of momentum, term structure and idiosyncratic volatility. Based on literature review it is found that there is a lack of study which combines the methodology of both momentum and idiosyncratic volatility strategy to design a combined strategy. In addition, very few studies have been conducted in relation to the formation of combined strategies by making the strategic combination of momentum, term structure and idiosyncratic volatility in the Indian context. Hence, there is a need to design a combined strategy which incorporates methodology of both momentum and idiosyncratic volatility strategies.

2.6 SUMMARY

This chapter provides an extensive review of the available literature with respect to the inflation hedging and diversification benefits of commodity futures. In addition, an elaborate literature review is also conducted on the ability of commodity futures to generate abnormal returns by the implementation of active investment strategies. The literature review provides a direction to draw a literature map which highlights the important studies that were conducted and helps to identify the research gap. These research gaps are indicated as the need for study in the literature map. The literature review helps to conceptualize the research design and methodology required for the study which is discussed in the subsequent chapter.



***(Source:** Literature Review)*

Figure 2.1: Literature Map

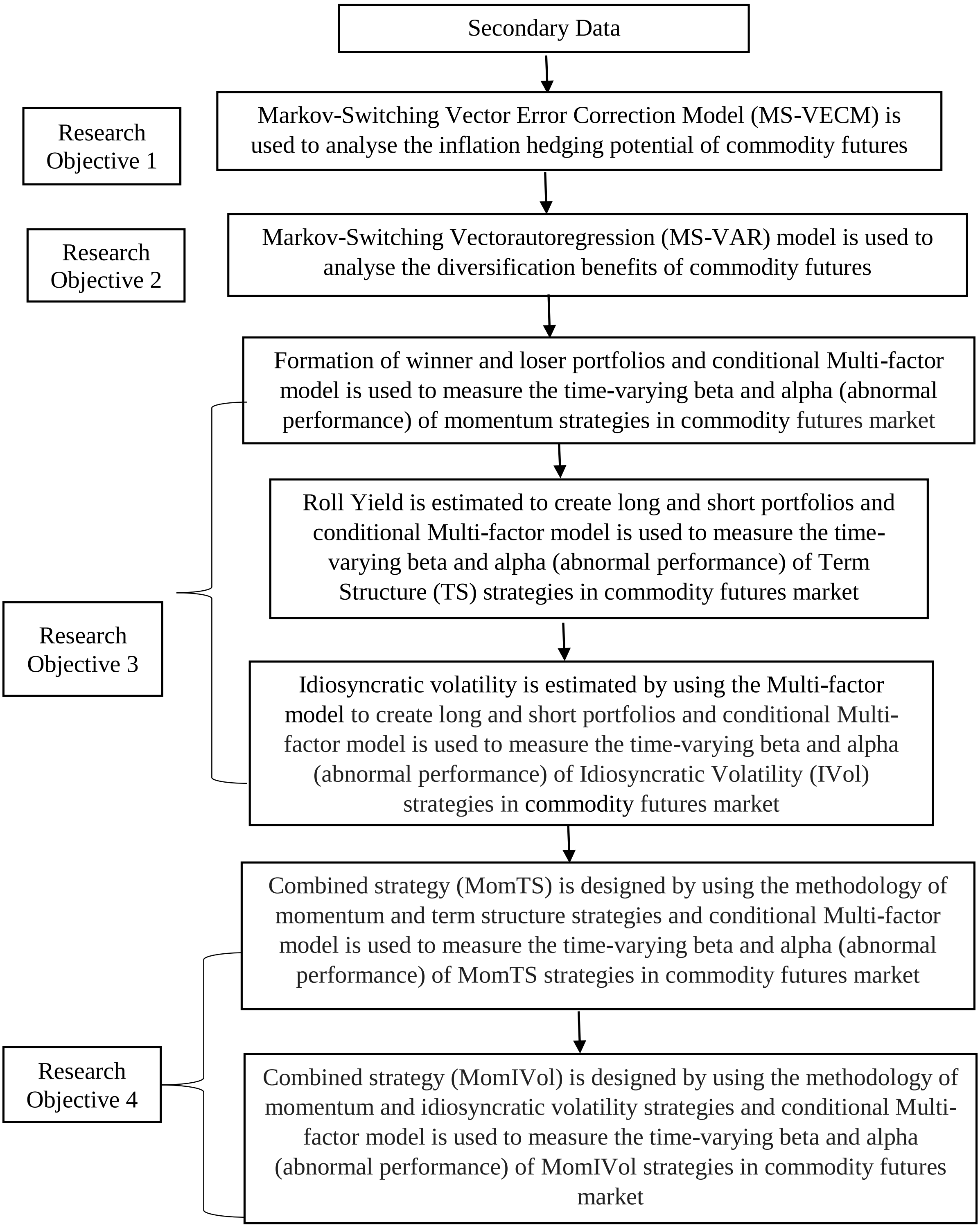
CHAPTER 3
RESEARCH METHODOLOGY

3.1 CHAPTER OVERVIEW

The chapter discusses in detail the research methodology adopted for the study and is organized into the following sections. Section 3.2 outlines the research design of the study. Section 3.3 gives a detailed discussion of the methodology used to analyse the inflation hedging potential of commodity futures. Section 3.4 discusses the methodology which assesses the hedging and diversification benefits of commodity futures. Section 3.5 analyses the implementation of momentum strategy and Section 3.6 discusses the methodology used to implement the term structures strategy in commodity futures market. Section 3.7 highlights the implementation of idiosyncratic volatility strategy in commodity futures market while Section 3.8 discusses in detail about the methodology used to implement the combined strategy-MomTS. Section 3.9 gives details of the methodology used to implement the combined strategy-MomIVol in commodity futures market and Section 3.10 outlines the summary.

3.2 RESEARH DESIGN

The current study investigates hedging & diversification role of commodity indices and commodity futures in the conventional portfolio of stocks & bonds. It defines passive and active strategies with the allocation of commodity futures in a portfolio. The research design for the study is a quantitative research paradigm which uses the deductive reasoning approach. A deductive approach uses theory in the beginning of the study for the purpose of verifying it. Hence, it is used in quantitative studies where it becomes the framework for the entire study. The current study basically uses the time series data analysis techniques on secondary data which is collected from the secondary data sources. Different methodologies used to analyse the inflation hedging potential of commodity futures, diversification benefits of commodity futures and risk-adjusted return performance of different active strategies, are elaborated in the subsequent paragraphs of the chapter. The study uses the nonlinear approach of the regime switching framework to analyse the inflation hedging and diversification benefits of commodity futures. In addition, it analyses the time-varying risk-adjusted return performance of different active strategies which are designed in this study for the commodity futures market. The schematic representation of the research methodology used for different research objectives of the current study is shown in Figure 3.1



***(Source:** Time Series Data Analysis Techniques)*

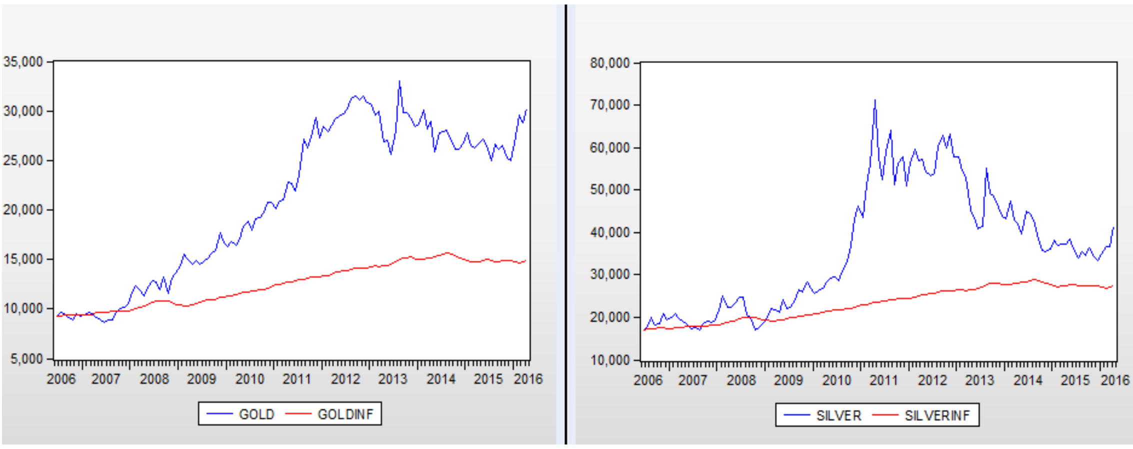
Figure 3.1: Schematic Representation of Research Methodology

3.3 COMMODITY FUTURES AS AN INFLATION HEDGE

Theoretically, the validity of any commodity futures as an inflation hedge is justified if it shows a long-run equilibrium relationship with inflation as the variables deviate from their equilibrium relationship, due to short-run price volatility (Ghosh et al., 2004). Similarly, according to Aggarwal (1992), gold may act as a hedge against inflation in the long-run, while their effectiveness as a hedge against inflation in short and medium-term is questionable. Hence, the cointegration approach is required for the situations when the series is integrated of order one and characterized by diverse long and short-run dynamics of inflation hedging potential. The cointegration of an asset with inflation gives an evidence of at least partial hedging ability of the asset against inflation in the long-run, whereas, evaluation of the hedging properties of this asset at a shorter horizon defines the short-run dynamics. Hence, a cointegrating relationship is characterized as a long-term or equilibrium phenomenon (Brooks, 2014). In addition, Mahdavi and Zhou (1997) suggested that the cointegration of commodity prices with inflation justifies the ability of commodity prices to forecast the inflation rate with the help of Error Correction (EC) term which incorporates the information of cointegration relationship. Consequently, the cointegration technique is an appropriate technique to verify the long and short-run dynamics of inflation hedging potential of commodity futures (Beckmann and Czudaj, 2013). Many previous studies (Kolluri, 1981; Moore, 1990; Laurent, 1994; Mahdavi and Zhou, 1997; Harmston, 1998; Ghosh et al., 2004; Levin et al., 2006) have adopted the conventional cointegration technique to assess the role of commodities as a leading indicator of inflation. However, there is a lack of studies which analyse the short and long-run dynamics of the cointegrating relationship between inflation and commodity futures in the Indian scenario. Hence, there is a need to explore the feasible implications of commodity futures, as an inflation hedge in the Indian scenario by utilizing the cointegrating information into the dynamic modeling of EC term.

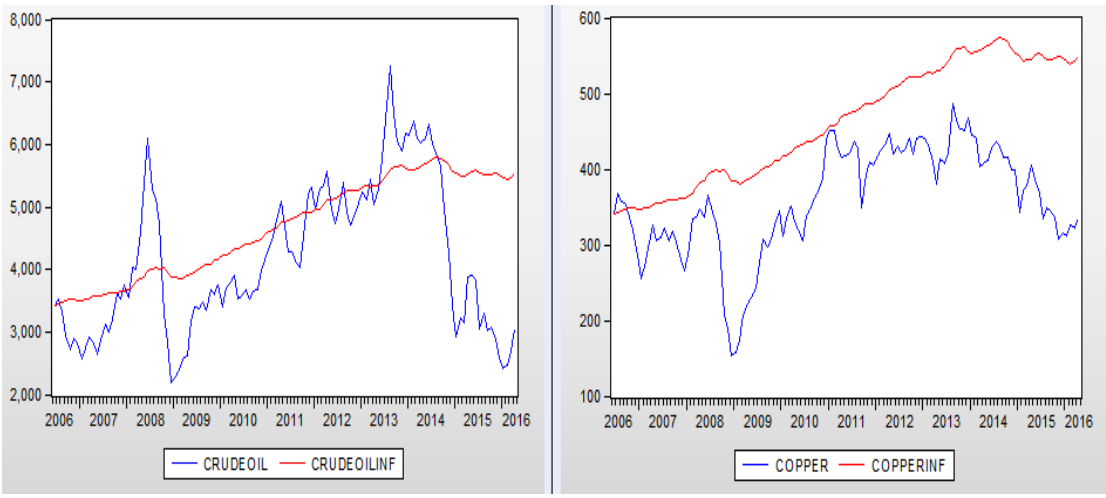
Figures 3.2, 3.3, 3.4, 3.5, 3.6, 3.7, 3.8 and 3.9 show monthly nominal prices and 'inflation hedge'[1] prices of gold, silver, crude oil, copper, lead, nickel, CPO, Cotton, mentha oil, zinc, cardamom, aluminium, MCXENERGY, MCXMETAL, natural gas and MCXAGRI. The average monthly increase in the futures prices of gold, silver, copper, crude oil, lead, nickel, CPO and cotton over the period of June 2006 to April 2016 are 0.3954, 0.4113, 0.3051, 0.5161, 0.4521, 1.327, 0.4252 and 0.5323 percent, respectively. This is in contrast to 0.4041 percent average monthly increase in the value of Wholesale

Price Index (WPI)[2]. It provides a preliminary evidence of inflation hedging potential of these commodity futures, as these results indicate that short-run changes in futures prices of these commodities may not be accompanied by changes in price level. However, these variables may be cointegrated as they do not drift far apart in the long-term (Worthington and Pahlavani, 2007). Conversely, an average monthly increase in the futures prices of zinc, aluminium, natural gas, mentha oil, cardamom, MCXMETAL, MCXENERGY and MCXAGRI is -0.436, -0.238, -1.58, -0.0306, -0.1929, -0.3807, -0.561 and -0.112. These results provide an elementary evidence of the inability of these commodity futures and commodity indices to hedge inflation risks.



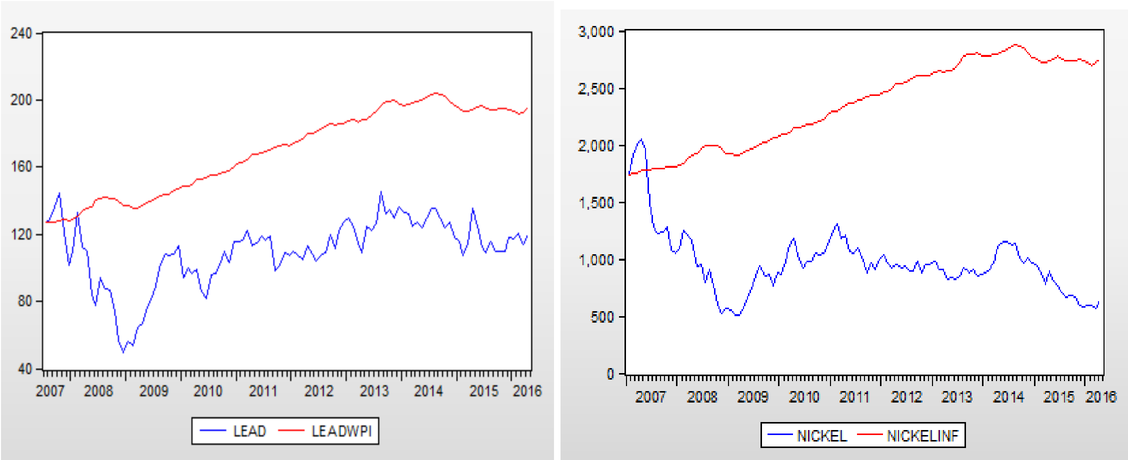
*(**Source:** Secondary Data Analysis)*

Figure 3.2: Monthly Nominal and Inflation Hedge Prices of Gold and Silver from June 2006-April 2016



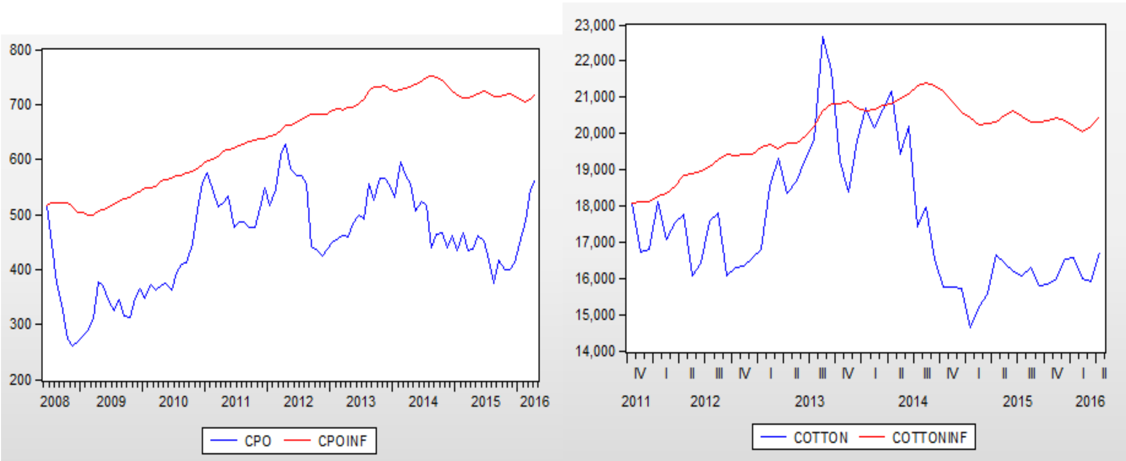
*(**Source:** Secondary Data Analysis)*

Figure 3.3: Monthly Nominal and Inflation Hedge Prices of Copper and Crude Oil from June 2006-April 2016



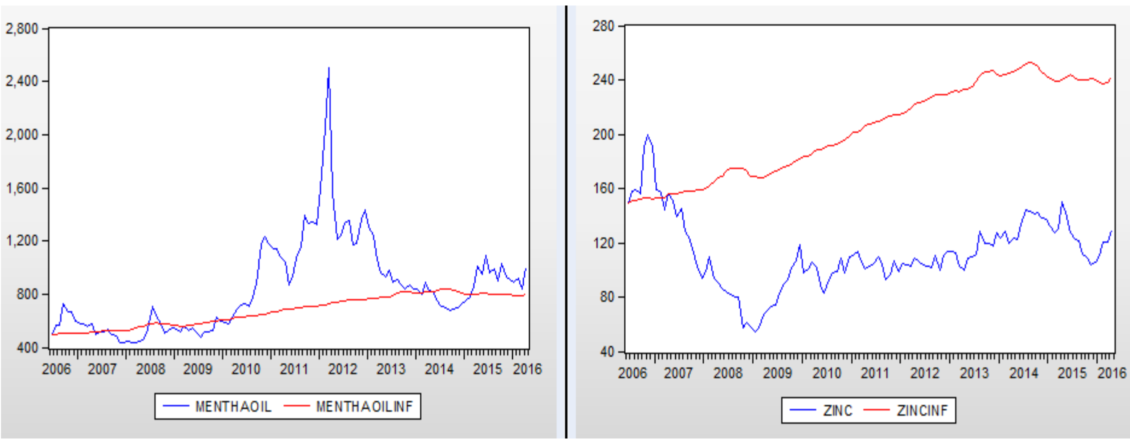
*(**Source:** Secondary Data Analysis)*

Figure 3.4: Monthly Nominal and Inflation Hedge Prices of Lead and Nickel from January 2007-April 2016



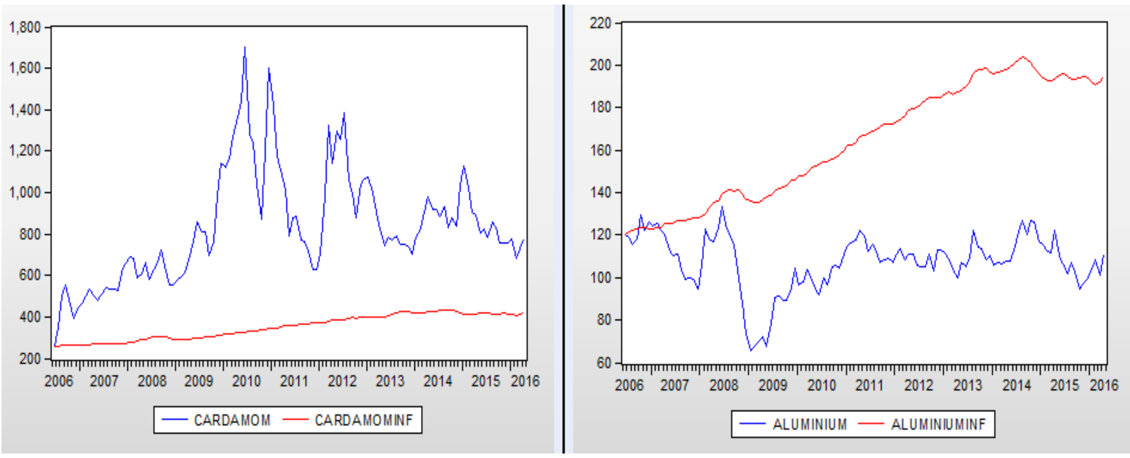
*(**Source:** Secondary Data Analysis)*

Figure 3.5: Monthly Nominal and Inflation Hedge Prices of CPO and Cotton from June 2008-April 2016



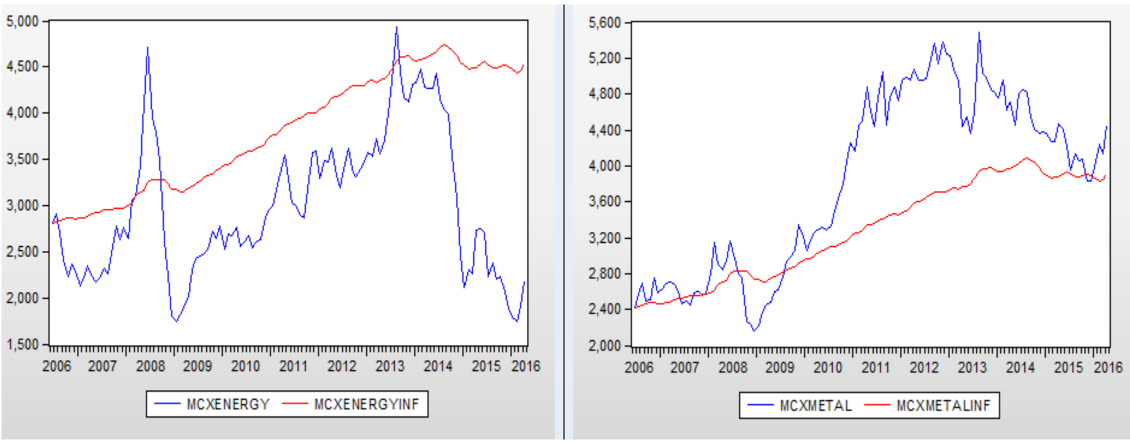
*(**Source:** Secondary Data Analysis)*

Figure 3.6: Monthly Nominal and Inflation Hedge Prices of Mentha Oil and Zinc from June 2006-April 2016



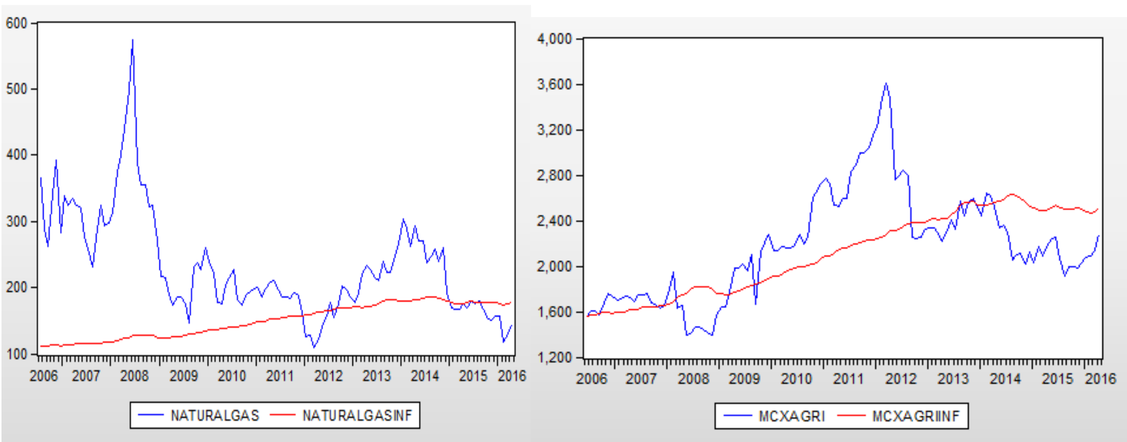
*(**Source:** Secondary Data Analysis)*

Figure 3.7: Monthly Nominal and Inflation Hedge Prices of Cardamom and Aluminium from June 2006-April 2016



*(**Source:** Secondary Data Analysis)*

Figure 3.8: Monthly Nominal and Inflation Hedge Prices of MCXENERGY and MCXMETAL from June 2006-April 2016



*(**Source:** Secondary Data Analysis)*

Figure 3.9: Monthly Nominal and Inflation Hedge Prices of Natural Gas and MCXAGRI from June 2006-April 2016

Nevertheless, the structural changes in commodity prices and inflation due to a major economic crisis or changes in monetary policies show significant variation in time series (Hamilton, 2010). The graphs in Figures 3.2, 3.3, 3.4, 3.5, 3.6, 3.7, 3.8 and 3.9 indicate the abrupt movements in the futures prices of all the commodity futures and commodity indices. These abrupt movements cause the presence of different regimes in the economy such as bull phase during the subprime crisis, a bear phase during the European crisis and the recent economic slowdown in China. These regimes depict different equilibrium relationships between commodity and inflation (Worthington and Pahlavani, 2007). Application of a conventional linear model for these scenarios will not give a prudent analysis of inflation hedging potential of commodity futures because parameter values do not change with the switching of regimes in a linear model (Beckmann and Czudaj, 2013). Thus, from a theoretical perspective, it is important to do a regime-specific analysis of commodity futures, as a hedge against inflation. In this vein, Wang et al. (2011) and Beckmann and Czudaj (2013) have examined the inflation hedging potential of gold by using a nonlinear approach. According to them, the presence of different economic states and imbalance of gold demand and supply, cause the presence of nonlinearity in the gold price movements. Wang et al. (2011) used a threshold cointegration framework which assumes the regime variable as an endogenous variable. On the contrary, Beckmann and Czudaj (2013) adopted Markov Switching-Vector Error Correction Model (MS-VECM) to capture the effect of exogenous factors such as major economic shocks. However, MS-VECM is more suitable for nonlinear estimation than any other conventional threshold model, since it is based on the state-dependent time series model where the regime shifts are stochastic as opposed to deterministic.

Hence, MS-VECM is used in this study to analyse the inflation hedging potential of commodity futures and commodity indices. The Markov-Switching model was originally proposed by Hamilton (1989) and was further continued by Krolzig (1997, 1998), who provided the overview of Markov-Switching Vector Autoregression (MS-VAR) Model. The Markov-Switching model takes into consideration the shift of some estimated parameters between the stochastic and unobservable regimes. These unobservable regimes are generated by using a stationary, irreducible and ergodic Markov chain. The maximum likelihood estimation of MS-VECM includes the additional process of adjustments of divergence in the long-run equilibrium relationship for each regime.

MS-VECM is a generalized form of VECM with the finite order p and r cointegrating vector. Thus, VECM for a k-dimensional time series vector is $X_t = (x_{1t}, \ldots. , x_{kt}),\ t = 1, \ldots \ldots, T$ with autoregressive of order p and r cointegrating vector is defined in Equation (3.1).

$$\Delta x_t = \upsilon + \sum_{i=1}^{p} P_i \, \Delta x_{t-1} + \sum_{j=1}^{r} C_j \, V_{t-1} + \varepsilon_t \tag{3.1}$$
$$\varepsilon_t \sim \text{IID } (0, \Sigma)$$

Where IID refers to Independent and Identically Distributed, υ is the intercept term, P_i is the autoregressive parameter of order p, C_j measures the speed of error correction and V_{t-1} contains the residuals from the cointegrating equation.

The cointegrating equation for k variables each integrated of order d_i where, $X_{i,t} \sim I(d_i)$ for i = 1, 2, 3….. k, is shown in Equation (3.2) (Brooks, 2014).

$$X_{1,t} = \sum_{i=2}^{k} \beta_i \, X_{i,t} + V_t \tag{3.2}$$

Where V_t is a disturbance term which is the linear combination of variables integrated of order I (1). Typically, this linear combination of I (1) variables will be I(0) or stationary, if the variables are cointegrated.

VECM (p, r) in Equation (3.1) is extended to MS-VECM of M-regimes, autoregressive of order p with r cointegrating vector. This model estimates the regime-dependent intercept term, autoregressive parameter, error correction speed coefficient and variance-covariance matrix of residuals as depicted in Equation (3.3).

$$\Delta x_t = \upsilon\,(S_t) + \sum_{i=1}^{p} P_i(S_t)\ \Delta x_{t-1} + \sum_{j=1}^{r} C_j\ (S_t)\, V_{t-1} + \varepsilon_t \tag{3.3}$$
$$\varepsilon_t |\, S_t \sim NID\ (0, \textstyle\sum(S_t)), \qquad t = 1, \ldots \ldots, T$$
$$S_t = 1,2, \ldots. M$$

Where NID refers to Normally and Independently Distributed, Δx_t shows column vector of observation at time t, S_t represents the regime at time t, $\upsilon(S_t)$ shows the vector of regime-dependent intercept term. $P_i(S_t)$ is a row vector of autoregressive parameters of order p in the regime S_t. $C_j(S_t)$ measures the speed of error correction in the regime (S_t) and V_{t-1} is the column vector representing the residuals from the cointegrating equation.

In order to provide regime specific equilibrium correction and unconditional cointegration, it requires that the error correction term should have negative coefficients and it should be statistically different from zero. The constant transition probabilities determine the regime generating process with a finite number of regimes, $S_t \in \{1, \dots \dots \dots, M\}$ which follow the guidelines of the Markov chain. The process of switching from regime i to regime j at time $t + 1$ is guided by transition probability and it does not depend on the history of the switching process, as depicted in Equation (3.4) (Hamilton, 1994).

$$P_{ij} = P_r(S_{t+1} = j \mid S_t = i), \; P_{ij} > 0, \quad \sum_{j=1}^{M} P_{ij} = 1 \; \forall \; _i, j \in (1, \dots \dots, M) \quad (3.4)$$

State variable S_t follows the transition matrix (3.5) which is derived by the Markov process with M number of states.

$$P = \begin{pmatrix} P_{11} & P_{12} \dots \dots & P_{1M} \\ P_{21} & P_{22} \dots \dots & P_{2M} \\ \vdots & \vdots & \vdots \\ P_{i1} & P_{i2} \dots \dots & P_{im} \end{pmatrix} \quad (3.5)$$

Where $P_{im} = 1 - P_{i1} - \dots - P_{i,m-1}$ for $i = 1, \dots \dots . M$.

The unconditional probability or ergodic probability of being in the first regime is estimated by using Equation (3.6) (Hamilton, 1994).

$$P\{S_t = 1\} = \frac{1 - P_{22}}{2 - P_{11} - P_{22}} \quad (3.6)$$

The smoothed probability estimated in the Markov-Switching model shows the conditional probability, based on information in the data up to future date T, as a result, it represents the ex-post measure. In Markov-Switching model, smoothed probability is estimated at each point in time and based on this smoothed probability each observation is classified into the regimes. The classification rule specifies that observations x_t of available information set X_t should map to the regime with the highest smoothed probability as depicted in Equation (3.7) (Krolzig, 2003).

$$S_t = \underset{1, \dots . M}{\arg\max} \; P_r \left(S_t \mid X_t\right) \quad (3.7)$$

Hence, classification rule of Equation (3.7) is simplified to assign the observations into the first regime if $P_r(S_t = 1|X_t) > 0.5$ and into the second regime if $P_r(S_t = 1|X_t) < 0.5$ for two regimes case. The average duration of the first and the second regimes is computed using Equations (3.8) and (3.9).

$$\text{Average Duration of First Regime} = 1/(1 - P_{11}) \tag{3.8}$$

$$\text{Average Duration of Second Regime} = 1/(1 - P_{22}) \tag{3.9}$$

The MS-VECM model is estimated by using Grocer toolbox for Scilab (Dubois and Michaux, 2013). The parameters of the MS-VECM model are estimated by maximum log likelihood function via Expected Maximum (EM) algorithm.

Regime Classification Measure (RCM) is applied to ascertain the quality of regime classification. The RCM is computed using Equation (3.10) (Ang and Bekaert, 2002).

$$RCM = 100M^2 \ \frac{1}{T} \sum_{t=1}^{T} \prod_{i=1}^{M} P_{i,t} \tag{3.10}$$

Where $P_{i,t}$ shows the ex-post smoothed probability of regime i at time t. M is the total number of regimes. RCM is a sample estimate of its variance as the regime variable is Bernoulli random variable. RCM takes the value between 0 and 100, where 0 depicts the perfect regime classification, while 100 shows that regimes-switching model is not able to distinguish between regimes from the behaviour of data which leads to the misspecification of regime-dependent information.

3.4 COMMODITY FUTURES AS A DIVERSIFIER

Many studies such as Jensen et al. (2002), Gorton and Rouwenhorst (2006), Chong and Miffre (2010), Conover et al. (2010) and Creti et al. adopted the linear approach and examined the risk-return trade off performance of commodity futures in a portfolio consisting of stocks and bonds. However, from a theoretical perspective, it is essential to perform a nonlinear estimation to check the diversification benefits of commodity futures under the regime-dependent approach (Jaiswal and Uchil, 2016). In literature, different measures are adopted to test the safe haven role of assets under the time-varying framework. To check the safe haven hypothesis of gold under extreme stock and bond markets movements, Baur and Lucey (2010) took the threshold of 5, 2.5 and 1 percent quantile of stock and bond returns distribution. If returns exceeded these quantiles, then the dummy variable took the value as zero. Similarly, to capture the extreme stock market movements Baur and McDermott (2010) considered the threshold of 10, 5 and 1 percent of returns distribution. The dummy variable accepted the value as one if the stock returns exceeded these thresholds. In order to avoid using these arbitrary and discrete patterns of capturing extreme market movements, Beckmann et al. (2015) adopted the exponential transition function of Smooth Transition Regression (STR) model. STR splits the regression model into two extreme regimes. One regime characterizes the period of average return while the other regime accounts for a high volatility in stock returns. The present study follows the regime-dependent framework of Beckmann et al. (2015). However, it uses the regime-switching framework of MS-VAR model to capture the extreme market movements instead of STR. It is considered that MS-VAR model is more suitable for nonlinear estimation than any other conventional threshold model as the regime shifts are stochastic in this model as opposed to deterministic (Beckmann and Czudaj, 2013). It is based on the state-dependent time series model which captures the effect of exogenous factors such as major economic shocks.

Hence, the hedge and safe haven role of commodity futures and commodity indices are analysed using the Markov-Switching Vector Autoregression (MS-VAR) Model. MS-VAR is the generalisation of basic VAR model with the finite order p. Thus, VAR model for *k*-dimensional time series vector $X_t = (x_{1t}, \ldots ., x_{kt}),\ t = 1, \ldots \ldots, T$ and with autoregressive order p is defined in Equation (3.11):

$$x_t = \upsilon + R_1 x_{t-1} + \ldots . . + R_p x_{t-p} + \varepsilon_t \tag{3.11}$$

$$\varepsilon_t \sim \text{IID}\ (0, \Sigma)$$

Where IID refers to Independent and Identically Distributed data, υ is the intercept term and R_p, R_1 are the autoregressive parameters.

MS-VAR follows the nonlinear data generating process which restricts the process to be linear in each regime. A regime-switching framework is based on the assumption that the estimated parameters of data generation process of the time series vector X_t, depend on unobservable state variable S_t. The process of regime generation is guided by the Markov stochastic process with the finite number of regimes, $S_t \in \{1, \ldots \ldots . ., \text{M}\}$ and constant transition probabilities. The transition probability of switching from regime i to regime j at time $t + 1$ is independent of process history is depicted in Equation (3.4) (Hamilton, 1994). In addition, state variable S_t follows transition matrix (3.5) which is derived by an irreducible and ergodic *M* state Markov process.

In this study, VAR (p) model is extended to MS-VAR with autoregressive order p and M number of regimes. This model allows regime shift in intercept term, autoregressive parameter, and variance-covariance matrix of the residuals as shown in Equation (3.12).

$$x_t = \upsilon(S_t) + R_1(S_t)\, x_{t-1} + \ldots\ldots + R_p(S_t)\, x_{t-p} + \varepsilon_t \tag{3.12}$$
$$\varepsilon_t | S_t \sim NID\,(0, \textstyle\sum(S_t)), \qquad t = 1, \ldots\ldots, T$$

Where NID refers to Normally and Independently Distributed data, $\upsilon(S_t)$ shows the vector of regime-dependent intercept term. $R_1(S_t)$ and $R_p(S_t)$ are autoregressive parameters of order p in the regime S_t. $\upsilon(S_t)$, $R_1(S_t)$,..., $R_p(S_t)$ and $\sum(S_t)$ are the parameter shift functions which show the dependence of parameters υ, $R_{1,\ldots,}R_p$ and $\sum$ on the unobservable regime S_t.

The classification rule of assigning the observations into regimes based on the smoothed probabilities estimated in the Markov-Switching model is depicted in Equation (3.7). In addition, the average duration of the first and the second regimes is computed using Equations (3.8) and (3.9).

The MS-VAR model is estimated by using Grocer toolbox for Scilab (Dubois and Michaux, 2013). The parameters of MS-VAR model are estimated by maximum log likelihood function via Expected Maximum (EM) algorithm.

The theoretical justification for subsequent empirical analysis is based on the definitions of a hedge and safe haven, given by Baur and Lucey (2010). According to them, an asset is qualified to be a hedge (safe haven) if it is uncorrelated or negatively correlated with other assets on an average (during the extreme stock market movements). Baur and McDermott (2010) extended the work of Baur and Lucey (2010) and gave definitions of the weak and strong form of hedge and safe haven. According to them, an asset is qualified to be a strong (weak) hedge if it is negatively correlated (uncorrelated) with another asset or portfolio on an average. Based on the above definitions, this study attempts to analyse the hedge and safe haven role of commodity futures and commodity indices against stock and bond market movements.

3.5 MOMENTUM STRATEGIES IN COMMODITY FUTURES MARKET

Based on the work of Jegadeesh and Titman (1993, 2001) in equity market and Miffre and Rallis (2007) in commodity futures market, this study analyses the momentum payoffs in the Indian commodity futures market for different combinations of Ranking (R) periods (1, 3, 6 and 12 months) and Holding (H) periods (1, 3, 6, 12, 18 and 24 months). This study assesses the 24 momentum strategies for the combination of R-H such as 1-1, 1-3, 1-6, 1-12, 1-18, 1-24, 3-1, 3-3, 3-6, 3-12, 3-18, 3-24, 6-1, 6-3, 6-6, 6-12, 6-18, 6-24, 12-1, 12-3, 12-6, 12-12, 12-18 and 12-24. For instance, returns of the 3-6 momentum strategy are based on the preceding three months' average return (ranking period of three months) which is held for subsequent six months (holding period of six months).

Jagadeesh and Titman (1993, 2001) have classified the futures contract into deciles based on their average returns over the previous R-month. Due to limited cross section, Miffre and Rallis (2007) created the quintiles at the end of each month based on the average returns over the previous R-month. However, the present study adopts a slightly different strategy to create the winner and loser portfolios. Due to the small study period and the limited cross section, the commodity futures contracts are divided into only two portfolios, winner and loser portfolios, based on their positive and negative returns in the previous R-month. For both the winner and loser portfolios, equal weights are assigned to the respective commodity futures. Based on their performance in the subsequent H months, R-H momentum strategy is constructed, which buys the winner portfolios and shorts the loser portfolios.

Following the approach of Moskowitz and Grinblatt (1999), Jagadeesh and Titman (2001) and Miffre and Rallis (2007), overlapping winner and loser portfolios are created. For instance, in the case of 3-6 momentum strategy, the returns of the winner portfolio in July is the sum of previous six overlapping positive return portfolios. These six overlapping portfolios are formed at the end of January (ranking period from October to December returns), February (ranking period from November to January returns), March (ranking period from December to February returns), April (ranking period from January to March returns), May (ranking period from February to April returns) and June (ranking period from March to May returns). A similar approach is applied for estimating the return of the loser portfolio in July which is the sum of the six overlapping negative returns portfolios created at the end of January, February, March, April, May and June. Finally, the returns of the momentum strategy, 3-6 for the month of July are estimated by subtracting the July returns of the loser portfolios from the returns of the winner portfolios. A similar procedure is followed to estimate the momentum payoffs for the subsequent months.

The risk-adjusted returns of the momentum strategy are estimated by using the Multi-factor model shown in Equation (3.13).

$$R_{Mt} = \alpha + \beta_S \left(R_{St} - R_{ft}\right) + \beta_B \left(R_{Bt} - R_{ft}\right) + \beta_C \left(R_{Ct} - R_{ft}\right) + \varepsilon_{Mt} \qquad (3.13)$$

$$t = 1, \ldots \ldots, T$$

Where, R_{Mt} is the returns of the winner, loser and momentum portfolios. R_{St}, R_{Bt} and R_{Ct} represent the log returns of Nifty stock index, CCIL total return bond index and MCXCOMDEX composite commodity index. R_{ft} and ε_{Mt} show the risk-free rate and error term, respectively. The three-month Treasury bill rate is taken as a risk-free rate.

Unconditional alpha and beta estimated through the unconditional Multi-factor model in Equation (3.13) provides an incorrect performance evaluation of momentum strategies if the momentum payoffs are a compensation for the time-varying risk (Chordia and Shivakumar, 2002). Ferson and Schadt (1996) proposed a conditional model where betas are the linear function of a vector of pre-specified information variables Z_{t-1} as shown in Equation (3.14). Information variables Z_{t-1} represent the publicly available information at time t-1 which reflects the different business cycles.

$$\beta_P\,(Z_{t-1}) = \beta_{P0} + \beta_{P1}\, z_{t-1} \qquad (3.14)$$

Where, z_{t-1} is the vector of the deviation of individual information variable Z_{t-1} from their unconditional mean value. β_{P1} is the conditional beta which measures the impact of information variables on the conditional beta. β_{P0} is the unconditional beta which is the unconditional mean of the conditional betas.

Christopherson et al. (1998) have extended the model of Ferson and Schadt (1996) and proposed a model for explicit time-varying conditional alpha. Like conditional beta, conditional alpha is the linear function of a vector of pre-specified information variables Z_{t-1} shown in Equation (3.15).

$$\alpha_P\,(Z_{t-1}) = \alpha_{P0} + \alpha_{P1}\, z_{t-1} \qquad (3.15)$$

Where α_{P0} is the unconditional average alpha and α_{P1} measures the impact of information variables on the conditional alpha. Conditional single-factor model with time-varying alphas and betas is shown in Equation (3.16) which is a combination of Equations (3.14) and (3.15) (Leite et al., 2009).

$$R_{Pt} = \alpha_{P0} + \alpha_{P1} z_{t-1} + \beta_{P0}\, R_{mt} + \beta_{P1}\,(z_{t-1}\, R_{mt}) + \varepsilon_{Pt} \qquad (3.16)$$

Where R_{Pt} represents the excess returns of portfolio P over period t. R_{mt} is the markets' excess returns during the same time period.

The conditional Multi-factor model to measure the time-varying beta and alpha (abnormal performance) of momentum strategies which is a linear function of information variable Z_{t-1} is shown in Equation (3.17) (Miffre and Rallis 2007).

$$R_{Pt} = \alpha_{P0} + \alpha_{P1} z_{t-1} + \beta_{S0}\left(R_{St} - R_{ft}\right) + \beta_{S1}\left(R_{St} - R_{ft}\right) z_{t-1} + \\ \beta_{B0}\left(R_{Bt} - R_{ft}\right) + \beta_{B1}\left(R_{Bt} - R_{ft}\right) z_{t-1} + \\ \beta_{C0}\left(R_{Ct} - R_{ft}\right) + \beta_{C1}\left(R_{Ct} - R_{ft}\right) z_{t-1} + \varepsilon_{Pt} \quad (3.17)$$

Where β_{S0}, β_{B0} and β_{C0} are the unconditional beta of Nifty stock index, CCIL liquid total return bond index and composite commodity index (MCXCOMDEX), respectively while β_{S1}, β_{B1} and β_{C1} represent the conditional beta of the respective asset classes. The insignificant value of unconditional alpha (α_0) in equation (3.17) shows that abnormal returns of momentum strategies are merely a compensation for time-varying risk which is consistent with the semi-strong form of the market efficiency given by Malkiel and Fama (1970).

The information variables (Z_{t-1}) represent the proxy for the business cycle which include the first lag of following information variables such as one-month Mumbai Inter-Bank Offer Rate (MIBOR), the dividend yield on the Nifty stock index and the term structure of interest rates. The term structure is estimated as a difference between ten-year Indian Treasury bond yield and three-month Treasury-bill rate. For the justification of the model shown in Equation (3.17), it is essential that the following hypotheses should be rejected (Miffre and Rallis, 2007).

H_7 Conditional Alpha $(\alpha_1) = 0$,

H_8 Conditional Beta $(\beta_1) = 0$

H_9 $\alpha_1 = \beta_1 = 0$

The transaction costs are estimated based on the work of DeMiguel (2009), Daskalaki and Skiadopoulos (2011) and Fuertes et al. (2010). The portfolio turnover is estimated to find out the amount of trading required to implement the momentum strategies. The portfolio turnover PT_m, for a strategy m is the average absolute change in the weights across N number of assets and over the $T-1$ rebalancing points in time. It is estimated using Equation (3.18) (DeMiguel, 2009; Kostakis et al., 2011).

$$PT_m = \frac{1}{T-1} \sum_{t=1}^{T-1} \sum_{J=1}^{N} \left(\left|w_{m,j,t+1} - w_{c,j,t+}\right|\right) \quad (3.18)$$

Where $w_{m,j,t+1}$ and $w_{c,j,t+}$ are the optimal weights of asset j for strategy m at time t and $t+1$, respectively. The value of $|w_{m,j,t+1} - w_{c,j,t+}|$ shows the absolute changes in weights for asset j at the $t+1$ rebalancing point.

The net momentum return is computed for the realized portfolio return $MR_{m,p,t+1}$ at $t+1$ using the estimated transaction costs tc of 0.033 percent of Locke and Venkatesh (1997) and 0.146 percent of Shen et al. (2007), as shown in Equation (3.19).

$$NW_{m,t+1} = NW_{m,t}\left(1 + MR_{m,p,t+1}\right)[\,1 - tc * \textstyle\sum_{j=1}^{N}(|w_{m,j,t+1} - w_{c,j,t+}|)] \qquad (3.19)$$

Where $NW_{m,t+1}$ and $NW_{m,t}$ are the net of transaction costs wealth for strategy m at t and $t+1$. Hence, the return net of transaction costs $NMR_{c,t+1}$ is estimated using the Equation (3.20).

$$NMR_{c,t+1} = \frac{NW_{m,t+1}}{NW_{m,t}} \text{-1} \qquad (3.20)$$

3.6 TERM STRUCTURE (TS) STRATEGIES IN COMMODITY FUTURES MARKET

Based on hedging pressure hypothesis which defines the propensity of hedgers to be net long and net short, one can design an active strategy called as term structure strategy to earn abnormal returns. The backwardated and contango state of commodity market is identified by the shape of the term structure curve which arises due to the gap in the prices of different maturity contracts called as “roll yield” or “implied yield”. It is estimated by using the Equation (3.21) (Fuertes et al., 2010).

$$R_t = \left[\ln\left(P_{t,n}\right) - \ln\left(P_{t,d}\right)\right] * \frac{365}{N_{t,d} - N_{t,n}} \qquad (3.21)$$

Where $\left(P_{t,n}\right)$ is the price of the nearest maturity contract and $P_{t,d}$ is the price of the distant maturity contract at time ‘t’. $N_{t,n}$ is the number of days between time ‘t’ and the maturity date of the nearest contract and $N_{t,d}$ is the number of days between time ‘t’ and the maturity date of the distant contract. If the price of the nearest contract exceeds the price of the distant contract then it gives a positive R_t and the downward sloping term structure curve of commodity futures prices. It indicates the backwardated state of the market. On the contrary, negative R indicates the contangoed state of the market and the upward sloping term structure of the commodity futures prices. Based on the dynamic asset allocation strategy using term structure curve given by Erb and Harvey (2006) and Fuertes et al. (2010), this study designs term structure strategy which take a long position in backwardated contracts and a short position in contangoed contract.

Three different strategies are adopted to perform the performance evaluation of term structure strategies and the robustness analysis of term structure profitability. Basic term structure strategy is TS_1 where roll yield is estimated by taking the difference in the prices of nearest and second nearest maturity contracts. This strategy takes the long position in the backwardated contracts with positive roll yield and a short position in the contangoed contracts with negative roll yield and holds the long-short position for a month. The contracts in each long and short portfolio are equally-weighted.

Three different strategies TS_{1a} ,TS_{1b} and TS_{1c} are used for sensitivity analysis of term structure profitability. First strategy $\mathrm{TS_{1a}}$ is applied to check the impact of distant maturity contract instead of second nearest contract on the profitability of term structure strategy. This strategy basically assesses the impact of liquidity risk which arises due to the use of distant maturity contract on the profitability of term structure strategy.

Second strategy TS_{1b} is formulated to assess the impact of increasing the frequency of rebalancing of long-short portfolios on the profitability of term structure strategies. Hence, instead of rebalancing of portfolio once in a month and holding that portfolio for subsequent month, this strategy allows for a rebalancing of long-short portfolios twice in a month. The mid-date of the total number of trading days in a month is taken for the first rebalancing and the last trading day of the month is taken for the second rebalancing. The frequency of rebalancing can be increased to three or four times in a month.

Third strategy TS_{1c} is designed to check if the changes in the rolling date have an impact on term structure profitability. The rolling date is changed from the end of the month to the 15^{th} of the maturity month. If trading is not done on 15^{th} then the trading date previous to the 15^{th} is considered for the formation of the future price series.

3.7 IDIOSYNCRATIC VOLATILITY (IVol) STRATEGIES IN COMMODITY FUTURES MARKET

Based on the work of Ang et al. (2009) and Miffre et al. (2012) this study analyses the payoffs of idiosyncratic volatility strategy in the Indian commodity futures market for different combinations of R periods (1, 3, 6 and 12 months) and H periods (1, 3, 6, 12, 18 and 24 months). This study assesses the 24 idiosyncratic volatility strategies for the combination of R-H such as 1-1, 1-3, 1-6, 1-12, 1-18, 1-24, 3-1, 3-3, 3-6, 3-12, 3-18, 3-24, 6-1, 6-3, 6-6, 6-12, 6-18, 6-24, 12-1, 12-3, 12-6, 12-12, 12-18 and 12-24. For instance, returns of the 3-6 idiosyncratic strategy is based on the preceding three months' average idiosyncratic volatility (ranking period of three months) which is held for subsequent six months (holding period of six months).

Due to the small study period and limited cross section, the commodity futures contracts are sorted into only two portfolios, long and short portfolios based on their low and high idiosyncratic volatility in the previous R-month. For both the long and short portfolios, equal weights are assigned to the respective commodity futures. Based on their performance in the subsequent H months, R-H idiosyncratic strategy is constructed which buys the long portfolios and sells the short portfolios.

The methodology to extract the idiosyncratic volatility signals is based on the model used by Ang et al. (2006, 2009), Miffre et al. (2012) and Fuertes et al. (2015). Unlike the momentum and term structure signals, idiosyncratic volatility signals need to be extracted from the chosen benchmark model. Ang et al. (2006, 2009) defined the idiosyncratic volatility for the equity market as the standard deviation of the residuals from a regression of daily stock returns on the three-factor model of Fama and French (1993). On the contrary, Fuertes et al. (2015) selected the best model between traditional and fundamental asset pricing model. Their traditional asset pricing model includes the equity market risk premium (Rm-Rf), the size and value premia of Fama and French (1993), the S&P-GSCI (Standard & Poor's-Goldman Sachs Commodity Index) or equally-weighted portfolio of the commodity futures. On the contrary, the fundamental model captures the backwardated and contangoed state of the commodity market via momentum, term structure and hedging pressure portfolios. Their empirical results have shown that the model based on the benchmark S&P GSCI has given the best idiosyncratic volatility portfolios which earn a highest average Sharpe ratio of 0.38.

Based on the above rationale, the idiosyncratic volatility signal is defined in this study as the standard deviation of the residuals from a regression of monthly commodity futures returns on the Multi-factor model which includes monthly returns of Nifty stock index, CCIL liquid total return bond index and MCXCOMDEX as commodity index. The Multi-factor model used to extract the idiosyncratic volatility is shown in Equation (3.13).

3.8 COMBINED STRATEGY-MomTS

Combined strategy (MomTS) is designed by using the methodology of both momentum and term structure strategies. Based on the methodology adopted by Fuertes et al. (2010), following steps are used to design a MomTS strategy. First, the roll return is computed at the end of each month for all the 13 commodity futures included in the study. Second, at the end of each month, the cross section of commodity futures splits into two portfolios, namely 'high roll return' and 'low roll return' based on their roll returns. Third, the commodities in the 'high roll return' are sorted into two sub-portfolios namely 'winner' and 'loser' based on the log returns of the commodity futures over the past R-month. The final portfolio is called as 'high-winner' and 'high-loser'. Thus, 'high-winner' contains only those commodity futures which have the highest roll return and given the best performance in terms of their log returns. Conversely, 'high-loser' includes the commodity futures with low roll returns and low log returns. Fourth, the commodity futures under 'low roll return' are sorted into two sub-portfolios namely, 'low-winner' and 'low-loser' based on their log returns for the past R-month. Hence, the 'low-loser' contains only those commodity futures which have the lowest roll returns and lowest log returns showing their worst past performance. Finally, the combined strategy is created which takes a long position in 'high-winner' portfolios and a short position in 'low-loser' portfolios and holds this position for next 1, 3, 6, 12, 18 and 24 months.

3.9 COMBINED STRATEGY-MomIVol

Combined strategy (MomIVol) is designed by using the methodology of both momentum and idiosyncratic volatility strategies. The following steps are used to design a MomIVol strategy based on momentum and idiosyncratic volatility. First, the idiosyncratic volatility is estimated at the end of each month for all the 13 commodity futures included in the study. The idiosyncratic volatility signal is defined as the standard deviation of the residuals from a regression of monthly commodity futures returns on the Multi-factor model which is shown in Equation (3.13). Second, at the end of each month, the cross section of commodity futures splits into two portfolios namely 'high IVol' and 'low IVol' based on their past idiosyncratic volatility. Third, the commodities in the 'low IVol' are sorted into two sub-portfolios namely 'winner' and 'loser' based on the log returns of the commodity futures over the past R-month. The final portfolio is called as 'low-winner' and 'low-loser'. Thus, 'low-winner' contains only those commodity futures which have the lowest idiosyncratic volatility and given the best performance in terms of their log returns. Conversely, ‘low-loser’ includes the commodity futures with the lowest idiosyncratic volatility and lowest log returns over the past R-month. Fourth, the commodity futures under ‘high IVol’ are sorted into two sub-portfolios namely, ‘high-winner’ and high-loser’ based on their log returns for the past R-month. Hence, the ‘high-loser’ contains only those commodity futures which have the highest idiosyncratic volatility and lowest log returns showing their worst past performance. Finally, the combined strategy is created which takes a long position in ‘low-winner’ portfolios and a short position in ‘high-loser’ portfolios and holds this position for next 1, 3, 6, 12, 18 and 24 months.

3.10 DATA USED FOR THE STUDY

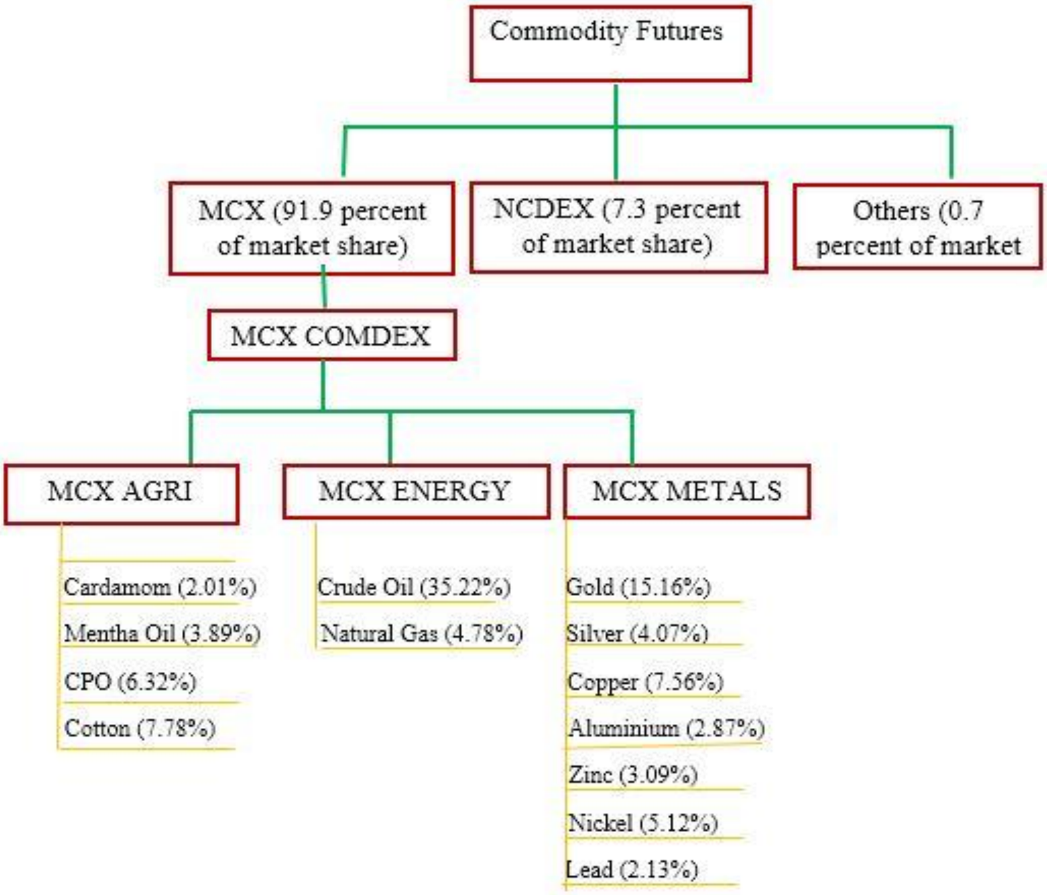
The data source is secondary and it is collected from the website of Multi Commodity Exchange (MCX). List of indices considered for the study are as follows: MCXMETALS, MCXENERGY, MCXAGRI of the composite commodity index MCXCOMDEX. MCXCOMDEX is designed & developed by the Research & Planning Department of MCX in association with the Indian Statistical Institute, Kolkata. The index is a significant barometer of the performance of commodity market in India. MCXCOMDEX is the simple weighted average of the three group indices – MCXAGRI, MCXMETAL and MCXENERGY, developed to represent different commodity segments (Multi Commodity Exchange, 2010). Rebalancing of MCXCOMDEX is done annually or as required by the index committee results in dropping out and the inclusion of commodities from index to ensure the highest risk-adjusted return. (Multi Commodity Exchange, 2010). Further, the 13 commodity futures under study are part of these sub-indices viz. MCXMETAL, MCXAGRI and MCXENERGY as shown in Table 3.1.

Table 3.1: List of Indices and Commodities under Multi Commodity Exchange

Index	Sub-indices	Index	Commodity (Wt. %)	Index	Commodity (Wt. %)	Index	Commodity (Wt. %)
MCX COMDEX	MCX METAL	MCX METAL	Gold(15.16)	MCX ENERGY	Crude Oil (35.22)	MCX AGRI.	Crude Palm Oil (6.32)
	MCX ENERGY		Silver (4.07)		Natural Gas (4.78)		Mentha Oil (3.89)
	MCX AGRI.		Copper(7.56)				Cardamom (2.01%)
			Zinc(3.09)				Cotton (7.78)
			Lead(2.13)				
			Nickel(5.12)				
			Aluminium(2.87)				

*(**Source**: Multi Commodity Exchange, 2010)*

The inclusion criteria of these commodities are their liquidity in the exchange for the specified time period. In addition, these commodity futures are the highly traded contracts in MCX based on their average daily turnover, volume and open interest. These commodity futures are categorized into energy (crude oil, natural gas), bullion (gold, silver), base metals (copper, zinc, aluminium, lead and nickel) and agricultural (CPO, mentha oil, cardamom and cotton). The monthly historical futures prices of MCXMETAL, MCXENERGY, MCXAGRI and commodities listed under these indices are collected from MCX website. CNX Nifty, a leading stock market index in India, is taken as a proxy for stock index and monthly closing prices are extracted from NSE website. The Liquid total return bond index of Clearing Corporation of India Ltd. (CCIL) is taken as a proxy for a bond index and its monthly prices are extracted from the website of CCIL (www.ccilindia.com). WPI is used as an inflation index and its monthly values are retrieved from the RBI website. The hierarchical tree which shows the selection of commodity futures for the study is depicted in Figure 3.10.



(***Source:*** *Multi Commodity Exchange, 2010*)

Figure 3.10: Hierarchical Tree of Commodity Futures under Study

The study is conducted for the study period from June 2006 to April 2016. However, due to the non-availability of data, futures prices of few commodity futures such as nickel, lead, natural gas, CPO and cotton futures are not considered from the year June 2006. Table 3.2 shows the study period of all the commodity futures and commodity indices.

Table 3.2: Study Periods of all the Commodity Futures and Commodity Indices

Commodity Futures and Indices	Start Date	End Date
Gold	June-2006	April-2016
Silver	June-2006	April-2016
Copper	June-2006	April-2016
Aluminium	June-2006	April-2016
Zinc	June-2006	April-2016
Nickel	January-2007	April-2016
Lead	July-2007	April-2016
Crude Oil	June-2006	April-2016
Natural Gas	July-2006	April-2016
Mentha Oil	June-2006	April-2016
Cardamom	June-2006	April-2016
CPO	June-2008	April-2016
Cotton	October-2011	April-2016
MCXMETAL	June-2006	April-2016
MCXENERGY	June-2006	April-2016
MCXAGRI	June-2006	April-2016

(***Source:*** *Multi Commodity Exchange 2010*)

3.10.1 Compiling the Futures Time Series of Commodity Futures

The nearby futures contracts are used to construct futures price series as these are the most actively traded contracts. The rollover of the series is performed by the first nearby contract to next nearby contract during the rolling periods which adopts MCX rolling mechanism. During the rolling period, series incorporates the next nearby futures price series in a predetermined manner of rolling 20 percent for each day.

3.10.2 Compiling the Futures Time Series of Commodity Futures for Momentum Strategies

This study adopts three different approaches to construct the futures price series in order to perform the sensitivity analysis of momentum strategy. Continuously compounded logarithmic returns are used to construct the futures return for all the three approaches which are estimated by taking the first difference of natural logarithm of futures prices of commodities.

First, the nearby futures contracts are used to construct the futures price series as these are the most actively traded contracts. The first nearby contracts are held for one month before maturity. Taking into account the rolling mechanism adopted by MCX, rollover of the series is performed by first nearby contract to the second nearby contract at the end of every month and hold this contract up to one month before maturity. The same procedure is rolled forward to construct the series of futures prices. Second, the same procedure is repeated for the second approach with the only difference is, instead of the second nearby contract, the most distant contract is used to compile the futures price series. Third, the rolling date is changed from the end of the month to the 15th of the maturity month. If trading is not done on 15th then the trading date previous to the 15th is considered for the formation of the futures price series.

These sensitivity analyses help to analyse the impact of liquidity risk and change of rolling date on the momentum profits. Normally, it is considered that lack of liquidity in distant maturity contract has a negative impact on the momentum profits (Miffre and Rallis, 2007). However, liquidity risk can be compensated by the abnormal profit which is generated due to the trading in distant maturity contract, if momentum profits follow the Theory of Normal Backwardation of Keynes (1930), Hicks (1939), Kolb (1992) and Miffre (2000).

3.10.3 Compiling the Futures Time Series of Commodity Futures for Term Structure Strategies

This study adopts four different approaches to compile the futures price series to evaluate the sensitivity of term structure returns. Continuously compounded logarithmic returns are used to construct the futures returns which are estimated by taking the first difference of natural logarithm of futures prices of commodities.

First, the nearby futures contracts are used to construct the futures price series as these are the most actively traded contracts. The first nearby contracts are held for one month before maturity. Taking into account the rolling mechanism adopted by MCX, rollover of the series is performed by first nearby contract to the second nearby contract at the end of every month and to hold this contract up to one month before maturity. The same procedure is rolled forward to construct the series of futures returns. Second, the same procedure is repeated for the second approach with the only difference being that instead of the second nearby contract, the most distant contract is used to compile the futures price series. Third, the rolling date is changed from the end of the month to the 15^{th} of the maturity month. Fourth, rolling is done twice in a month to construct the futures price series. The first rolling is done on the mid-date which is the mid-point of the total number of the trading days in a month. The second rolling is performed on the last trading date of the month.

3.11 SUMMARY

This chapter focuses on the research methodology used to investigate the role of commodity futures as an alternative asset class. It helps to earn abnormal returns, in addition, to diversify a portfolio. The research design for the study is a quantitative research paradigm where the deductive reasoning approach is used. The time series data analysis techniques are used in the study to analyse the secondary data which is collected from the secondary data sources. The time-varying nonlinear approach is used to investigate the benefits of passive and active strategies of investment in commodity futures. The analysis and interpretation of the data are presented in the following chapter.

[1]Inflation hedge prices are the prices of the commodity futures which is required in order to maintain their 2006 purchasing power. It is measured by using the general WPI.

[2]WPI is selected as an inflation index instead of Consumer Price Index (CPI) as aforementioned commodities are not the part of CPI in India.

CHAPTER 4

DATA ANALYSIS, RESULTS AND INTERPRETATIONS

4.1 CHAPTER OVERVIEW

The study analyses the hedging and diversification benefits of individual commodity futures and commodity indices. In addition to the passive investment strategy in commodity futures market, active strategies based on momentum, term structure and idiosyncratic volatility signals are designed to earn abnormal returns. Section 4.2 analyses the inflation hedging potential of commodity futures and commodity indices while Section 4.3 assesses the hedge and safe haven role of commodity futures and commodity indices. In Section 4.4, an active strategy is designed using the momentum signals available in the commodity market and its time-varying risk-return trade-off performance is evaluated. Similarly, Section 4.5 discusses the formation of active strategy based on term structure signals while Section 4.6 deals with the formation of an active strategy based on idiosyncratic volatility signals. Section 4.7 deals with the construction of combined strategy-MomTS which uses the methodology of both momentum and term structure strategies. In Section 4.8, combined strategy-MomIVol is designed which incorporates the methodology of both momentum and idiosyncratic volatility strategies. The chapter ends with a summary in Section 4.9.

4.2 COMMODITY FUTURES AS AN INFLATION HEDGE

The inflation hedging potential of commodity futures and commodity indices is analysed against the Wholesale Price Index (WPI) using cointegration approach. Based on the extensive outline of MS-VAR given by Krolzig (1997), the analysis of inflation hedging potential of commodity futures and indices is performed in two stages. In the first stage, Johansen cointegration test is used to identify the cointegrating relationship and the number of cointegrating vectors among the variables. In the second stage, Vector Error Correction Model (VECM) and Markov Switching-Vector Error Correction Model (MS-VECM) are estimated for each pair of commodity futures-WPI and the best model is selected by methodically considering the information criterion: Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQ) and Schwarz Information

Criterion (SIC). It is crucial to select the autoregressive order and order of integration of variables in cointegration analysis, details of which are given in the subsequent sub-sections.

4.2.1 Unit Root Test

The Augmented Dickey Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt Shin (KPSS) tests are applied to check if time series data are stationary and integrated of order one. In addition, Zivot and Andrews (1992) unit root test is used to incorporate the possibility of a structural break. This test allows for a single break both in the intercept and in the trend. These test results confirm that the time series of all the 13 commodity futures, three commodity sub-indices and WPI are stationary at first difference as depicted in Table 1 of Appendix I.

4.2.2 Selection of Autoregressive Order

Based on the results of AIC, SIC and HQ information criterion, the autoregressive order of one is selected for the models of Copper-WPI, Aluminium-WPI, Zinc-WPI, Natural gas-WPI, Cardamom-WPI, Mentha oil-WPI, MCXMETAL-WPI, MCXENERGY-WPI and MCXAGRI-WPI. Conversely, the autoregressive order of two is selected for Gold-WPI, Silver-WPI, Nickel-WPI, Crude oil-WPI and CPO-WPI and the autoregressive order of three is selected for Lead-WPI and Cotton-WPI as shown in Table 2 of Appendix I.

4.2.3 Johansen Cointegration Test

Johansen cointegration test is performed to check the existence of a cointegrated vector for the models as exhibited in Table 4.1. The results of Johansen trace statistics and max-eigen statistics confirm the existence of one cointegrating vector for the model of Gold-WPI, Silver-WPI, Copper-WPI, Nickel-WPI, Lead-WPI, Crude oil-WPI, CPO-WPI and Cotton-WPI. The estimated values of the normalized cointegrating vector for all the above models are exhibited in Table 4.2. In all the vectors, except for the model of Nickel-WPI, the expected sign of coefficients of cointegrated vector confirms a positive relationship in the long-run between commodity prices and WPI. In the model of Nickel-WPI, the positive sign of the coefficient (0.884) of cointegrating vector casts a doubt on the long-run positive relationship between nickel futures and WPI. Conversely, gold, silver, lead, CPO and crude oil coefficients are -0.341, -0.412, -0.109, -0.443 and -0.122, respectively, which are less than unity in magnitude and suggest the partial hedging ability of gold, silver, lead, CPO and crude oil. Similarly, copper (-0.011) and cotton (-0.007) coefficients are comparatively very low in magnitude which indicate the marginal inflation hedging potential of copper and cotton futures.

Table 4.1: Johansen Cointegration Test

Models	r (No. of Cointegration)	Trace Statistics	Probability	Max-Eigen Statistics	Probability
Gold-WPI	0	18.65	0.033	16.15	0.029
	1	2.50	0.157	2.50	0.157
Silver-WPI	0	23.33	0.013	20.97	0.007
	1	2.36	0.465	2.36	0.465
Copper-WPI	0	21.09	0.006	17.39	0.016
	1	3.70	0.054	3.70	0.054
Zinc-WPI	0	11.29	0.375	9.49	0.358
	1	1.80	0.763	1.80	0.763
Aluminium-WPI	0	14.03	0.138	12.56	0.098
	1	1.48	0.669	1.48	0.669
Nickel-WPI	0	20.49	0.012	19.17	0.008
	1	1.33	0.713	1.33	0.713
Lead-WPI	0	18.46	0.017	16.60	0.021
	1	1.86	0.172	1.86	0.172
Crude oil-WPI	0	16.10	0.040	14.13	0.052
	1	1.97	0.161	1.97	0.161
Natural Gas-WPI	0	8.02	0.655	6.43	0.694
	1	1.59	0.430	1.59	0.430
Cardamom-WPI	0	10.55	0.321	8.14	0.416
	1	2.41	0.286	2.41	0.286
Mentha Oil-WPI	0	13.78	0.240	9.54	0.368
	1	4.24	0.365	4.24	0.365
Cotton-WPI	0	16.18	0.039	12.40	0.097
	1	3.77	0.052	3.77	0.052
CPO-WPI	0	18.42	0.018	15.99	0.026
	1	2.42	0.119	2.42	0.119
MCXMETAL	0	12.00	0.185	10.21	0.211
	1	1.79	0.393	1.79	0.393
MCXENERGY	0	13.64	0.147	11.59	0.185
	1	2.05	0.151	2.05	0.151
MCXAGRI	0	12.17	0.168	9.55	0.252
	1	2.62	0.349	2.62	0.349

*(**Source:** Secondary Data Analysis)*
** shows the significance level at 1%, ** at 5% and ***at 10% level of significance.*

In the accompanying models of Aluminium-WPI, Zinc-WPI, Natural gas-WPI, Mentha oil-WPI, Cardamom-WPI, MCXMETAL-WPI, MCXENERGY-WPI and MCXAGRI-WPI, Johansen trace test and max-eigen tests confirm zero cointegrating vector between commodity futures and inflation. These cointegrating vectors show the long-run equilibrium relationship between commodity futures and inflation. Hence, hypothesis H_1 is rejected for the models Aluminium-WPI, Zinc-WPI, Natural gas-WPI, Mentha oil-WPI and Cardamom-WPI and hypothesis H_2 is rejected for MCXMETAL-WPI, MCXENERGY-WPI and MCXAGRI-WPI. These outcomes affirm the absence of long-run association of aluminium, zinc, natural gas, mentha oil, cardamom, MCXMETAL, MCXENERGY and MCXAGRI with WPI and suggest that these commodity futures and commodity indices cannot be used to hedge inflation.

Table 4.2: Cointegrating Vectors from Johansen Estimation

Variables	Vector # 1	Vector # 2
Log(WPI)	1	-0.327
Log(Gold)	-0.341	1.686
Log(WPI)	1	-1.45
Log(Silver)	-0.412	-0.994
Log(WPI)	1	-7.02
Log(Copper)	-0.011	4.42
Log(WPI)	1	-20.39
Log(Nickel)	0.884	1.1054
Log(WPI)	1	-0.079
Log(Lead)	-0.109	1.478
Log(WPI)	1	-0.510
Log(CPO)	-0.443	1.68
Log(WPI)	1	-0.032
Log(Cotton)	-0.007	31.72
Log(WPI)	1	-1.522
Log(Crude Oil)	-0.122	1.88

***(Source:** Secondary Data Analysis)*

4.2.4 Nonlinearity Test

Brock, Dechert and Scheinkman (BDS) as a test of nonlinearity is applied on the residual of the linear VECM which is estimated for the models of Gold-WPI, Silver-WPI, Copper-WPI, Nickel-WPI, Lead-WPI, Crude oil-WPI, CPO-WPI and Cotton-WPI. It tests the null hypothesis of Independent and Identically Distributed (IID) data. The BDS test is performed with embedding dimension equalling to two and ε equalling to the standard deviation of the dataset. Based on the results, the null hypothesis of BDS test for the models of Gold-WPI, Silver-WPI, Nickel-WPI, Lead-WPI, Crude oil-WPI, CPO-WPI and Cotton-WPI is accepted which confirms the absence of nonlinearity in the residual of the linear VECM as shown in Table 3 of Appendix I. Conversely, the null hypothesis is rejected for Copper-WPI which suggests the presence of nonlinearity in the residual of VECM estimated for Copper-WPI.

4.2.5 VECM and MS-VECM Estimation

In the wake of setting up the cointegrating relationship among the variables, VECM and different variants of MS-VECM are estimated for each model. The information criterion test results are used to determine the number of regimes for each model.

4.2.5.1 Gold-WPI

Table 4.3 shows a comparison between the linear VECM and distinctive specification of nonlinear MS-VECM based on the information criterion (AIC, HQ, SIC) and log-likelihood value. According to AIC and HQ criterion, the best model specification is MSIAH (2) VECM (2, 1)[1] with two regimes, heteroscedastic errors and an autoregressive order of two. Conversely, SIC favours linear VECM (2, 1). SIC supports a more parsimonious model and protects from over-parameterization by imposing stiffer penalty term associated with the number of parameters than AIC and HQ. The preference is given to SIC test results as the selection is made between a more parsimonious linear model and a less parsimonious nonlinear model. Hence, from the econometric perspective, the linear VECM (2, 1) is selected for assessing the inflation hedging potential of gold and it is inferred that there is a frail evidence in favour of two and three regimes[2].

Table 4.3: Information Criterion of VECM and MS-VECM of Gold-WPI Model

Model (Lag=2)	Estimation Period	No. of Obs.	AIC	SIC	HQ	Log-likelihood
VECM(2,1)	2006m10-2016m04	115	-904.72	-853.15	-899.92	446.41
MSIA(2)VECM(2,1)	2006m10-2016m04	115	-838.18	-745.35	-800.73	446.09
MSIAH(2)VECM(2,1)	2006m10-2016m04	115	-945.93	-835.91	-901.55	504.96
MSIA(3)VECM(2,1)	2006m10-2016m04	115	-886.32	-738.48	-826.68	486.16
MSIAH(3)VECM(2,1)	2006m10-2016m04	115	-895.57	-839.47	-900.23	498.25

*(**Source:** Secondary Data Analysis)*

Estimated results of VECM for Gold-WPI model are shown in Table 4.4. The coefficient of error correction term outlines the speed of convergence towards the long-run relationship. The error correction coefficient is the product of cointegrating vector and speed coefficient. The long-run equilibrium relationship between the variables is delineated by the cointegrating vector, whereas the speed of correction of disequilibrium caused by deviation in the short-run is presented by the speed coefficient. The positive sign of the error correction coefficient (0.086) in the equation of gold shows the divergence of gold futures price from inflation though, it is not significant. In order to hedge the inflation risk, it is essential that current high gold futures price results in a high inflation for the subsequent day. Convergence of WPI towards gold futures price is essential to activate this reverse causality. There is an evidence of equilibrium adjustment in the equation of WPI as the error correction coefficient (-0.021) has a negative sign and is statistically significant with t-statistics (-2.83). This convergence of WPI towards gold futures' price indicates that the inflation responds to the adjustment in the price of gold futures. It affirms that gold futures price movements contribute significantly to the direction of inflationary expectation and can be used as a hedge against inflation.

Table 4.4: Estimated Results of VECM (2, 1) of the Gold-WPI Model

Parameters		Δ Gold	Δ WPI
Intercept		0.398[0.595]	-0.949[-2.81]**
Δ Gold(-1)		-0.071[-0.428]	0.272[3.23]**
Δ Gold(-2)		-0.014[-0.097]	0.017[0.234]
Δ WPI(-1)		-0.159[-0.728]	-0.173[-1.57]
Δ WPI(-2)		0.197[1.25]	0.122[1.54]
Error Correction		0.086[0.577]	-0.021[-2.83]**
Standard Errors		0.0515	0.0259
Correlation	Δ Gold	1.00	0.948
	Δ WPI	0.948	1.00

*(**Source:** Secondary Data Analysis)*

*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and *** at 10% level of significance*
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Short-run dynamics are shown by the significant and positive relationship (0.272) between changes in WPI and the lagged (-1) changes in gold price. Hence, hypothesis H_1 is accepted for the model of Gold-WPI. It gives the positive indication of inflation hedging potential of gold futures in the short-run. Thus, results of long and short-run equilibrium adjustment and cointegrating vectors conclude that gold futures can provide a partial hedge against inflation. This outcome is consistent with the findings of Beckmann and Czudaj (2013) who found that gold is a partial hedge against inflation.

4.2.5.2 Silver-WPI

According to AIC and HQ information criterion, the best model specification to analyse the inflation hedging potential of silver futures is MSIAH (3) VECM (2, 1) with three regimes, heteroscedastic errors and an autoregressive order of two. On the contrary, SIC proposes the linear VECM (2, 1) as an appropriate model. Hence, based on the results of SIC, linear VECM (2, 1) is selected to assess the inflation hedging potential of silver futures[2] as depicted in Table 4.5.

Table 4.6 exhibits the estimation results of VECM for Silver-WPI model. The negative coefficient (-0.029) of error correction term and its t-statistics (-3.45) in the equation of WPI, depicts the convergence of inflation towards the silver futures price. This convergence proves that the inflationary expectation is a mirror image of the movement of silver futures prices. Hence, silver futures can be used as a hedge against inflation. Short-run dynamics show a significant positive correlation (0.179) between lagged (-1) changes in silver futures prices and changes in WPI. This result indicates the acceptance of hypothesis H_1 for the model of Silver-WPI which justify the inflation hedging potential of silver futures in short-run. Thus, the results of long and short-run dynamics and cointegrating vectors indicate that silver futures can be used to partially hedge the inflation risk.

Table 4.5: Information Criterion of VECM and MS-VECM of Silver-WPI Model

Model (Lag=2)	Estimation Period	No. of Obs.	AIC	SIC	HQ	Log-likelihood
VECM(2,1)	2006m10-2016m04	115	-697.75	-676.18	-699.95	347.13
MSIA(2)VECM(2,1)	2006m10-2016m04	115	-620.91	-556.27	-594.81	329.46
MSIAH(2)VECM(2,1)	2006m10-2016m04	115	-701.45	-618.14	-718.14	374.70
MSIA(3)VECM(2,1)	2006m10-2016m04	115	-710.10	-604.62	-704.52	386.05
MSIAH(3)VECM(2,1)	2006m10-2016m04	115	-732.48	-599.77	729.90	405.24

*(**Source:** Secondary Data Analysis)*

Table 4.6: Estimated Results of VECM (2, 1) of the Silver-WPI Model

Parameters		Δ Silver	Δ WPI
Intercept		0.175[0.182]	-1.54[-3.26]**
Δ Silver(-1)		-0.165[-0.845]	0.179[1.87]***
Δ Silver(-2)		-0.208[-1.31]	-0.006[-0.078]
Δ WPI(-1)		0.365[1.48]	0.033[0.268]
Δ WPI(-2)		-0.051[-0.307]	-0.070[-0.865]
Error Correction		0.188[1.07]	-0.029[-3.45]**
Standard Errors		0.0855	0.0421
Correlation	Δ Silver	1.00	0.716
	Δ WPI	0.716	1.00

*(**Source:** Secondary Data Analysis)*

*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%,** at 5% and *** at 10% level of significance.*

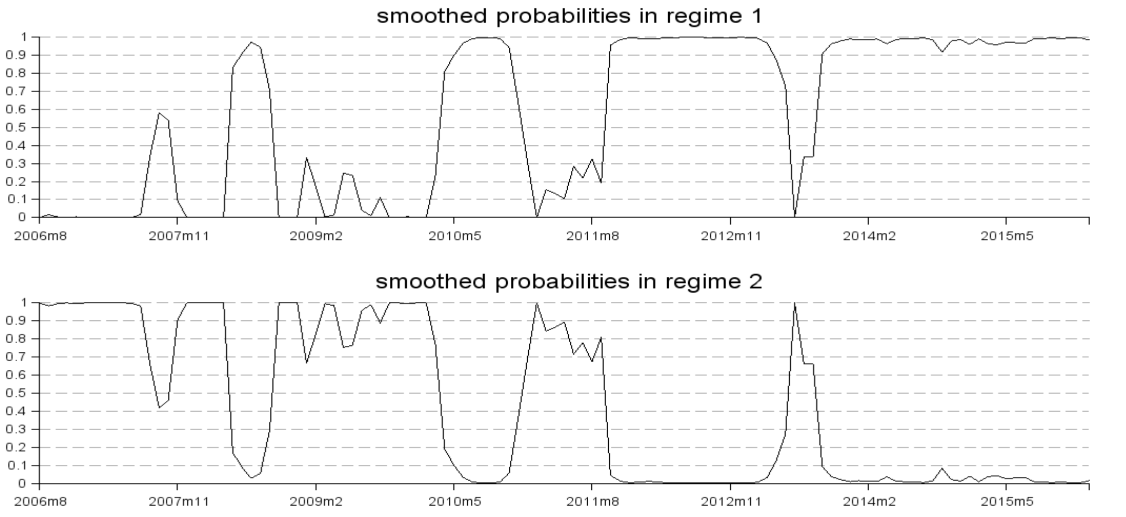
4.2.5.3 Copper-WPI

In the Copper-WPI model, all the information criterion and log likelihood value support a nonlinear model in contrast to linear model as shown in Table 4.7. Based on the information criterion results of HQ and SIC, the nonlinear MSIAH (2) VECM (1, 1) with two regimes, heteroscedastic error and an autoregressive order of one is selected to evaluate the inflation hedging potential of copper futures.

Table 4.7: Information Criterion of VECM and MS-VECM of Copper-WPI Model

Model (Lag=1)	Estimation Period	No. of Obs.	AIC	SIC	HQ	Log-likelihood
VECM(1,1)	2006m10-2016m04	115	-951.68	-920.74	-939.20	468.00
MSIA(2)VECM(1,1)	2006m10-2016m04	115	-755.94	-690.61	729.59	396.97
MSIAH(2)VECM(1,1)	2006m10-2016m04	115	-1023.83	-941.32	-990.55	535.92
MSIA(3)VECM(1,1)	2006m10-2016m04	115	-822.51	-715.93	-779.51	442.25
MSIAH(3)VECM(211)	2006m10-2016m04	115	-1056.85	-913.78	-965.45	548.00

*(**Source:** Secondary Data Analysis)*



*(**Source:** Secondary Data Analysis)*

Figure 4.1: Smoothed Probabilities of Regimes of the Copper-WPI Model

Considering the estimated value of smoothed probability, observations are classified into two regimes as depicted in Figure 4.1. The characterization of regimes based on monthly volatility and mean returns is considered as a reliable and accurate process of defining the different regimes of a market (Cakmakli et al., 2011). Hence, this study has taken the estimated value of monthly volatility and mean returns for each regime as a criterion to define the regimes. The monthly volatility and mean returns are estimated by the standard deviation and mean of copper futures returns for the set of observations that fall under the respective regimes. The regime characterization process defines the first regime as a period of ‘normal’ time which shows a steady and low volatile period with estimated monthly volatility of 5.94 percent in copper futures return and a positive mean return of 1.05 percent. On the contrary, the second regime shows a period of ‘extreme’ or ‘bear’ time with the estimated highest monthly volatility of 8.67 percent and the negative mean return of -0.958 percent in the copper futures return. The highly volatile months occur during the sub-prime crisis period between the years 2007 to 2009, which fall under the second regime. For instance, October 2008 and March 2009 are reported to have the highest fluctuation in the copper futures prices for the entire study period as -37.86 percent and 17.38 percent and occur in the second regime. The ergodic probability and transition matrix suggest the predominance of the second regime rather than the first regime. The first regime persists for 43 percent of the month and lasts for 3.90 months on an average, while the second regime remains for 57 percent of the month and continues for 5.18 months on an average.

Table 4.8: Estimated Results of MSIAH (2) VECM (1, 1) of the Copper-WPI Model

Parameters	Regime 1		Regime 2	
	Δ Copper	Δ WPI	Δ Copper	Δ WPI
Intercept	3.82[13.76]*	-0.137[-11.72]	1.28[0.846]	0.951[8.32]*
Δ Copper(-1)	-0.198[-1.59]	0.007[1.56]	0.401[3.13]*	0.069[3.20]*
Δ WPI(-1)	1.17[0.887]	0.082[1.74]***	-0.461[-0.703]	-0.125[-1.09]
Error Correction	-0.725[-13.73]*	0.03[11.73]*	0.003[-0.851]	-0.181[-8.37]*
Variance-Covariance Matrix	0.003[4.13]*	0.000032[1.87]***	0.0063[5.46]*	-0.00008[-0.6]
Δ Copper	0.000032[1.87]***	0.000004[7.51]*	-0.00008[-0.6]	0.0002[4.07]*
Δ WPI				

	Transition Matrix		Persistence of Regimes		
	Regime 1	Regime 2	Observations	Ergodic Probability	Duration
Regime 1	0.744	0.193	52	0.43	3.90
Regime 2	0.256	0.807	63	0.57	5.18

*(**Source:** Secondary Data Analysis)*

*Values in the square bracket exhibit ‘t’ statistics and * shows significance level at 1%, ** at 5% and *** at 10% level of significance.*

In the first regime, the positive sign of the error correction coefficient (0.03) and its t-statistics (11.73) in the equation of WPI shows the inability of copper futures prices to anticipate the future inflation as shown in Table 4.8. On the contrary, the negative sign of error correction term (-0.181) and its t-statistics (-8.37) in the WPI index of the second regime confirms the convergence of inflation towards the copper futures series. This convergence reveals that copper futures price movements can be used to foresee future inflation during the second regime which represents the ‘extreme’ or ‘bear’ period. Moreover, it shows that the ability of copper futures as an inflation hedge essentially relies on the time horizon of investment. Thus, during a certain time period when general price levels do not demonstrate the adjustment pattern, copper is not able to hedge the portfolio from the negative impact of inflation. The short-run dynamics are depicted by the positive and insignificant relationship between change in lagged (-1) value of copper and change in WPI in the first regime. The second regime shows a significant and positive dependence (0.069) of changes in WPI over changes in lagged (-1) value of copper. It indicates the acceptance of hypothesis H_1 in the second regime which gives evidence of inflation hedging potential of copper for the second regime rather than the first regime in the short-run. Hence, based on the results of cointegrating vector and long and short-run dynamics of both the regimes, it is inferred that copper futures provide a marginal hedge against inflation.

Regime Classification Measure (RCM) is estimated using Equation (3.10) to ascertain the quality of regime classification. In the Copper-WPI model, RCM equals to 21.38 which is lesser than 50. Hence, the RCM statistic suggests that MS-VECM model is properly specified and appropriate for the investigation of inflation hedging potential of copper futures.

4.2.5.4 Lead-WPI

According to AIC and HQ information criterion, the most appropriate model to assess the inflation hedging potential of lead futures is MSIAH (2) VECM (3,1) with two regimes, heteroscedastic error and an autoregressive order of three. Conversely, SIC suggests that linear VECM (3, 1) is the best model specification as depicted in Table 4.9. Preference is given to the SIC results as SIC supports a more parsimonious model. Hence, VECM (3,1) is selected to investigate the inflation hedging potential of lead futures[2].

The estimated results of VECM (3, 1) are shown in Table 4.10. The error correction coefficient of WPI has a negative sign (-0.079) and is statistically significant with t-statistics (-2.11). It gives an indication that inflation converges towards lead futures prices and lead futures price movements, contribute significantly to the direction of inflationary expectation. Hence, it can be used as a hedge against inflation. Conversely, short-run dynamics are shown by the negative and significant relationship between changes in WPI and the lagged (-3) changes in lead futures prices. It suggests the rejection of hypothesis H_1 which confirms the lack of inflation hedging potential of lead futures in the short-run. However, the results of error correction coefficient and cointegrating vector conclude that lead futures can provide a marginal hedge against inflation.

Table 4.9: Information Criterion of VECM and MS-VECM of Lead-WPI Model

Model (Lag=3)	Estimation Period	No. of Obs.	AIC	SIC	HQ	Log-likelihood
VECM(3,1)	2007m11-2016m04	102	-891.38	-874.98	-868.57	620.78
MSIA(2)VECM(3,1)	2007m11-2016m04	102	-875.25	-821.65	-832.35	585.77
MSIAH(2)VECM(3,1)	2007m11-2016m04	102	-905.57	-850.89	-890.78	655.78
MSIA(3)VECM(3,1)	2007m11-2016m04	102	-899.45	-827.42	-847.64	601.54
MSIAH(3)VECM(3,1)	2007m11-2016m04	102	-900.01	-809.87	-877.98	674.25

*(**Source:** Secondary Data Analysis)*

Table 4.10: Estimated Results of VECM (3, 1) of the Lead-WPI Model

Parameters		Δ Lead	Δ WPI
Intercept		5.18E-05[5.86E-05]	0.056[0.636]
Δ Lead(-1)		-0.029[-0.291]	0.0002[0.022]
Δ Lead(-2)		-0.055[-0.573]	0.007[0.761]
Δ Lead(-3)		-0.052[-0.534]	-0.019[-1.94]***
Δ WPI(-1)		-0.942[-0.902]	0.048[0.465]
Δ WPI(-2)		-2.24[-2.15]**	-0.283[-2.74]**
Δ WPI(-3)		-1.12[-0.998]	0.046[0.419]
Error Correction		-0.161[3.38]**	-0.079[-2.11]**
Standard Errors		8.849	0.875
Correlation	Δ Lead	1.00	0.074
	Δ WPI	0.074	1.00

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*

4.2.5.5 Nickel-WPI

In the model of Nickel-WPI, the results of AIC suggest that the best model specification is nonlinear MSIAH (2) VECM (2, 1) with two regimes, heteroscedastic error and an autoregressive order of two. Conversely, information criterion SIC and HQ propose the linear VECM (2, 1) as an appropriate model for assessing the inflation hedging potential of nickel futures[2] as depicted in Table 4.11.

Table 4.11: Information Criterion of VECM and MS-VECM of Nickel-WPI Model

Model (Lag=2)	Estimation Period	No. of Obs.	AIC	SIC	HQ	Log-likelihood
VECM(2,1)	2007m5-2016m04	108	-939.83	-889.20	-919.38	521.23
MSIA(2)VECM(2,1)	2007m5-2016m04	108	-950.23	-850.14	-860.25	485.22
MSIAH(2)VECM(2,1)	2007m5-2016m04	108	-1062.04	-847.03	-878.47	563.02
MSIA(3)VECM(2,1)	2007m5-2016m04	108	-977.87	-831.55	-881.23	499.46
MSIAH(3)VECM(2,1)	2007m5-2016m04	108	-992.78	-838.56	-901.33	601.23

*(**Source:** Secondary Data Analysis)*

The estimated results of VECM (2, 1) are given in Table 4.12. The positive sign of the long-run error correction coefficient (0.003) and its t-statistics (0.648) in the equation of WPI demonstrates the inverse of convergence of WPI towards nickel futures prices. This outcome depicts the inefficiency of nickel futures prices to give a direction to future inflationary expectation. Hence, it cannot be used as a hedge against inflation. Conversely, short-run dynamics show a positive and significant relationship between lagged (-1) changes in nickel and changes in WPI. It suggests the acceptance of hypothesis H_1 which gives the positive indication of inflation hedging potential of nickel futures in the short-run. However, long-run dynamics and cointegrating vector show the inefficiency of convergence of WPI towards nickel futures price which is a weak evidence in support of the inflation hedging potential of nickel futures.

Table 4.12: Estimated Results of VECM (2, 1) of the Nickel-WPI Model

Parameters		Δ Nickel	Δ WPI
Intercept		1.78[4.13]*	-0.027[-0.629]
Δ Nickel(-1)		0.068[0.731]	0.018[1.94]***
Δ Nickel(-2)		0.074[0.777]	0.015[1.57]
Δ WPI(-1)		1.67[1.65]	0.209[2.06]**
Δ WPI(-2)		1.24[1.23]	0.020[0.200]
Error Correction		-0.143[-4.16]*	0.003[0.648]
Standard Errors		0.0844	0.0084
Correlation	Δ Nickel	1.00	0.212
	Δ WPI	0.212	1.00

*(**Source:** Secondary Data Analysis)*

*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and *** at 10% level of significance.*

4.2.5.6 Crude oil-WPI

The AIC, SIC and HQ values of the VECM and distinctive specification of MS-VECM are shown in Table 4.13. According to AIC, the best model specification is MSIAH (2)

VECM (2, 1) with two regimes, heteroscedastic errors and an autoregressive order of two. Conversely, SIC and HQ criterion favour linear VECM (2, 1). Hence, from the econometric perspective, the linear VECM (2, 1) is selected for assessing the inflation hedging potential of crude oil and it is inferred that there is a weak evidence in favour of two and three regimes[2].

Table 4.13: Information Criterion of VECM and MS-VECM of Crude oil-WPI Model

Model (Lag=2)	Estimation Period	No. of Obs.	AIC	SIC	HQ	Log-likelihood
VECM(2,1)	2006m10-2016m04	115	-495.10	-487.41	-497.08	398.34
MSIA(2)VECM(2,1)	2006m10-2016m04	115	-477.35	-373.21	-401.36	322.24
MSIAH(2)VECM(2,1)	2006m10-2016m04	115	-539.68	-429.66	-495.29	301.84
MSIA(3)VECM(2,1)	2006m10-2016m04	115	-501.67	-399.24	-437.31	357.64
MSIAH(3)VECM(2,1)	2006m10-2016m04	115	-521.89	-412.88	-487.32	412.54

*(**Source:** Secondary Data Analysis)*

Table 4.14: Estimated Results of VECM (2, 1) of the Crude oil-WPI Model

Parameters	Δ Crude Oil	Δ WPI
Intercept	1.13[3.71]*	0.252[0.888]
Δ Crude oil(-1)	0.329[3.11]*	0.483[4.92]*
Δ Crude oil(-2)	0.249[2.15]**	0.052[0.483]
Δ WPI(-1)	-0.093[-0.801]	-0.223[-2.08]**
Δ WPI(-2)	-0.024[-0.219]	-0.096[-0.959]
Error Correction	0.126[3.71]*	0.027[0.872]
Standard Errors	0.085	0.079
Correlation Δ Crude oil	1.00	0.748
Δ WPI	0.748	1.00

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and *** at 10% level of significance.*

The estimated results of VECM (2, 1) are given in Table 4.14. The positive sign of the long-run error correction coefficient (0.027) and its t-statistics (0.872) in the equation of WPI index demonstrates the inverse of convergence of inflation towards crude futures prices. This outcome depicts the inefficiency of crude futures price to give a direction to future inflationary expectation. Hence, it cannot be used as a hedge against inflation. Conversely, short-run dynamics show a positive and significant relationship (0.483) between lagged (-1) changes in crude oil and changes in WPI. Hence, hypothesis H_1 is accepted which confirms the inflation hedging potential of crude oil futures in the short-run. However, long-run dynamic shows the inefficiency of WPI to converge towards crude futures prices which is a weak evidence in support of the inflation hedging potential of crude oil futures.

4.2.5.7 CPO-WPI

In the model of CPO-WPI, information criterion AIC suggests that MSIAH (2) VECM (2, 1) with two regimes, heteroscedastic errors and an autoregressive order of two is an appropriate model to assess the inflation hedging potential of CPO futures. Conversely, SIC and HQ information criterion indicate the linear VECM (2, 1) as the best model specification which is shown in Table 4.15. Hence, by giving preference to SIC and HQ test results, linear VECM (2, 1) is estimated to analyse the inflation hedging potential of CPO futures[2].

Table 4.15: Information Criterion of VECM and MS-VECM of CPO-WPI Model

Model (Lag=2)	Estimation Period	No. of Obs.	AIC	SIC	HQ	Log-likelihood
VECM(2,1)	2008m10-2016m04	91	-798.52	-787.81	-795.64	459.23
MSIA(2)VECM(2,1)	2008m10-2016m04	91	-725.87	-685.78	-747.23	401.56
MSIAH(2)VECM(2,1)	2008m10-2016m04	91	-809.10	-706.57	-767.54	436.55
MSIA(3)VECM(2,1)	2008m10-2016m04	91	-775.24	-699.24	-721.45	433.21
MSIAH(3)VECM(2,1)	2008m10-2016m04	91	-798.45	-712.87	-789.23	506.12

*(**Source:** Secondary Data Analysis)*

Table 4.16: Estimated Results of VECM (2, 1) of the CPO-WPI Model

Parameters		**Δ CPO**	**Δ WPI**
Intercept		0.227[0.302]	0.025[0.357]
Δ CPO(-1)		-0.229[-1.60]	0.019[2.01]**
Δ CPO(-2)		-0.191[-1.77]***	-0.016[-1.60]
Δ WPI(-1)		0.433[0.404]	-0.367[-3.74]*
Δ WPI(-2)		-2.46[-2.25]**	-0.334[-3.34]*
Error Correction		1.32[3.45]*	-0.131[-3.75]*
Standard Errors		7.14	0.654
Correlation	Δ CPO	1.00	0.614
	Δ WPI	0.614	1.00

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and *** at 10% level of significance.*

The estimated results of linear VECM (2, 1) are reported in Table 4.16. The negative sign of the error correction coefficient (-0.131) and its t-statistics (-3.75) on the WPI indicates that the WPI responds positively to the changes in the CPO futures prices. It shows that

CPO futures prices influence the value of WPI and give the direction to the future inflationary expectations. Hence, CPO futures can be used as a hedge against inflation. Short-run dynamics are shown by positive and significant correlation (0.019) between changes in WPI and lagged (-1) changes in CPO futures prices. It suggests the acceptance of hypothesis H_1 which confirms the short-run inflation hedging potential of CPO futures. Thus, the results of long and short-run dynamics and cointegrating vectors indicate that CPO futures can be used to partially hedge the inflation risk.

4.2.5.8 Cotton-WPI

The values of AIC, SIC and HQ information criterion of VECM and different specification of MS-VECM are shown in Table 4.17. The results of information criterion AIC indicates that MSIAH (2) VECM (3, 1) with two regimes, heteroscedastic errors and an autoregressive order of three is a suitable model to assess the inflation hedging potential of copper futures. On the contrary, SIC and HQ information criterion suggest the linear VECM (3, 1) as an appropriate model specification. Based on the results of SIC and HQ information criterion, linear VECM (3, 1) is estimated to assess the inflation hedging potential of cotton futures[2].

Table 4.17: Information Criterion of VECM and MS-VECM of Cotton-WPI Model

Model (Lag=3)	Estimation Period	No. of Obs.	AIC	SIC	HQ	Log-likelihood
VECM(3,1)	2012m02-2016m04	51	-541.86	-533.87	-557.63	427.56
MSIA(2)VECM(3,1)	2012m02-2016m04	51	-516.78	-401.99	-509.78	389.48
MSIAH(2)VECM(3,1)	2012m02-2016m04	51	-572.62	-467.62	-530.10	326.31
MSIA(3)VECM(3,1)	2012m02-2016m04	51	-533.15	-418.89	-522.78	403.78
MSIAH(3)VECM(3,1)	2012m02-2016m04	51	-548.23	-447.56	-550.46	455.12

*(**Source:** Secondary Data Analysis)*

The estimated results of VECM (3, 1) for the model of Cotton-WPI are shown in Table 4.18. The negative sign of the error correction coefficient (-0.032) and its t-statistics (-2.23) on the equation of WPI depicts the convergence of WPI towards cotton futures prices. It indicates that cotton futures prices contribute significantly to the movements of the inflation index. Hence, cotton futures can be used as a hedge against inflation. Short-run dynamics are shown by the positive and significant correlation between lagged (lag -1 and -2) changes in cotton futures return and changes in WPI which suggest the acceptance of hypothesis H_1. It confirms the inflation hedging potential of cotton futures in the short-run. Thus, the results of long and short-run dynamics and cointegrating vectors indicate that cotton futures can provide a marginal hedge against inflation risk.

Table 4.18: Estimated Results of VECM (3, 1) of the Cotton-WPI Model

Parameters		Δ Cotton	Δ WPI
Intercept		-203.09[-1.22]	0.275[2.39]**
Δ Cotton(-1)		-0.017[-0.089]	0.0003[2.67]**
Δ Cotton(-2)		-0.379[-2.05]**	0.0002[1.92]***
Δ Cotton(-3)		-0.216[-1.11]	-1.32E-05[-0.098]
Δ WPI(-1)		678.56[2.86]**	0.273[1.66]
Δ WPI(-2)		-284.81[-1.26]	0.049[0.315]
Δ WPI(-3)		105.95[0.523]	-0.069[-0.498]
Error Correction		-0.222[1.54]	-0.032[-2.23]**
Standard Errors		987.85	0.685
Correlation	Δ Cotton	1.00	0.231
	Δ WPI	0.231	1.00

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and *** at 10% level of significance.*

4.2.6 Combined Results

The outcomes of cointegration test suggest that zinc, aluminium, natural gas, cardamom, and mentha oil futures and sub-indices MCXMETAL, MCXENERGY and MCXAGRI cannot be used as a hedge against inflation. Empirical results give evidence in support of partial inflation hedging potential of gold, silver, lead and CPO futures. Conversely, estimated results for nickel and crude oil futures show a feeble confirmation in favour of its inflation hedging potential. Moreover, the results indicate a marginal inflation hedging potential of copper and cotton futures. However, the price adjustment pattern in copper futures depends on the respective regimes. The regime classification characterizes the first regime as a period of 'normal' time with low volatility**,** not much influenced by real shocks and the second regime as a period of 'extreme' time with the highest monthly volatility. During the first regime, copper has not been able to sustain its inflation hedging potential due to lack of price adjustment by an inflation index. Notably, classification of regimes confirms that data fits well with regime-switching approach since both the regimes can be clearly distinguished with their unique characteristics.

After analysing the inflation hedging potential of commodity futures and commodity indices, it is necessary to assess the hedging and diversification benefits of commodity futures and indices against stock and bond market plunge. Section 4.3 analyses the hedging and diversification benefits of commodity futures and commodity indices.

4.3 COMMODITY FUTURES AS A HEDGE AND DIVERSIFIER AGAINST EQUITY AND BOND RISK

The hedging and diversification benefits of commodity futures and commodity indices are analysed using nonlinear Markov Switching-Vector Autoregression (MS-VAR) model. It is essential to perform the comparative performance evaluation of the return distributions of commodity futures with the return distributions of the Nifty (CNX Nifty stock index) and bond (CCIL liquid total return bond index) before proceeding with the implementation of MS-VAR. Summary statistics shown in Table 4.19, give the values of mean, median, standard deviation, skewness and kurtosis of commodity futures, Nifty and bond indices.

Table 4.19: Summary Statistics

Commodity	Mean	Median	SD*	Skewness	Kurtosis	Obs.
Gold	1.00	0.925	5.17	0.141	3.38	118
Silver	0.756	0.449	8.53	0.064	3.75	118
Copper	-0.014	0.411	7.54	-1.17	7.80	118
Zinc	-0.123	-0.218	7.87	-0.646	5.05	118
Aluminium	-0.067	-0.436	5.87	0.098	3.39	118
Nickel	-0.917	0.154	8.96	-0.361	2.86	111
Lead	-0.060	0.463	9.02	-0.424	3.66	105
Crude Oil	-0.104	1.12	9.20	-0.778	4.64	118
Natural Gas	-0.795	-0.417	12.42	-0.139	4.44	117
Cardamom	0.934	0.50	12.32	0.40	3.56	118
Mentha Oil	0.591	0.117	10.56	-0.301	6.15	118
CPO	0.096	0.513	7.45	-0.527	3.82	94
Cotton	-0.143	1.07	5.59	-0.423	3.32	54
MCXMETAL	0.518	0.519	5.23	-0.283	4.59	118
MCXENERGY	-0.201	0.799	8.33	-0.551	3.83	118
MCXAGRI	0.323	0.701	6.47	-0.846	7.56	118
Nifty	0.779	0.634	7.01	-0.637	6.65	118
Bond	0.648	0.616	2.36	1.58	15.05	118

*(**Source:** Secondary Data Analysis)*
**SD refers to the Standard Deviation.*

The results show that gold futures give the highest mean returns and lowest standard deviation compared to other commodity futures and Nifty stock index. Gold, silver, cardamom, mentha oil, CPO, MCXMETAL, MCXAGRI, Nifty and bond index give positive mean returns while copper, zinc, aluminium, nickel, lead, crude oil, natural gas, cotton futures and MCXENERGY index show negative mean returns. The return distributions of gold, silver, aluminium, cardamom futures and bond index are positively skewed while Nifty index and other commodity futures and commodity indices are negatively skewed. The median value of Nifty and bond index returns are higher than the median value of silver, copper, zinc, aluminium, nickel, lead, crude oil, natural gas, cardamom, mentha oil, CPO, cotton futures and MCXMETAL index while they are less than gold futures, MCXENERGY and MCXAGRI indices. Hence, the returns distributions of Nifty and bond indices are different from the returns distributions of other commodity futures and commodity indices.

The analysis of hedging and diversification benefits of commodity futures are performed in three different stages using a broad overview of MS-VAR given by Krolzig (1997). Primarily, a unit root test is conducted to check if commodity futures and Nifty are integrated of the same order. In the next step, nonlinearity test is conducted before proceeding with a nonlinear estimation. In the last stage, estimation of MS-VAR is performed for all the models.

4.3.1 Unit Root Test

The ADF and KPSS unit root tests are applied to check the stationarity of time series data. In addition, Zivot and Andrews unit root test is conducted to incorporate the possibility of a structural break. This test allows for a single break both in the intercept and in the trend. These test results confirm that the time series of all the commodity futures, commodity indices, Nifty and bond indices are stationary at first difference as shown in Table 4 in Appendix I.

4.3.2 Selection of Autoregressive Order

The autoregressive order of one is selected for the models of Nifty-Bond-Gold, Nifty-Bond-Silver, Nifty-Bond-Copper, Nifty-Bond-Zinc, Nifty-Bond-Aluminium, Nifty-Bond-Nickel, Nifty-Bond-Lead, Nifty-Bond-Crude Oil, Nifty-Bond-Natural Gas, Nifty-Bond-Cardamom, Nifty-Bond-Mentha Oil, Nifty-Bond-CPO, Nifty-Bond-Cotton, Nifty-Bond-MCXMETAL, Nifty-Bond-MCXENERGY and Nifty-Bond-MCXAGRI as depicted in Table 5 of Appendix I.

4.3.3 Nonlinearity Test

BDS as a test of nonlinearity is applied on the residual of linear Vector Autoregression (VAR), estimated for all the models. It tests the null hypothesis of IID data. The BDS test is performed with embedding dimension equalling to two and ε equalling to the standard deviation of the dataset. The null hypothesis of BDS test is rejected for all the models of commodity futures and commodity indices which confirm the presence of nonlinearity in the residual of linear VAR model as shown in Table 6 of Appendix I. This result suggests the application of nonlinear model to assess the hedging and diversification benefits of commodity futures and commodity indices.

4.3.4 Estimation of MS-VAR

Based on the BDS test and information criterion, the nonlinear model is selected for all the pairs of commodity, Nifty and bond as depicted in Table 7 of Appendix I. Subsequently, in view of the information criterion results, two regimes are selected for Nifty-Bond-Gold, Nifty-Bond-Silver, Nifty-Bond-Copper, Nifty-Bond-Zinc, Nifty-Bond-Aluminium, Nifty-Bond-Nickel, Nifty-Bond-Lead, Nifty-Bond-Crude Oil, Nifty-Bond-Natural Gas, Nifty-Bond-Cardamom, Nifty-Bond-Mentha Oil, Nifty-Bond-CPO, Nifty-Bond-Cotton, Nifty-Bond-MCXMETAL, Nifty-Bond-MCXENERGY and Nifty-Bond-MCXAGRI.

Values of information criterion shown in Table 7 of Appendix I suggests that MSIAH (2) VAR (1) with two regimes, heteroscedastic error and an autoregressive order of one, as the most appropriate model[3] to define the hedge and safe haven role of all the commodity futures and commodity indices.

4.3.4.1 Regimes Characterization

The regimes are constructed by using observations which are classified into the regimes based on smoothed probabilities estimated by Markov switching model for Nifty-Bond-Gold, Nifty-Bond-Silver, Nifty-Bond-Copper, Nifty-Bond-Zinc, Nifty-Bond-Aluminium, Nifty-Bond-Nickel, Nifty-Bond-Lead, Nifty-Bond-Crude Oil, Nifty-Bond-Natural Gas, Nifty-Bond-Cardamom, Nifty-Bond-Mentha Oil, Nifty-Bond-CPO, Nifty-Bond-Cotton, Nifty-Bond-MCXMETAL, Nifty-Bond-MCXENERGY and Nifty-Bond-MCXAGRI, respectively. The next step is the characterization of regimes. In the previous study, Beckmann et al. (2015) evaluated the hedge and safe haven role of gold with two regimes. They used the low and high deviation of stock returns, above and below the threshold value, as criteria to discriminate between the state of 'normal' time and state of 'extreme' time. In the present study, hedge and safe haven role of all the commodity futures are evaluated for two regimes. The characterization of regimes, based on daily volatility and mean returns is considered as a reliable and accurate process of identifying the different regimes of the market (Cakmakli et al., 2011). Hence, in contrast to threshold level criteria adopted by Beckmann et al. (2015), this study has considered the estimated value of daily volatility and mean returns for each regime as a criterion to define the regimes. The daily volatility and mean returns are estimated by the standard deviation and mean of Nifty and bond returns for the set of observations that occur under the respective regimes. The regime with the highest volatility and lowest mean return depict the period of 'extreme' or 'bear' time and the regime with the lowest volatility and highest mean return shows the period of 'normal' time. Daily volatility and mean return of the regimes for all the commodities are shown in Table 4.20.

The first regime of Nifty-Bond-Gold model is characterized as 'extreme' or 'bear' period with the highest monthly volatility of 11.69 percent in Nifty and 3.73 percent in bond and the highest negative mean returns of -1.01 percent in Nifty and -0.192 percent in bond. It persists during the months when volatility in returns of Nifty is more due to major shocks such as the most volatile periods during the sub-prime crisis are from January 2008 to September 2009, which occurs in the first regime and allow to judge the safe haven role of gold futures. For instance, the highest monthly fluctuations in the prices of Nifty for the study period are -30.21 percent and 24.74 percent and for the bond are -7.93 percent and 13.93 percent which are included in the first regime. Conversely, the second regime is characterized as 'normal' period with a low monthly volatility of 5.42 percent in Nifty and 1.89 percent in bond and the positive mean return of 1.19 percent in Nifty and 0.839 percent in bond. The ergodic probability and transition matrix suggest the predominance of the second regime over the first regime. The first regime persists for 19.1 percent of the time and lasts for 3.16 months on an average. The second regime accounts for 80.9 percent of the time and persists for 13.34 months on an average as shown in Table 4.21.

A similar procedure is used for the regime characterization of the all the other models. In all the models, the first regime is defined as 'extreme' or 'bear' period and the second regime as 'normal' period. The first regime helps to analyse the safe haven property of commodities and the second regime depicts the hedging potential of commodity futures. In addition, the ergodic probability and transition matrix suggest a predominance of the second regime over the first regime for all the models.

Table 4.20: Estimated Results of Daily Volatility and Mean Return for all the Models

		Nifty Stock Index		CCIL Bond Index	
Models	Parameters	Regime 1	Regime 2	Regime 1	Regime 2
Nifty-Bond-Gold	Volatility	11.69	5.42	3.73	1.89
	Mean Return	-1.01	1.19	-0.192	0.839
Nifty-Bond-Silver	Volatility	12.11	5.17	5.21	1.05
	Mean Return	-2.35	1.46	0.458	0.689
Nifty-Bond-Copper	Volatility	11.89	5.03	4.96	1.07
	Mean Return	-2.23	1.51	0.394	0.709
Nifty-Bond-Zinc	Volatility	14.72	5.76	5.25	1.85
	Mean Return	-1.53	1.02	-0.36	0.751
Nifty-Bond-Aluminium	Volatility	11.80	5.09	4.97	1.05
	Mean Return	-2.13	1.48	0.401	0.707
Nifty-Bond-Lead	Volatility	10.83	5.23	4.55	0.963
	Mean Return	-1.89	1.41	0.486	0.677
Nifty-Bond-Nickel	Volatility	13.45	5.40	5.89	1.11
	Mean Return	-2.46	1.10	0.64	0.625
Nifty-Bond-Crude Oil	Volatility	12.98	4.91	5.08	1.18
	Mean Return	-0.69	1.09	0.539	0.671
Nifty-Bond-Natural Gas	Volatility	13.88	4.99	4.41	1.74
	Mean Return	-0.418	1.00	-0.359	0.836
Nifty-Bond-Cardamom	Volatility	12.37	5.38	4.83	1.45
	Mean Return	-0.387	1.02	1.00	0.575
Nifty-Bond-CPO	Volatility	13.52	5.22	5.31	1.89
	Mean Return	-1.53	1.00	-0.447	0.862
Nifty-Bond-Mentha Oil	Volatility	13.45	5.32	5.86	1.15
	Mean Return	-2.24	1.25	0.921	0.604
Nifty-Bond-Cotton	Volatility	2.96	4.43	2.88	0.974
	Mean Return	-4.12	1.59	-0.041	0.874
Nifty-Bond-MCXMETAL	Volatility	11.63	5.02	4.87	1.06
	Mean Return	-2.32	1.57	0.474	0.692
Nifty-Bond-MCXENERGY	Volatility	12.67	4.77	4.90	1.13
	Mean Return	-0.817	1.17	0.537	0.674
Nifty-Bond-MCXAGRI	Volatility	11.42	5.09	4.68	1.05
	Mean Return	-1.20	1.34	0.375	0.725

*(**Source:** Secondary Data Analysis)*

4.3.4.2 Nifty-Bond-Gold

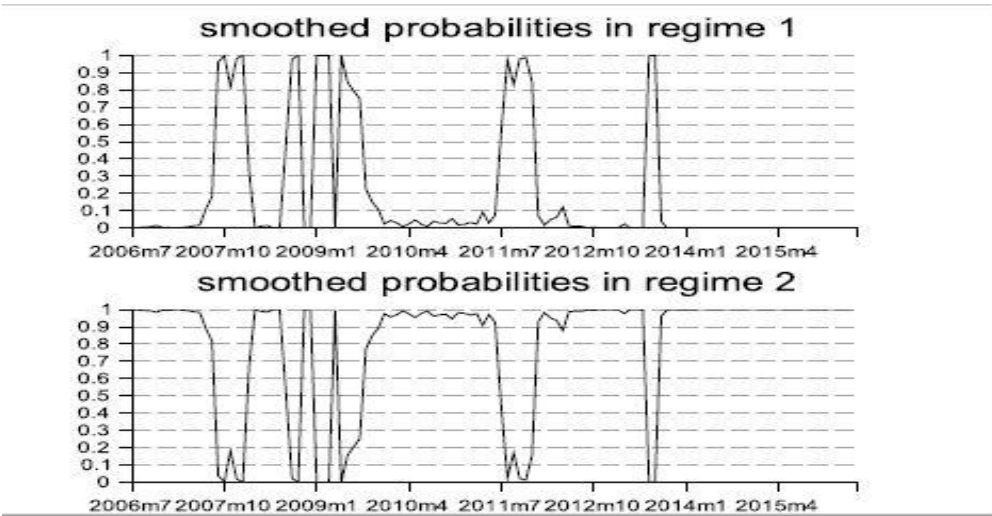
Estimated results of MSIAH (2) VAR (1) for Nifty-Bond-Gold model and smoothed probabilities are depicted in Table 4.21 and Figure 4.2, respectively. Table 4.21 shows a significant and positive correlation of gold with Nifty (0.141) and bond (0.462) for the first regime. Based on the definition given by Baur and McDermott (2010), this result signifies that the gold futures cannot be used as a safe haven against extreme movements of stock and bond markets. Similarly, the negative and insignificant correlation of gold with Nifty (-1) and positive and insignificant correlation of gold with the bond (-1) in the second regime confirm the weak hedging potential of gold futures.

Table 4.21: Estimated Results of MSIAH (2) VAR (1) of Nifty-Bond-Gold Model

Parameters	Regime 1 (Extreme or Bear)			Regime 2 (Normal)		
	Δ Gold	Δ Nifty	Δ Bond	Δ Gold	Δ Nifty	Δ Bond
Intercept	-3.08[-2.94]*	-1.41[-0.728]	1.92[4.59]*	-0.067[-0.393]	0.255[1.28]	-0.046[-0.715]
Δ Gold(-1)	0.856[12.86]*	-0.18[-1.49]	0.106[4.38]*	0.949[39.45]*	0.021[0.725]	-0.017[-1.86]
Δ Nifty(-1)	0.141[2.47]**	0.973[9.25]*	-0.00[-0.001]	-0.034[-0.989]	0.871[21.62]*	-0.081[-6.01]*
Δ Bond(-1)	0.462[2.54]**	0.469[1.39]	0.589[8.14]*	0.119[1.76]	0.092[1.18]	1.13[42.99]*
Variance-Covariance Matrix						
Δ Gold	0.003[3.2]*	0.0001[0.1]	-0.003[-1.25]	0.002[6.68]*	-0.06[-2.49]**	-0.004[-0.64]
Δ Nifty	0.0001[0.1]	0.011[3.2]*	-0.001[-2.1]**	-0.06[-2.49]**	0.002[6.77]*	0.003[3.03]**
Δ Bond	-0.003[-1.25]	-0.001[-2.1]**	0.0004[3.17]**	-0.004[-0.64]	0.003[3.03]**	0.0002[6.4]*

	Transition Matrix		Persistence of Regimes		
	Regime 1	Regime 2	Observations	Ergodic Probability	Duration
Regime 1	0.684	0.075	22	0.191	3.16
Regime 2	0.316	0.925	96	0.809	13.34

(***Source:*** *Secondary Data Analysis*)
*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*



(***Source:*** *Secondary Data Analysis*)
Figure 4.2: Smoothed Probabilities of Regimes of Nifty-Bond-Gold Model

4.3.4.3 Nifty-Bond-Silver

The estimated values of MSIAH (2) VAR (1) and smoothed probabilities for the model Nifty-Bond-Silver are depicted in Table 4.22 and Figure 4.3, respectively. Table 4.22 shows a positive and significant correlation of silver with Nifty (0.208) and bond (0.658) for the first regime. It confirms that silver futures cannot be used as a safe haven against extreme stock and bond market movements. Conversely, the positive and insignificant correlation of silver with Nifty (0.0004) and bond (0.001) in the second regime signifies the weak hedging potential of silver futures.

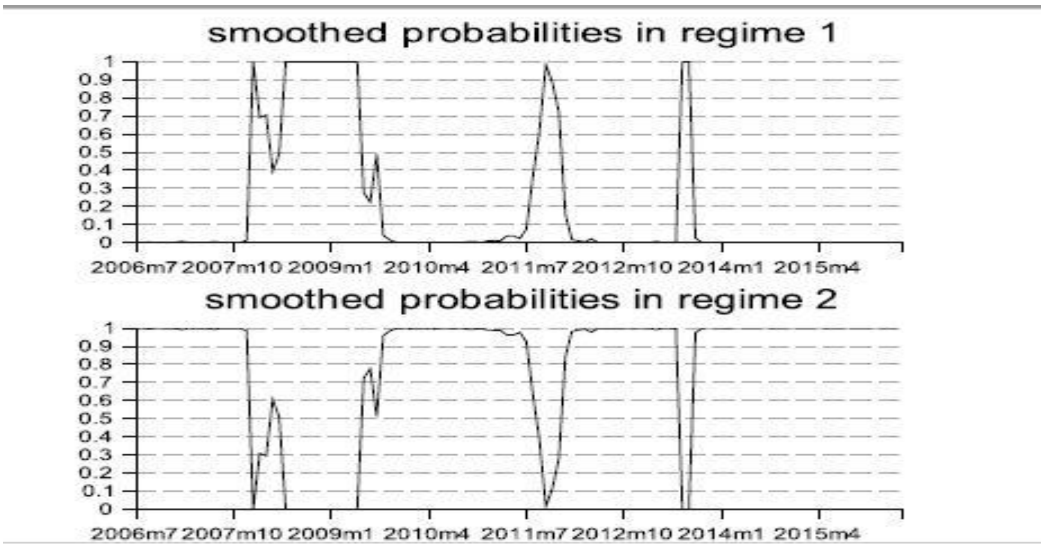
Table 4.22: Estimated Results of MSIAH (2) VAR (1) of Nifty-Bond-Silver Model

Parameters	Regime 1 (Extreme or Bear)			Regime 2 (Normal)		
	Δ Silver	Δ Nifty	Δ Bond	Δ Silver	Δ Nifty	Δ Bond
Intercept	-4.22[-2.75]**	0.099[0.027]	1.53[2.12]**	0.33[1.17]	0.485[2.62]**	-0.016[-0.351]
Δ Silver(-1)	0.782[8.57]*	0.057[0.397]	0.036[0.906]	0.967[29.85]*	-0.028[-1.39]	-0.001[-0.229]
Δ Nifty(-1)	0.208[1.90]***	0.775[3.81]*	-0.067[-1.29]	0.0004[0.005]	0.897[16.39]*	-0.007[-0.499]
Δ Bond(-1)	0.658[3.09]**	0.164[0.347]	0.813[8.06]*	0.001[0.011]	0.097[1.26]	1.01[53.80]*
Variance-Covariance Matrix						
Δ Silver	0.008[2.97]**	0.0025[1.18]	-0.0006[-0.69]	0.006[5.99]*	0.0004[1.12]	0.00005[0.64]
Δ Nifty	0.0025[1.18]	0.010[3.16]**	-0.001[-1.07]	0.0004[1.12]	0.0024[6.51]*	0.0002[3.3]**
Δ Bond	-0.0006[-0.69]	-0.001[-1.07]	0.002[2.78]**	0.00005[0.64]	0.0002[3.3]**	0.0001[5.34]*

Transition Matrix			Persistence of Regimes		
	Regime 1	Regime 2	Observations	Ergodic Probability	Duration
Regime 1	0.809	0.042	21	0.179	5.24
Regime 2	0.191	0.958	97	0.821	23.81

*(**Source:** Secondary Data Analysis)*

*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and*** at 10% level of significance.*



*(**Source:** Secondary Data Analysis)*

Figure 4.3: Smoothed Probabilities of Regimes of Nifty-Bond-Silver Model

4.3.4.4 Nifty-Bond-Copper

The estimated results of MSIAH (2) VAR (1) and smoothed probabilities of the model Nifty-Bond-Copper are depicted in Table 4.23 and Figure 4.4, respectively. Table 4.23 shows a significant and positive correlation (0.458) between returns of copper and Nifty (-1) for regime one which signifies that copper futures cannot be used as a safe haven against extreme stock market movements. However, regime two depicts negative and significant correlation (-0.094) between copper and Nifty (-1) which confirms the strong hedging potential of copper futures against stock market movements. Similarly, the positive and insignificant correlation (0.228) of copper with the bond (-1) in regime one shows that copper futures can be used as a weak safe haven. On the contrary, positive and significant correlation (0.121) of copper futures with the bond (-1) depicts that copper futures cannot be used as a hedge against bond market movements.

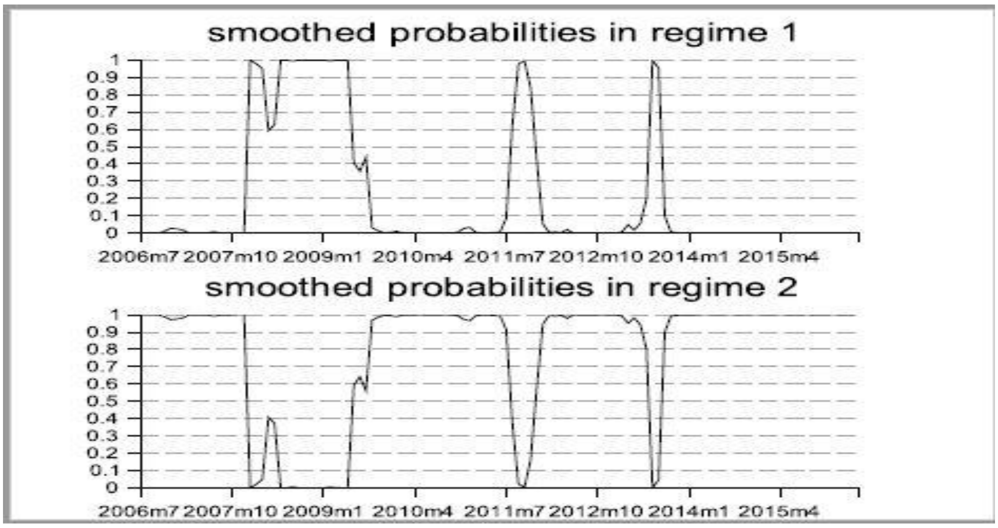
Table 4.23: Estimated Results of MSIAH (2) VAR (1) of Nifty-Bond-Copper Model

Parameters	Regime 1 (Extreme or Bear)			Regime 2 (Normal)		
	Δ Copper	Δ Nifty	Δ Bond	Δ Copper	Δ Nifty	Δ Bond
Intercept	-3.35[-2.23]**	-0.09[-0.054]	1.32[2.22]**	0.511[1.89]***	0.406[1.75]***	-0.06[-0.997]
Δ Copper(-1)	0.627[4.88]*	0.06[0.484]	0.066[1.26]	0.902[20.38]*	0.008[0.203]	0.012[1.23]
Δ Nifty(-1)	0.458[2.84]**	0.763[4.50]*	-0.104[-1.59]	-0.094[-2.13]**	0.931[18.69]*	-0.03[-0.230]
Δ Bond(-1)	0.228[1.33]	0.237[1.23]	0.886[12.85]*	0.121[2.01]**	0.022[0.356]	1.00[71.10]*
Variance-Covariance Matrix						
Δ Copper	0.011[3.21]**	0.005[2.18]**	-0.03[-2.37]**	0.003[6.62]*	-0.0002[-0.58]	-0.0008[-1.27]
Δ Nifty	0.005[2.18]**	0.01[3.32]**	-0.001[-1.13]	-0.0002[-0.58]	0.002[6.51]*	0.002[3.41]**
Δ Bond	-0.03[-2.37]**	-0.001[-1.13]	0.002[3.16]**	-0.0008[-1.27]	0.002[3.41]**	0.001[5.91]*

	Transition Matrix		Persistence of Regimes		
	Regime 1	Regime 2	Observations	Ergodic Probability	Duration
Regime 1	0.836	0.039	95	0.191	6.09
Regime 2	0.164	0.961	23	0.809	25.64

*(**Source**: Secondary Data Analysis)*

*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*



*(**Source**: Secondary Data Analysis)*

Figure 4.4: Smoothed Probabilities of Regimes of Nifty-Bond-Copper Model

4.3.4.5 Nifty-Bond-Zinc

The estimated results of MSIAH (2) VAR (1) of Nifty-Bond-Zinc are presented in Table 4.24 and smoothed probabilities of the model are depicted in Figure 4.5.

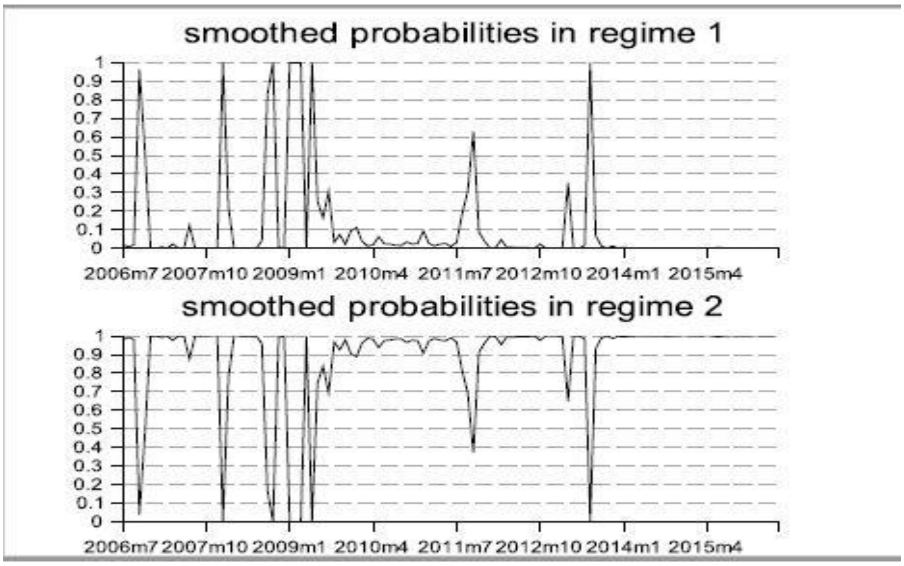
Table 4.24: Estimated Results of MSIAH (2) VAR (1) of Nifty-Bond-Zinc Model

Parameters	Regime 1 (Extreme or Bear)			Regime 2 (Normal)		
	Δ Zinc	Δ Nifty	Δ Bond	Δ Zinc	Δ Nifty	Δ Bond
Intercept	0.101[0.054]	-1.41[-0.852]	1.25[2.15]**	0.00008[0.00]	0.136[0.604]	0.027[0.397]
Δ Zinc(-1)	1.13[7.78]*	0.188[1.62]	-0.024[-0.72]	0.923[28.76]*	0.042[1.49]	-0.0006[-0.07]
Δ Nifty(-1)	-0.146[-0.857]	0.694[4.83]*	0.07[1.72]***	-0.061[-1.18]	0.88[20.47]*	-0.06[-4.64]*
Δ Bond(-1)	0.078[0.311]	0.43[1.96]***	0.76[10.62]*	0.122[2.13]**	0.094[1.77]***	1.07[65.98]*
Variance-Covariance Matrix						
Δ Zinc	0.015[2.39]**	0.008[1.81]***	-0.003[-1.96]***	0.004[6.77]*	0.0002[0.67]	-0.0002[-1.4]
Δ Nifty	0.008[1.81]***	0.011[2.33]**	-0.002[-1.54]	0.0002[0.67]	0.003[7.13]*	0.003[2.92]**
Δ Bond	-0.003[-1.96]***	-0.002[-1.54]	0.0008[2.36]***	-0.0002[-1.4]	0.003[2.92]**	0.0003[6.82]*

	Transition Matrix		Persistence of Regimes		
	Regime 1	Regime 2	Observations	Ergodic Probability	Duration
Regime 1	0.366	0.079	11	0.111	1.58
Regime 2	0.634	0.821	107	0.889	5.59

*(**Source:** Secondary Data Analysis)*

*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and ***at 10% level of significance.*



*(**Source:** Secondary Data Analysis)*

Figure 4.5: Smoothed Probabilities of Regimes of Nifty-Bond-Zinc Model

The results show an insignificant correlation of zinc futures with returns of Nifty (-1) and bond (-1) in the first regime. It suggests that zinc futures can be used as a weak safe haven against extreme movements of stock and bond markets. Similarly, negative and insignificant correlation (-0.061) between the returns of zinc futures and Nifty (-1) confirms the weak hedging potential of zinc futures against stock market movements. On the contrary, positive and significant correlation (0.122) between zinc futures and bond (-1) shows that zinc futures cannot be used as a hedge against bond market movements.

4.3.4.6 Nifty-Bond-Aluminium

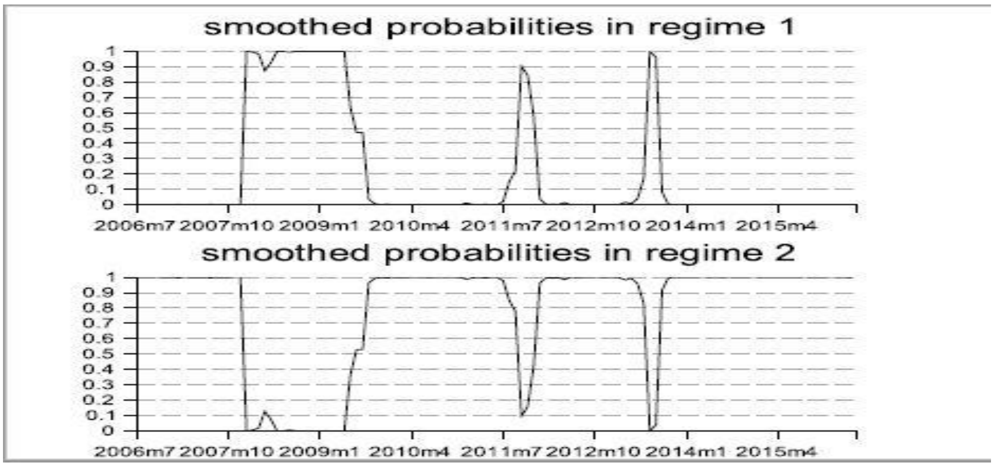
The estimated results of MSIAH (2) VAR (1) and smoothed probabilities of the model Nifty-Bond-Aluminium, are depicted in Table 4.25 and Figure 4.6, respectively.

Table 4.25: Estimated Results of MSIAH (2) VAR (1) of Nifty-Bond-Aluminium Model

Parameters	Regime 1 (Extreme or Bear)			Regime 2 (Normal)		
	Δ Aluminium	Δ Nifty	Δ Bond	Δ Aluminium	Δ Nifty	Δ Bond
Intercept	-0.253[-0.283]	0.312[0.207]	0.994[1.41]	0.949[2.50]**	0.59[1.63]	-0.082[-0.92]
Δ Aluminium(-1)	0.648[8.16]*	-0.103[-0.71]	0.044[0.702]	0.801[12.16]*	-0.032[-0.52]	0.014[0.955]
Δ Nifty(-1)	0.372[6.23]*	0.89[7.84]*	-0.063[-1.29]	-0.015[-0.33]	0.933[19.14]*	-0.006[-0.527]
Δ Bond(-1)	-0.173[-1.61]	0.147[0.784]	0.907[10.64]*	0.015[0.286]	0.021[0.355]	1.00[81.39]*
Variance-Covariance						
Matrix	0.003[3.33]**	0.0006[0.58]	-0.0007[-1.4]	0.002[6.77]*	0.00008[0.36]	-0.00002[-0.04]
Δ Aluminium	0.0006[0.58]	0.010[3.14]*	-0.0008[-0.9]	0.00008[0.36]	0.0024[6.64]*	0.0002[3.32]**
Δ Nifty	-0.0007[-1.4]	-0.0008[-0.9]	0.002[3.13]**	-0.00002[-	0.0002[3.32]**	0.0001[5.57]*
Δ Bond				0.04]		

Transition Matrix			Persistence of Regimes		
	Regime 1	Regime 2	Observations	Ergodic Probability	Duration
Regime 1	0.858	0.032	23	0.185	7.04
Regime 2	0.142	0.968	95	0.815	31.25

(***Source:*** *Secondary Data Analysis*)
Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and at *** 10% level of significance.



(***Source:*** *Secondary Data Analysis*)

Figure 4.6: Smoothed Probabilities of Regimes of Nifty-Bond-Aluminium Model

Results show an insignificant correlation between aluminium futures and bond (-1) for both the regimes. It signifies that aluminium futures possess weak hedge and weak safe haven properties against bond market movements. The significant and positive correlation (0.372) of aluminium with the returns of Nifty (-1) in regime one, shows that aluminium futures cannot be used as a safe haven against extreme stock market movements. However, aluminium futures have a weak hedging potential due to the negative and insignificant correlation (-0.015) of aluminium futures with Nifty (-1) returns in the second regime.

4.3.4.7 Nifty-Bond-Nickel

The results of the MSIAH (2) VAR (1) estimation and smoothed probabilities of the model Nifty-Bond-Nickel are shown in Table 4.26 and Figure 4.7, respectively.

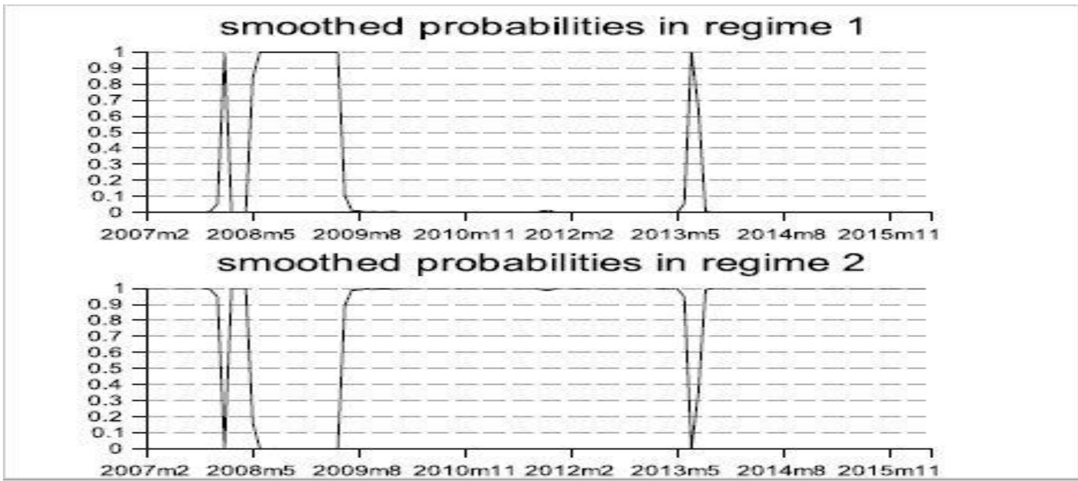
Table 4.26: Estimated Results of MSIAH (2) VAR (1) of Nifty-Bond-Nickel Model

Parameters	Regime 1 (Extreme or Bear)			Regime 2 (Normal)		
	Δ Nickel	Δ Nifty	Δ Bond	Δ Nickel	Δ Nifty	Δ Bond
Intercept	2.34[1.55]	0.792[0.356]	2.69[2.72]**	2.23[3.09]**	0.173[0.342]	-0.225[-2.21]**
Δ Nickel(-1)	-0.072[-0.34]	-0.247[-0.76]	-0.228[-1.67]	0.852[17.63]*	0.016[0.481]	0.012[1.72]***
Δ Nifty(-1)	0.912[4.79]*	1.01[3.52]*	0.143[1.17]	-0.089[-1.12]	0.919[16.91]*	-0.005[-0.409]
Δ Bond(-1)	-0.399[-2.04]**	0.101[0.346]	0.669[5.26]*	-0.06[-0.535]	0.059[0.761]	1.03[65.56]*
Variance-Covariance Matrix						
Δ Nickel	0.005[2.77]**	0.005[1.99]**	-0.001[-1.18]	0.006[6.75]*	0.0004[1.04]	-0.00009[-1.17]
Δ Nifty	0.005[1.99]**	0.012[2.77]**	-0.002[-1.13]	0.0004[104]	0.003[6.89]*	0.0002[2.94]**
Δ Bond	-0.001[-1.18]	-0.002[-1.13]	0.002[2.79]**	-0.00009[-1.17]	0.0002[2.94]*	0.00012[6.73]*

	Transition Matrix		Persistence of Regimes		
	Regime 1	Regime 2	Observations	Ergodic Probability	Duration
Regime 1	0.799	0.031	16	0.134	4.98
Regime 2	0.201	0.969	95	0.866	32.26

(***Source:*** *Secondary Data Analysis*)

*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*



(***Source:*** *Secondary Data Analysis*)

Figure 4.7: Smoothed Probabilities of Regimes of Nifty-Bond-Nickel Model

It indicates the insignificant correlation of nickel futures with Nifty (-0.089) and bond (-0.06) for the second regime. It suggests that nickel futures have a weak hedging potential against stock and bond market movements. On the contrary, positive and significant correlation (0.912) between nickel and Nifty (-1) in the first regime, shows that nickel futures cannot be used as a safe haven against extreme stock market movements. However, nickel futures can be used as a strong safe haven against extreme bond market movements due to negative and significant correlation (-0.399) between nickel futures and bond (-1) returns.

4.3.4.8 Nifty-Bond-Lead

The smoothed probabilities to classify the observations into regimes of the model Nifty-Bond-Lead are depicted in Figure 4.8. The estimated results of the MSIAH (2) VAR (1) of the Nifty-Bond-Lead model show the insignificant correlation of lead with nifty (-1) and bond (-1) for the second regime as indicated in Table 4.27. This result justifies the weak hedging potential of lead futures against stock and bond market movements. Similarly, the positive and insignificant correlation (0.14) between lead and bond (-1) in the first regime, confirms the weak safe haven property against extreme bond market movements. On the contrary, lead futures cannot be used as a safe haven against stock market movements owing to the positive and significant correlation (0.658) between lead and Nifty (-1) returns.

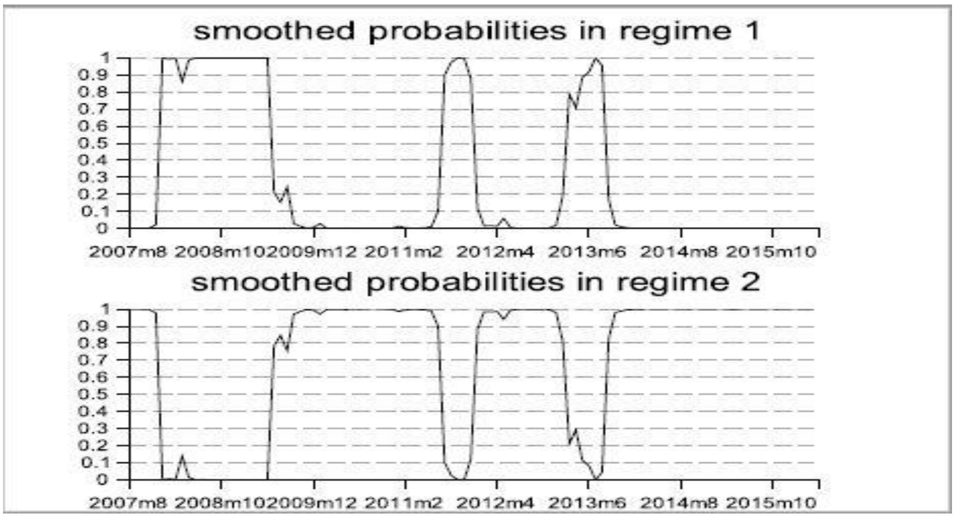
Table 4.27: Estimated Results of MSIAH (2) VAR (1) of Nifty-Bond-Lead Model

Parameters	Regime 1 (Extreme or Bear)			Regime 2 (Normal)		
	Δ Lead	Δ Nifty	Δ Bond	Δ Lead	Δ Nifty	Δ Bond
Intercept	-3.62[-2.59]**	-0.04[-0.023]	1.05[2.04]**	0.783[2.08]***	0.352[1.22]	-0.122[-2.13]
Δ Lead(-1)	0.353[1.87]***	0.069[0.346]	0.106[1.49]	0.783[12.06]	0.076[1.53]	0.019[1.95]***
Δ Nifty(-1)	0.658[3.11]**	0.765[3.28]**	-0.128[-1.61]	-0.073[-0.96]	0.887[15.46]*	-0.009[-0.909]
Δ Bond(-1)	0.14[0.984]	0.234[1.54]	0.937[17.35]*	0.120[1.41]	0.04[0.612]	1.02[96.54]*
Variance-Covariance Matrix						
Δ Lead	0.011[3.64]*	0.004[2.15]**	-0.001[-1.32]	0.004[5.99]*	0.006[1.68]***	-0.00009[-1.24]
Δ Nifty	0.004[2.15]**	0.009[3.56]*	-0.0008[-1.08]	0.006[1.68]***	0.002[6.07]*	0.0002[3.2]**
Δ Bond	-0.001[-1.32]	-0.0008[-1.08]	0.002[3.64]*	-0.00009[-1.24]	0.0002[3.2]**	0.00008[4.71]*

Transition Matrix			Persistence of Regimes		
	Regime 1	Regime 2	Observations	Ergodic Probability	Duration
Regime 1	0.869	0.043	28	0.248	7.63
Regime 2	0.131	0.957	77	0.752	23.26

*(**Source:** Secondary Data Analysis)*

*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and *** at 10% level of significance.*



(***Source:*** *Secondary Data Analysis*)

Figure 4.8: Smoothed Probabilities of Regimes of Nifty-Bond-Lead Model

4.3.4.9 Nifty-Bond-Crude Oil

The estimated results of MSIAH (2) VAR (1) and smoothed probabilities of the model Nifty-Bond-Crude Oil are shown in Table 4.28 and Figure 4.9, respectively. Table 4.28 shows a positive and significant correlation of crude oil futures with Nifty (0.385) and bond (0.349) in the first regime. It confirms that crude oil futures cannot be used as a safe haven. In contrast, the second regime shows an insignificant correlation of crude oil futures with Nifty (-0.118) and bond (0.139) which confirms the weak hedging ability of crude oil futures against stock and bond market movements.

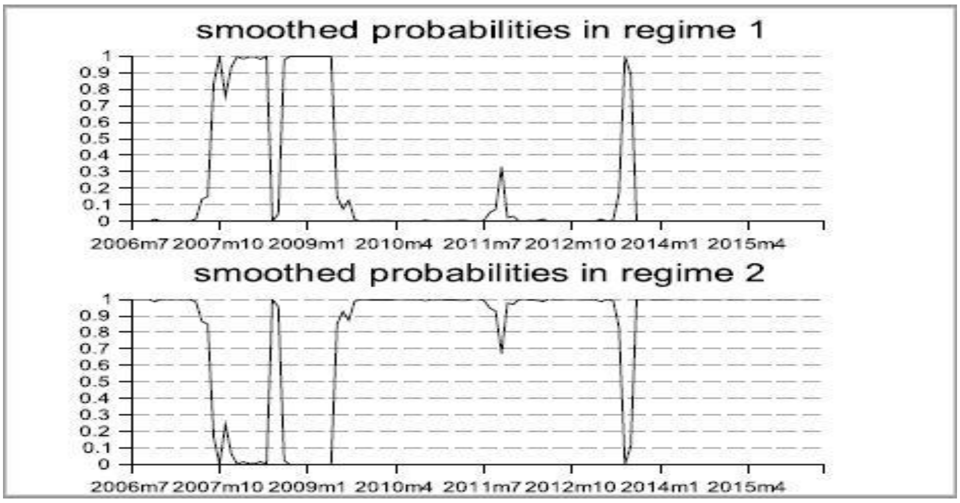
Table 4.28: Estimated Results of MSIAH (2) VAR (1) of Nifty-Bond-Crude Oil Model

Parameters	Regime 1 (Extreme or Bear)			Regime 2 (Normal)		
	Δ Crude Oil	Δ Nifty	Δ Bond	Δ Crude Oil	Δ Nifty	Δ Bond
Intercept	-3.61[-2.10]**	-0.186[-0.125]	1.65[2.49]**	0.494[1.49]	0.199[0.957]	-0.049[-0.975]
Δ Crude Oil(-1)	0.746[6.32]*	-0.328[-3.14]**	0.072[1.73]***	0.94[32.65]*	0.017[0.941]	0.003[0.745]
Δ Nifty(-1)	0.385[2.89]**	1.16[10.04]*	-0.11[-2.33]**	-0.118[-1.37]	0.88[16.48]*	-0.0012[-0.091]
Δ Bond(-1)	0.349[2.21]**	0.209[1.24]	0.816[10.99]*	0.139[1.29]	0.096[1.44]	1.00[63.31]*
Variance-Covariance Matrix						
Δ Crude Oil	0.012[3.23]*	0.006[2.12]**	-0.003[-2.59]**	0.0056[6.87]*	-0.006[-1.73]***	-0.002[-2.04]**
Δ Nifty	0.0057[2.12]**	0.009[3.22]**	0.0003[0.31]	-0.006[-1.73]***	0.002[6.77]*	0.001[2.28]**
Δ Bond	-0.003[-2.59]**	0.0003[0.31]	0.0016[3.2]**	-0.002[-2.04]**	0.001[2.28]**	0.001[6.43]*

	Transition Matrix		Persistence of Regimes		
	Regime 1	Regime 2	Observations	Ergodic Probability	Duration
Regime 1	0.818	0.039	97	0.175	5.49
Regime 2	0.182	0.961	21	0.825	25.64

(***Source:*** *Secondary Data Analysis*)

*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*



(*Source:* *Secondary Data Analysis*)

Figure 4.9: Smoothed Probabilities of Regimes of Nifty-Bond-Crude Oil Model

4.3.4.10 Nifty-Bond-Natural Gas

Table 4.29 and Figure 4.10 show the estimated results of MSIAH (2) VAR (1) and smoothed probabilities of the model Nifty-Bond-Natural Gas. Results of Table 4.29 indicate the insignificant correlation of natural gas with Nifty (-1) and bond (-1) for the second regime. It suggests the weak hedging potential of natural gas futures. On the contrary, the positive and significant correlation (0.386) between natural gas and Nifty (-1) in the first regime, shows that natural gas futures cannot be used as a safe haven against extreme stock market movements. However, natural gas futures exhibit strong safe haven potential against bond market movements due to negative and significant correlation (-5.90) between natural gas and bond (-1).

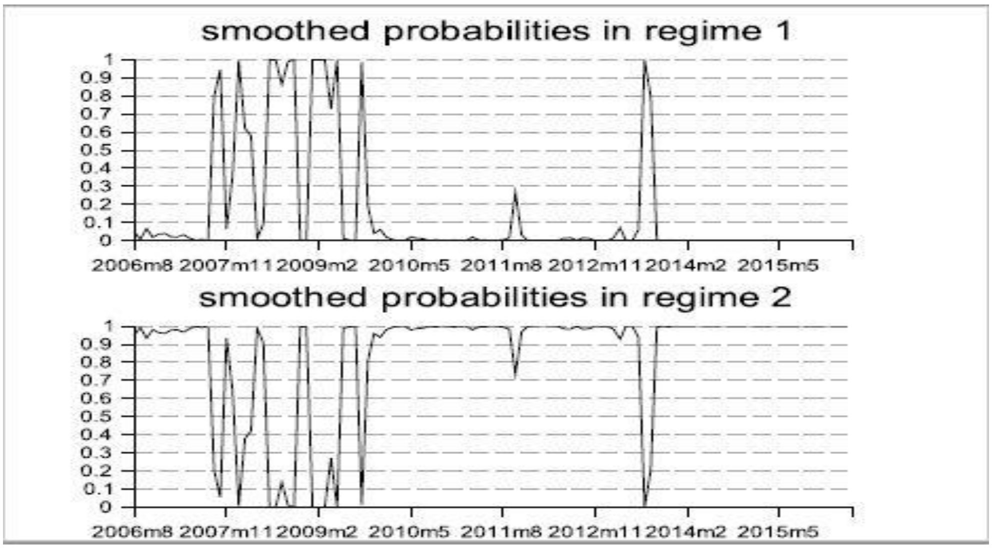
Table 4.29: Estimated Results of MSIAH (2) VAR (1) of Nifty-Bond-Natural Gas Model

Parameters	Regime 1 (Extreme or Bear)			Regime 2 (Normal)		
	Δ Natural Gas	Δ Nifty	Δ Bond	Δ Natural Gas	Δ Nifty	Δ Bond
Intercept	3.39[1.50]	3.66[1.69]***	1.81[2.37]**	0.941[1.33]	-0.018[-0.084]	-0.211[-2.19]**
Δ Natural Gas(-1)	0.574[5.80]	-0.228[-2.37]**	-0.054[-1.84]***	0.903[17.95]*	0.025[1.37]	0.022[3.27]**
Δ Nifty(-1)	0.386[3.00]**	0.903[8.28]*	0.019[0.554]	0.098[1.09]	0.907[19.47]*	-0.068[-4.97]*
Δ Bond(-1)	-5.90[-2.43]**	-0.220[-0.946]	0.766[9.83]*	-0.175[-1.33]	0.096[1.58]	1.09[55.54]*
Variance-Covariance Matrix						
Δ Natural Gas	0.011[2.67]**	-0.0024[-0.81]	-0.0009[-1.01]	0.012[6.79]*	-0.00008[-0.15]	-0.001[-1.11]
Δ Nifty	-0.0024[-0.81]	0.012[2.87]**	-0.002[-2.02]**	-0.00008[-0.15]	0.0024[6.58]*	0.00013[1.66]
Δ Bond	-0.0009[-1.01]	-0.002[-2.02]**	0.001[2.84]**	-0.001[-1.11]	0.00013[1.66]	0.0002[6.71]*

	Transition Matrix		Persistence of Regimes		
	Regime 1	Regime 2	Observations	Ergodic Probability	Duration
Regime 1	0.601	0.072	18	0.152	2.51
Regime 2	0.399	0.928	99	0.848	13.89

(*Source:* *Secondary Data Analysis*)

*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*



(***Source:*** *Secondary Data Analysis*)

Figure 4.10: Smoothed Probabilities of Regimes of Nifty-Bond-Natural Gas Model

4.3.4.11 Nifty-Bond-Cardamom

Figure 4.11 depicts the smoothed probabilities of the Nifty-Bond-Cardamom model. The estimated results of MSIAH (2) VAR (1) in Table 4.30, show the insignificant correlation of cardamom with Nifty (-1) and bond (-1) returns in the second regime, which indicates the weak hedging potential of cardamom futures. Similarly, the insignificant correlation of cardamom with Nifty (-1) and bond (-1) returns in the first regime, confirms the weak safe haven potential of cardamom futures.

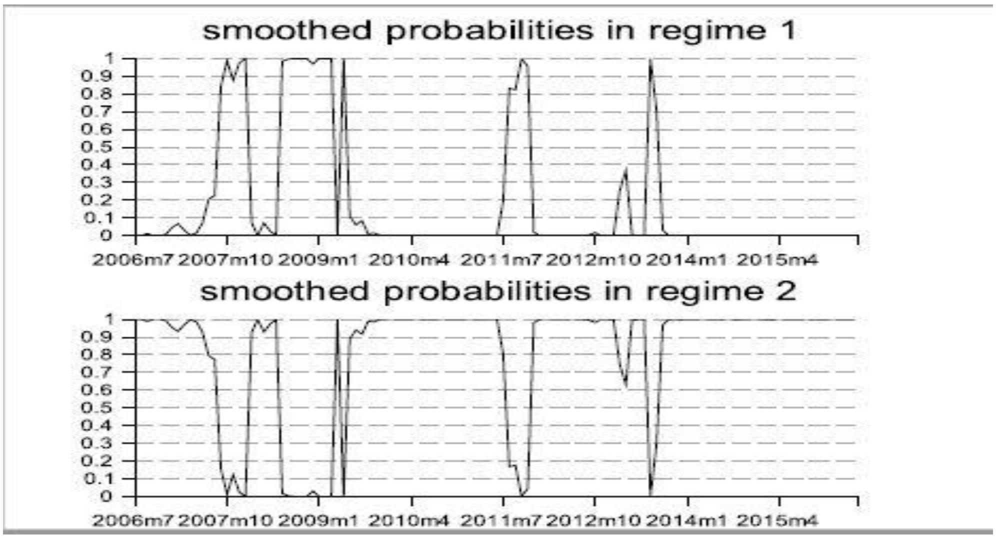
Table 4.30: Estimated Results of MSIAH (2) VAR (1) of Nifty-Bond-Cardamom Model

Parameters	Regime 1 (Extreme or Bear)			Regime 2 (Normal)		
	Δ Cardamom	Δ Nifty	Δ Bond	Δ Cardamom	Δ Nifty	Δ Bond
Intercept	1.16[1.30]	0.234[0.154]	0.873[2.83]**	0.868[1.93]***	0.237[1.26]	-0.038[-0.852]
Δ Cardamom (-1)	0.682[4.69]*	-0.351[-1.49]	0.184[3.19]**	0.873[20.87]*	-0.006[-0.365]	-0.0029[-0.712]
Δ Nifty(-1)	0.072[1.06]	1.02[9.31]*	-0.017[-0.719]	-0.130[-1.13]	0.811[16.86]*	-0.035[-3.01]**
Δ Bond(-1)	0.043[0.317]	0.265[1.18]	0.731[14.40]*	0.154[1.07]	0.198[3.27]**	1.05[72.50]*
Variance-Covariance Matrix						
Δ Cardamom	0.0046[3.09]**	0.0023[1.34]	-0.009[-2.34]**	0.015[6.85]*	0.0004[0.65]	0.0002[1.54]
Δ Nifty	0.0023[1.34]	0.012[3.11]**	-0.001[-2.13]**	0.0004[0.65]	0.0025[6.71]*	0.0003[4.31]*
Δ Bond	-0.009[-2.34]**	-0.001[-2.13]**	0.0005[2.86]**	0.0002[1.54]	0.0003[4.31]*	0.0001[6.22]*

	Transition Matrix		Persistence of Regimes		
	Regime 1	Regime 2	Observations	Ergodic Probability	Duration
Regime 1	0.724	0.061	98	0.181	3.62
Regime 2	0.276	0.939	20	0.819	16.39

(***Source:*** *Secondary Data Analysis*)

*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*



(***Source:*** *Secondary Data Analysis*)

Figure 4.11: Smoothed Probabilities of Regimes of Nifty-Bond-Cardamom Model

4.3.4.12 Nifty-Bond-Mentha Oil

Table 4.31 and Figure 4.12 show the estimated results of MSIAH (2) VAR (1) and smoothed probabilities of the model Nifty-Bond-Mentha Oil. It shows the insignificant correlation of mentha oil with Nifty (-1) and bond (-1) returns for the first regime which confirms the weak safe haven potential of mentha oil. Similarly, the insignificant correlation of mentha oil with Nifty (-1) and bond (-1) returns in the second regime signifies the weak hedging potential of mentha oil.

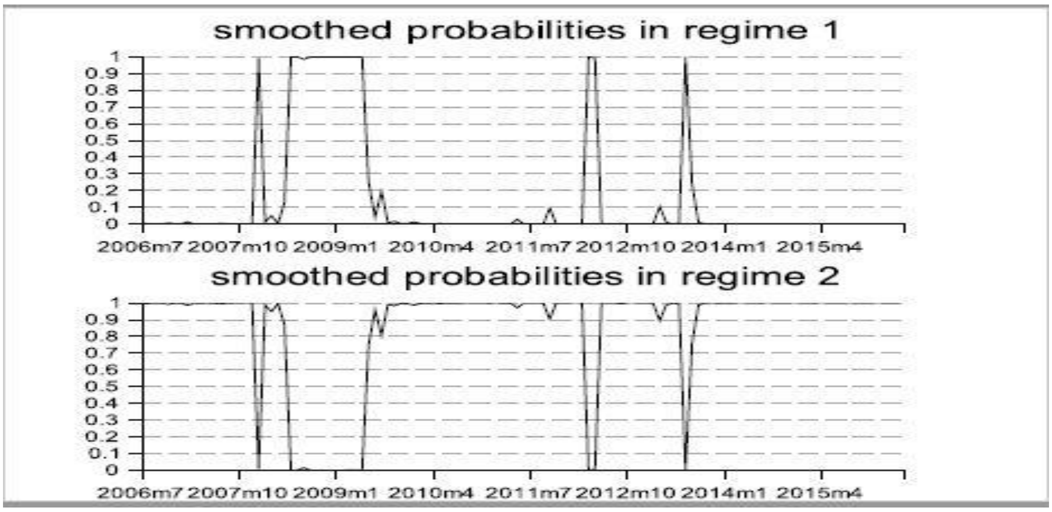
Table 4.31: Estimated Results of MSIAH (2) VAR (1) of Nifty-Bond-Mentha Oil Model

Parameters	Regime 1 (Extreme or Bear)			Regime 2 (Normal)		
	Δ Mentha Oil	Δ Nifty	Δ Bond	Δ Mentha Oil	Δ Nifty	Δ Bond
Intercept	0.829[0.516]	-0.325[-0.173]	1.89[2.29]**	0.059[0.187]	0.450[2.44]**	-0.028[-0.678]
Δ Mentha Oil (-1)	0.674[9.68]*	0.016[0.192]	0.053[1.49]	1.00[28.22]*	-0.037[-1.84]	0.0004[0.081]
Δ Nifty(-1)	0.073[0.747]	0.789[6.82]*	-0.068[-1.35]	-0.064[-0.674]	0.863[16.14]*	-00042[-0.349]
Δ Bond(-1)	0.090[0.452]	0.272[1.13]	0.768[7.32]*	0.063[0.497]	0.136[1.92]***	1.00[63.68]*
Variance-Covariance Matrix						
Δ Mentha Oil	0.0074[2.78]**	0.004[1.62]	-0.0015[-1.44]	0.008[7.05]*	-0.0003[-0.68]	-0.0008[-0.07]
Δ Nifty	0.004[1.62]	0.011[2.88]**	-0.0011[-0.88]	-0.0003[-0.68]	0.0025[7.03]*	0.0002[3.46]*
Δ Bond	-0.0015[-1.44]	-0.0011[-0.88]	0.0022[2.88]**	-0.0008[-0.07]	0.0002[3.46]*	0.00013[6.44]*

	Transition Matrix		Persistence of Regimes		
	Regime 1	Regime 2	Observations	Ergodic Probability	Duration
Regime 1	0.732	0.044	16	0.141	3.73
Regime 2	0.268	0.956	102	0.859	22.73

(***Source:*** *Secondary Data Analysis*)

*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*



(*Source:* *Secondary Data Analysis*)

Figure 4.12: Smoothed Probabilities of Regimes of Nifty-Bond-Mentha Oil Model

4.3.4.13 Nifty-Bond-CPO

The estimated results of MSIAH (2) VAR (1) and smoothed probabilities of the model Nifty-Bond-CPO are presented in Table 4.32 and Figure 4.13, respectively. It shows the insignificant correlation of CPO with Nifty (-1) and bond (-1) for the second regime. It indicates the weak hedging potential of CPO futures. On the contrary, the negative and significant correlation (-0.278) between CPO and Nifty (-1) confirms the strong safe haven property of CPO against extreme stock market movements. However, the positive and significant correlation (0.469) between the returns of CPO and bond (-1) suggests that CPO futures cannot be used as a safe haven against bond market movements.

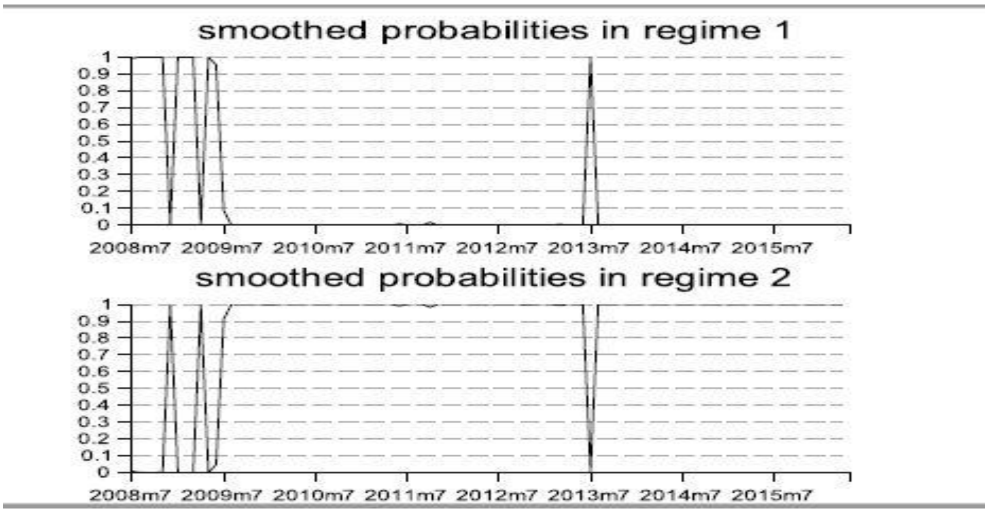
Table 4.32: Estimated Results of MSIAH (2) VAR (1) of Nifty-Bond-CPO Model

Parameters	Regime 1 (Extreme or Bear)			Regime 2 (Normal)		
	Δ CPO	Δ Nifty	Δ Bond	Δ CPO	Δ Nifty	Δ Bond
Intercept	-1.59[-2.47]**	-1.57[-1.08]	1.71[3.30]**	0.544[1.34]	0.207[0.690]	0.072[0.715]
Δ CPO(-1)	1.08[11.22]*	0.836[3.49]*	-0.205[-2.72]**	0.898[21.90]*	-0.0094[-0.309]	-0.019[-1.80]***
Δ Nifty(-1)	-0.278[-2.92]**	0.194[0.804]	0.195[2.63]**	-0.066[-1.09]	0.852[18.92]*	-0.071[-4.61]*
Δ Bond(-1)	0.469[6.14]*	0.454[2.67]**	0.706[11.62]*	0.091[0.962]	0.156[2.23]**	1.09[46.27]*
Variance-Covariance Matrix						
Δ Cardamom	0.0012[2.34]	0.0014[1.38]	-0.005[-1.62]	0.004[6.43]*	-00005[-1.57]	-0.00017[-1.43]
Δ Nifty	0.0014[1.38]	0.006[1.89]***	-0.0007[-0.9]	-0.0005[-1.57]	0.0023[6.44]*	0.00013[1.51]
Δ Bond	-0.005[-1.62]	-0.0007[-0.9]	0.0008[2.13]**	-0.0002[-1.43]	0.00013[1.51]	0.0002[6.32]*

Transition Matrix			Persistence of Regimes		
	Regime 1	Regime 2	Observations	Ergodic Probability	Duration
Regime 1	0.689	0.047	11	0.132	3.22
Regime 2	0.311	0.953	83	0.868	21.28

(*Source:* *Secondary Data Analysis*)

*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*



(***Source:*** *Secondary Data Analysis*)

Figure 4.13: Smoothed Probabilities of Regimes of Nifty-Bond-CPO Model

4.3.4.14 Nifty-Bond-Cotton

The estimated results of MSIAH (2) VAR (1) and smoothed probabilities of the model Nifty-Bond-Cotton are shown in Table 4.33 and Figure 4.14, respectively.

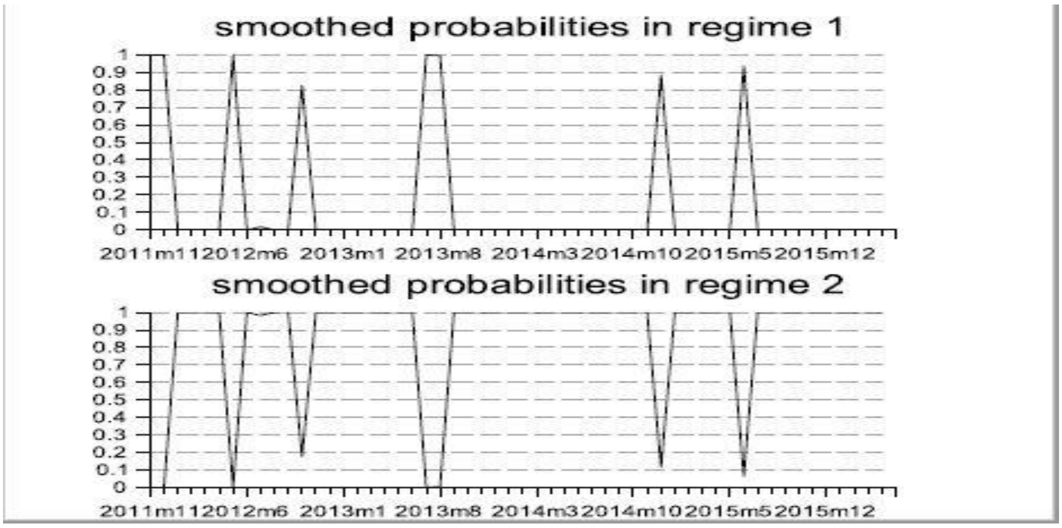
Table 4.33: Estimated Results of MSIAH (2) VAR (1) of Nifty-Bond-Cotton Model

Parameters	Regime 1 (Extreme or Bear)			Regime 2 (Normal)		
	Δ Cotton	Δ Nifty	Δ Bond	Δ Cotton	Δ Nifty	Δ Bond
Intercept	-1.01[-0.089]	0.121[0.119]	3.31[4.57]*	3.01[3.22]**	-0.351[-0.773]	-0.085[-0.85]
Δ Cotton(-1)	0.910[1.00]	-0.235[-2.91]**	-0.173[-2.64]**	-0.754[10.54]*	0.083[2.04]***	0.004[0.603]
Δ Nifty(-1)	-0.296[-1.50]	0.726[51.62]	0.129[2.72]**	-0.113[-2.30]**	0.952[32.51]*	0.005[0.539]
Δ Bond(-1)	0.602[2.09]**	0.61[21.14]*	0.629[7.74]*	0.051[0.85]	-0.0039[-0.32]	1.00[53.69]*
Variance-Covariance Matrix						
Δ Cotton	0.0032[0.9]	0.0003[0.77]	-0.002[-0.06]	0.0025[4.19]*	-0.007[-2.01]***	-0.02[-2.08]**
Δ Nifty	0.0003[0.77]	0.00003[0.8]	-0.003[-0.58]	-0.007[-2.01]***	0.002[4.49]*	0.03[3.09]*
Δ Bond	-0.002[-0.06]	-0.003[-0.58]	0.0001[1.4]	-0.02[-2.08]***	0.03[3.09]*	0.0001[4.15]*

	Transition Matrix		Persistence of Regimes		
	Regime 1	Regime 2	Observations	Ergodic Probability	Duration
Regime 1	0.424	0.173	8	0.231	1.74
Regime 2	0.576	0.827	46	0.769	5.78

(***Source:*** *Secondary Data Analysis*)
*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and *** at 10% level of significance.*

It indicates the negative and significant correlation (-0.113) between cotton and Nifty (-1) returns for the second regime which confirms the strong hedging potential of cotton futures against stock market movements. On the contrary, cotton futures possess weak hedging potential against bond market movements. Similarly, the negative and insignificant correlation (-0.296) between cotton and Nifty (-1) in the first regime, confirms the weak safe haven potential of cotton futures. However, the cotton futures cannot be used as a safe haven against extreme bond market movements owing to the positive and significant correlation (0.602) between cotton and bond (-1) returns.



(Source: Secondary Data Analysis)

Figure 4.14: Smoothed Probabilities of Regimes of Nifty-Bond-Cotton Model

4.3.4.15 Nifty-Bond-MCXMETAL

Table 4.34 and Figure 4.15 present the estimated results of MSIAH (2) VAR (1) and smoothed probabilities of the model Nifty-Bond-MCXMETAL.

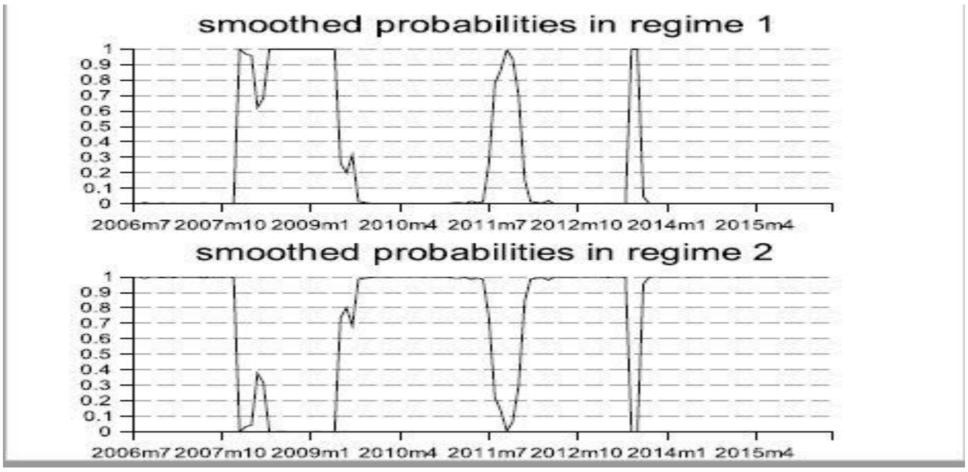
Table 4.34: Estimated Results of MSIAH (2) VAR (1) of Nifty-Bond-MCXMETAL Model

Parameters	Regime 1 (Extreme or Bear)			Regime 2 (Normal)		
	Δ MCXMETAL	Δ Nifty	Δ Bond	Δ MCXMETAL	Δ Nifty	Δ Bond
Intercept	-3.27[-3.59]*	0.002[0.07]	1.54[2.49]**	0.315[1.97]***	0.462[2.45]**	-0.024[-0.568]
Δ MCXMETAL (-1)	0.750[8.50]*	0.05[0.345]	0.082[1.39]	0.939[33.10]*	-0.013[-0.379]	0.004[0.554]
Δ Nifty(-1)	0.247[2.99]**	0.789[5.21]*	-0.097[-1.71]***	-0.044[-1.00]	0.923[18.16]*	-0.002[-0.136]
Δ Bond(-1)	0.449[3.59]*	0.185[0.687]	0.805[9.34]*	0.078[1.23]	0.045[0.598]	1.00[58.16]*
Variance-Covariance Matrix						
Δ MCXMETAL	0.004[3.32]**	0.002[1.5]	-0.0006[-1.21]	0.002[6.48]*	0.00003[0.14]	-0.0008[-0.19]
Δ Nifty	0.002[1.5]	0.01[3.36]*	-0.001[-1.12]	0.00003[0.14]	0.002[6.65]*	0.0002[3.56]*
Δ Bond	-0.0006[-1.21]	-0.001[-1.12]	0.002[3.23]*	-0.0008[-0.19]	0.0002[3.56]*	0.0001[6.16]*

	Transition Matrix		Persistence of Regimes		
	Regime 1	Regime 2	Observations	Ergodic Probability	Duration
Regime 1	0.841	0.037	24	0.189	6.29
Regime 2	0.159	0.963	94	0.811	27.03

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and at *** at 10% level of significance.*

Results show the insignificant correlation of MCXMETAL with Nifty (-1) and bond (-1) for the second regime. It suggests the weak hedging potential of MCXMETAL index. On the contrary, the positive and significant correlation of MCXMETAL with Nifty (-1) and bond (-1) in the first regime, indicates that MCXMETAL index cannot be used as a safe haven against extreme movements of stock and bond markets.



*(**Source:** Secondary Data Analysis)*

Figure 4.15: Smoothed Probabilities of Regimes of Nifty-Bond-MCXMETAL Model

4.3.4.16 Nifty-Bond-MCXENERGY

Table 4.35 and Figure 4.16 show the estimated results of the MSIAH (2) VAR (1) and smoothed probabilities of the model Nifty-Bond-MCXENERGY.

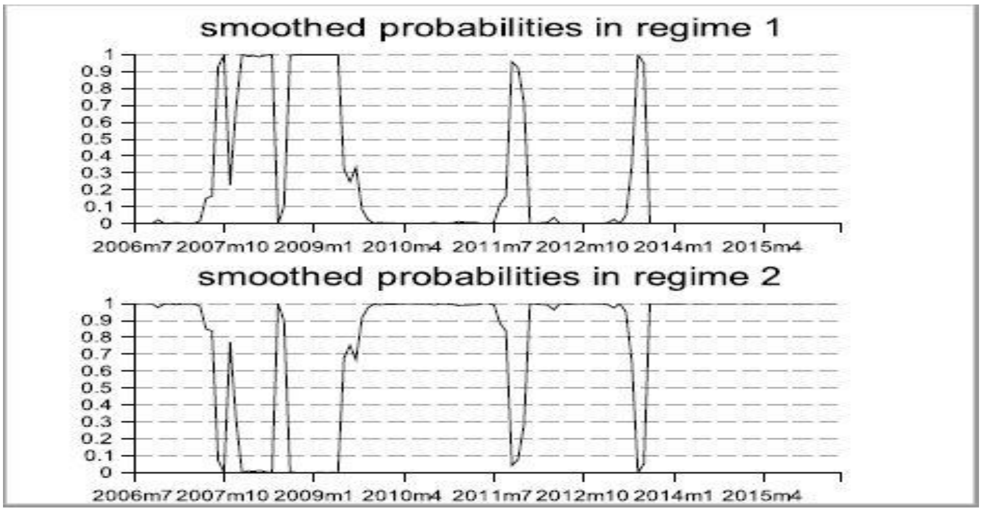
Table 4.35: Estimated Results of MSIAH (2) VAR (1) of Nifty-Bond-MCXENERGY Model

Parameters	Regime 1 (Extreme or Bear)			Regime 2 (Normal)		
	Δ MCXENERGY	Δ Nifty	Δ Bond	Δ MCXENERGY	Δ Nifty	Δ Bond
Intercept	-2.39[-1.87]***	0.538[0.444]	1.29[2.15]**	0.517[1.59]	0.128[0.584]	-0.049[-0.896]
Δ MCXENERGY (-1)	0.786[7.18]*	-0.343[-3.19]*	0.069[1.58]	0.929[32.26]*	0.027[1.39]	0.0029[0.605]
Δ Nifty(-1)	0.343[2.89]**	1.13[10.48]*	-0.091[-1.99]**	-0.107[-1.43]	0.88[16.76]*	-0.004[-0.303]
Δ Bond(-1)	0.175[1.17]	0.145[1.02]	0.862[13.39]*	0.131[1.41]	0.096[1.47]	1.00[67.49]*
Variance-Covariance Matrix						
Δ MCXENERGY	0.009[3.38]*	0.004[2.17]**	-0.02[-2.41]**	0.005[6.71]*	-0.04[-1.11]	-0.01[-1.72]***
Δ Nifty	0.004[2.17]*	0.009[3.34]*	-0.002[-0.03]	-0.04[-1.11]	0.002[6.52]*	0.02[2.85]**
Δ Bond	-0.02[-2.41]**	-0.002[-0.03]	0.0016[3.33]*	-0.01[-1.72]***	0.02[2.85]**	0.001[6.27]*

	Transition Matrix		Persistence of Regimes		
	Regime 1	Regime 2	Observations	Ergodic Probability	Duration
Regime 1	0.785	0.054	23	0.200	4.65
Regime 2	0.215	0.946	95	0.799	18.52

*(**Source:** Secondary Data Analysis)*

*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*



(*Source:* Secondary Data Analysis)

Figure 4.16: Smoothed Probabilities of Regimes of Nifty-Bond-MCXENERGY Model

Results show the insignificant correlation of MCXENERGY with the bond (-1) for both the first and second regimes which confirm the weak hedge and safe haven capability of MCXENERGY index against bond market movements. Similarly, the negative and insignificant correlation (-0.107) of MCXENERGY with Nifty (-1) in the second regime suggests the weak hedging potential of MCXENERGY against stock market movements. On the contrary, MCXENERGY index cannot be used as a safe haven against extreme stock market movements owing to its positive and significant correlation (0.343) with Nifty (-1) for the first regime.

4.3.4.17 Nifty-Bond-MCXAGRI

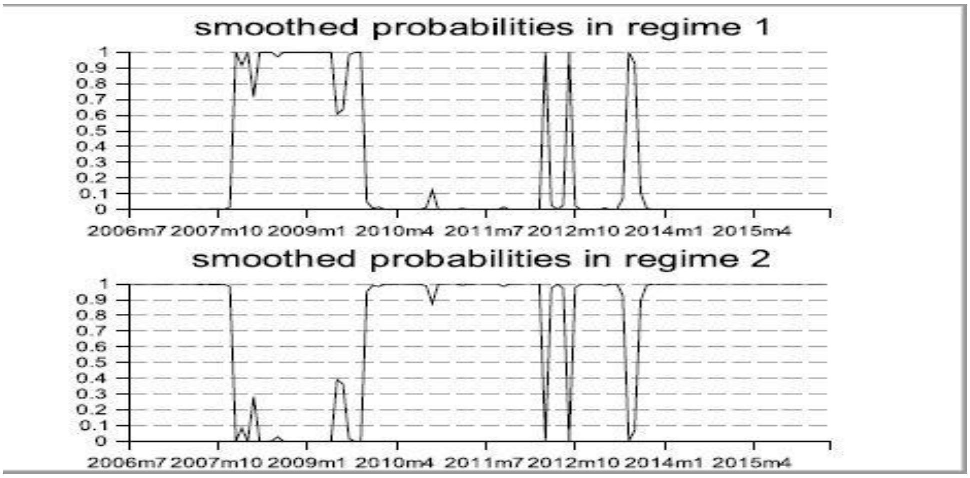
The estimated results of MSIAH (2) VAR (1) and smoothed probabilities are shown in Table 4.36 and Figure 4.17, respectively. Results show the insignificant correlation of MCXAGRI with Nifty (-1) for both the first and second regimes. It suggests the weak hedge and weak safe haven potential of MCXAGRI index against stock market movements. Similarly, the positive and insignificant correlation (0.051) of MCXAGRI with the bond (-1) in the second regime, confirms the weak hedging potential of MCXAGRI index against bond market movements. On the contrary, the positive and significant correlation (0.589) of MCXAGRI with the bond (-1) in the first regime, suggests that MCXAGRI index cannot be used as a safe haven against extreme bond market movements.

Table 4.36: Estimated Results of MSIAH (2) VAR (1) of Nifty-Bond-MCXAGRI Model

Parameters	Regime 1 (Extreme or Bear)			Regime 2 (Normal)		
	Δ MCXAGRI	Δ Nifty	Δ Bond	Δ MCXAGRI	Δ Nifty	Δ Bond
Intercept	-0.945[-0.731]	0.734[0.539]	1.35[2.17]**	0.149[0.747]	0.717[2.89]**	0.033[0.622]
Δ MCXAGRI (-1)	0.451[3.09]*	0.295[1.93]***	0.068[0.984]	0.993[39.51]*	-0.052[-1.66]	-0.008[-1.15]
Δ Nifty(-1)	0.099[1.07]	0.728[7.45]*	-0.063[-1.42]	-0.053[-1.26]	0.914[17.98]*	-0.005[-0.443]
Δ Bond(-1)	0.589[2.71]**	-0.095[-0.411]	0.814[7.73]*	0.051[0.954]	0.059[0.933]	1.01[73.61]*
Variance-Covariance Matrix						
Δ MCXAGRI	0.008[3.38]*	0.002[1.08]	0.0003[0.43]	0.002[6.24]*	-0.002[-1.05]	-0.002[-0.53]
Δ Nifty	0.002[1.08]	0.009[3.5]*	-0.009[-1.12]	-0.002[-1.05]	0.002[6.79]*	0.0001[2.69]**
Δ Bond	0.0003[0.43]	-0.009[-1.12]	0.002[3.48]*	-0.002[-0.53]	0.0001[2.69]**	0.0001[6.68]*
	Transition Matrix			Persistence of Regimes		
	Regime 1	Regime 2		Observations	Ergodic Probability	Duration
Regime 1	0.794	0.053		26	0.205	4.85
Regime 2	0.206	0.947		92	0.795	18.87

*(**Source:** Secondary Data Analysis)*

*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and at 10% level of significance.*



*(**Source:** Secondary Data Analysis)*

Figure 4.17: Smoothed Probabilities of Regimes of Nifty-Bond-MCXAGRI Model

4.3.5 Combined Results

The combined results of hedge and safe haven role of all the commodity futures and indices are shown in Table 4.37 (Jaiswal and Uchil, 2017). Results show that copper and cotton futures have the negative and significant correlation with Nifty which suggests the acceptance of hypothesis H_3. It indicates the strong hedging potential of copper and cotton futures against stock market movements. Conversely, gold, silver, zinc, aluminium, lead, nickel, crude oil natural gas, cardamom, mentha oil, and CPO futures show insignificant correlation with the Nifty stock index which indicates the rejection of hypothesis H_3. It shows that these commodity futures cannot be used as a hedge against stock market movements. However, based on the definition given by Baur McDermott (2010), this result signifies that these commodity futures can be used as a weak hedge against stock market movements. Copper and zinc futures show positive and significant correlation with the bond index which suggests rejection of hypothesis H_5. This result signifies that copper and zinc futures cannot be used as a hedge against bond market movements. Similarly, hypothesis H_5 is rejected for gold, silver, aluminium, lead, nickel, crude oil, natural gas, cardamom, mentha oil, cotton and CPO futures due to their insignificant correlation with bond index. It confirms their weak hedging potential against bond market movements.

Table 4.37: Results of Hedge and Safe Haven of all the Commodity Futures

Commodity Futures	Stock		Bond	
	Hedge	*Safe Haven*	*Hedge*	*Safe Haven*
Gold	Weak	No	Weak	No
Silver	Weak	No	Weak	No
Copper	Strong	No	No	Weak
Zinc	Weak	Weak	No	Weak
Aluminium	Weak	No	Weak	Weak
Lead	Weak	No	Weak	Weak
Nickel	Weak	No	Weak	Strong
Crude Oil	Weak	No	Weak	No
Natural Gas	Weak	No	Weak	Strong
Cardamom	Weak	Weak	Weak	Weak
Mentha Oil	Weak	Weak	Weak	Weak
Cotton	Strong	Weak	Weak	No
CPO	Weak	Strong	Weak	No
MCXMETAL	Weak	No	Weak	No
MCXENERGY	Weak	No	Weak	Weak
MCXAGRI	Weak	Weak	Weak	No

*(**Source:** Secondary Data Analysis)*

Results of the hedging potential of commodity indices show that hypotheses H_4 and H_6 are rejected due to the insignificant correlation of commodity indices such as MCXMETAL, MCXENERGY and MCXAGRI with stock and bond indices. It shows the weak hedging potential of these indices against stock and bond market movements.

Results with respect to the safe haven property of commodity futures against stock market indicate that hypothesis H_3 is accepted for CPO futures due to its negative and significant correlation with stock. It shows the strong safe haven property of CPO futures against stock market movements. Conversely, hypothesis H_3 is rejected for gold, silver, copper, aluminium, lead, nickel, crude oil and natural gas due to their positive and significant correlation with stock. It confirms that these commodity futures cannot be used as a safe haven against stock market movements. Similarly, hypothesis H_3 is rejected for zinc, mentha oil, cardamom and cotton futures due to their insignificant correlation with stock. It confirms their weak safe haven property.

Results of safe haven property of commodity futures against bond market movements show that hypothesis H_5 is accepted for nickel and natural gas due to their negative and significant correlation with the bond. It indicates the strong safe haven property of nickel and natural gas against bond market movements. Conversely, hypothesis H_5 is rejected for gold, silver, crude oil, cotton and CPO futures due to their positive and significant correlation with the bond. It signifies that these commodity futures cannot be used as a safe haven against bond market movements. Similarly, hypothesis H_5 is rejected for copper, zinc, aluminium, lead, cardamom and mentha oil because of their insignificant correlation with the bond. It shows the weak safe haven property of these commodity futures against bond market movements.

Results of commodity futures indices as a safe haven, suggest the rejection of hypothesis H_4 for MCXMETAL and MCXENERGY due to their positive and significant correlation with stock. It confirms their inability to act as a safe haven against stock market movements. Similarly, hypothesis H_4 is rejected for MCXAGRI due to their insignificant correlation with stock. It shows the weak safe haven property of MCXAGRI against stock market movements. With respect to the safe haven property of commodity indices against bond market shows the rejection of hypothesis H_6 for MCXMETAL and MCXAGRI. The reason is the positive and significant correlation of these indices with the bond which signifies that these commodity indices cannot be used as a safe haven against bond market movements. Similarly, hypothesis H_6 is rejected for MCXENERGY due to their insignificant correlation with the bond. It shows the weak safe haven property of MCXENERGY against bond market movements.

4.3.6 Regime Classification Measure

Regime Classification Measure (RCM) is estimated using Equation (3.10) to ascertain the quality of regime classification for all the regimes. For all the models, RCMs are between zero to 16 which are lesser than 50 as shown in Table 8 in Appendix I. It shows a perfect regime classification. Hence, RCM statistics suggest that MS-VAR model is properly specified and appropriate to investigate hedge and safe haven property of all the commodity futures and indices.

4.3.7 Portfolio Analysis

As a final step of evaluation for hedging and diversification benefits of commodity futures, portfolio analysis is performed instead of out-of-sample analysis to check the performance of MS-VAR. It confirms that the results of MS-VAR estimation for all the commodity futures provide a significant direction to investors in the context of portfolio management. It indicates the importance of using regime-based strategy in contrast to benchmark strategy for portfolio construction.

Taking into account, both benchmark and regime-based strategy, portfolio analysis is performed in two ways. Firstly, naïve portfolio diversification as a benchmark strategy is used to show the linear strategy of portfolio construction (DeMiguel et al., 2009). As a benchmark strategy, the portfolio is constructed using two options. The first option allocates 25 percent of the portfolio in commodity futures and 75 percent of the portfolio in Nifty and bond index. The second option allocates a fraction of 1/N of the portfolio to each of the N assets for constructing an equal-weighted portfolio. In addition, portfolio analysis is conducted for the scenarios where investors invest either 100 percent of the portfolio in Nifty and bond or in commodity futures.

Secondly, the regime-based strategy is used to construct the portfolio based on different regimes which represent hedge and safe haven role of commodity futures. Based on MS-VAR results for all the commodity futures, five different scenarios of portfolio composition are considered. The first scenario is for gold, silver, aluminium, lead, nickel, crude oil, natural gas, MCXMETAL and MCXENERGY where the first regime accounts for no safe haven and the second regime for a weak hedge. Based on the work of Beckmann et al. (2015), it is assumed that investors allocate 20 percent of the portfolio in commodity futures as a weak hedge and zero percent of the portfolio in commodities during the first regime, as these commodity futures do not act as a safe haven. The second scenario is for zinc, cardamom, mentha oil and MCXAGRI where the first regime accounts for a weak safe haven and the second regime accounts for a weak hedge. The portfolio is constructed for this scenario by allocating 20 percent of the portfolio in these commodity futures as a weak hedge and 30 percent of the portfolio in these commodities as a weak safe haven (Beckmann et al., 2015).

The third scenario is for copper futures, where the first regime accounts for no safe haven and the second regime for a strong hedge. The portfolio is constructed by allocating 50 percent of the portfolio in copper futures as a strong hedge and zero percent of the portfolio in copper during the first regime, as copper futures do not act as a safe haven.

The fourth scenario is for cotton futures where the first regime accounts for weak safe haven and the second regime for a strong hedge. The portfolio is constructed by allocating 50 percent of the portfolio in cotton futures as a strong hedge and 30 percent of the portfolio in cotton during the first regime, as cotton futures act as a weak safe haven.

The last scenario is for CPO futures where the first regime accounts for strong safe haven and the second regime for a weak hedge. The portfolio is constructed by allocating 20 percent of the portfolio in CPO futures as a weak hedge and 60 percent of the portfolio in CPO during the first regime, as CPO futures acts as a strong safe haven.

Sharpe ratio has been used to assess the risk-adjusted performance of all the strategies. The findings of Sharpe ratio (Table 4.38) indicate that regime-based strategy of portfolio construction, based on the hedge and safe haven property of regimes, performs better in contrast to benchmark strategies for all the commodity futures

Table 4.38: Portfolio Analysis

Portfolios		Nifty and Bond	Benchmark Strategy		Regime-Based Strategy	Commodity Futures
		50:50:00	*37.5:37.5:25*	*33.3:33.3:33.3*		*00:00:100*
	Return (μ)	0.714	0.787	0.811	0.712	1.00
Nifty-Bond-	Risk (σ2)	3.68	2.83	2.73	2.23	5.17
Gold	Sharpe Ratio	0.194	0.278	0.297	0.319	0.195
Nifty-Bond-	Return (μ)	0.714	0.724	0.728	0.719	0.756
Silver	Risk (σ2)	3.68	3.64	3.93	3.56	8.53
	Sharpe Ratio	0.194	0.199	0.185	0.202	0.088
Nifty-Bond-	Return (μ)	0.714	0.532	0.471	0.543	-0.014
Copper	Risk (σ2)	3.68	3.34	3.51	3.32	7.54
	Sharpe Ratio	0.194	0.159	0.134	0.164	-0.002
Nifty-Bond-	Return (μ)	0.714	0.504	0.435	0.582	-0.123
Zinc	Risk (σ2)	3.68	3.65	3.88	3.67	7.87
	Sharpe Ratio	0.194	0.138	0.112	0.159	-0.016

Nifty-Bond-Aluminium	Return (μ)	0.714	0.518	0.453	0.549	-0.067
	Risk (σ2)	3.68	3.04	3.03	3.09	5.87
	Sharpe Ratio	0.194	0.170	0.149	0.177	-0.011
Nifty-Bond-Nickel	Return (μ)	0.608	0.227	0.099	0.316	-0.917
	Risk (σ2)	3.74	3.97	4.31	3.74	8.96
	Sharpe Ratio	0.163	0.057	0.023	0.085	-0.102
Nifty-Bond-Lead	Return (μ)	0.575	0.416	0.363	0.495	-0.060
	Risk (σ2)	3.78	3.87	4.19	3.72	9.02
	Sharpe Ratio	0.152	0.107	0.086	0.133	-0.007
Nifty-Bond-Crude Oil	Return (μ)	0.714	0.509	0.441	0.524	-0.104
	Risk (σ2)	3.68	3.56	3.89	3.51	9.20
	Sharpe Ratio	0.194	0.143	0.113	0.149	-0.011
Nifty-Bond-Natural Gas	Return (μ)	0.717	0.339	0.213	0.471	-0.795
	Risk (σ2)	3.69	4.13	4.78	3.88	12.42
	Sharpe Ratio	0.194	0.082	0.045	1.121	-0.064
Nifty-Bond-Cardamom	Return (μ)	0.714	0.769	0.787	0.760	0.934
	Risk (σ2)	3.68	4.46	5.11	4.13	12.32
	Sharpe Ratio	0.194	0.173	0.154	0.184	0.076
Nifty-Bond-Mentha Oil	Return (μ)	0.714	0.683	0.673	0.696	0.591
	Risk (σ2)	3.68	3.88	4.35	3.83	10.56
	Sharpe Ratio	0.194	0.176	0.155	0.181	0.056
Nifty-Bond-Cotton	Return (μ)	0.728	0.510	0.438	0.524	-0.143
	Risk (σ2)	2.66	2.10	2.19	2.13	5.59
	Sharpe Ratio	0.274	0.243	0.199	0.246	-0.025
Nifty-Bond-CPO	Return (μ)	0.707	0.555	0.504	0.565	0.096
	Risk (σ2)	3.43	3.24	3.45	3.25	7.45
	Sharpe Ratio	0.207	0.171	0.146	0.174	0.013
Nifty-Bond-MCXMETAL	Return (μ)	0.714	0.665	0.648	0.689	0.518
	Risk (σ2)	3.68	3.07	3.03	3.16	5.23
	Sharpe Ratio	0.194	0.217	0.214	0.218	0.099
Nifty-Bond-MCXENERGY	Return (μ)	0.714	0.483	0.406	0.513	-0.209
	Risk (σ2)	3.68	3.43	3.68	3.51	8.33
	Sharpe Ratio	0.194	0.140	0.110	0.146	-0.025
Nifty-Bond-MCXAGRI	Return (μ)	0.714	0.616	0.583	0.633	0.323
	Risk (σ2)	3.68	3.20	3.27	3.28	6.47
	Sharpe Ratio	0.194	0.192	0.178	0.193	0.049

*(**Source:** Secondary Data Analysis)*

Previous Sections 4.2 and 4.3 discuss the inflation hedging and diversification benefits of commodity futures which basically indicate the benefits of passive investment in commodity futures market. Following Sections 4.4, 4.5, 4.6, 4.7 and 4.8 discuss the active strategies of investment in commodity futures market based on momentum, term structure and idiosyncratic volatility signals.

4.4 MOMENTUM STRATEGIES IN COMMODITY FUTURES MARKET

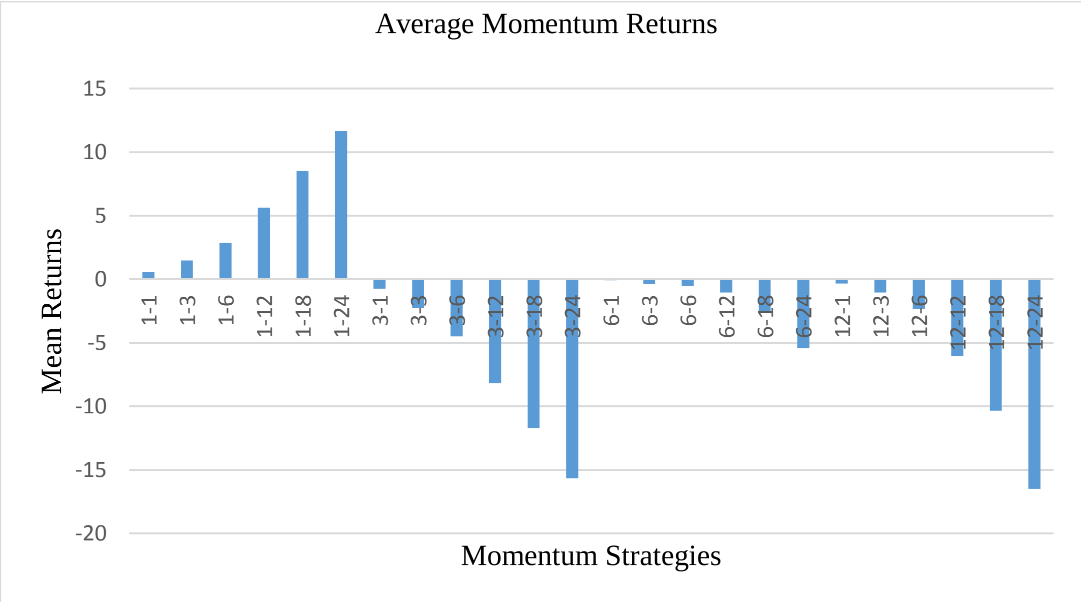
Momentum strategies are implemented by taking a long position in commodity futures that outperform the market with the highest historical return and a short position in commodity futures that underperform the market with the lowest returns. These strategies are based on the perception that assets which have given positive returns over the past year will continue to perform well in future (Jegadeesh and Titman, 1993). Based on the works of Jegadeesh and Titman (1993, 2001), Erb and Harvey (2006) and Miffre and Rallies (2007), this study investigates the profitability of 24 momentum strategies in commodity futures markets. The performance evaluation of the relative strength portfolios of the momentum strategies is performed in the following stages.

4.4.1 Momentum Profits

The performance evaluation of momentum payoffs is analysed from the perspective of their sub-period and sensitivity analysis.

4.4.1.1 Momentum Profits for whole Study Period

The mean, standard deviation and risk-adjusted return performance i.e. Sharpe ratio of all the momentum strategies are shown in Table 4.39. Results show that profits of four momentum strategies of the ranking period of one month and holding period of 6, 12, 18 and 24 months are positive and significant. These four momentum strategies yield an average monthly return of 7.17 percent and an annualized return of 43.03 percent by consistently buying commodity futures with past positive returns and selling the commodity futures with past negative returns. On the contrary, nine momentum strategies of the ranking period of 3, 6 and 12 months which give negative and significant results are depicted in Figure 4.18. The negative returns of these momentum strategies are basically due to the positive returns yielded by loser portfolios for the respective ranking periods, which indicate the presence of price reversal pattern in the dataset. Over the same period, the composite commodity index (MCXCOMDEX), Nifty stock index and CCIL bond index yield an annualized return of 4.76, 10.29 and 8.30 percent, respectively. In addition, the momentum strategy (1-24) with the ranking period of one month and holding period of 24 months is most profitable and gives the highest monthly return of 11.65 percent. It indicates that momentum profits increase with the holding period.

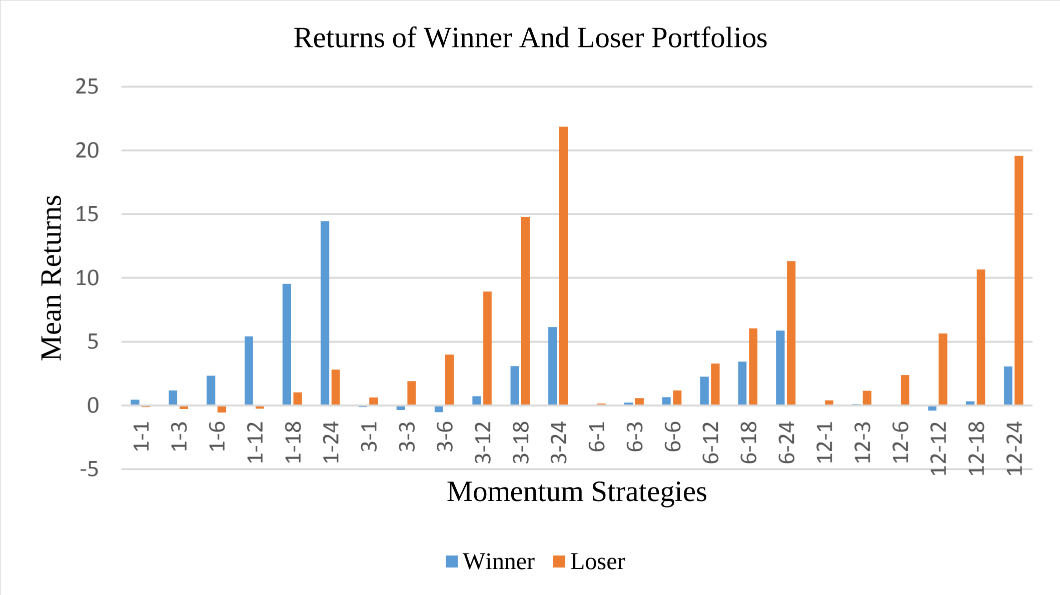


*(**Source:** Secondary Data Analysis)*

Figure 4.18: Average Momentum Returns over different Momentum Strategies

Table 4.39 shows that seven winner portfolios out of 24 momentum strategies yield a positive and significant returns which are in the range between a monthly return of 2.33 percent to 14.46 percent. On the contrary, nine loser portfolios yield a positive and significant returns from a low of 3.99 percent to a high of 21.85 percent. It indicates that loser portfolios outperform the winner portfolios as loser portfolios yield a monthly average return of 11.42 percent compared to winner portfolios which yield 6.74 percent return as depicted in Figure 4.19. However, in the case of four profitable momentum strategies, profits are basically driven by the respective winner portfolios due to their positive and significant returns.

The standard deviation of momentum strategies indicates that the momentum profits are not the compensation for risk. Table 4.39 shows that standard deviation increases with the increase in momentum returns. For instance, in the group of the ranking period one, the most profitable strategy is 1-24 which yields the highest average monthly return of 11.65 percent and highest standard deviation of 21.42. On the contrary, lowest profitable strategy in the group of the ranking period of one month is 1-1, with the lowest average return of 0.563 percent and the lowest standard deviation of 6.59. Similar is the case with other ranking periods of 3, 6 and 12 months. These outcomes are in line with the findings of Miffre and Rallis (2007) and of the normal market perception that higher returns are associated with higher risk.



(Source: *Secondary Data Analysis*)

Figure 4.19: Average Returns of Winner and Loser Portfolios over different Momentum Strategies

Sharpe ratio shown in Table 4.39 helps to analyse the risk-adjusted performance of all the momentum strategies. In the group of a ranking period of one month, Sharpe ratio increases with the increase in momentum payoffs and ranges from 0.085 to 0.544. For example, the most profitable strategy 1-24 has the highest Sharpe ratio of 0.544. On the contrary, Sharpe ratio of momentum strategies for ranking periods of 3, 6 and 12 months are negative due to the negative returns, given by these momentum strategies. Over the same period, MCXCOMDEX, Nifty stock index and CCIL bond index have the Sharpe ratio of 0.038, 0.102 and 0.269, respectively. This indicates that the momentum strategies of a ranking period of one month in commodity futures market, perform better with respect to their risk-adjusted return performance compared to passive investment in equity, bond and commodity futures market.

Table 4.39: Mean, Standard Deviation and Sharpe Ratio of Momentum Strategies (Monthly)

	Ranking Period 1			Ranking Period 3			Ranking Period 6			Ranking period 12		
	Winner	Loser	Mom[1]	Winner	Loser	Mom	Winner	Loser	Mom	Winner	Loser	Mom
Holding Period 1												
Mean	0.447	-0.116	0.563	-0.118	0.635	-0.753	0.062	0.154	-0.092	0.053	0.391	-0.338
	[0.955]	[-0.211]	[0.922]	[-0.225]	[1.10]	[-1.17]	[0.133]	[0.253]	[-0.142]	[0.11]	[0.649]	[-0.561]
SD[2]	5.04	5.95	6.59	5.61	6.16	6.89	4.88	6.39	6.84	4.94	6.17	6.18
Sharpe Ratio	0.089	-0.019	0.085	-0.021	0.103	-0.109	0.013	0.024	-0.013	0.011	0.063	-0.055
Holding Period 3												
Mean	1.19	-0.272	1.47	-0.36	1.92	-2.28	0.226	0.591	-0.364	0.097	1.15	-1.05
	[1.43]	[-0.257]	[1.49]	[-0.399]	[1.63]	[-2.12]**	[0.251]	[0.529]	[-0.317]	[0.104]	[0.947]	[-0.979]
SD	8.95	11.31	10.49	9.56	12.45	11.39	9.41	11.66	12.00	9.38	12.32	10.92
Sharpe Ratio	0.134	-0.024	0.139	-0.038	0.154	-0.200	0.024	0.051	-0.03	0.01	0.093	-0.096
Holding Period 6												
Mean	2.33	-0.544	2.87	-0.524	3.99	-4.51	0.648	1.17	-0.526	0.042	2.39	-2.35
	[1.86]***	[-0.331]	[2.19]**	[-0.392]	[2.26]**	[-3.12]**	[0.491]	[0.743]	[-0.376]	[0.029]	[1.25]	[-1.41]
SD	13.21	17.31	13.84	13.93	18.45	15.09	13.58	16.28	14.39	14.75	19.19	16.67
Sharpe Ratio	0.176	-0.031	0.208	-0.038	0.216	-0.299	0.048	0.072	-0.037	0.003	0.125	-0.141
Holding Period 12												
Mean	5.41	-0.238	5.64	0.732	8.93	-8.19	2.25	3.29	-1.04	-0.401	5.65	-6.05
	[3.23]*	[-0.102]	[3.09]**	[0.379]	[3.35]*	[-3.52]*	[1.25]	[1.40]	[-0.469]	[-0.198]	[1.96]***	[-2.31]**
SD	17.14	23.93	18.73	19.64	27.10	23.63	17.97	23.47	22.28	19.64	27.89	25.39
Sharpe Ratio	0.315	-0.009	0.301	0.037	0.329	-0.347	0.125	0.140	-0.047	-0.021	0.202	-0.238
Holding Period 18												
Mean	9.53	1.02	8.51	3.09	14.79	-11.71	3.43	6.06	-2.63	0.324	10.66	-10.34
	[4.47]*	[0.386]	[4.01]*	[1.31]	[4.11]*	[-3.89]*	[1.70]***	[2.00]**	[-0.94]	[0.143]	[3.06]**	[-3.49]*
SD	21.22	26.29	21.12	23.29	35.47	29.67	19.54	29.34	27.08	21.28	32.67	27.74
Sharpe Ratio	0.449	0.039	0.403	0.132	0.417	-0.395	0.176	0.206	-0.097	0.015	0.326	-0.373
Holding Period 24												
Mean	14.46	2.81	11.65	6.16	21.85	-15.68	5.88	11.32	-5.44	3.06	19.56	-16.49
	[5.74]*	[0.881]	[5.24]*	[2.21]**	[4.89]*	[-4.48]*	[2.62]**	[3.17]**	[-1.72]***	[1.12]	[5.52]*	[-6.22]*
SD	24.30	30.77	21.42	26.63	42.64	33.38	21.08	33.55	29.67	24.78	32.06	24.00
Sharpe Ratio	0.595	0.091	0.544	0.231	0.512	-0.469	0.279	0.338	-0.184	0.123	0.61	-0.687

*(**Source:** Secondary Data Analysis)*

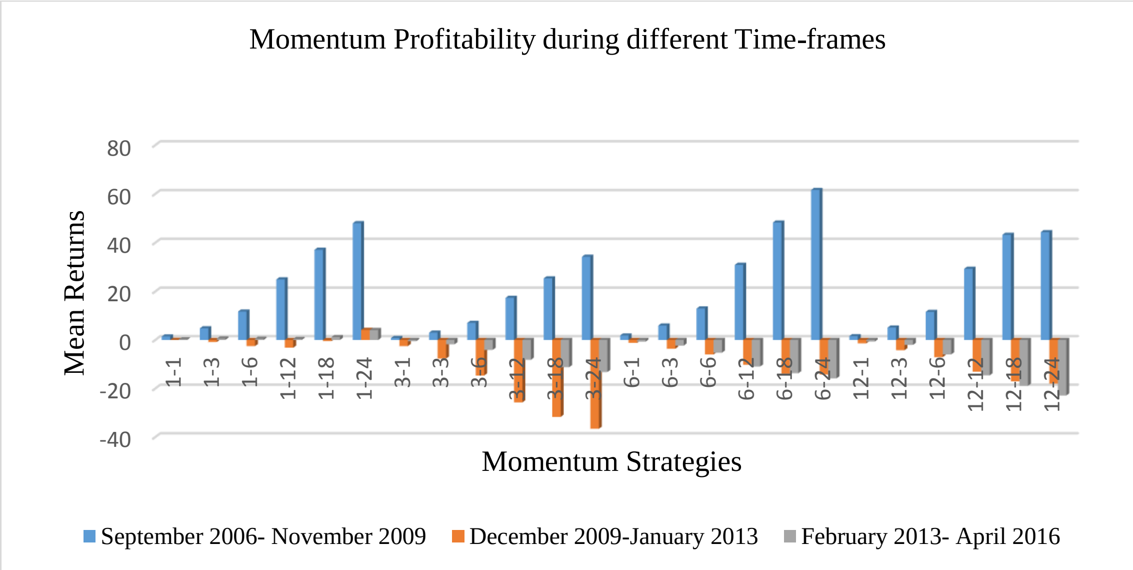
*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*

[1] Mom refers to momentum portfolio.

[2] SD refers to standard deviation.

4.4.1.2 Momentum Profits for Sub-Periods

Table 4.40 shows the momentum payoffs of all the 24 strategies during different time frames. These results help to analyse the impact of commodity cycle on the consistency of momentum profits in the future. The whole study period is divided into three equal sub-periods. The momentum risk-adjusted return of later periods (February 2013-April 2016) is compared with the risk-adjusted return of earlier periods (September 2006-November 2009, December 2009-January 2013). Results indicate that the momentum strategies of all the four ranking periods of the initial sub-period of September 2006-November 2009 have yielded positive returns as depicted in Figure 4.20.



*(**Source**: Secondary Data Analysis)*

Figure 4.20: Average Returns of Momentum Strategies over different Time-frames

On the contrary, all the momentum strategies for the subsequent sub-period, December 2009-January 2013 have yielded negative returns except for the momentum strategy 1-24 which has given the positive and significant return. Similarly, with the exception of the momentum strategies with the ranking period of one month, all the strategies with the ranking period of 3, 6 and 12 months have yielded a negative and significant return for the next sub-period, February 2013-April 2016. These results indicate that momentum strategies perform better for the earlier sub-periods of September 2006-November 2009 compared to later sub-periods of December 2009-January 2013 and February 2013-April 2016. It confirms the time-varying profitability of momentum strategies.

Table 4.40: Momentum Profitability during different Time-frames

Holding Periods	September 2006-November 2009	December 2009-January 2013	February 2013-April 2016	September 2006-April 2016
		Ranking Period of One Month		
1	1.43 [1.03]	0.018 [0.017]	0.231 [0.364]	0.563 [0.920]
3	4.79 [2.34]**	-0.848 [-0.472]	0.575 [0.537]	1.47 [1.49]
6	11.67 [5.62]*	-2.53[-0.996]	0.472 [0.319]	2.87 [2.19]**
12	24.92 [10.12]*	-3.18 [-1.07]	0.399 [0.214]	5.64 [3.09]**
18	37.04 [11.85]*	-0.467 [-0.181]	1.17 [0.547]	8.51 [4.00]*
24	47.96 [13.45]*	4.14 [1.69]***	4.07 [2.15]**	11.65 [5.24]*
		Ranking Period of Three Months		
1	0.769 [0.794]	-2.51 [-1.89]***	-0.490 [-0.495]	-0.753 [-1.17]
3	3.02 [1.71]***	-7.68 [-3.67]*	-1.78 [-1.39]	-2.28 [-2.12]**
6	7.02 [3.26]**	-14.65 [-6.45]*	-4.09 [-2.45]**	-4.51 [-3.12]**
12	17.33 [4.64]*	-25.71 [-9.64]*	-8.16 [-3.26]*	-8.19 [-3.52]*
18	25.34 [5.07]*	-31.72 [-7.93]*	-11.21[-4.35]*	-11.71 [-3.89]*
24	34.20 [6.38]*	-36.58 [-7.25]*	-13.23 [-5.82]*	-15.68 [-4.48]*
		Ranking Period of Six Months		
1	1.84 [1.33]	-1.19 [-0.938]	-0.701 [-1.18]	-0.092 [-0.142]
3	5.91 [2.22]**	-3.62 [-1.85]***	-2.34 [-2.49]**	-0.364 [-0.317]
6	12.95 [5.13]*	-5.97 [-2.81]**	-5.25 [-3.69]*	-0.526 [-0.376]
12	30.88 [7.97]*	-10.21 [-4.48]*	-10.94 [-6.88]*	-1.04 [-0.469]
18	48.22 [12.73]*	-14.04 [-6.33]*	-13.67 [-8.62]*	-2.63 [-0.940]
24	61.58 [21.46]*	-14.22 [-4.27]*	-15.80 [-10.18]*	-5.45 [-1.72]***
		Ranking Period of Twelve Months		
1	1.54 [1.39]	-1.39 [-1.11]	-0.655 [-0.964]	-0.338 [-0.560]
3	5.09 [2.11]**	-4.23 [-2.25]**	-2.05 [-1.76]***	-1.05 [-0.979]
6	11.54 [2.95]**	-7.07 [-3.11]**	-5.94 [-2.79]**	-2.35 [-1.41]
12	29.26 [5.23]*	-13.07 [-4.35]*	-14.59 [-4.96]*	-6.05 [-2.31]**
18	43.20 [6.49]*	-17.04 [-5.24]*	-18.90 [-6.89]*	-10.34 [-3.49]*
24	44.27 [15.36]*	-17.96 [-5.08]*	-22.87 [-9.40]*	-16.49 [-6.22]*

*(**Source:** Secondary Data Analysis)*

*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*

4.4.1.3 Sensitivity Analysis of Momentum Profits

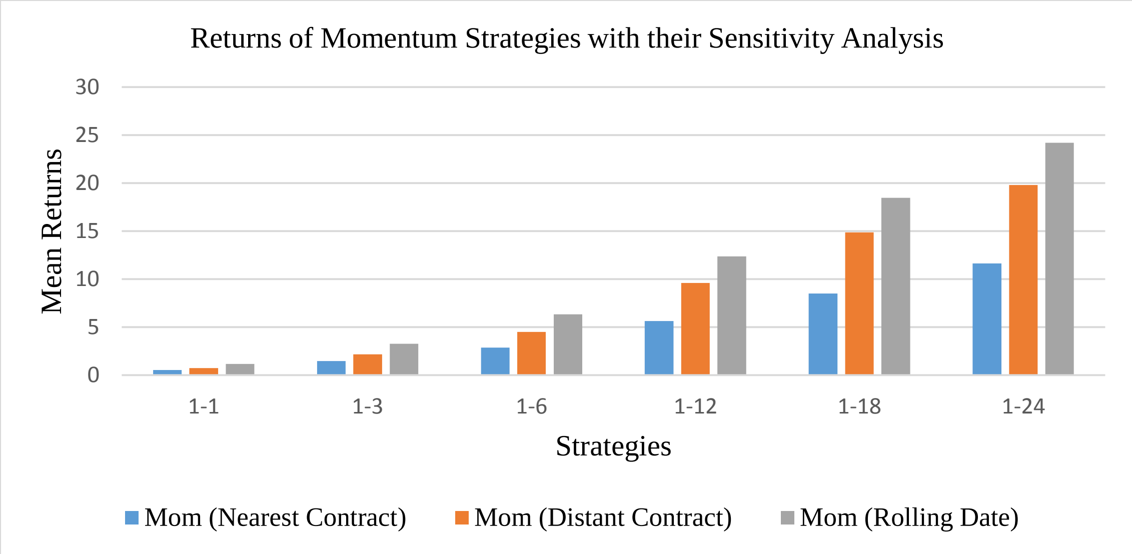
Sensitivity analysis of momentum profits is performed in two different ways. First, at the end of the month, the most distant maturity contract is used for rolling and to compile the futures price series compared to the second nearest contract. Second, the rolling date is set to 15th of the maturity month as opposed to the end of the month. Results of the mean return, standard deviation and Sharpe ratio are shown in Table 4.41. It suggests that the strategies based on the most distant maturity contract perform better than the strategies based on the second nearest contract. Results show that returns of all the momentum strategies of the ranking period of one month are positive and significant and yield an average monthly return of 10.19 percent. The most profitable momentum strategy is 1-24 with the average return of 19.79 percent and the highest standard deviation of 28.99. These results are in line with the normal market perception which suggests that higher returns are associated with higher risk. In addition, Sharpe ratio increases with the increase in momentum payoffs. All these findings are in line with the results shown in Table 4.39, where the second nearest contract is used, as opposed to the most distant contract. However, the magnitude of momentum profitability is very high for the distant maturity contract, which suggests that the use of the distant contract for rolling, is more profitable rather than the use of the nearest one.

Figure 4.21 depicts that the use of distant maturity contract and setting the 15th of the expiry month as the rolling date to compile the future time series is highly profitable compared to the use of nearest maturity contract and end of the month as a rolling date.

Table 4.41: Mean, Standard Deviation and Sharpe Ratio of Momentum Strategies based on Sensitivity Analysis (Monthly)

	Ranking Period 1 (Rolling using Distant Contract)			Ranking Period 1 (Change in Rolling Date)		
	Winner	Loser	Mom[1]	Winner	Loser	Mom
Holding Period 1						
Mean	0.317	-0.437	0.754	0.855	-0.320	1.17
	[0.691]	[-0.895]	[1.38]	[1.55]	[-0.656]	[2.05]**
SD[2]	4.95	5.25	5.87	5.93	5.26	6.16
Sharpe Ratio	0.064	-0.083	0.128	0.144	-0.061	0.190
Holding Period 3						
Mean	0.881	-1.31	2.19	2.33	-0.961	3.29
	[1.05]	[-1.54]	[2.63]**	[2.58]**	[-1.07]	[3.71]*
SD	8.97	9.32	8.89	9.64	9.63	9.46
Sharpe Ratio	0.098	-0.141	0.246	0.241	-0.099	0.347
Holding Period 6						
Mean	1.85	-2.66	4.51	4.58	-1.78	6.36
	[1.45]	[-2.19]**	[4.10]*	[3.60]*	[-1.38]	[5.45]*
SD	13.45	12.79	11.59	13.38	13.65	12.29
Sharpe Ratio	0.138	-0.208	0.389	0.342	-0.130	0.518
Holding Period 12						
Mean	4.61	-4.98	9.60	9.67	-2.70	12.38
	[2.63]**	[-3.08]**	[5.48]*	[5.89]*	[-1.52]	[6.97]*
SD	17.95	16.57	17.94	16.83	18.21	18.20
Sharpe Ratio	0.257	-0.301	0.535	0.575	-0.149	0.680
Holding Period 18						
Mean	8.09	-6.77	14.86	15.41	-3.07	18.48
	[3.73]*	[-3.53]*	[6.19]*	[7.11]*	[-1.45]	[7.88]*
SD	21.60	19.07	23.87	21.56	21.02	23.34
Sharpe Ratio	0.375	-0.355	0.623	7.11	-1.45	0.792
Holding Period 24						
Mean	11.79	-7.99	19.79	21.32	-2.89	24.21
	[4.35]*	[-3.32]*	[6.58]*	[7.91]*	[-1.18]	[8.36]*
SD	26.15	23.25	28.99	25.99	23.74	27.92
Sharpe Ratio	0.451	-0.344	0.683	0.820	-0.122	0.867

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*
[1]Mom refers to the momentum portfolio.
[2]SD refers to the standard deviation.



*(**Source:** Secondary Data Analysis)*

Figure 4.21: Average Returns of Momentum Strategies with their Sensitivity Analysis

Similarly, results shown in Table 4.41 where the 15th day of the maturity month is taken as rolling date, indicate that the returns of all the momentum strategies of the ranking period of one month are positive and significant with an average monthly return of 10.98 percent. In addition, the most profitable strategy is 1-24 with an average return of 24.21 percent and highest standard deviation of 27.92, which confirms that highest momentum payoffs are associated with the highest risk. Similarly, the Sharpe ratio of momentum strategies increases with the increase in momentum payoffs.

4.4.2 Risk-Based Analysis of Momentum Strategies

The risk-based analysis of momentum returns and their time-varying aspects are discussed in this Section.

4.4.2.1 Sensitivity Analysis of Momentum Payoffs against Market Risk

Table 4.42 shows the abnormal performance (α)[4] of momentum strategies and their sensitivity to the Nifty (CNX Nifty stock index), bond (CCIL liquid bond index) and commodity index (MCXCOMDEX) for the ranking period of one month. Out of six momentum strategies, two have a positive and significant beta for bond index and one has a positive and significant beta for the Nifty index. However, the rest of the momentum returns are neutral to the risk of Nifty index. The results show that out of four profitable momentum strategies, two strategies of 18 and 24 months holding periods yield positive and significant abnormal returns (α). On an average, the monthly abnormal return of the profitable strategies equal to 21.00 percent, ranging between 12.29 percent of the strategy 1-18 to 29.72 percent of the strategy 1-24. Hence, the returns of the momentum strategies of longer holding periods are not merely a compensation for different market risk factors. It indicates that investors with long-term investment horizon can earn abnormal returns, by using momentum strategies in commodity futures market. In addition, the abnormal returns of momentum strategies are driven by winner portfolios due to their significant alpha value.

Table 4.42: Risk-Based Performance of Momentum Strategies

		Ranking Period of One month		
	Parameters	Winner	Loser	Momentum
Holding Period of 1 Month	α	0.512 [0.391]	2.52 [1.65]	-2.01 [-1.18]
	β_S	-0.0006[-0.0094]	-0.052 [-0.656]	0.051 [0.579]
	β_B	-0.096[-0.582]	0.255 [1.33]	-0.350 [-1.64]
	β_C	0.099[1.17]	0.191 [1.93]***	-0.092 [-0.829]
	Adjusted R^2	21.22%	25.45%	35.85%
Holding Period of 3 Months	α	2.22 [0.992]	4.95 [1.70]***	-2.74 [-1.02]
	β_S	0.235 [2.03]**	0.076 [0.502]	0.159 [1.15]
	β_B	-0.339 [-1.21]	0.462 [1.27]	-0.801 [-2.39]**
	β_C	0.250 [1.71]***	0.255 [1.34]	-0.005 [-0.029]
	Adjusted R^2	23.54%	20.87%	29.87%
Holding Period of 6 Months	α	5.55 [1.58]	6.12 [1.34]	-0.567 [-0.155]
	β_S	-0.004 [-0.023]	-0.119 [-0.512]	0.115 [0.617]
	β_B	0.214 [0.493]	0.874 [1.54]	-0.659 [-1.45]
	β_C	0.272 [1.19]	0.259 [0.868]	0.013 [0.055]
	Adjusted R^2	27.85%	26.15	33.32%
Holding period of 12 Months	α	11.59 [2.50]**	6.22 [0.960]	5.37 [1.05]
	β_S	-0.081 [-0.346]	-0.170 [-0.517]	0.089 [0.343]
	β_B	0.746 [1.31]	1.07 [1.34]	-0.325 [-0.519]
	β_C	0.271[0.903]	0.088 [0.210]	0.183 [0.554]
	Adjusted R^2	31.95%	22.88%	20.54%
Holding Period of 18 Months	α	17.06 [2.94]**	4.77 [0.652]	12.29 [2.16]**
	β_S	0.133 [0.428]	-0.105 [-0.269]	0.239 [0.763]
	β_B	0.446 [0.628]	0.365 [0.409]	0.081 [0.113]
	β_C	0.533 [1.42]	0.296 [0.626]	0.237 [0.626]
	Adjusted R^2	32.74%	27.23%	36.47%
Holding Period of 24 Months	α	23.94 [3.44]*	-5.79 [-0.658]	29.72 [5.15]*
	β_S	-0.115 [-0.296]	-0.732 [-1.49]	0.617 [1.91]***
	β_B	0.726 [0.854]	-0.896 [-0.835]	1.62 [2.30]**
	β_C	0.789 [1.67]***	0.259 [0.434]	0.531 [1.36]
	Adjusted R^2	26.56%	29.45%	39.14%

(***Source:*** *Secondary Data Analysis*)

*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%,** at 5% and *** at 10% level of significance.*

4.4.2.2 Time-Varying Risk-Based Analysis of Momentum Strategies

As a robustness check, it is essential to analyse whether returns of the momentum strategies are due to exposure to the time-varying risk. To assess this, the time-varying abnormal performance (α) and risk are measured based on the vector of business cycle variables represented by one-month MIBOR, the dividend yield on the Nifty index and term structure of interest rates. For the justification of the model shown in Equation (3.17), it is essential that the hypotheses H_7, H_8 and H_9 should be rejected (Miffre and Rallis, 2007).

Table 4.43: Time-Varying Risk-Based Performance of Momentum Strategies

	HP [1]	α_0	α_{TS}	α_{DY}	α_{MIBOR}	P(α_1=0)	P(β_1=0)	P ($\alpha_1 = \beta_1$=0)	Adjusted R^2
RP [2]-1M	1	-6.54 [-2.47]**	1.71 [0.448]	4.05 [0.654]	2.55 [0.802]	0.3609	0.043**	0.089***	45.56%
	3	-3.60 [-0.897]	-8.36 [-1.45]	21.20 [2.25]**	-4.24 [-0.881]	0.0021**	0.009**	0.0083**	15.9%
	6	-2.67 [-0.512]	2.49 [0.337]	34.73 [2.92]**	3.63 [0.590]	0.0043**	0.0012**	0.0001*	23.5%
	12	-5.69 [-0.771]	4.76 [0.471]	56.18 [3.53]*	-1.67 [-0.194]	0.0066**	0.0002*	0.00*	28.4%
	18	-17.84 [-2.79]**	-21.61 [-2.07]**	70.58 [3.77]*	-33.53 [-3.73]*	0.00*	0.00*	0.00*	42.2%
	24	3.69 [0.346]	-2.76 [-0.235]	63.09 [2.94]**	-16.68 [-1.57]	0.001**	0.00*	0.00*	41.11%

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and at ***10% level of significance.*
[1] refers to the holding period.
[2] refers to the ranking period

The alpha of all the information variables and the probability value of all the hypotheses are reported in Table 4.43. The results demonstrate that five out of six strategies have a significant time-dependent conditional alpha (α_1) and all the six strategies have a significant time-dependent conditional beta (β_1). In addition, all the strategies have shown the joint significance for both conditional alpha and beta. Hence, the application of the model shown in Equation (3.17) is justified with respect to the measure of time-varying alpha and beta. The negative and insignificant values of the monthly conditional measure of abnormal return (α_0) of all the strategies indicate that momentum strategies do not yield abnormal performance when the vector of lagged macroeconomic variables are used to indicate the business cycle. It indicates that the abnormal returns of the momentum strategies are basically time-varying.

4.4.3 Transaction Costs Estimation for Momentum Strategies

Normally, it is assumed that abnormal profitability of momentum strategies could be eroded by transaction costs, incurred to implement these strategies (Lesmond et al., 2004). Hence, it is essential to estimate the net momentum profits by considering the transaction costs to implement the active strategies. In this vein, Fuertes et al. (2010) computed the net momentum returns by taking conservative estimates of transaction costs of 0.033 percent given by Locke and Venkatesh (1997). They found that though transaction costs have an impact on momentum profits, it cannot convert the positive momentum profits to a negative one. They suggested that rolling of contracts, change in the constituents of the active portfolio and active rebalancing of the portfolio are the key factors which affect the portfolio turnover and consequently the momentum profits. They restricted their analysis to the round-trip transaction costs and ignored the costs involved to perform the monthly rebalancing of weights of the constituents to achieve the equal weights in a portfolio. According to them, the costs of monthly rebalancing are minimal compared to other costs. Hence, they have computed the portfolio turnover by counting the number of contracts that are bought and sold in a given month.

In the present study, more importance is given to the trading costs incurred to do the monthly rebalancing of constituents to get the equal weights. This is because all the 13 commodity futures are included in the portfolio for all the rebalancing months. In addition, the position and weights of the constituents are constantly changing for all the months to get the equal weights for both the winner and loser portfolios. The portfolio turnover and net momentum returns are estimated using Equations (3.18), (3.19) and (3.20).

Table 4.44: Portfolio Turnover and Net Momentum Returns of the Profitable Momentum Strategies

	Holding Period	Momentum Returns (%)	Portfolio Turnover (%)	Net Momentum Returns (0.033%)	Net Momentum Returns (0.146%)
Ranking Period of one Month	6	2.87	0.973	1.61	1.42
	12	5.64	0.973	4.86	4.29
	18	8.51	0.973	7.98	7.05
	24	11.65	0.973	11.23	9.91

(***Source:*** *Secondary Data Analysis*)

The results, shown in Table 4.44 clearly indicate that though transaction costs reduced the magnitude of momentum payoffs, they could not erode the positive momentum returns. On an average, momentum strategies earn a monthly net return of 6.42 percent at transaction costs of 0.033 percent. In addition, at the highest level of transaction costs, 0.146 percent reported by Shen et al. (2007), these strategies earn a monthly average net return of 5.67 percent.

4.4.4 Momentum Portfolio: Diversification and Inflation Hedge

Commodity futures are basically used by institutional investors for the purpose of portfolio diversification. Table 4.45 shows the correlation between momentum returns and the returns of Nifty, bond and commodity index.

Table 4.45: Correlation of Momentum Portfolios with Nifty, Bond, Commodity Index and Inflation Index

	Holding Periods	Commodity Index	NIFTY Index	Bond Index	Inflation Index(WPI)
Ranking Period of 1 Month	6	0.0783	0.0630	-0.0923	-0.2574**
	12	0.0650	0.0322	-0.1091	-0.3678**
	18	0.0349	0.0633	-0.1168	-0.4558**
	24	0.0411	0.1991	-0.0352	-0.5578**

*(**Source:** Secondary Data Analysis)*
** shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*

The returns of all the profitable momentum strategies depict a positive and insignificant correlation with commodity index and Nifty index. On the contrary, the correlation of momentum returns of all the four strategies and CCIL bond index is negative and insignificant. The average correlation between the momentum returns and the Nifty stock index is 0.0894, which ranges between 0.0322 of the strategy 1-12 to 0.1991 of the strategy 1-24. This result is in line with the findings of Table 4.42 which confirms that momentum returns are neutral to the risk of the equity market. These results confirm that tactical allocation of commodity futures in a portfolio of traditional asset classes can be used as an excellent tool for portfolio diversification.

Table 4.45 also shows the correlation between the momentum returns and the inflation index. The results demonstrate the negative and significant correlation of momentum returns with inflation index for all the four profitable momentum strategies. These results suggest that the momentum portfolios cannot be used as a hedge against inflation. Hence, the abnormal returns of the momentum strategies and their diversification benefits, result in the loss of basic inflation hedging potential of momentum portfolios. These findings are in line with the outcomes of Erb and Harvey (2006) and Miffre and Rallis (2007).

This section has discussed the time-varying risk-adjusted return performance of momentum strategies in commodity futures market. Section 4.5, deals with the implementation of term structure strategies and analyses their time-varying performance.

4.5 TERM STRUCTURE (TS) STRATEGIES IN COMMODITY FUTURES MARKET

An investor can use the hedging pressure hypothesis to design an active strategy called as term structure strategy to earn an abnormal return by taking a long position in the backwardated contract and short position in the contangoed contract. Based on the work of Erb and Harvey (2006) and Miffre and Rallies (2007), the profitability of 24 term structure strategies is investigated for the Indian commodity futures markets. The performance evaluation of the relative strength portfolios of the term structure strategies is performed in the following stages.

4.5.1 Term Structure (TS) Profits

The performance evaluation of momentum payoffs is analysed from the perspective of their sub-sample and sensitivity analysis in this section.

4.5.1.1 Performance Evaluation of TS Strategies

The mean return, standard deviation and Sharpe ratio of the term-structure strategies for ranking periods of 1 month (TS_1), 3 months (TS_3), 6 months (TS_6) and 12 months (TS_{12}) are shown in Table 4.46. Out of 24 strategies, five strategies of the ranking period of one month (TS_1) and holding periods of 3, 6, 12, 18 and 24 months yield positive and statistically significant returns. The profitable TS_1 strategies give an average monthly return of 9.54 percent (average annualized return of 49.04 percent) by taking the long position in backwardated contracts and the short position in contangoed contracts. On the contrary, over the same study period, a long-only composite commodity index of same 13 commodity futures earns annualized return of 4.76 percent (monthly return 0.205 percent). For the TS_1 strategies, the long position in most backwardated portfolios yields a positive and significant average monthly mean return of 8.98 percent and a short position in most contangoed portfolios earns a negative and insignificant monthly mean loss of -0.533 percent. Hence, the profits of the TS_1 strategies are driven by a long position in the backwardated portfolio. In addition, the most profitable strategy is TS_{1-24} which yields a return of 17.04 percent and the least profitable strategy is TS_{1-3} with a monthly return of 2.50 percent. It indicates that returns of TS_1 strategies increase with the holding periods.

The standard deviation of TS_1 strategies helps to analyse that the TS_1 profits are not the compensation for risk. Table 4.46 shows that as standard deviation increases, there is an increase in TS_1 returns. For instance, the most profitable strategy is TS_{1-24} which gives a highest standard deviation of 35.93. On the contrary, the lowest profitable strategy is TS_{1-3} with the lowest standard deviation of 9.29. These outcomes are in line with the findings of Miffre and Rallis (2007) and normal market perception of higher returns are associated with the higher risk.

The Sharpe ratio of term structure strategies TS_1 increases with an increase in the TS_1 returns. The most profitable strategy TS_{1-24} gives the highest Sharpe ratio of 0.474 compared to the Sharpe ratio 0.269 given by the lowest profitable strategy TS_{1-3}. The results indicate that the TS_1 strategies in commodity futures market perform better with respect to their risk-adjusted return performance compared to passive investment in equity, bond and commodity futures market.

4.5.1.2 Sensitivity analysis of TS Profits

Three different strategies TS_{1a} ,TS_{1b} and TS_{1c} are used for sensitivity analysis of term structure profitability. The first strategy TS_{1a}, is formed to check the impact of using the distant maturity contract for the estimation of the roll yield, on the profitability of term structure strategy. The comparison between term structure strategies with nearest maturity contract (TS_1) and with distant maturity contract (TS_{1a}) is shown in Table 4.47. It suggests that TS_1 performs better than TS_{1a} in terms of mean returns and Sharpe ratio as all the TS_{1a} strategies give insignificant returns. This result indicates that the use of a second nearest contract for the estimation of roll yield gives a better performance compared to the use of a distant contract. Hence, it suggests that profitability of term structure strategy is sensitive to the liquidity risk which arises due to trading in distant maturity contract.

Second strategy TS_{1b} is formulated to assess the impact of increasing the frequency of rebalancing the long-short portfolios on the profitability of term structure strategies. Hence, instead of rebalancing of portfolio once in a month and holding that portfolio for next one month, this strategy allows for a rebalancing of long-short portfolios twice in a month. The negative mean returns and negative Sharpe ratio of TS_{1b} strategies show that strategy TS_1 where rebalancing of the portfolio is done once in a month performs better than strategy TS_{1b} as shown in Table 4.48.

Table 4.46: Mean, Standard Deviation and Sharpe Ratio of TS Strategies (Monthly)

	Ranking Period 1 ($\mathbf{TS_1}$)			Ranking Period 3 ($\mathbf{TS_3}$)			Ranking Period 6 ($\mathbf{TS_6}$)			Ranking period 12 ($\mathbf{TS_{12}}$)		
	Long	Short	TS [1]	Long	Short	TS	Long	Short	TS	Long	Short	TS
Holding Period 1												
Mean	0.696	-0.051	0.753	0.046	-0.029	0.076	-0.294	-0.030	-0.264	-0.452	-0.368	-0.084
	[1.15]	[-0.123]	[1.38]	[0.071]	[-0.071]	[0.122]	[-0.355]	[-0.072]	[-0.329]	[0.128]	[-0.069]	[-0.875]
SD [2]	6.52	4.52	5.90	7.03	4.47	6.70	8.78	4.43	8.48	9.87	5.68	9.12
Sharpe Ratio	0.107	-0.011	0.127	0.007	-0.007	0.011	-0.034	-0.007	-0.031	-0.046	-0.065	-0.009
Holding Period 3												
Mean	2.12	-0.363	2.50	0.270	-0.163	0.433	-0.613	-0.051	-0.562	-0.978	-0.087	-0.891
	[2.05]**	[-0.439]	[2.89]**	[0.201]	[-0.196]	[0.351]	[-0.401]	[-0.061]	[-0.386]	[-0.587]	[-0.098]	[-0.458]
SD	11.09	8.88	9.29	14.29	8.84	13.11	16.02	8.76	15.26	18.45	10.15	17.65
Sharpe Ratio	0.192	-0.041	0.269	0.019	-0.018	0.033	-0.038	-0.006	-0.037	-0.053	-0.009	-0.055
Holding Period 6												
Mean	4.05	-0.91	4.99	0.745	-0.273	1.02	-1.006	-0.177	-0.829	-1.89	-0.247	-1.64
	[3.03]**	[-0.687]	[4.24]*	[0.400]	[-0.204]	[0.583]	[-0.506]	[-0.129]	[-0.417]	[-0.879]	[-0.198]	[-0.658]
SD	14.17	14.02	12.45	19.51	14.03	18.31	20.58	14.14	20.58	26.48	17.14	23.98
Sharpe Ratio	0.286	-0.065	0.401	0.038	-0.019	0.055	-0.049	-0.013	-0.040	-0.071	-0.014	-0.07
Holding Period 12												
Mean	8.45	-1.15	9.63	3.00	0.241	2.77	-0.765	0.459	-1.22	-0.987	0.875	-1.86
	[4.31]*	[-0.624]	[4.82]*	[1.13]	[0.129]	[1.06]	[-0.299]	[0.245]	[-0.431]	[-0.458]	[0.489]	[-0.678]
SD	20.18	18.98	20.58	27.05	19.05	26.66	25.72	18.85	28.56	27.98	21.58	33.96
Sharpe Ratio	0.418	-0.060	0.468	0.111	0.013	0.104	-0.029	0.024	-0.043	-0.035	0.041	-0.055
Holding Period 18												
Mean	12.83	-0.699	13.55	5.86	1.41	4.45	-1.74	1.34	-3.08	-2.01	1.68	-3.69
	[4.78]*	[-0.315]	[4.85]*	[1.72]***	[0.655]	[1.52]	[-0.514]	[0.625]	[-0.899]	[-0.623]	[0.965]	[-1.23]
SD	26.80	22.19	27.98	33.62	21.26	28.96	32.91	20.94	33.39	39.45	23.65	36.87
Sharpe Ratio	0.478	-0.032	0.485	0.174	0.066	0.154	-0.053	0.064	-0.092	-0.051	0.071	-0.10
Holding Period 24												
Mean	17.46	0.459	17.04	9.19	2.95	6.24	-3.60	3.72	-7.33	-5.89	6.45	-12.34
	[4.95]*	[0.169]	[4.59]*	[2.14]**	[1.15]	[1.96]***	[-0.859]	[1.46]	[-1.81]***	[-1.29]	[1.59]	[1.45]
SD	34.19	26.35	35.93	41.14	24.58	30.52	39.57	24.08	38.09	41.23	26.07	41.12
Sharpe Ratio	0.510	0.017	0.474	0.224	0.120	0.205	-0.091	0.155	-0.192	-0.143	0.248	-0.30

***(Source:** Secondary Data Analysis)*

*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*

[1] *TS refers to the term structure portfolio.*

[2] *SD refers the standard deviation.*

Table 4.47: Mean, Standard Deviation and Sharpe Ratio of Term Structure (TS_{1a}) Strategies (Sensitivity Analysis: Use of Distant Contract)

Ranking Period of One month				
	Parameters	Long	Short	Long-Short
TS_{1a-1}	Mean	0.188 [0.269]	0.007 [0.016]	0.181 [0.263]
	Standard Deviation	7.56	4.62	7.45
	Sharpe Ratio	0.025	0.0015	0.024
TS_{1a-3}	Mean	0.444 [0.364]	-0.201 [-0.236]	0.645 [0.527]
	Standard Deviation	13.07	9.17	13.12
	Sharpe Ratio	0.034	-0.022	0.049
TS_{1a-6}	Mean	0.393 [0.258]	-0.477 [-0.355]	0.870 [0.548]
	Standard Deviation	16.11	14.24	16.83
	Sharpe Ratio	0.024	-0.034	0.052
TS_{1a-12}	Mean	0.122 [0.054]	-0.172 [-0.092]	0.294 [0.130]
	Standard Deviation	23.13	19.26	23.25
	Sharpe Ratio	0.005	-0.009	0.013
TS_{1a-18}	Mean	0.168 [0.054]	0.975 [0.425]	-0.807 [-0.259]
	Standard Deviation	30.92	22.93	31.14
	Sharpe Ratio	0.005	0.043	-0.026
TS_{1a-24}	Mean	0.750 [0.196]	2.83 [0.986]	-2.08 [-0.525]
	Standard Deviation	37.03	27.88	38.50
	Sharpe Ratio	0.020	0.102	-0.054

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*

Table 4.48: Mean, Standard Deviation and Sharpe Ratio of Term Structure (TS_{1b}) Strategies (Sensitivity Analysis: Frequent Rebalancing of Long and Short Portfolio)

Ranking Period of One month				
	Parameters	Long	Short	Long-Short
TS_{1b-1}	Mean	-0.359 [-0.566]	0.142 [0.341]	-0.502 [-0.837]
	Standard Deviation	6.89	4.53	6.52
	Sharpe Ratio	-0.052	0.032	-0.077
TS_{1b-3}	Mean	-1.15 [-0.959]	0.263 [0.319]	-1.42 [-1.27]
	Standard Deviation	12.94	8.88	12.04
	Sharpe Ratio	-0.089	0.029	-0.118
TS_{1b-6}	Mean	-2.59 [-1.52]	0.230 [0.178]	-2.82 [-1.76]***
	Standard Deviation	18.13	13.76	17.07
	Sharpe Ratio	-0.143	0.017	-0.165
TS_{1b-12}	Mean	-6.13 [-2.44]**	1.05 [0.627]	-7.18 [-3.37]*
	Standard Deviation	25.99	17.35	22.06
	Sharpe Ratio	-0.236	0.06	-0.325
TS_{1b-18}	Mean	-8.26 [-2.56]**	2.67 [1.39]	-10.93 [-4.16]*
	Standard Deviation	32.42	19.18	26.39
	Sharpe Ratio	-0.255	0.139	-0.414
TS_{1b-24}	Mean	-9.32 [-2.52]**	4.85 [2.00]**	-14.18 [-4.33]*
	Standard Deviation	36.04	23.62	31.88
	Sharpe Ratio	-0.259	0.206	-0.444

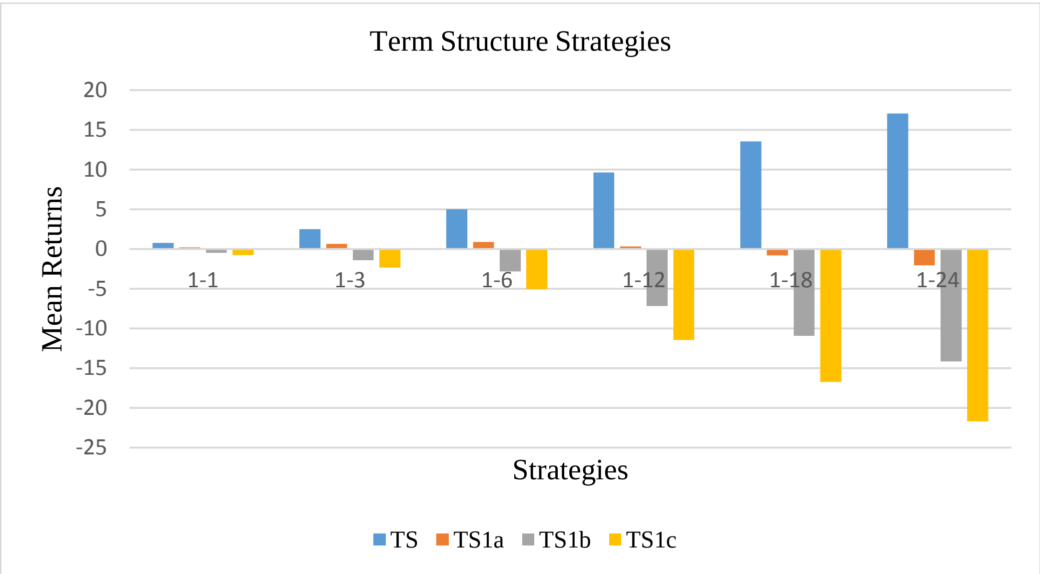
*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and *** at 10% level of significance.*

Table 4.49: Mean, Standard Deviation and Sharpe Ratio of Term Structure (TS_{1c}) Strategies (Sensitivity Analysis: Use of 15th of Month as Rolling Date)

	Ranking Period of One month			
	Parameters	Long	Short	Long-Short
TS_{1c-1}	Mean	-0.620 [-1.39]	0.166 [0.548]	-0.787 [-1.72]***
	Standard Deviation	4.82	3.28	4.94
	Sharpe Ratio	-0.129	0.050	-0.159
TS_{1c-3}	Mean	-2.04 [-2.44]**	0.319 [0.493]	-2.36 [-2.78]**
	Standard Deviation	8.98	6.94	9.09
	Sharpe Ratio	-0.227	0.046	-0.259
TS_{1c-6}	Mean	-4.26 [-3.48]*	0.803 [0.816]	-5.06 [-3.96]*
	Standard Deviation	12.94	10.40	13.51
	Sharpe Ratio	-0.329	0.077	-0.374
TS_{1c-12}	Mean	-9.11 [-5.77]*	2.35 [2.17]**	-11.46 [-7.27]*
	Standard Deviation	16.24	11.16	16.23
	Sharpe Ratio	-0.561	0.211	-0.706
TS_{1c-18}	Mean	-12.94 [-6.99]	3.81 [2.99]*	-16.75 [-9.35]*
	Standard Deviation	18.51	12.73	17.91
	Sharpe Ratio	-0.699	0.299	-0.935
TS_{1c-24}	Mean	-16.19 [-9.29]*	5.49 [3.62]*	-21.69 [-11.12]*
	Standard Deviation	16.91	14.73	18.92
	Sharpe Ratio	-0.958	0.373	-1.15

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*

The performance of term structure strategies with their sensitivity analysis is depicted in Figure 4.22.



*(**Source:** Secondary Data Analysis)*

Figure 4.22: Average Monthly Returns of the Term Structure Strategies with their Sensitivity Analysis

Third strategy TS_{1c} is designed to assess the sensitivity of the term structure profitability to the selection of rolling date. For the strategy TS_{1c}, the rolling date is changed from the end of the month to the 15th of the maturity month. The negative mean returns and negative Sharpe ratio of TS_{1c} strategies show that the strategy TS_1 where end of the month is selected for rolling performs better than strategy TS_{1c} as depicted in Table 4.49. Hence, results confirm that profitability of term structure strategies is sensitive to the selection of rolling dates.

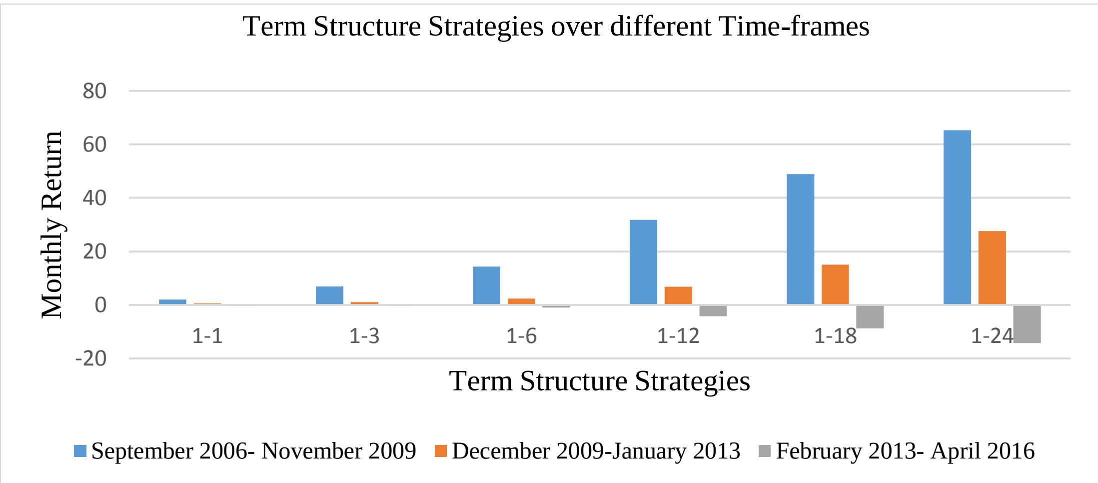
4.5.1.3 TS_1 Profits for Sub-Periods

Table 4.50 shows the TS_1 payoffs of all the six strategies during different time-frames. These results help to analyse the impact of commodity cycle on the consistency of TS_1 profits in the future.

Table 4.50: TS_1 Profitability during different Time-frames

	September 2006-November 2009	December 2009-January 2013	February 2013-April 2016	September 2006-April 2016
	2.05 [2.29]**	0.563 [0.472]	-0.394 [-0.584]	0.753 [1.38]
TS_{1-3}	6.87 [4.69]*	1.07 [0.621]	-0.347 [-0.338]	2.50 [2.89]**
TS_{1-6}	14.37 [7.29]*	2.41 [1.35]	-0.916 [-0.607]	4.99 [4.24]*
TS_{1-12}	31.85 [11.79]*	6.86 [2.93]**	-4.18 [-1.72]***	9.63 [4.82]*
TS_{1-18}	48.95 [17.07]*	15.03 [4.59]*	-8.76 [-3.37]*	13.55 [4.85]*
TS_{1-24}	65.34 [25.99]*	27.56 [6.14]*	-14.27 [-6.17]*	17.04 [4.59]*

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*



*(**Source:** Secondary Data Analysis)*

Figure 4.23: Average Monthly Returns of all the Term Structure Strategies over different Time-frames

The whole sample period is divided into three equal sub-periods. The TS_1 risk-adjusted return of later period (February 2013-April 2016) is compared with the risk-adjusted return of earlier periods (September 2006-November 2009, December 2009-January 2013). The sub-periods analysis reveals that TS_1 strategies perform better for the earlier sub-periods, September 2006-November 2009 and December 2009-January 2013 compared to later sub-period of February 2013-April 2016 as shown in Table 4.50. At the same time, Figure 4.23 depicts that comparison among earlier sub-periods confirms the better performance of sub-period September 2006-November 2009 compared to sub-period December 2009-January 2013. It indicates that TS_1 profits are basically time-varying.

4.5.2 Risk-Based Analysis of TS_1 Strategies

The risk-based analysis of TS_1 returns and their time-varying aspects are discussed in this section.

4.5.2.1 Sensitivity Analysis of TS_1 Payoffs against Market Risk

Table 4.51 shows the abnormal performance (α)[4] of TS_1 strategies and their sensitivity to the Nifty (CNX Nifty stock index), bond (CCIL liquid bond index) and commodity index (MCXCOMDEX). Out of six TS_1 strategies, four strategies have a positive and significant beta for the bond index. However, all the TS_1 returns are neutral to the risk of Nifty index. In addition, three strategies have a positive and significant beta for commodity index and the rest are neutral to the ups and downs of a commodity index. The results show that out of six profitable TS_1 strategies, five strategies of holding periods of 3, 6, 12, 18 and 24 months provide a positive and significant abnormal returns (α). On an average, the monthly abnormal return of the profitable strategies equals to 36.02 percent, ranging between 4.37 percent of the strategy TS_{1-3} to 70.88 percent of the strategy TS_{1-24}. Hence, the returns of the TS_1 strategies of longer holding period are not merely a compensation for different market risk factors. It indicates that investors with long-term investment horizon can earn abnormal returns by using TS_1 strategies in commodity futures market. In addition, the abnormal returns of TS_1 strategies are driven by long portfolios due to their significant alpha value.

Table 4.51: Risk-Based Performance of TS_1 Strategies

	Ranking Period of One month			
	Parameters	Long	Short	Long-Short
TS_{1-1}	α	2.29 [1.37]	0.425 [0.364]	1.86 [1.22]
	β_S	0.096 [1.12]	0.016 [0.259]	0.081 [1.02]
	β_B	-0.006 [-0.028]	-0.040 [-0.276]	0.033 [0.175]
	β_C	0.149 [1.36]	0.093 [1.22]	0.055 [0.552]
	Adjusted R^2	21.78%	45.23%	27.56%
TS_{1-3}	α	5.43 [1.89]***	1.05 [0.475]	4.37 [1.83]***
	β_S	0.098 [0.659]	0.293 [2.56]**	-0.196 [-1.58]
	β_B	0.202 [0.560]	-0.239 [-0.862]	0.439 [1.46]
	β_C	0.20 [1.06]	0.158 [1.09]	0.041 [0.264]
	Adjusted R^2	28.6%	47.56%	38.23%
TS_{1-6}	α	14.47 [3.99]*	-1.02 [-0.274]	15.50 [4.96]*
	β_S	-0.079 [-0.430]	0.063 [0.332]	-0.142 [-0.889]
	β_B	1.18 [2.64]**	-0.179 [-0.388]	1.36 [3.50]*
	β_C	0.473 [2.00]**	0.094 [0.385]	0.378 [1.85]***
	Adjusted R^2	44.89%	23.54%	44.87%
TS_{1-12}	α	26.73 [5.32]*	-8.08 [-1.60]	34.86 [7.26]*
	β_S	-0.266 [-1.02]	-0.164 [-0.632]	-0.099 [-0.399]
	β_B	2.19 [3.51]*	-0.563 [-0.903]	2.76 [4.62]*
	β_C	0.855 [2.58]**	-0.323 [-0.978]	1.18 [3.73]*
	Adjusted R^2	43.23%	23.67%	22.1%
TS_{1-18}	α	37.30 [5.46]*	-17.15 [-2.93]**	54.51 [8.76]*
	β_S	-0.349 [-0.989]	-0.035 [-0.115]	-0.318 [-0.989]
	β_B	2.67 [3.20]**	-1.89 [-2.65]**	4.56 [6.01]*
	β_C	1.37 [3.12]**	-0.564 [-1.49]	1.94 [4.85]*
	Adjusted R^2	27.54%	43.22%	33.20%
TS_{1-24}	α	44.22 [4.85]*	-26.68 [-3.94]*	70.88 [8.69]*
	β_S	-0.635 [-1.24]	-0.465 [-1.22]	-0.174 [-0.380]
	β_B	2.85 [2.58]**	-2.99 [-3.65]*	5.85 [5.91]*
	β_C	1.73 [2.85]**	-0.684 [-1.51]	2.41 [4.42]
	Adjusted R^2	32.56%	21.56%	33.9%

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*

4.5.2.2 Time-Varying Risk-Based Analysis of TS_1 Strategies

Similar to the procedure used in the case of momentum strategies, robustness analysis is performed to analyse whether returns of the TS_1 strategies are due to exposure to the time-varying risk. The alpha of all the information variables and the probability value of the hypotheses H_7, H_8 and H_9 are reported in Table 4.52. The results demonstrate that three out of the five strategies have a significant time-dependent conditional alpha (α_1) and the significant time-dependent conditional beta (β_1). In addition, the three strategies have shown joint significance for both conditional alpha and conditional beta. Hence, the application of the model shown in Equation (3.17) is justified with respect to the measure of time-varying alpha and beta. The average monthly conditional measure of abnormal return (α_0) equals to 11.54 percent which ranges from a low of 9.64 percent of the strategy TS_{1-6} to a high of 13.44 percent of the strategy TS_{1-12}. It indicates that the abnormal returns of the IVol strategies of holding period from 6 to 12 months cannot be wiped out by the time-varying risk. On the contrary, insignificant values of abnormal returns (α_0) of other profitable strategies TS_{1-3}, TS_{1-18} and TS_{1-24} indicate that the abnormal performance (α) of these strategies are time-varying.

Table 4.52: Time-Varying Risk-Based Performance of TS_1 Strategies

Combined Strategies	α_0	α_{TS}	α_{DY}	α_{MIBOR}	P(α_1=0)	P(β_1=0)	P ($\alpha_1 = \beta_1$=0)	Adj R^2
TS_{1-3}	1.89 [0.487]	-4.09 [-0.734]	6.72 [0.735]	-3.51 [-0.753]	0.7599	0.5340	0.6109	31.42%
TS_{1-6}	9.64 [1.95]***	-5.87 [-0.843]	14.13 [1.25]	-3.37 [-0.583]	0.2340	0.1610	0.1000	19.8%
TS_{1-12}	13.44 [1.92]***	-2.84 [-0.283]	43.25 [2.74]**	-4.83 [-0.573]	0.0590	0.0200	0.0004	39.23%
TS_{1-18}	13.19 [1.43]	-0.137 [-0.011]	53.19 [2.74]**	-11.90 [-1.13]	0.0037	0.072	0.00	53.9%
TS_{1-24}	11.53 [0.847]	-10.59 [-0.664]	42.01 [1.43]	-26.68 [-1.90]***	0.0014	0.0515	0.00	57.9%

*(**Source:** Secondary Data Analysis)*

*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*

4.5.3 Transaction Costs Estimation for TS_1 Strategies

Transaction costs for TS_1 strategies are estimated using Equations (3.18), (3.19) and (3.20). The results shown in Table 4.53 clearly indicate that though transaction costs reduced the magnitude of TS_1 payoffs, they could not erode the positive TS_1 returns.

Table 4.53: Portfolio Turnover and Net TS_1 Returns of the Profitable TS_1 Strategies

	Holding Period	TS_1 Returns (%)	Portfolio Turnover (%)	Net TS_1 Returns (0.033%)	Net TS_1 Returns (0.146%)
Ranking Period of one Month	3	2.50	0.824	1.95	1.72
	6	4.99	0.824	4.00	3.54
	12	9.63	0.824	6.59	5.83
	18	13.55	0.824	10.29	9.09
	24	17.04	0.824	12.91	11.40

*(**Source:** Secondary Data Analysis)*

On an average, TS_1 strategies earn a monthly net return of 7.15 percent at a transaction cost of 0.033 percent. In addition, at the highest level of transaction costs, 0.146 percent reported by Shen et al. (2007), these strategies earn a monthly average net return of 6.32 percent.

4.5.4 TS_1 Portfolio: Diversification and Inflation Hedge

The correlations between TS_1 returns and the returns of Nifty, bond and commodity indices are shown in Table 4.54.

Table 4.54: Correlation of TS_1 Strategies with Nifty, Bond, Commodity Index and Inflation Index

$\mathbf{TS_1}$ Strategies	Nifty	Bond	Commodity Index	Inflation Index(WPI)
TS_{1-3}	-0.180	-0.015	-0.102	-0.381*
TS_{1-6}	-0.067	0.074	-0.007	-0.571*
TS_{1-12}	0.00	-0.007	0.097	-0.730*
TS_{1-18}	-0.060	-0.008	0.104	-0.874*
TS_{1-24}	-0.015	-0.001	0.095	-0.945*

*(**Source:** Secondary Data Analysis)*
** shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*

The profitable term structure strategies TS_1 have an insignificant correlation with Nifty and bond indices. This result is in line with the findings of Table 4.51 which confirms that TS_1 returns are neutral to the risk of Nifty and bond index. Hence, it suggests that tactical allocation of commodity futures in a portfolio of traditional asset classes using term structure strategy can be efficiently used to diversify the portfolio and earn an abnormal return. In addition, the significant and negative correlation of TS_1 portfolios with inflation index, suggests that long-short portfolios of TS_1 strategies cannot be used as a hedge against inflation. Hence the abnormal returns of the term structure strategies TS_1 comes at the cost of losing its inflation hedging property.

The present section has discussed the time-varying risk-adjusted return performance of term structure strategies in commodity futures market. Section 4.6 deals with the implementation of idiosyncratic volatility strategies and analyses their time-varying performance.

4.6 IDIOSYNCRATIC VOLATILITY (IVol) STRATEGIES IN COMMODITY FUTURES MARKET

An investor can design an active strategy by exploiting the negative pattern between idiosyncratic volatility and expected return of an asset as shown by Ang et al. (2009) and Miffre et al. (2012). The long-short 24 idiosyncratic volatility strategies are designed in this study by allocating the wealth in the commodity futures with low idiosyncratic volatility and taking the short position in the commodities with high idiosyncratic volatility.

4.6.1 Idiosyncratic Volatility (IVol) Profits

The performance evaluation of relative strength portfolios of the idiosyncratic volatility (IVol) strategies is performed in following stages.

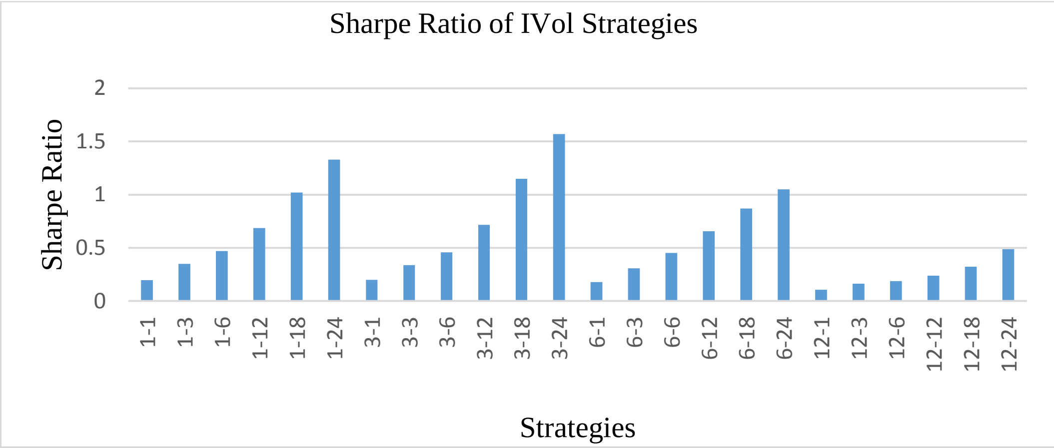
4.6.1.1 Performance Evaluation of IVol Strategies

The mean, standard deviation and risk-adjusted return performance i.e. Sharpe ratio of all the IVol strategies are shown in Table 4.55. Results show that out of 24 IVol strategies, 22 strategies give an average monthly return of 11.59 percent (average annualized return of 63.45 percent) by consistently buying the commodity futures with past low idiosyncratic volatility and selling the commodity futures with past high idiosyncratic volatility.

The positive and significant returns of long-short portfolios of IVol strategies are driven by the positive and significant returns of long portfolios as out of 22 profitable IVol strategies, 20 long portfolios give a positive and significant returns compared to negative and significant returns given by only six short portfolios. Besides, IVol strategies of the ranking period of 3 months are more profitable compared to ranking periods of 1, 6 and 24 months which give a monthly average return of 14.72 percent as shown by the Sharpe ratio in Figure 4.24. In addition, IVol strategy (3-24) with a ranking period of 3 months and holding period of 24 months is more profitable and gives the highest monthly return of 35.88 percent. It indicates that IVol profits increase with the holding period.

Table 4.55 shows that 20 long portfolios out of 24 IVol strategies yield a positive and significant returns ranging between monthly returns of 2.02 percent to 26.60 percent. On the contrary, six loser portfolios yield a negative and significant returns from a low of -4.22 percent to a high of -9.28 percent. Further, two loser portfolios with ranking period 12 months and holding periods of 18 and 24 months, respectively yield a positive and significant return of 6.79 percent and 11.99 percent, respectively.

Table 4.55 shows that the standard deviation increases with the increase in IVol returns. For instance, in the group of ranking period 3, the most profitable strategy is 3-24 which gives the highest average monthly return of 35.88 percent and highest standard deviation of 22.81. On the contrary, lowest profitable strategy in the group with a ranking period of 3 months is 3-1 with the lowest average return of 1.19 percent and the lowest standard deviation of 5.93. Similar is the case with other ranking periods of 1, 6 and 12 months. These outcomes suggest that higher returns are associated with the higher risk.



***(Source:** Secondary Data Analysis)*

Figure 4.24: Sharpe Ratio of IVol Strategies

Sharpe ratio shown in Table 4.55 helps to analyse the risk-adjusted performance of all the IVol strategies. In the group of a ranking period of 3 months, Sharpe ratio increases with the increase in momentum payoffs and ranges from 0.201 to 1.57. For example, the most profitable strategy 3-24 has a highest Sharpe ratio 1.57. Similar results are given by the IVol strategies of ranking periods of 1, 6 and 12 months. Moreover, the results indicate that the IVol strategies in commodity futures market perform better with respect to their risk-adjusted return performance compared to passive investment in equity, bond and commodity index.

4.6.1.2 Idiosyncratic Volatility Profits for Sub-Periods

The results of Table 4.56 help to analyse the impact of commodity cycle on the consistency of IVol profits in the future. Figure 4.25 shows the performance of all the IVol strategies during different time-frames. The whole sample period is divided into three equal sub-periods. The IVol risk-adjusted return of later period (February 2013-April 2016) is compared with the risk-adjusted return of earlier periods (September 2006-November 2009, December 2009-January 2013).The sub-period analysis reveals that IVol strategies perform better for the earlier sub-periods, September 2006-November 2009 and December 2009-January 2013 compared to later sub-period of February 2013-April 2016.

Table 4.55: Mean, Standard Deviation and Sharpe Ratio of Strategies Based on Idiosyncratic Volatility (Monthly)

	Ranking Period 1			Ranking Period 3			Ranking Period 6			Ranking Period 12		
	Long	Short	IVol[1]	Long	Short	IVol	Long	Short	IVol	Long	Short	IVol
Holding Period 1												
Mean	0.666	-0.454	1.12	0.691	-0.504	1.19	0.742	-0.269	1.01	0.787	0.151	0.636
	[1.32]	[-0.935]	[2.10]**	[1.37]	[-1.00]	[2.14]**	[1.48]	[-0.543]	[1.89]***	[1.45]	[0.287]	[1.09]
SD[2]	5.39	5.21	5.72	5.38	5.33	5.93	5.27	5.21	5.62	5.54	5.36	5.97
Sharpe Ratio	0.123	-0.087	0.196	0.129	-0.095	0.201	0.141	-0.052	0.179	0.142	0.028	0.106
Holding Period 3												
Mean	2.02	-1.41	3.43	2.13	-1.42	3.55	2.17	-0.892	3.06	2.37	0.544	1.83
	[2.19]**	[-1.41]	[3.73]*	[2.21]**	[-1.39]	[3.57]*	[2.25]**	[-0.859]	[3.19]*	[2.27]**	[0.489]	[1.65]
SD	9.78	10.62	9.78	10.15	10.77	10.49	10.03	10.78	9.98	10.55	11.24	11.23
Sharpe Ratio	0.206	-0.133	0.351	0.210	-0.132	0.339	0.216	-0.083	0.307	0.225	0.048	0.163
Holding Period 6												
Mean	4.06	-2.55	6.62	4.42	-2.64	7.06	4.49	-1.64	6.13	4.45	1.48	2.97
	[2.97]**	[-1.64]	[4.94]*	[3.06]*	[-1.65]	[4.76]*	[3.19]*	[-1.02]	[4.63]*	[2.88]**	[0.837]	[1.86]***
SD	14.35	16.28	14.05	15.03	16.66	15.41	14.42	16.43	13.56	15.35	17.59	15.90
Sharpe Ratio	0.283	-0.157	0.471	0.294	-0.158	0.458	0.312	-0.099	0.452	0.289	0.084	0.187
Holding Period 12												
Mean	9.26	-4.22	13.48	10.65	-4.54	15.19	9.89	-2.19	12.08	8.32	3.55	4.77
	[4.48]*	[-2.16]**	[7.02]*	[4.94]*	[-2.22]**	[7.24]*	[4.83]*	[-1.08]	[6.52]*	[3.94]*	[1.67]	[2.29]**
SD	21.08	19.96	19.60	21.79	20.65	21.19	20.35	20.16	18.43	20.39	20.48	20.06
Sharpe Ratio	0.439	-0.211	0.688	0.489	-0.219	0.717	0.486	-0.108	0.656	0.408	0.173	0.238
Holding Period 18												
Mean	15.91	-6.03	21.94	18.23	-7.17	25.40	15.19	-3.51	18.71	13.49	6.79	6.69
	[5.88]*	[-2.75]**	[10.07]*	[6.35]*	[-3.14]*	[11.22]*	[5.64]*	[-1.47]	[8.39]*	[5.07]*	[3.15]**	[3.00]**
SD	26.79	21.67	21.56	28.15	22.36	22.19	25.99	22.94	21.51	24.82	20.09	20.78
Sharpe Ratio	0.594	-0.278	1.02	0.648	-0.320	1.15	0.585	-0.153	0.869	0.543	0.338	0.322
Holding Period 24												
Mean	23.08	-7.95	31.03	26.60	-9.28	35.88	22.46	-2.27	24.73	21.09	11.99	9.10
	[6.80]*	[-2.92]**	[12.75]*	[7.33]*	[-3.37]*	[14.92]*	[6.89]*	[-0.824]	[9.79]*	[6.76]*	[5.30]*	[4.39]*
SD	32.55	26.06	23.35	34.43	26.11	22.81	30.41	25.68	23.57	28.07	20.36	18.67
Sharpe Ratio	0.709	-0.305	1.33	0.773	-0.355	1.57	0.739	-0.088	1.05	0.751	0.589	0.487

*(**Source:** Secondary Data Analysis)*

*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*

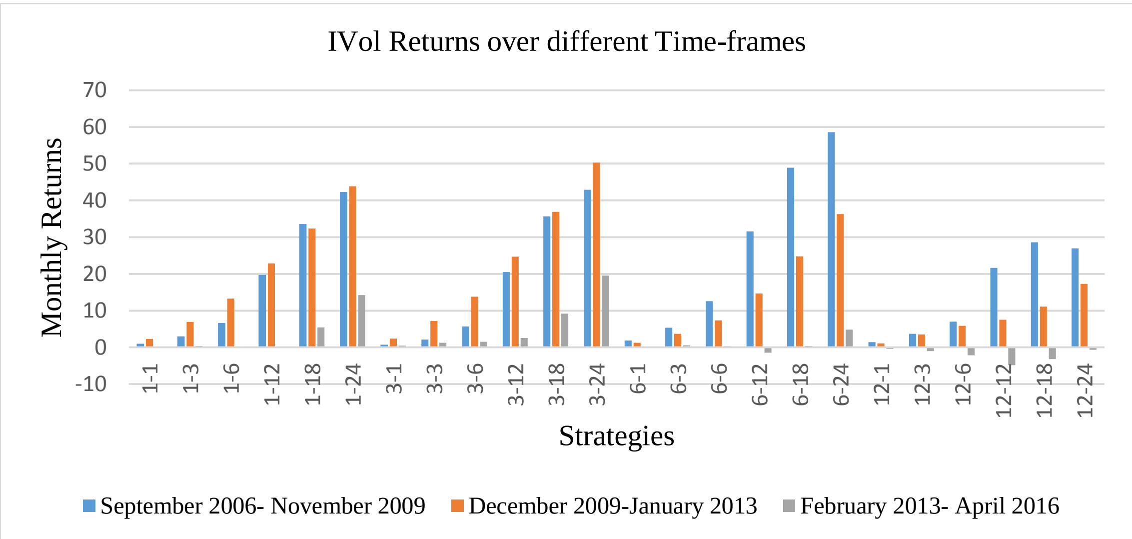
[1] IVol refers the Idiosyncratic Volatility portfolio.

[2] SD refers the standard deviation.

Table 4.56: IVol Profitability during different Time-frames

Holding Periods	September 2006-November 2009	December 2009-January 2013	February 2013-April 2016	September 2006-April 2016
		Ranking Period of One		
1	1.02 [1.08]	2.32 [2.10]**	0.047 [0.072]	1.12 [2.10]**
3	2.99 [1.50]	6.96 [4.85]*	0.402 [0.347]	3.43 [3.73]*
6	6.63 [2.06]**	13.25 [8.65]*	0.144 [0.087]	6.62 [4.94]*
12	19.73 [4.72]*	22.89 [9.09]*	-0.009 [-0.004]	13.48 [7.02]*
18	33.60 [9.81]*	32.39 [11.62]*	5.45 [1.95]**	21.94 [10.07]*
24	42.27 [13.14]*	43.84 [16.03]*	14.22 [4.10]*	31.03 [12.75]*
		Ranking Period of Three		
1	0.697 [0.683]	2.36 [2.08]**	0.515 [0.730]	1.19 [2.14]**
3	2.10 [0.944]	7.16 [4.42]*	1.30 [1.10]	3.55 [3.57]*
6	5.70 [1.52]	13.80 [7.33]*	1.56 [0.906]	7.06 [4.76]*
12	20.48 [3.75]*	24.70 [9.66]*	2.53 [1.09]	15.19 [7.24]*
18	35.63 [7.03]*	36.89 [15.16]*	9.22 [3.18]*	25.40 [11.22]*
24	42.85 [20.52]*	50.30 [20.67]*	19.52 [5.55]*	35.88 [14.92]*
		Ranking Period of Six		
1	1.84 [1.77]***	1.22 [1.13]	0.104 [0.162]	1.01 [1.89]***
3	5.39 [2.69]**	3.73 [2.07]**	0.552 [0.480]	3.06 [3.19]*
6	12.61 [4.58]*	7.36 [3.34]*	0.274 [0.167]	6.13 [4.63]*
12	31.54 [10.43]*	14.65 [6.30]*	-1.40 [-0.712]	12.08 [6.52]*
18	48.91 [14.48]*	24.76 [14.34]*	0.420 [0.199]	18.71 [8.39]*
24	58.59 [19.33]*	36.27 [15.36]*	4.81 [2.19]*	24.73 [9.79]*
		Ranking Period of Twelve		
1	1.43 [1.01]	1.10 [1.04]	-0.374 [-0.582]	0.636 [1.09]
3	3.69 [1.16]	3.48 [2.05]**	-0.970 [-0.799]	1.83 [1.65]
6	7.01 [1.32]	5.85 [3.08]*	-2.12 [-1.15]	2.97 [1.86]***
12	21.63 [3.38]*	7.57 [2.79]*	-4.87 [-2.05]**	4.77 [2.29]**
18	28.63 [3.11]*	11.06 [4.40]*	-3.19 [-1.15]	6.69 [3.00]*
24	26.93 [7.73]*	17.28 [9.26]*	-0.693 [-0.216]	9.10 [4.39]*

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and *** at 10% level of significance.*



*(**Source:** Secondary Data Analysis)*

Figure 4.25: Average Monthly Returns of all the IVol Strategies over different Time-frames

At the same time, comparison among earlier sub-periods confirms a better performance of sub-period, September 2006-November 2009 compared to sub-period, December 2009-January 2013. September 2006-November 2009 yields an average monthly return of 26.06 percent compared to 17.68 percent return given by sub-period December 2009-January 2013. It indicates that IVol profits are basically time-varying.

4.6.2 Risk-Based Analysis of IVol Strategies

The time-varying risk-based analysis of IVol returns is discussed in this section.

4.6.2.1 Sensitivity Analysis of IVol Payoffs against Market Risk

Table 4.57 and 4.58 show the abnormal performance (α)[4] of IVol strategies and their sensitivity to the Nifty (CNX Nifty stock index), bond (CCIL liquid bond index) and commodity index (MCXCOMDEX). The results in Table 4.57 and 4.58 show that out of 24 IVol strategies, one has a positive and significant beta for bond index and four strategies have a negative and significant beta for the Nifty index. However, the rest of the IVol returns are neutral to the risk of Nifty index. In addition, four strategies have a positive and significant beta for commodity index and rest are neutral to the ups and downs of a commodity index. In addition, out of 22 profitable momentum strategies, ten strategies with ranking periods of 1, 3 and 6 months and holding periods of 6, 12, 18 and 24 months provide positive and significant abnormal returns (α).

On an average, the monthly abnormal return of the profitable strategies is 28.61 percent, ranging between 9.06 percent of the strategy 6-6 to 47.97 percent of the strategy 6-24. This proves that returns of the IVol strategies with longer holding periods are not merely a compensation for different market risk factors. It indicates that investors with long-term investment horizon can earn abnormal returns by using IVol strategies in commodity futures market. In addition, the abnormal returns of IVol strategies are driven by long portfolios due to their significant alpha values.

4.6.2.2 Time-Varying Risk-Based Analysis of IVol Strategies

Robustness analysis is performed to analyse whether returns of the IVol strategies are due to exposure to the time-varying risk. The alpha of all the information variables and the probability values of the hypotheses H_7, H_8 and H_9 are reported in Table 4.59.

Table 4.57: Risk-Based Performance of IVol Strategies for One and Three Months Ranking Periods

		Ranking Period of One month			Ranking Period of Three months		
	Parameters	Long	Short	Long-Short	Long	Short	Long-Short
H[1]	α	0.642	-0.047	0.688	1.02	-0.276	1.29
-		[0.458]	[-0.035]	[0.469]	[0.722]	[-0.197]	[0.831]
1	β_S	-0.065	0.093	-0.157	-0.047	0.096	-0.143
		[-0.894]	[1.34]	[-2.07]**	[-0.654]	[1.35]	[-1.80]***
	β_B	-0.062	-0.147	0.085	-0.062	-0.139	0.078
		[-0.352]	[-0.879]	[0.461]	[-0.351]	[-0.809]	[0.406]
	β_C	0.116	0.112	0.004	0.150	0.074	0.076
		[1.26]	[1.28]	[0.046]	[1.64]	[0.818]	[0.751]
	Adjusted R^2	21.56%	22.23%	19.54%	24.32%	45.23%	34.23%
H-	α	1.44	1.35	0.089	2.39	1.17	1.22
3		[0.554]	[0.495]	[0.035]	[0.888]	[0.419]	[0.44]
	β_S	0.043	0.27	-0.227	0.072	0.241	-0.169
		[0.327]	[1.95]***	[-1.76]***	[0.526]	[1.69]	[-1.19]
	β_B	-0.233	-0.138	-0.094	-0.188 [-	-0.089	-0.098
		[-0.724]	[-0.410]	[-0.30]	0.563]	[-0.26]	[-0.286]
	β_C	0.095	0.276	-0.181	0.148	0.234	-0.087
		[0.563]	[1.56]	[-1.09]	[0.840]	[1.28]	[-0.480]
	Adjusted R^2	17.56%	51.23%	29.34%	12.32%	31.34%	36.23%
H-	α	3.46	-0.249	3.71	5.09	-0.554	5.64
6		[0.906]	[-0.058]	[1.01]	[1.27]	[-0.125]	[1.38]
	β_S	-0.204	0.005	-0.209	-0.127 [-	-0.037	-0.091
		[-1.04]	[0.024]	[-1.11]	0.615]	[-0.160]	[-0.429]
	β_B	0.142	-0.022	0.164	0.185	0.055	0.130
		[0.300]	[-0.041]	[0.362]	[0.371]	[0.099]	[0.256]
	β_C	-0.031	0.352	-0.383	0.044	0.287	-0.243
		[-0.124]	[1.24]	[-1.59]	[0.167]	[0.984]	[-0.904]
	Adjusted R^2	16.45%	19.34%	23.45%	25.34%	19.45%	24.46%
H-	α	6.55	-7.70	14.25	11.98	-9.44	21.43
12		[1.15]	[-1.43]	[2.66]**	[1.99]**	[-1.68]***	[3.73]*
	β_S	-0.267	-0.308	0.040	-0.004 [-	-0.375	0.371
		[-0.919]	[-1.12]	[0.148]	0.014]	[-1.29]	[1.25]
	β_B	0.0028	-0.101	0.104	0.200	-0.181	0.382
		[0.0039]	[-0.152]	[0.158]	[0.273]	[-0.264]	[0.543]
	β_C	-0.141	-0.116	-0.025	0.009	-0.165	0.173
		[-0.380]	[-0.330]	[-0.073]	[0.023]	[-0.455]	[0.467]
	Adjusted R^2	22.34%	45.34%	29.34%	29.25%	19.45%	23.34%
H-	α	9.97	-15.42	25.39	16.89	-19.15	36.04
18		[1.33]	[-2.58]**	[4.21]*	[2.13]**	[-3.13]**	[5.94]*
	β_S	-0.184	-0.228	0.043	0.068	-0.413	0.480
		[-0.463]	[-0.716]	[0.135]	[0.161]	[-1.26]	[1.48]
	β_B	-0.792	-1.06	0.269	-0.572 [-	-1.19	0.627
		[-0.873]	[-1.46]	[0.368]	0.597]	[-1.62]	[0.855]
	β_C	0.067	-0.131	0.198	0.271	-0.199	0.469
		[0.137]	[-0.336]	[0.501]	[0.525]	[-0.497]	[1.19]
	Adjusted R^2	18.34%	38.43%	29.23%	23.56%	32.23%	35.12%
H-	α	5.50	-26.04	31.55	10.23	-26.75	36.98
24		[0.598]	[-3.62]*	[4.63]*	[1.04]	[-3.75]*	[5.59]*
	β_S	-0.545	-0.575	0.029	-0.695	-1.09	0.398
		[-1.06]	[-1.43]	[0.078]	[-1.09]	[-2.37]**	[0.932]
	β_B	-2.08	-2.07	-0.010	-1.86	-1.16	-0.704
		[-1.86]***	[-2.36]**	[-0.013]	[-1.39]	[-1.19]	[-0.779]
	β_C	-0.116	-0.172	0.056	-0.021	-0.514	0.492
		[-0.185]	[-0.350]	[0.120]	[-0.031]	[-1.03]	[1.06]
	Adjusted R^2	33.12%	54.32%	34.23%	27.21%	24.12%	34.10%

*(**Source:** Secondary Data Analysis)*

*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and ***at 10% level of significance.*
H[1] refers to the holding period.

Table 4.58: Risk-Based Performance of IVol Strategies for Six and Twelve Months Ranking Periods

		Ranking Period of Six months			Ranking Period of Twelve months		
	Parameters	Long	Short	Long-Short	Long	Short	Long-Short
H^1-1	α	1.68	0.015	1.66	1.83	0.775	1.05
		[1.22]	[0.011]	[1.12]	[1.24]	[0.538]	[0.659]
	β_S	-0.057	0.072	-0.129	-0.106	0.055	-0.160
		[-0.812]	[1.02]	[-1.70]	[-1.41]	[0.749]	[-1.97]***
	β_B	-0.009	-0.115	0.107	0.064	-0.084	0.147
		[-0.05]	[-0.677]	[0.581]	[0.349]	[-0.472]	[0.748]
	β_C	0.198	0.083	0.115	0.194	0.118	0.076
		[2.19]**	[0.919]	[1.19]	[2.03]**	[1.26]	[0.733]
	Adjusted R^2	19.23%	24.12%	15.23%	17.23%	32.15%	43.23%
H-3	α	3.98	0.919	3.06	3.89	3.88	0.006
		[1.52]	[0.326]	[1.15]	[1.36]	[1.30]	[0.002]
	β_S	0.106	0.202	-0.096	0.061	0.269	-0.209
		[0.783]	[1.39]	[-0.697]	[0.411]	[1.75]***	[-1.32]
	β_B	-0.114	-0.1434	0.029	-0.110	-0.068	-0.042
		[-0.349]	[-0.408]	[0.087]	[-0.315]	[-0.187]	[-0.113]
	β_C	0.272	0.207	0.064	0.262	0.278	-0.02
		[1.57]	[1.12]	[0.368]	[1.42]	[1.45]	[-0.084]
	Adjusted R^2	14.23%	16.54	24.23%	24.34%	42.23%	24.43%
H-6	α	8.12	-0.939	9.06	6.55	5.49	1.06
		[2.08]**	[-0.209]	[2.46]**	[1.54]	[1.13]	[0.239]
	β_S	-0.115	-0.045	-0.070	-0.159	-0.023	-0.136
		[-0.579]	[-0.197]	[-0.374]	[-0.698]	[-0.087]	[-0.576]
	β_B	0.372	-0.044	0.416	0.214	0.355	-0.141
		[0.773]	[-0.081]	[0.917]	[0.411]	[0.595]	[-0.261]
	β_C	0.287	0.187	0.099	0.255	0.266	-0.010
		[1.13]	[0.643]	[0.417]	[0.925]	[0.840]	[-0.037]
	Adjusted R^2	14.12%	25.23%	21.12%	25.32%	21.43%	26.34%
H-12	α	13.29	-8.83	22.12	11.61	4.77	6.84
		[2.37] **	[-1.60]	[4.43]*	[1.99]**	[0.804]	[1.17]
	β_S	-0.349	-0.359	0.011	-0.527	-0.314	-0.214
		[-1.16]	[-1.22]	[0.041]	[-1.62]	[-0.945]	[-0.655]
	β_B	0.550	-0.334	0.885	0.837	0.475	0.362
		[0.801]	[-0.496]	[1.45]	[1.17]	[0.656]	[0.508]
	β_C	0.309	-0.292	0.600	0.194	0.032	0.162
		[0.847]	[-0.818]	[1.86]***	[0.489]	[0.079]	[0.409]
	Adjusted R^2	13.23%	24.54%	25.32%	24.54%	21.54%	27.23%
H-18	α	19.64	-21.66	41.29	14.62	6.85	7.77
		[2.61]**	[-3.43]*	[7.22]*	[1.75]***	[1.03]	[1.14]
	β_S	-0.314	-0.373	0.058	-0.242	-0.716	0.474
		[-0.746]	[-1.06]	[0.182]	[-0.508]	[-1.89]***	[1.22]
	β_B	0.464	-2.03	2.49	-0.107	0.940	-1.05
		[0.505]	[-2.63]**	[3.57]*	[-0.085]	[0.939]	[-1.02]
	β_C	0.496	-0.402	0.898	0.500	-0.289	0.789
		[0.969]	[-0.939]	[2.31]**	[0.953]	[-0.693]	[1.85]***
	Adjusted R^2	21.45%	43.23%	34.23%	23.27%	18.12%	31.21%
H-24	α	20.32	-27.65	47.97	20.04	14.29	5.74
		[1.99]**	[-3.63]*	[6.89]*	[1.86]***	[1.83]***	[0.808]
	β_S	-0.538	-1.16	0.617	-0.287	-0.587	0.299
		[-0.925]	[-2.65]**	[1.55]	[-0.437]	[-1.23]	[0.688]
	β_B	-0.436 [-0.283]	-1.78	1.34	-0.582	0.703	-1.28
			[-1.54]	[1.27]	[-0.375]	[0.626]	[-1.25]
	β_C	0.603	-1.02	1.62	0.680	0.207	0.473
		[0.940]	[-2.13]**	[3.71]*	[1.08]	[0.453]	[1.14]
	Adjusted R^2	24.53%	20.55	29.32%	37.21%	15.26%	37.43%

*(**Source:** Secondary Data Analysis)*

*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and ***at 10% level .of significance. H^1 refers to the holding period.*

Table 4.59: Time-Varying Risk-Based Performance of IVol Strategies

	H[1]	α_0	α_{TS}	α_{DY}	α_{MIBOR}	P(α_1=0)	P(β_1=0)	P ($\alpha_1 = \beta_1$=0)	Adj R^2
R[2]-1	12	15.74 [2.10]**	-2.87 [-0.283]	56.80 [3.54]*	-0.929 [-0.107]	0.0008*	0.1437	0.00*	34.00%
	18	16.69 [1.82]***	13.54 [1.12]	52.66 [2.39]**	4.51 [0.437]	0.068***	0.3674	0.00*	27.34%
	24	3.29 [0.242]	-9.21 [-0.614]	43.72 [1.59]	-20.59 [-1.51]	0.035**	0.034**	0.002**	19.32%
R-3	12	20.46 [2.59]**	-0.076 [-0.007]	60.97 [3.64]*	-2.16 [-0.237]	0.004**	0.3982	0.00*	39.6%
	18	33.46 [3.33]**	19.69 [1.53]	44.11 [1.87]***	8.59 [0.763]	0.064***	0.2586	0.00*	26.15%
	24	14.74 [1.04]	-7.11 [-0.462]	15.14 [0.542]	-18.48 [-1.32]	0.023**	0.037**	0.019**	14.41%
R-6	6	6.87 [1.12]	8.18 [0.976]	24.29 [1.84]***	6.98 [0.977]	0.1425	0.3958	0.0736***	51.21%
	12	10.15 [1.36]	-0.389 [-0.039]	45.73 [2.62]**	-3.57 [-0.426]	0.059***	0.015**	0.0702***	33.73%
	18	20.45 [1.88]***	13.85 [1.16]	60.63 [2.77]**	2.29 [0.211]	0.014**	0.1653	0.0001*	39.53%
	24	13.81 [1.14]	-2.05 [-0.154]	7.01 [0.249]	-16.74 [-1.36]	0.0004*	0.0035**	0.0002*	43.88%

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level .*
H[1] refers to the holding period.
R[2] refers to the ranking period.

The results demonstrate that nine out of the ten strategies have a significant time-dependent conditional alpha (α_1) and four strategies have a significant time-dependent conditional beta (β_1). In addition, all strategies have shown a joint significance for both conditional alpha and conditional beta. Hence, the application of model shown in Equation (3.17) is justified with respect to the measure of time-varying alpha and beta. The average monthly conditional measure of abnormal return (α_0) is 21.36 percent, ranging from a low of 15.74 percent of the strategy 1-12 to a high of 33.46 percent of the strategy 3-18. It indicates that the abnormal returns of the IVol strategies with holding periods from 12 to 18 months and ranking periods of 1, 3 and 6 months cannot be wiped out by the time-varying risk.

4.6.3 Transaction Costs Estimation for IVol Strategies

In line with the momentum strategies, transaction costs for IVol strategies are estimated using Equations (3.18), (3.19) and (3.20). The results, shown in Table 4.60 clearly indicate that though transaction costs reduce the magnitude of IVol payoffs, they could not erode the positive IVol returns. On an average, IVol strategies earn a monthly net return of 9.02 percent at a transaction cost of 0.033 percent. In addition, at the highest level of transaction costs, 0.146 percent reported by Shen et al. (2007), these strategies earn a monthly average net return of 7.21 percent.

Table 4.60: Portfolio Turnover and Net IVol Returns of the Profitable IVol Strategies

	Holding Period	IVol Returns (%)	Portfolio Turnover (%)	Net IVol Returns (0.033%)	Net IVol Returns (0.146%)
Ranking Period of One	1	1.12	0.869	0.912	0.745
	3	3.43	0.869	2.48	1.23
	6	6.62	0.869	5.12	3.98
	12	13.48	0.869	10.98	8.17
	18	21.94	0.869	18.15	15.89
	24	31.03	0.869	24.99	21.09
Ranking Period of Three	1	1.19	0.815	0.896	0.578
	3	3.55	0.815	1.98	1.02
	6	7.06	0.815	5.02	3.87
	12	15.19	0.815	11.35	9.22
	18	25.40	0.815	19.18	17.22
	24	35.88	0.815	27.98	25.68
Ranking Period of Six	1	1.01	0.895	0.786	0.387
	3	3.06	0.895	1.89	0.987
	6	6.13	0.895	4.18	2.93
	12	12.08	0.895	8.98	6.16
	18	18.71	0.895	14.89	11.79
	24	24.73	0.895	21.18	18.45
Ranking Period of Twelve	6	2.97	0.915	1.79	0.894
	12	4.77	0.915	3.76	1.79
	18	6.69	0.915	5.05	2.45
	24	9.10	0.915	6.93	3.99

***(Source**: Secondary Data Analysis*)

4.6.4 IVol Portfolios: Diversification and Inflation Hedge

Commodity futures are basically used by institutional investors for the purpose of portfolio diversification. Table 4.61 shows the correlation between IVol returns and the returns of stock, bond and commodity index. The returns of the two profitable IVol strategies have a positive and significant correlation with a commodity index and the rest have an insignificant correlation with commodity index. Similarly, two IVol strategies have a negative and significant correlation with Nifty index and others have an insignificant correlation with Nifty index. This result is in line with the findings of Tables 4.57 and 4.58 which confirms that IVol returns are neutral to the risk of the equity market. On the contrary, the correlation between IVol returns of the three strategies and bond index is negative and significant while the rest have an insignificant correlation. These results confirm that tactical allocation of commodity futures in a portfolio of traditional asset classes can be used as an excellent tool for portfolio diversification and also to earn abnormal returns.

Table 4.61: Correlation of IVol Portfolios with Nifty, Bond, Commodity and Inflation Index

	Holding Periods	NIFTY	Bond	MCXCOMDEX	Inflation Index(WPI)
Ranking Period of one Month	1	-0.1915**	0.0556	-0.0393	-0.0724
	3	-0.1922**	0.0334	-0.1226	-0.1294
	6	-0.1223	0.1598	-0.1622	-0.1894**
	12	0.0317	0.066	0.0121	-0.299**
	18	0.0291	0.0053	0.0413	-0.3985*
	24	0.0127	-0.0100	0.0163	-0.4149*
Ranking Period of Three Months	1	-0.1524	0.028	0.0377	-0.0062
	3	-0.1320	-0.0011	-0.0602	-0.0411
	6	-0.0502	0.0989	-0.0919	-0.0965
	12	0.1477	0.0350	0.0575	-0.2337**
	18	0.1745	-0.0296	0.100	-0.3901*
	24	0.0829	-0.115	0.1281	-0.4232*
Ranking Period of Six Months	1	-0.1428	-0.0052	0.0629	-0.1441
	3	-0.0743	-0.0417	0.0049	-0.2506**
	6	-0.0260	0.0517	-0.0007	-0.4260*
	12	0.0398	-0.0189	0.1153	-0.6475*
	18	0.0545	0.0478	0.0481	-0.7882*
	24	0.1648	-0.2327**	0.2648**	-0.8306*
Ranking Period of Twelve Months	6	-0.0563	0.0048	0.0055	-0.3183**
	12	-0.0417	0.0753	0.0262	-0.4207*
	18	0.1034	-0.2134**	0.1863***	-0.4350*
	24	0.0198	-0.1975***	0.1221	-0.4264*

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level .*

Table 4.61 also shows the correlation between the IVol returns and the inflation index. The results demonstrate that out of 22 profitable IVol strategies, 16 strategies have a negative and significant correlation with inflation index and others have an insignificant and negative correlation. These results suggest that the IVol portfolios cannot be used as a hedge against inflation. Hence, the abnormal returns of the IVol strategies and their diversification benefits lead to losing its basic inflation hedging potential. These findings are in line with the outcomes of Erb and Harvey (2006), Miffre and Rallis (2007) and Fernández et al. (2016).

Previous Sections 4.4, 4.5 and 4.6 have discussed the time-varying risk-adjusted return performance of momentum, term structure and idiosyncratic volatility strategies. Next Section 4.7 deals with the implementation of combined strategy which incorporates the methodology of both momentum and term structure strategies.

4.7 COMBINED STRATEGY (MomTS) BASED ON THE COMBINATION OF MOMENTUM AND TERM STRUCTURE STRATEGIES

The momentum strategies take a long position in the winner portfolio which basically contains the backwardated contract and short position in the loser portfolio which is skewed towards the contangoed contracts (Miffre and Rallis, 2007). Similarly, term structure strategies suggest taking a long position in backwardated contracts and a short position in contangoed contracts. This comparison shows that momentum and term structure strategies are similar. In line with the analysis of Fuertes et al. (2010), this study estimates the correlation between momentum and term structure portfolios as shown in Table 4.62. The results show a positive and insignificant correlation between momentum and term structure portfolios which indicates that winner (loser) portfolios of momentum strategies are not overlapping with backwardated (contangoed) portfolios of term structure strategies. These results provide a strong motivation to design a combined strategy using both momentum and term structure (TS) strategies.

Table 4.62: Correlation between Momentum and Term Structure Portfolios

Momentum /TS Strategies	$\boldsymbol{TS_{1-1}}$	$\boldsymbol{TS_{1-3}}$	$\boldsymbol{TS_{1-6}}$	$\boldsymbol{TS_{1-12}}$	$\boldsymbol{TS_{1-18}}$	$\boldsymbol{TS_{1-24}}$
$\boldsymbol{Mom_{1-1}}$	0.116	0.003	0.126	0.095	0.066	0.027
$\boldsymbol{Mom_{1-3}}$	0.077	0.082	0.150	0.155	0.097	0.076
$\boldsymbol{Mom_{1-6}}$	0.129	0.139	0.217**	0.308*	0.186	0.133
$\boldsymbol{Mom_{1-12}}$	0.127	0.112	0.130	0.314*	0.306*	0.197
$\boldsymbol{Mom_{1-18}}$	0.151	0.122	0.151	0.286*	0.359*	0.322*
$\boldsymbol{Mom_{1-24}}$	0.188	0.254**	0.353*	0.424*	0.461*	0.473*

*(**Source:** Secondary Data Analysis)*

** shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*

4.7.1 Combined Strategy-MomTS Profits

For the construction of a combined strategy, the momentum strategies for a ranking period of one month are considered, as the momentum strategies 1-1, 1-3, 1-6, 1-12, 1-18 and 1-24 are the most profitable strategies among 24 momentum strategies. Similarly, under term structure strategies, TS_1 strategies with a ranking period of one month are taken for the formation of combined strategies as they are the most profitable term structure strategies. The final combined strategies are called as TS_1Mom_{1-1}, TS_1Mom_{1-3}, TS_1Mom_{1-6}, TS_1Mom_{1-12}, TS_1Mom_{1-18} and TS_1Mom_{1-24}. The performance evaluation of relative strength portfolios of MomTS strategies is performed in following stages.

4.7.1.1 Performance Evaluation of MomTS Strategies

The mean, standard deviation and risk-adjusted return performance i.e. Sharpe ratio of all the MomTS strategies are shown in Table 4.63.

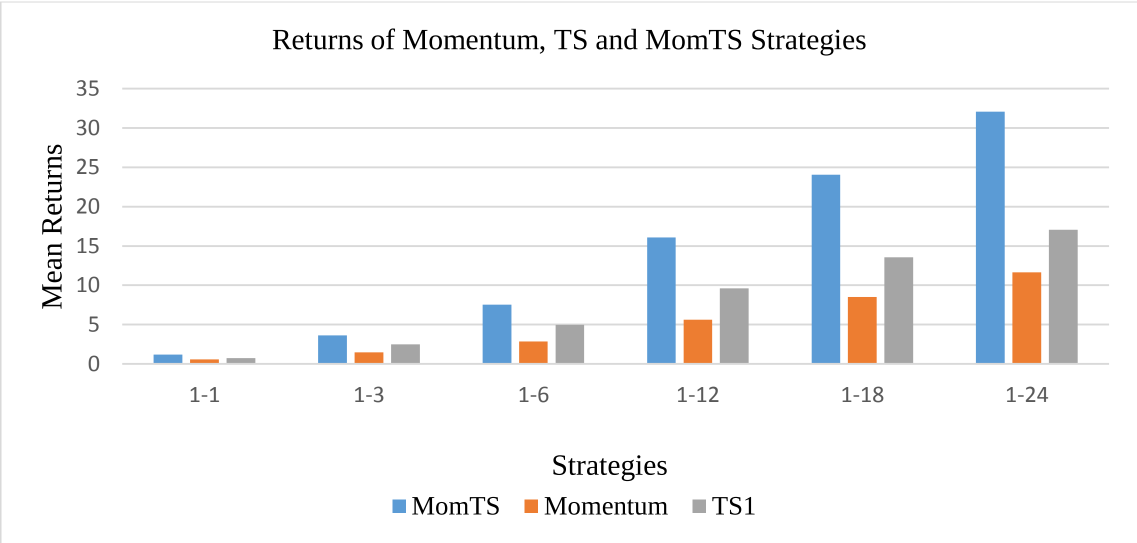
Table 4.63: Mean, Standard Deviation and Sharpe Ratio of MomTS Strategies (Monthly)

Ranking Period of One month				
	Parameters	Long	Short	Long-Short
$\boldsymbol{TS_1Mom_{1-1}}$	Mean	0.892 [1.21]	-0.288 [-0.480]	1.18 [1.26]
	Standard Deviation	7.89	6.42	10.07
	Sharpe Ratio	0.113	-0.045	0.117
$\boldsymbol{TS_1Mom_{1-3}}$	Mean	2.87 [2.38]**	-0.769 [-0.668]	3.64 [2.44]**
	Standard Deviation	12.90	12.28	15.93
	Sharpe Ratio	0.223	-0.063	0.229
$\boldsymbol{TS_1Mom_{1-6}}$	Mean	6.08 [3.54]*	-1.46 [-0.775]	7.54 [3.39]*
	Standard Deviation	18.10	19.81	23.36
	Sharpe Ratio	0.336	-0.074	0.323
$\boldsymbol{TS_1Mom_{1-12}}$	Mean	14.35 [5.33]*	-1.72 [-0.677]	16.07 [4.72]*
	Standard Deviation	27.57	26.08	34.90
	Sharpe Ratio	0.520	-0.066	0.460
$\boldsymbol{TS_1Mom_{1-18}}$	Mean	22.84 [6.17]*	-1.23 [-0.443]	24.07 [5.69]*
	Standard Deviation	36.85	27.72	42.08
	Sharpe Ratio	0.619	-0.045	0.572
$\boldsymbol{TS_1Mom_{1-24}}$	Mean	31.96 [6.83]	-0.117 [-0.033]	32.08 [6.09]*
	Standard Deviation	45.12	33.83	50.71
	Sharpe Ratio	0.708	-0.0035	0.633

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and *** at 10% level of significance.*

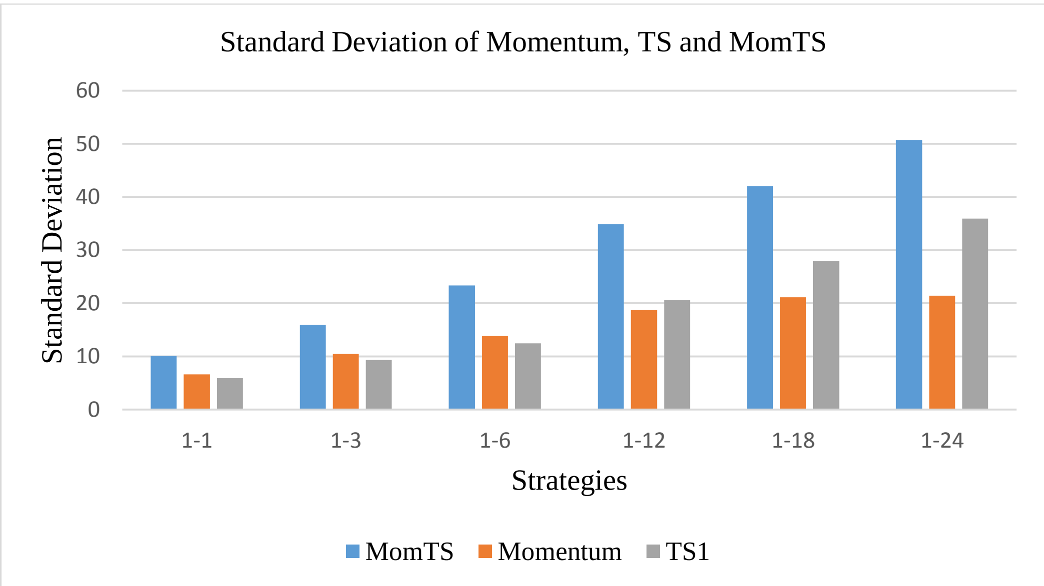
Results show that consistently buying the 'high winner' portfolios and selling the 'low losers', yields an average monthly return of 16.68 percent and an annualized return of 77.48 percent. This return is abnormally high compared to the annualized return of 21.32 percent shown by Fuertes et al. (2010). In addition, the combined strategy TS_1Mom_{1-24} is most profitable and gives a highest monthly return of 32.08 percent in contrast to TS_1Mom_{1-3} which yields a lowest monthly return of 3.64 percent. It indicates that MomTS profits increase with the holding period. The comparison of average monthly returns (16.68 percent) of MomTS strategies with the average monthly returns of momentum strategies (7.17 percent) and TS_1 strategies (9.54 percent) indicates that MomTS strategies give better performance compared to momentum and term structure strategies individually as indicated in Figure 4.26.

The best performance of MomTS strategies is driven by the performance of long portfolios in MomTS strategies compared to the performance in individual momentum and term structure strategies. The long portfolios for MomTS strategies earn an average monthly return of 15.62 percent in comparison to 7.93 percent in momentum strategies and 8.98 percent in TS_1 strategies. Similarly, the short portfolios in MomTS strategies reflect an average monthly loss of -1.06 percent in comparison to average monthly gain of 0.762 percent in momentum and loss of -0.533 percent in TS_1 strategies. Hence, the MomTS portfolios improve the profits of long portfolios and losses of short portfolios.



(*Source:* *Secondary Data Analysis*)

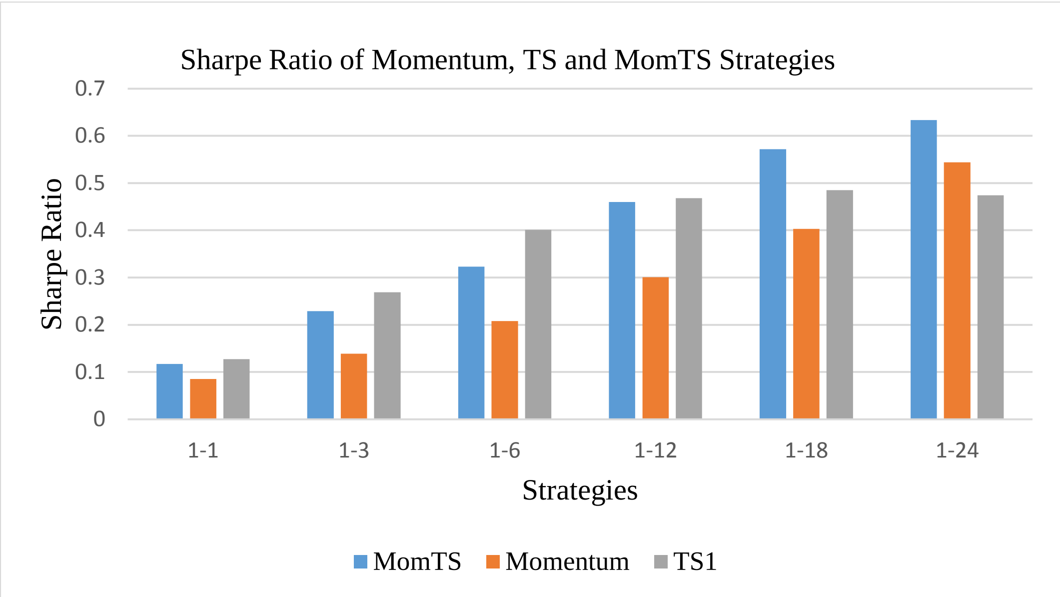
Figure 4.26: Monthly Mean Returns of Momentum, Term Structure and MomTS Strategies



(*Source*: *Secondary Data Analysis*)

Figure 4.27: Standard Deviation of Momentum, Term Structure and MomTS Strategies

Table 4.63 shows that standard deviation increases with the increase in MomTS returns. In addition, the standard deviation of MomTS strategies is higher than the standard deviation of individual momentum and term structure strategies as shown in Figure 4.27. Among all the six MomTS strategies, TS_1Mom_{1-24} is the most profitable, with the highest standard deviation of 50.71. The lowest profitable is TS_1Mom_{1-3} with the lowest standard deviation of 15.93. These outcomes are in the line with the normal market perception of higher returns associated with higher risk.



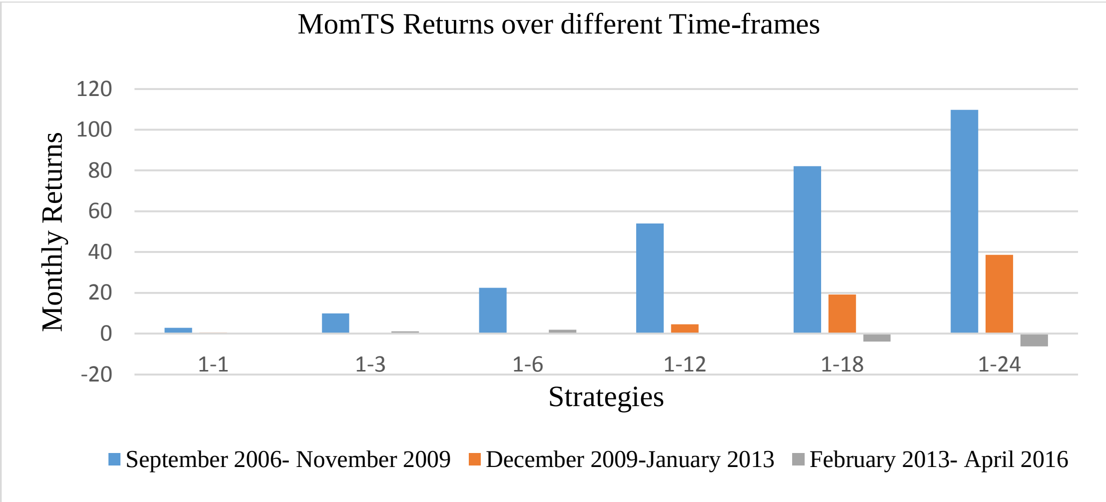
*(**Source:** Secondary Data Analysis)*

Figure 4.28: Sharpe Ratio of Momentum, Term Structure and MomTS Strategies

Sharpe ratio shown in Table 4.63 helps to analyse the risk-adjusted performance of all the MomTS strategies. Results show that Sharpe ratio increases with the increase in payoffs of MomTS strategies. For example, highest profitable combined strategy TS_1Mom_{1-24} gives the highest Sharpe ratio of 0.633 and lowest profitable strategy TS_1Mom_{1-3} has the lowest Sharpe ratio of 0.229. Moreover, the MomTS strategies in commodity futures market perform better with respect to their risk-adjusted return performance compared to passive investment in equity, bond and commodity futures market. In addition, MomTS strategies perform better than individual momentum and term structure strategies with respect to their Sharpe ratio as shown in Figure 4.28.

4.7.1.2 MomTS Profits for Sub-Periods

Table 4.64 shows the MomTS payoffs of all the strategies during different time-frames. The whole sample period is divided into three equal sub-periods. The MomTS risk-adjusted return of later period (February 2013-April 2016) is compared with the risk-adjusted returns of earlier periods (September 2006-November 2009, December 2009-January 2013). The sub-periods analysis reveals that MomTS strategies perform better for the earlier sub-periods, September 2006-November 2009 and December 2009-January 2013 compared to later sub-period of February 2013-April 2016. At the same time, Figure 4.29 depicts that the comparison among earlier sub-periods confirms a better performance of sub-period September 2006-November 2009 compared to sub-period December 2009-January 2013. This shows that MomTS profits are basically time-varying.



(**Source:** *Secondary Data Analysis*)

Figure 4.29: Average Monthly Returns of MomTS Strategies over different Time-frames

Table 4.64: MomTS Profitability during different Time-frames

Strategies	September 2006-November 2009	December 2009-January 2013	February 2013-April 2016	September 2006-April 2016
$\boldsymbol{TS_1Mom_{1-1}}$	2.89 [1.84]***	0.535 [0.249]	0.094 [0.099]	1.18 [1.26]
$\boldsymbol{TS_1Mom_{1-3}}$	9.92 [3.94]*	0.174 [0.053]	1.06 [0.761]	3.64 [2.44]**
$\boldsymbol{TS_1Mom_{1-6}}$	22.54 [5.17]*	-0.147 [-0.038]	1.94 [0.929]	7.54 [3.39]*
$\boldsymbol{TS_1Mom_{1-12}}$	53.99 [8.24]*	4.51 [1.07]	0.113 [0.037]	16.07 [4.72]*
$\boldsymbol{TS_1Mom_{1-18}}$	82.11 [10.48]*	19.23 [4.17]*	-3.95 [-1.54]	24.07 [5.69]*
$\boldsymbol{TS_1Mom_{1-24}}$	109.78 [16.92]*	38.62 [5.60]*	-6.18 [-3.56]*	32.08 [6.09]*

(**Source:** *Secondary Data Analysis*)

*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and *** at 10% level of significance.*

4.7.2 Risk-Based Analysis of MomTS Strategies

The risk-based analysis of MomTS returns and their time-varying aspects are discussed in this Section.

4.7.2.1 Sensitivity Analysis of MomTS Payoffs against Market Risk

The abnormal performance (α)[4] of MomTS strategies and their sensitivity to the Nifty (CNX Nifty stock index), bond (CCIL liquid bond index) and commodity index (MCXCOMDEX) are depicted in Table 4.65.

Table 4.65: Risk-Based Performance of MomTS Strategies

	Ranking Period of One month			
	Parameters	Long	Short	Long-Short
TS_1Mom_{1-1}	α	2.10 [1.02]	2.20 [1.33]	-0.100 [-0.038]
	β_S	-0.016 [-0.152]	-0.056 [-0.689]	0.043 [0.313]
	β_B	0.063 [0.243]	0.218 [1.06]	-0.156 [-0.472]
	β_C	0.132 [0.985]	0.210 [1.97]***	-0.079 [-0.461]
	Adjusted R^2	18.45%	43.23%	23.78%
TS_1Mom_{1-3}	α	7.72 [2.30]**	3.99 [1.26]	3.73 [0.898]
	β_S	-0.117 [-0.676]	0.130 [0.794]	-0.247 [-1.15]
	β_B	0.628 [1.50]	0.315 [0.795]	0.313 [0.604]
	β_C	0.224 [1.02]	0.275 [1.33]	-0.052 [-0.189]
	Adjusted R^2	43.32%	24.32%	32.12%
TS_1Mom_{1-6}	α	20.42 [4.47]*	3.82 [0.725]	16.60 [2.69]**
	β_S	-0.289 [-1.24]	-0.094 [-0.352]	-0.195[-0.622]
	β_B	1.81 [3.18]**	0.609 [0.932]	1.19 [1.57]
	β_C	0.660 [2.21]**	0.284 [0.826]	0.377 [0.936]
	Adjusted R^2	26.21%	45.12%	26.20%
TS_1Mom_{1-12}	α	42.05 [6.09]*	-1.71 [-0.241]	43.76 [4.85]*
	β_S	-0.200 [-0.570]	-0.115 [-0.319]	-0.085 [-0.185]
	β_B	3.09 [3.64]*	0.315 [0.360]	2.77 [2.49]**
	β_C	1.29 [2.89]**	-0.186 [-0.404]	1.48 [2.53]**
	Adjusted R^2	13.45%	24.12%	29.12%
TS_1Mom_{1-18}	α	70.89 [8.09]*	-6.58 [-0.855]	77.47 [7.66]*
	β_S	0.032 [0.067]	-0.015 [-0.037]	0.047 [0.087]
	β_B	5.01 [4.68]*	-0.672 [-0.713]	5.69 [4.59]*
	β_C	2.16 [3.81]*	-0.123 [-0.246]	2.29 [3.49]*
	Adjusted R^2	24.90%	25.98%	28.20%
TS_1Mom_{1-24}	α	90.13 [8.04]*	-22.57 [-2.39]**	112.69 [9.81]*
	β_S	-0.281 [-0.449]	-0.622 [-1.18]	0.341 [0.531]
	β_B	5.63 [4.11]*	-2.48 [-2.15]	8.10 [5.78]
	β_C	3.41 [4.48]*	-0.377 [-0.589]	3.79 [4.86]
	Adjusted R^2	25.12%	47.43%	37.70%

*(**Source:** Secondary Data Analysis)*

*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and *** at 10% level of significance.*

The commodity beta of two MomTS strategies out of six strategies has a positive and significant value which indicates that returns of MomTS strategies follow the movements of a commodity index. Similarly, two MomTS strategies have a positive and significant beta for the bond index which shows that MomTS returns reflect the ups and downs of bond index. However, the returns of the MomTS strategies are neutral to the risk of the equity market. The results show that four profitable MomTS strategies with holding periods of 6, 12, 18 and 24 months provide a positive and significant abnormal returns (α). On an average, the monthly abnormal return of the four profitable strategies is 62.93 percent, ranges between 16.60 percent of the TS_1Mom_{1-6}, strategy to 112.69 percent of TS_1Mom_{1-24} strategy. It indicates that the returns of the MomTS strategies with longer holding period are not merely a compensation for different market risk factors which is important for the investors of the long-term investment horizon.

The comparison of average monthly abnormal performance (α) of MomTS strategies (62.93 percent) with momentum strategies (21.00 percent) and term structure strategies (36.02 percent) indicates that the MomTS strategies perform better than individual momentum and term structure strategies. In addition, the returns of the MomTS strategies are driven by long portfolios due to their significant and positive alphas.

4.7.2.2 Time-Varying Risk-Based Analysis of MomTS Strategies

Robustness analysis is performed to analyse whether returns of the MomTS strategies are due to exposure to the time-varying risk. The alpha of all the information variables and a probability value of the hypotheses H_7, H_8 and H_9 are reported in Table 4.66. The results demonstrate that all the four profitable strategies have a significant time-dependent conditional alpha (α_1) and significant time-dependent conditional beta (β_1). In addition, all the four strategies have shown a joint significance for both conditional alpha and conditional beta. Hence, the application of model shown in Equation (3.17) is justified with respect to the measure of time-varying alpha and beta. The results show that out of four profitable strategies, only one strategy TS_1Mom_{1-24} yields a monthly conditional abnormal return (α_0) equals to 43.92 percent which indicates that the abnormal return of this strategy is not the compensation for time-varying risk. On the contrary, insignificant values of other profitable strategies such as TS_1Mom_{1-6}, TS_1Mom_{1-12} and TS_1Mom_{1-18}, indicate that abnormal performance (α) of these strategies are time-varying.

Table 4.66: Time-Varying Risk-Based Performance of MomTS Strategies

Combined Strategies	α_0	α_{TS}	α_{DY}	α_{MIBOR}	P(α_1=0)	P(β_1=0)	P ($\alpha_1 = \beta_1$=0)	Adj R^2
TS_1Mom_{1-6}	10.35 [1.12]	9.60 [0.735]	62.70 [2.98]**	8.86 [0.814]	0.0081**	0.0537***	0.0036**	15.90%
TS_1Mom_{1-12}	6.22 [0.473]	7.78 [0.433]	116.95 [4.13]*	-7.17 [-0.467]	0.0007*	0.0054**	0.00*	34.81%
TS_1Mom_{1-18}	4.49 [0.337]	-14.97 [-0.86]	135.89 [4.34]*	-42.62 [-2.83]**	0.00*	0.00**	0.00*	59.17%
TS_1Mom_{1-24}	43.92 [1.96]***	17.75 [1.28]	83.36 [1.91]***	-11.65 [-0.783]	0.0013**	0.0562	0.00*	56.93%

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and *** at 10% level of significance.*

4.7.3 Transaction Costs Estimation for MomTS Strategies

In line with the momentum strategy, the portfolio turnover and net MomTS returns are estimated using Equations (3.18), (3.19) and (3.20). The results, shown in Table 4.67 clearly indicate that though transaction costs reduced the magnitude of MomTS payoffs, they could not erode the positive MomTS returns. On an average, MomTS strategies earn a monthly net return of 14.38 percent at a transaction cost of 0.033 percent. In addition, at the highest level of transaction costs, 0.146 percent reported by Shen et al. (2007), these strategies earn a monthly average net return of 12.95 percent.

Table 4.67: Portfolio Turnover and Net MomTS Returns of the Profitable MomTS Strategies

Combined Strategies	MomTS Returns (%)	Portfolio Turnover (%)	Net MomTS Returns (0.033%)	Net MomTS Returns (0.146%)
TS_1Mom_{1-3}	3.64	0.925	3.05	2.25
TS_1Mom_{1-6}	7.54	0.925	6.44	5.47
TS_1Mom_{1-12}	16.07	0.925	13.47	11.78
TS_1Mom_{1-18}	24.07	0.925	21.26	19.45
TS_1Mom_{1-24}	32.08	0.925	27.67	25.78

*(**Source:** Secondary Data Analysis)*

4.7.4 MomTS Strategies: Diversification and Inflation Hedging

The correlation between the returns of MomTS strategies and the returns of stock, bond and commodity index are shown in Table 4.68. The returns of all the MomTS strategies have an insignificant correlation with a commodity index. The average correlation between the MomTS returns and the Nifty is -0.0069 ranging between -0.1363 of TS_1Mom_{1-2} strategy to 0.1015 of TS_1Mom_{1-24} strategy. On the contrary, the average correlation of the returns of all the six MomTS strategies and bond index is very low which equals to -0.0254. However, all the MomTS strategies have an insignificant correlation with Nifty and bond indices. This result is in line with the findings of Table 4.65 which confirms that MomTS returns are neutral to the risk of the equity market. These results confirm that tactical allocation of commodity futures in a portfolio of traditional asset classes, can be used as an excellent tool for portfolio diversification and also to earn abnormal returns by reducing the risk of their portfolios.

Table 4.68 also shows the correlation between the MomTS returns and the WPI. The results demonstrate the negative and significant correlation of MomTS returns with inflation index for all the six MomTS strategies. These results suggest that the MomTS portfolios cannot be used as a hedge against Inflation. Hence, the abnormal returns of the MomTS strategies and their diversification benefits lead to losing its basic inflation hedging potential.

Table 4.68: Correlation of MomTS Portfolios with Nifty, Bond, Commodity Index and Inflation Index

Combined Strategies	Nifty	Bond	Commodity Index	Inflation Index(WPI)
$\boldsymbol{TS_1Mom_{1-1}}$	0.0097	-0.0450	-0.0357	-0.1441
$\boldsymbol{TS_1Mom_{1-3}}$	-0.1363	-0.0087	-0.0881	-0.2666**
$\boldsymbol{TS_1Mom_{1-6}}$	-0.0489	0.0380	0.0062	-0.3907*
$\boldsymbol{TS_1Mom_{1-12}}$	0.0001	-0.0658	0.0904	-0.5727*
$\boldsymbol{TS_1Mom_{1-18}}$	0.0326	-0.0217	0.0699	-0.7703*
$\boldsymbol{TS_1Mom_{1-24}}$	0.1015	-0.0492	0.1408	-0.9035*

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and ***at 10% level .*

The present Section 4.7 has discussed the time varying risk-adjusted return performance of MomTS strategies. The next Section 4.8 deals with the implementation of one more combined active strategy, MomIVol which uses the methodology of both momentum and idiosyncratic volatility strategies.

4.8 COMBINED STRATEGY (MomIVol) BASED ON THE COMBINATION OF MOMENTUM AND IDIOSYNCRATIC VOLATILITY STRATEGIES

According to Ang et al. (2006, 2009), Miffre et al. (2012) and Fernández et al. (2016), the average return of a portfolio with the lowest idiosyncratic volatility is higher compared to the portfolio with the highest idiosyncratic volatility. Based on their theoretical anomaly, an active strategy is designed which combines the theoretical concept of both momentum and idiosyncratic volatility strategies. In addition, the estimated values of the Pearson correlation between the portfolios of momentum strategies and IVol strategies are very low and insignificant as depicted in Table 4.69. Hence, the combined strategy is created which buys commodities with low idiosyncratic volatility and high momentum returns and sells commodities with high idiosyncratic volatility and low momentum returns.

For the construction of MomIVol strategy, the momentum strategies for a ranking period with one month are considered, as the portfolios 1-1, 1-3, 1-6, 1-12, 1-18 and 1-24 are most profitable strategies among all the 24 momentum strategies. Similarly, under IVol strategies, IVol strategies with a ranking period of 3 months are more profitable compared to ranking periods with 1, 6 and 12 months. Hence, IVol portfolios of ranking period of 3 months are considered for the formation of MomIVol strategies. The final MomIVol strategies are called as $IVol_3Mom_{1-1}$, $IVol_3Mom_{1-3}$, $IVol_3Mom_{1-6}$, $IVol_3Mom_{1-12}$, $IVol_3Mom_{1-18}$ and $IVol_3Mom_{1-24}$.

Table 4.69: Correlation between Momentum and IVol Portfolios

Momentum /IVol Strategies	$\boldsymbol{IVol_{3-1}}$	$\boldsymbol{IVol_{3-3}}$	$\boldsymbol{IVol_{3-6}}$	$\boldsymbol{IVol_{3-12}}$	$\boldsymbol{IVol_{3-18}}$	$\boldsymbol{IVol_{3-24}}$
$\boldsymbol{Mom_{1-1}}$	0.128	0.094	0.184	0.116	0.021	0.047
$\boldsymbol{Mom_{1-3}}$	0.086	0.159	0.220**	0.284*	0.078	0.051
$\boldsymbol{Mom_{1-6}}$	-0.011	-0.003	0.160	0.407*	0.163	0.076
$\boldsymbol{Mom_{1-12}}$	0.040	0.050	0.129	0.390*	0.413*	0.162
$\boldsymbol{Mom_{1-18}}$	0.053	0.045	0.141	0.376*	0.406*	0.356*
$\boldsymbol{Mom_{1-24}}$	0.003	0.074	0.224**	0.486*	0.474*	0.378*

*(**Source:** Secondary Data Analysis)*

*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and ***at 10% level .*

4.8.1 Combined Strategy (MomIVol) Profits

The performance evaluation of the relative strength portfolios of MomIVol strategies is performed in following stages.

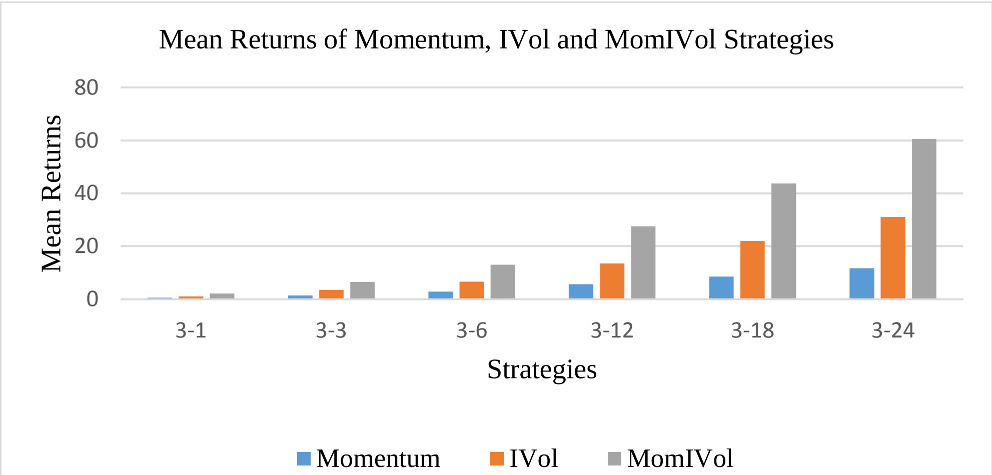
4.8.1.1 Performance Evaluation of MomIVol Strategies

The mean, standard deviation and risk-adjusted return performance i.e. Sharpe ratio of all the MomIVol strategies are shown in Table 4.70. Results show that consistently buying the 'low winner' portfolios and selling the 'high losers', yields an average monthly return of 25.57 percent and an annualized return of 89.45 percent. In addition, combined strategy $IVol_3Mom_{1-24}$ is most profitable and yields a highest monthly return of 60.51 percent in contrast to $IVol_3Mom_{1-1}$, which yields a lowest monthly return of 2.12 percent. It indicates that momentum profits increase with the holding period. The comparison of average monthly return (25.57 percent) of MomIVol strategies with the average monthly returns of momentum strategies (7.17 percent) and IVol strategies (11.59 percent) indicates that combined strategies give better performance compared to momentum and IVol strategies individually as shown in Figure 4.30.

Table 4.70: Mean, Standard Deviation and Sharpe Ratio of MomIVol Strategies (Monthly)

	Ranking Period of One month			
	Parameters	Long	Short	Long-Short
$IVol_3Mom_{1-1}$	Mean	1.55 [2.36]**	-0.572 [-0.902]	2.12 [2.43]**
	Standard Deviation	6.95	6.71	9.24
	Sharpe Ratio	0.223	-0.085	0.229
$IVol_3Mom_{1-3}$	Mean	4.70 [3.95]*	-1.84 [-1.53]	6.54 [4.36]*
	Standard Deviation	12.55	12.64	15.81
	Sharpe Ratio	0.375	-0.145	0.414
$IVol_3Mom_{1-6}$	Mean	9.50 [5.11]*	-3.53 [-2.14]**	13.04 [5.89]*
	Standard Deviation	19.31	17.18	22.99
	Sharpe Ratio	0.492	-0.206	0.567
$IVol_3Mom_{1-12}$	Mean	20.48 [6.33]*	-7.03 [-3.09]*	27.52 [7.47]*
	Standard Deviation	32.69	22.99	37.20
	Sharpe Ratio	0.626	-0.306	0.739
$IVol_3Mom_{1-18}$	Mean	32.76 [7.14]*	-10.95 [-4.29]*	43.71 [9.15]*
	Standard Deviation	44.94	25.01	46.78
	Sharpe Ratio	0.729	-0.438	0.934
$IVol_3Mom_{1-24}$	Mean	46.63 [8.20]*	-13.87 [-4.19]*	60.51 [10.47]*
	Standard Deviation	53.94	31.38	54.81
	Sharpe Ratio	0.864	-0.442	1.10

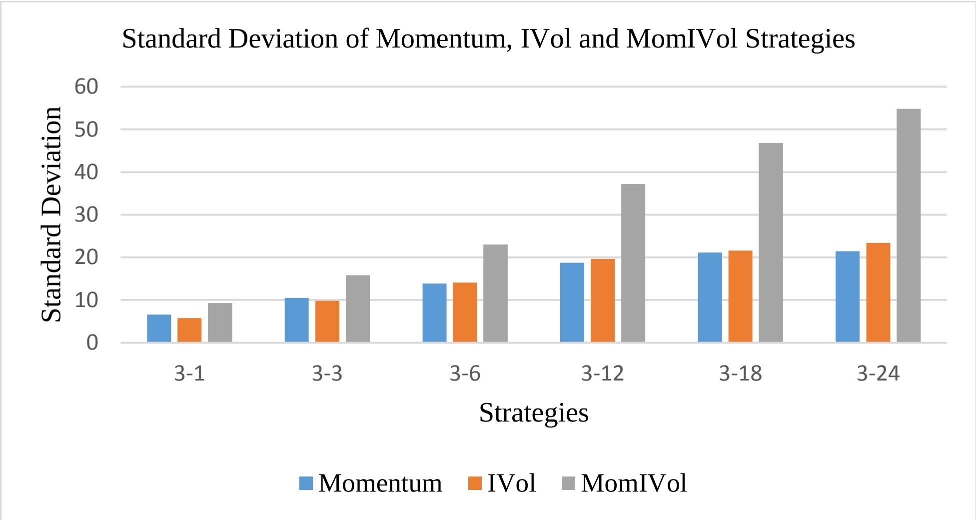
*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and ***at 10% level .*



*(**Source:** Secondary Data Analysis)*

Figure 4.30: Monthly Mean Returns of Momentum, IVol and MomIVol Strategies

The best performance of MomIVol strategies is driven by the performance of both long and short portfolios in MomIVol strategies. The long portfolios for MomIVol strategies earn an average monthly return of 19.27 percent in comparison to 7.93 percent in momentum strategies and 11.02 percent in IVol strategies. Similarly, the short portfolios in MomIVol strategies yield an average monthly loss of -6.29 percent compared to the average monthly gain of 0.762 percent in momentum and loss of -1.67 percent in IVol strategies. Hence, the MomIVol strategies improve the profits of long portfolios and losses of short portfolios.

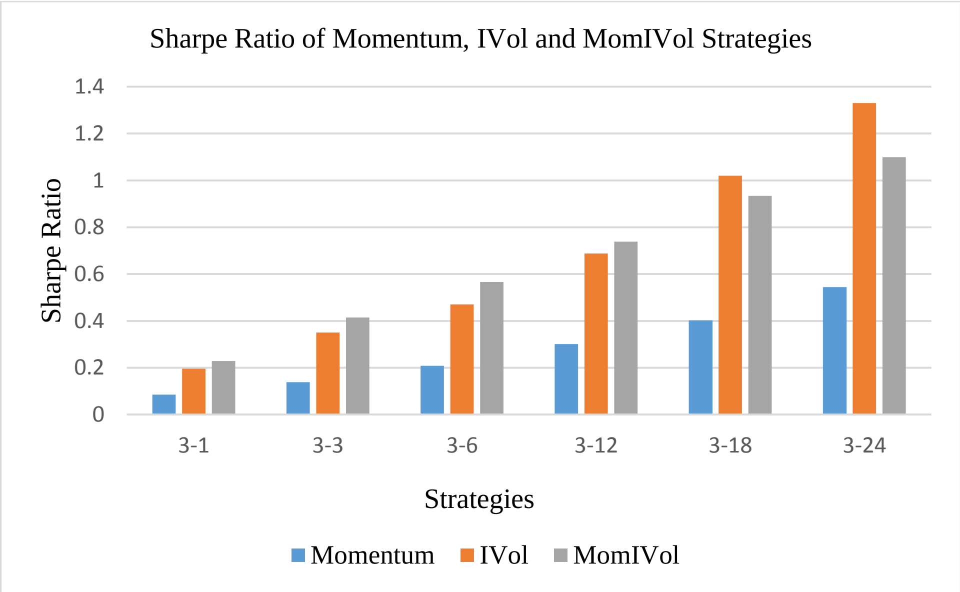


*(**Source**: Secondary Data Analysis)*

Figure 4.31: Standard Deviation of Momentum, IVol and MomIVol Strategies

Table 4.70 shows that standard deviation increases with the increase in MomIVol returns. In addition, the standard deviation of MomIVol strategies is more than the standard deviation of individual momentum and IVol strategies as shown in Figure 4.31. Among all the six MomIVol strategies, the most profitable is $IVol_3Mom_{1-24}$ with the highest standard deviation of 54.81, and lowest profitable is $IVol_3Mom_{1-1}$ with the lowest standard deviation of 9.24. These outcomes are in line with the normal market perception of higher returns are associated with higher risk.

Sharpe ratio shown in Table 4.70 indicates that Sharpe ratio increases with the increase in payoffs of MomIVol strategies. For example, highest profitable MomIVol strategy $IVol_3Mom_{1-24}$, gives a highest Sharpe ratio of 1.10, and lowest profitable strategy $IVol_3Mom_{1-1}$ has the lowest Sharpe ratio of 0.229. The results indicate that the MomIVol strategies in commodity futures market, perform better with respect to their risk-adjusted return performance compared to passive investment in equity, bond and commodity indices. However, the comparison of Sharpe ratio of momentum, IVol and MomIVol strategies indicates that MomIVol strategies with holding periods of 1, 3, 6 and 12 months outperform the individual momentum and IVol strategies. Conversely, IVol strategies outperform the momentum and MomIVol strategies for the holding periods of 18 and 24 months as shown in Figure 4.32.



(**Source:** *Secondary Data Analysis*)

Figure 4.32: Sharpe Ratio of Momentum, IVol and MomIVol Strategies

4.8.1.2 MomIVol Profits for Sub-Periods

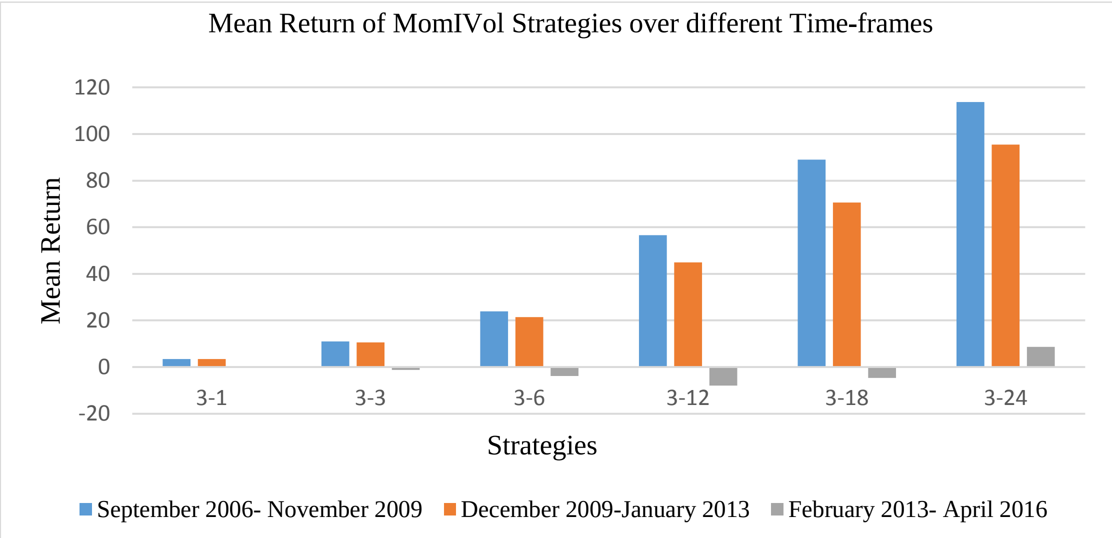
Table 4.71 shows the MomIVol payoffs of all the strategies during different time-frames. The whole sample period is divided into three equal sub-periods. The MomIVol risk-adjusted return of later period (February 2013-April 2016) is compared with the risk-adjusted return of earlier periods (September 2006-November 2009, December 2009-January 2013). The sub-period analysis reveals that MomIVol strategies perform better for the earlier sub-periods, September 2006-November 2009 and December 2009-January 2013 in comparison with later sub-period of February 2013-April 2016 as shown in Table 4.71. Conversely, sub-period, September 2006-November 2009 has given the average monthly return of 49.06 percent compared to 41.09 percent given by sub-period December 2009-January 2013. It confirms a better performance of sub-period September 2006-

November 2009 compared to sub-period December 2009-January 2013 as shown in Figure 4.33. This shows that MomIVol profits are basically time-varying.

Table 4.71: MomIVol Profitability during different Time-frames

	September 2006-November 2009	December 2009-January 2013	February 2013- April 2016	September 2006- April 2016
$IVol_3Mom_{1-1}$	3.39 [2.48]**	3.50 [1.82]***	-0.397 [-0.378]	2.12 [2.43]**
$IVol_3Mom_{1-3}$	11.00 [4.23]*	10.57 [3.64]*	-1.28 [-0.749]	6.54 [4.36]*
$IVol_3Mom_{1-6}$	23.94 [6.94]*	21.42 [5.74]*	-3.79 [-1.58]	13.04 [5.89]*
$IVol_3Mom_{1-12}$	56.54 [12.56]*	44.90 [10.10]*	-8.03 [-2.30]**	27.52 [7.47]*
$IVol_3Mom_{1-18}$	89.05 [20.98]*	70.66 [20.76]*	-4.64 [-1.07]	43.71 [9.15]*
$IVol_3Mom_{1-24}$	113.72 [31.78]*	95.50 [24.16]*	8.66 [1.42]	60.51 [10.47]*

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit the 't' statistics and * shows the significance level at 1%, ** at 5% and ***at 10% level .*



*(**Source:** Secondary Data Analysis)*

Figure 4.33: Average Monthly Returns of all the MomIVol Strategies over different Time-frames

4.8.2 Risk-Based Analysis of MomIVol Strategies

The risk-based analysis of MomIVol returns and their time-varying aspects are discussed in this section.

4.8.2.1 Sensitivity Analysis of MomIVol Payoffs against Market Risk

The abnormal performance $(\alpha)^4$ of MomIVol strategies and their sensitivity to the Nifty (CNX Nifty stock index), bond (CCIL liquid bond index) and commodity index (MCXCOMDEX) are depicted in Table 4.72.

Table 4.72: Risk-Based Performance of MomIVol Strategies

Ranking Period of One month				
	Parameters	Long	Short	Long-Short
$\boldsymbol{IVol_3Mom_{1-1}}$	α	1.76 [0.960]	-0.649 [-0.365]	2.40 [0.992]
	β_S	-0.089 [-0.950]	0.113 [1.25]	-0.202 [-1.63]
	β_B	-0.066 [-0.293]	-0.088 [-0.398]	0.021 [0.071]
	β_C	0.176 [1.48]	-0.036 [-0.307]	0.212 [1.34]
	Adjusted R^2	16.21%	19.23%	18.12%
$\boldsymbol{IVol_3Mom_{1-3}}$	α	6.95 [2.09]**	1.33 [0.397]	5.62 [1.34]
	β_S	0.025 [0.148]	0.09 [0.528]	-0.065 [-0.305]
	β_B	0.029 [0.07]	0.312 [0.749]	-0.283 [-0.543]
	β_C	0.278 [1.28]	0.081 [0.369]	0.197 [0.718]
	Adjusted R^2	25.23%	16.78%	18.78%
$\boldsymbol{IVol_3Mom_{1-6}}$	α	15.07 [2.94]**	-1.85 [-0.402]	16.92 [2.76]**
	β_S	-0.196 [-0.742]	-0.069 [-0.294]	-0.126 [-0.399]
	β_B	0.637 [1.00]	0.308 [0.539]	0.329 [0.432]
	β_C	0.399 [1.18]	0.022 [0.072]	0.377 [0.935]
	Adjusted R^2	19.48%	26.75%	29.90%
$\boldsymbol{IVol_3Mom_{1-12}}$	α	31.21 [3.51]*	-13.45 [-2.15]**	44.66 [4.45]*
	β_S	-0.252 [-0.546]	-0.245 [-0.757]	-0.006 [-0.012]
	β_B	1.09 [1.01]	-0.355 [-0.464]	1.45 [1.19]
	β_C	0.762 [1.33]	-0.349 [-0.864]	1.11 [1.72]***
	Adjusted R^2	22.21%	24.32%	23.14%
$\boldsymbol{IVol_3Mom_{1-18}}$	α	47.13 [3.75]*	-27.17 [3.99]*	74.30 [5.83]*
	β_S	-0.234 [-0.348]	-0.368 [-1.01]	0.134 [0.197]
	β_B	1.29 [0.847]	-1.64 [-1.99]**	2.92 [1.89]***
	β_C	1.07 [1.30]	-0.44 [-0.993]	1.51 [1.81]***
	Adjusted R^2	27.74%	37.32%	32.21%
$\boldsymbol{IVol_3Mom_{1-24}}$	α	74.18 [4.74]*	-35.58 [-4.22]*	109.76 [7.30]*
	β_S	-0.269 [-0.267]	-1.08 [-2.00]	0.816 [0.845]
	β_B	1.58 [0.747]	-1.98 [-1.75]	3.56 [1.76]***
	β_C	2.72 [2.47]**	-0.517 [-0.874]	3.23 [3.07]**
	Adjusted R^2	39.65%	24.12%	27.23%

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and ***at 10% level .*

The commodity beta of three MomIVol strategies out of six strategies has a positive and significant value which indicates that returns of combined strategies follow the movements of a commodity index. Similarly, two MomIVol strategies have a positive and significant beta for the bond index which shows that MomIVol returns reflect the ups and downs of bond index. However, the returns of the MomIVol strategies are neutral to the risk of the equity market. The results show that out of six profitable MomIVol strategies, four strategies of holding periods 6, 12, 18 and 24 months provide positive and significant abnormal returns (α). On an average, the monthly abnormal return of these strategies is 61.41 percent, ranging between 16.92 percent of the $IVol_3Mom_{1-6}$, strategy to 109.76 percent of $IVol_3Mom_{1-24}$ strategy. Hence, the returns of the MomIVol strategies are not merely a compensation for different market risk factors. The comparison of average monthly abnormal performance (α) of MomIVol strategies (61.41 percent) with momentum strategies (21.00 percent) and IVol strategies (28.61 percent) indicates that the MomIVol strategies perform better than individual momentum and IVol strategies. In addition, the returns of MomIVol strategies are driven by both long and short portfolios due to their significant alphas.

4.8.2.2 Time-Varying Risk-Based Analysis of MomIVol Strategies

Robustness analysis is performed to analyse whether returns of the MomIVol strategies are due to exposure to the time-varying risks. The alpha of all the information variables and a probability value of all the hypotheses, H_7, H_8 and H_9 are reported in Table 4.73.

Table 4.73: Time-Varying Risk-Based Performance of MomIVol Strategies

Combined Strategies	$\boldsymbol{\alpha_0}$	$\boldsymbol{\alpha_{TS}}$	$\boldsymbol{\alpha_{DY}}$	$\boldsymbol{\alpha_{MIBOR}}$	P($\boldsymbol{\alpha_1}$=0)	P($\boldsymbol{\beta_1}$=0)	P ($\boldsymbol{\alpha_1} = \boldsymbol{\beta_1}$=0)	Adj R^2
$\boldsymbol{IVol_3Mom_{1-6}}$	7.10 [0.787]	-2.06 [-0.161]	39.38 [1.92]***	-5.23 [-0.491]	0.2861	0.2477	0.0013**	17.30%
$\boldsymbol{IVol_3Mom_{1-12}}$	21.73 [1.52]	-6.85 [-0.359]	66.92 [2.21]**	-14.17 [-0.864]	0.1429	0.0154**	0.00*	35.19%
$\boldsymbol{IVol_3Mom_{1-18}}$	33.46 [3.33]**	19.69 [1.53]	44.11 [1.87]***	8.59 [0.763]	0.0638***	0.2586	0.0005*	26.15%
$\boldsymbol{IVol_3Mom_{1-24}}$	38.16 [1.19]	1.81 [0.052]	34.89 [0.554]	-24.76 [-0.782]	0.0427**	0.1223	0.0091**	24.13%

*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit ‘t’ statistics and * shows significance level at 1%, ** at 5% and ***at 10% level .*

The results demonstrate that two strategies out of four combined strategies have a significant time-dependent conditional alpha (α_1) and one strategy has a significant time-dependent conditional beta (β_1). In addition, all the four strategies have shown a joint significance for both conditional alpha and conditional beta. Hence, the application of model shown in Equation (3.17) is justified with respect to the measure of time-varying alpha and beta. The results show that out of four profitable strategies, only one strategy $IVol_3Mom_{1-18}$ yields a monthly conditional abnormal return (α_0) equals to 33.46 percent which indicates that the abnormal return of this strategy is not a compensation for time-varying risk. On the contrary, insignificant values of other profitable strategies such as $IVol_3Mom_{1-6}$, $IVol_3Mom_{1-12}$ and $IVol_3Mom_{1-24}$ indicate that abnormal performance (α) of these strategies is time-varying.

4.8.3 Transaction Costs Estimation for MomIVol Strategies

In line with the procedure used in momentum strategies, the portfolio turnover and net IVol returns are estimated using Equations (3.18), (3.19) and (3.20). The results, shown in Table 4.74 clearly indicate that though transaction costs reduced the magnitude of MomIVol payoffs, they could not erode the positive MomIVol returns. On an average, MomIVol strategies earn a monthly net return of 18.82 percent at transaction costs of 0.033 percent. In addition, at the highest level of transaction costs (0.146 percent) reported by Shen et al. (2007), these strategies earn a monthly average net return of 17.42 percent.

Table 4.74: Portfolio Turnover and Net MomIVol Returns of the MomIVol Strategies

Combined Strategies	MomIVol Returns (%)	Portfolio Turnover (%)	Net MomIVol Returns (0.033%)	Net MomIVol Returns (0.146%)
$\boldsymbol{IVol_3Mom_{1-1}}$	2.12	0.875	0.895	0.389
$\boldsymbol{IVol_3Mom_{1-3}}$	6.54	0.875	4.25	2.21
$\boldsymbol{IVol_3Mom_{1-6}}$	13.04	0.875	9.16	6.88
$\boldsymbol{IVol_3Mom_{1-12}}$	27.52	0.875	21.89	18.78
$\boldsymbol{IVol_3Mom_{1-18}}$	43.71	0.875	35.15	32.10
$\boldsymbol{IVol_3Mom_{1-24}}$	60.51	0.875	47.56	44.18

*(**Source:** Secondary Data Analysis)*

4.8.4 MomIVol Strategies: Diversification and Inflation Hedging

The correlation between the returns of MomIVol strategies and the returns of stock, bond and commodity indices are shown in Table 4.75.

Table 4.75: Correlation of MomIVol Portfolios with Nifty, Bond, Commodity Index and Inflation Index

MomIVol Strategies	Nifty	Bond	Commodity Index	Inflation Index(WPI)
$\boldsymbol{IVol_3Mom_{1-1}}$	-0.1432	-0.0763	0.0852	-0.1840***
$\boldsymbol{IVol_3Mom_{1-3}}$	-0.0375	-0.1288	0.0596	-0.3351*
$\boldsymbol{IVol_3Mom_{1-6}}$	-0.0189	-0.0116	0.0686	-0.4808*
$\boldsymbol{IVol_3Mom_{1-12}}$	0.0256	-0.0244	0.1118	-0.6096*
$\boldsymbol{IVol_3Mom_{1-18}}$	0.0420	-0.0136	0.0792	-0.7102*
$\boldsymbol{IVol_3Mom_{1-24}}$	0.1113	-0.0964	0.1870	-0.7244*

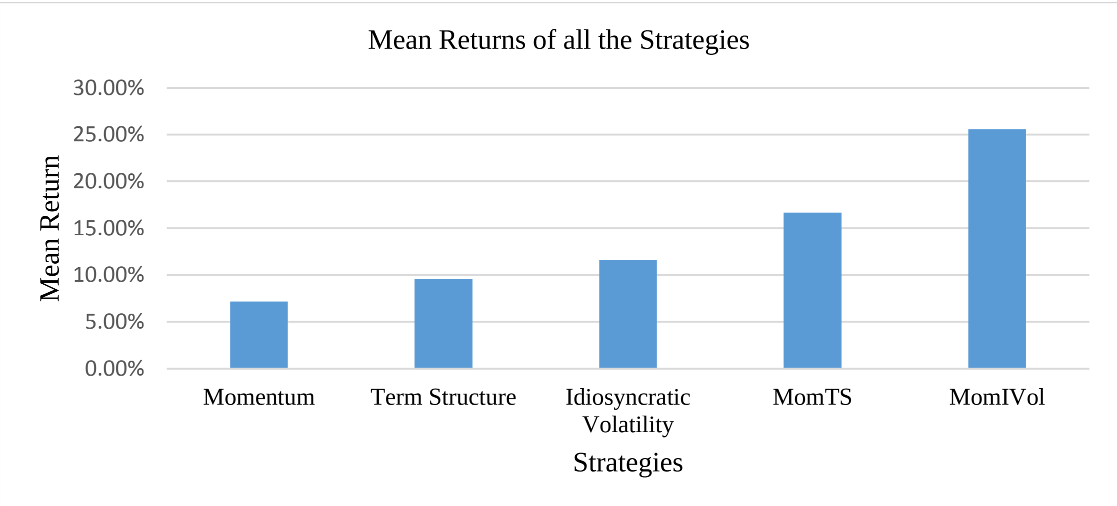
*(**Source:** Secondary Data Analysis)*
*Values in the square bracket exhibit 't' statistics and * shows significance level at 1%, ** at 5% and ***at 10% level .*

The returns of all the MomIVol strategies have a positive and insignificant correlation with a commodity index. The average correlation between the MomIVol returns and the Nifty is -0.0035, ranging between -0.1432 of $IVol_3Mom_{1-1}$ strategy to 0.1113 of $IVol_3Mom_{1-24}$ strategy. On the contrary, the average correlation of the returns of all the six MomIVol strategies and bond index is very low which equals to -0.0585. However, all the MomIVol strategies have an insignificant correlation with Nifty and bond indices. This result is in line with the findings of individual strategies which confirms that MomIVol returns are neutral to the risk of the equity market. These results confirm that tactical allocation of commodity futures in a portfolio of traditional asset classes can be used as an excellent tool for portfolio diversification, in addition, to earn abnormal returns by reducing the risk of their portfolios.

Table 4.75 also shows the correlation between the MomIVol returns and the WPI. The results demonstrate the negative and significant correlation of MomIVol returns with WPI for all the six MomIVol strategies. These results suggest that the MomIVol portfolios cannot be used as a hedge against Inflation. Hence, the abnormal returns of the MomIVol strategies and their diversification benefits lead to losing its basic inflation hedging potential.

4.9 COMBINED PERFORMANCE OF MOMENTUM, TS_1, IVol, MomTS and MomIVol STRATEGIES

The average monthly mean returns of all the strategies i.e. momentum, TS_1, IVol, MomTS and MomIVol strategies indicate that MomIVol strategies based on momentum and idiosyncratic volatilities are most profitable compared to other strategies as depicted in Figure 4.34.



*(**Source:** Secondary Data Analysis)*

Figure 4.34: Average Mean Returns of Momentum, TS_1, IVol, MomTS and MomIVol Strategies

MomIVol strategy yields a monthly average return of 25.57 percent (annualized return of 89.45 percent) compared to momentum, TS_1, IVol and MomTS strategies which yield average monthly returns of 7.17, 9.54, 11.59 and 16.68 percent (annualized return of 43.03, 49.04, 63.45 and 77.48 percent), respectively. On the contrary, long-only passive investment in composite commodity index- MCXCOMDEX, Nifty stock index and CCIL bond index yields an annualized return of 4.76, 10.29 and 8.30 percent, respectively.

4.10 SUMMARY

This chapter analyses the inflation hedging and diversification benefits of commodity futures. It helps in the identification of passive investment benefits in commodity futures markets. The results give evidence in support of a partial inflation hedging potential of gold, silver, lead and CPO futures. Conversely, the results indicate the marginal inflation hedging potential of copper and cotton futures. In addition, results indicate that copper and cotton futures possess strong hedging potential against stock market movements. CPO futures act as a strong safe haven against extreme stock market movements while nickel and natural gas act as a strong safe haven against extreme bond market movements.

In addition to the passive investment, active investment strategies are also discussed in this chapter. Active strategies are designed based on the momentum, term structure and idiosyncratic volatility signals in the commodity futures market. In addition, combined strategies (MomTS and MomIVol) which incorporate the methodology of momentum, term structure and idiosyncratic volatility strategies are designed and their time-varying risk-adjusted return performance is analysed. The results clearly indicate that these strategies not only yield exceptionally high abnormal return but can be used to diversify the portfolio of traditional asset classes such as stocks and bonds. Thus, overall results give a clear indication that the commodity futures possess all the features of a good alternative asset class. The main findings, conclusions, recommendations and future direction for research are presented in the following chapter.

Notes:

[1]These models are referred to as Markov-Switching-Intercept-Autoregressive-heteroscedastic-VECM or MSIAH-VECM which follow the notation as given by Krolzig (1997).

[2] The movements of nominal and inflation hedge prices of crude oil futures, depicted in Figure 3.3, show high volatility and abrupt movements in crude oil futures prices. In addition, the prices of gold and silver futures show the change in pattern after 2011 and 2012 as indicated in Figure 3.2. Similarly, lead, nickel, CPO and cotton futures prices show abrupt movements after 2008 as depicted in Figures 3.4 and 3.5. These abrupt movements suggest, to use regime-specific

analysis. However, from the econometric perspective, information selection criterion justify, to use linear VECM. Thus, in this study more weightage is given to the econometric reasoning. Based on this theory, linear VECM is executed to investigate the inflation hedging potential of gold, silver, lead, nickel, crude oil, CPO and cotton futures.

[3]The preference is given to SIC test results for the selection of most appropriate model. SIC supports more parsimonious model and protects from over-parameterization by imposing stiffer penalty term associated with the number of parameters than AIC and HQ. The preference is given to SIC test results as the selection is made between a more parsimonious linear model and a less parsimonious nonlinear model.

[4]Abnormal performance (α) is the value of intercept which is obtained by the execution of Multi-factor model shown in Equation (3.13).

CHAPTER 5

CONCLUSIONS

5.1 CHAPTER OVERVIEW

The chapter elaborates the major findings of the study, conclusions, recommendations and future direction of research. Section 5.2 gives the summary of the study which includes the purpose of the study, methodology used in the study and main findings of the study. Section 5.3 discusses the conclusions and recommendations given in the study based on the findings. Section 5.4 outlines the theoretical and policy implications of the study and section 5.5 throws light on the direction for future research.

5.2 SUMMARY OF THE STUDY

The study is summarized in the following sections.

5.2.1 Purpose of Study

The major concern of a long-term investor is to intensify the stability of the investment return from the risk of unexpected inflation which is consistent with their investment goal. Chronic inflation causes a long-run erosive impact on assets' return and purchasing power over time. Consequently, investors ought to invest in an asset which moves with inflation and is immune to inflation risk without overly exposing to other risk factors (Spierdijk and Umar, 2014). In addition, the worldwide growth of financial markets and instruments gives more diversification benefits to investors (Baur and Lucey, 2010). However, it also propagates financial crisis through contagion effect which is evident from the subprime and European crises including the economic crisis of China (Kassim et al., 2011; Rannou, 2011; Bagchi and Ryu, 2011). It increases the volatility and uncertainty in the stock and bond markets' returns (Rastogi, 2014). Hence, it is necessary for portfolio managers and investors to diversify their portfolios by including alternative assets in the portfolio as the prime concern of any investor is to diversify the portfolio and to earn an abnormal return. To earn an abnormal return, it is essential that investors should design an active strategy which can be used for dynamic asset allocation. Commodity futures are considered as one of such risk management tools which are designed to provide the benefits of alternative investments. Hence, the overall purpose of the study is to investigate the role of commodity futures as a risk management tool which not only helps to diversify the portfolio by mitigating the risk but also provides the high abnormal returns.

5.2.2 Methodology Used in the Study

The current study builds on the quantitative research paradigms which use the time series data analysis technique to analyse the secondary data. The time-varying nonlinear approach is used to analyse the inflation hedging and diversification benefits of commodity futures and to estimate the risk-adjusted return performance of different active strategies which is shown below.

a. *Inflation hedging potential of commodity futures:* The Markov Switching-Vector Error Correction Model (MS-VECM) is used in this study to analyse the inflation hedging potential of commodity futures and commodity indices.
b. *Diversification benefits of commodity futures:* The hedge and safe haven role of commodity futures and commodity indices are analysed using the Markov Switching-Vector Autoregression (MS-VAR) Model.
c. *Momentum strategies in commodity futures market:* Winner, loser and winner-loser portfolios are constructed based on the past returns of commodity futures and the conditional Multi-factor model is used to measure the time-varying beta and alpha (abnormal performance) of momentum strategies in the commodity futures market.
d. *Term Structure (TS) strategies in commodity futures market:* Roll yield is estimated to create long, short and long-short (TS) portfolios and their time-varying performance is measured using conditional Multi-factor model.
e. *Idiosyncratic Volatility (IVol) strategies in commodity futures market:* Idiosyncratic volatility is estimated by using the Multi-factor model which is used to create the long, short and long-short (IVol) portfolios. In addition, their time-varying abnormal performance is measured by the application of the conditional Multi-factor model.
f. *Combined Strategies (MomTS) in commodity futures market:* Combined strategy (MomTS) is designed by using the methodology of momentum and term structure strategies and time-varying beta and alpha of MomTS strategies are measured using conditional Multi-factor model.

g. *Combined Strategies (MomIVol) in commodity futures market:* Combined strategy (MomIVol) is designed by using the methodology of momentum and idiosyncratic volatility strategies and conditional Multi-factor model is used to measure their time-varying performance.

5.2.3 Main Findings

The study has attempted to highlight the inflation hedging and diversification benefits of 13 highly traded commodity futures contracts of Multi Commodity Exchange (MCX). These commodity futures are chosen based on their average daily turnover, volume and open interest. The study has also constructed five active strategies by using these commodity futures contracts based on momentum, term structure and idiosyncratic volatility signals. The main findings of the study are elaborated in the following paragraphs:

a. *Inflation Hedging Potential of Commodity Futures*:

   The major findings of this analysis justify the achievement of research objective 1.

1. The results of cointegration test suggest that zinc, aluminium, natural gas, cardamom, and mentha oil futures and sub-indices MCXMETAL, MCXENERGY and MCXAGRI cannot be used as a hedge against inflation.
2. The results of Vector Error Correction Model (VECM) give an evidence in support of partial inflation hedging potential of gold, lead, CPO and silver futures.
3. Estimated results of VECM provide a feeble confirmation in favor of inflation hedging potential of nickel and crude oil futures.
4. The results of VECM indicate the marginal inflation hedging potential of cotton futures.
5. The estimated results of MS-VECM show the marginal inflation hedging potential of copper futures. However, the price adjustment pattern in copper futures depends on the respective regimes. The regime classification characterizes the first regime as a period of 'normal' time with low volatility in the returns of copper futures prices and the second regime as a period of 'extreme' time with the highest monthly volatility. During the first regime, copper is not able to sustain its inflation hedging potential due to lack of price adjustment by an inflation index.

b. *Diversification Benefits of Commodity Futures:*

The key findings of this analysis justify the achievement of research objective 2 (Jaiswal and Uchil, 2017).

1. The results confirm that gold and silver futures can be used as a weak hedge against stock and bond market movements but cannot be used as a safe haven against extreme movements of stock and bond markets.
2. Under energy sector, crude oil and natural gas possess weak hedging potential against stock and bond markets movements. However, natural gas shows a strong safe haven property against bond market movements while crude oil futures cannot be used as a safe haven against extreme movements of stock and bond markets.
3. In the section of the agricultural sector, cotton futures possess strong hedging potential and CPO futures possess strong safe haven potential against stock market movements. Conversely, cardamom and mentha oil provide weak hedging and safe haven potential against stock and bond market movements.
4. Under industrial metals, copper futures can be used as a strong hedge against stock market movements and nickel futures can be used as a strong safe haven against bond market. Conversely, zinc, nickel, aluminium and lead futures possess weak hedging potential against the stock and bond markets movements while copper, aluminium, lead and nickel cannot be used as a safe haven against stock market movements.
5. In the case of commodity sub-indices, MCXMETAL, MCXAGRI and MCXENERGY give a weak hedging potential against stock and bond markets movements while MCXMETAL and MCXENERGY cannot be used as a safe haven against stock market movements.
6. The above results indicate that commodity futures possess varying capability of hedge and safe haven properties against stock and bond markets movements.
7. In addition, portfolio analysis confirms that the results of MS-VAR estimation for all the commodity futures provide a significant direction to investors in the context of portfolio management.

c. *Active Strategies in Commodity Futures Markets using Momentum, Term Structure and Idiosyncratic Volatility Signals*

The major findings of this analysis are elaborated in the following paragraphs which justify the achievement of research objectives 3 and 4.

1. The average monthly mean returns of all the active strategies i.e. Momentum, TS, IVol, MomTS and MomIVol are 7.17, 9.54, 11.59, 16.68 and 25.57 percent, respectively. On the contrary, long-only passive investment in composite commodity index-MCXCOMDEX, Nifty stock index and CCIL bond index yields an annualized return of 4.76, 10.29, and 8.30 percent, respectively. In addition, the average mean returns of these strategies indicate that MomIVol strategies based on momentum and IVol strategies are more profitable compared to other strategies as depicted in Figure 4.34.
2. For all the strategies, it is shown that longer holding periods are more profitable rather than shorter holding periods. This indicates that investors with a long-term investment horizon can earn a better result in commodity futures market.
3. The momentum and term structures strategies based on lag one month returns are more profitable rather than the strategies based on the average returns of the past ranking periods of 3, 6 and 12 months. Similarly, idiosyncratic volatility strategies based on past 3 months ranking period are more profitable compared to the strategies based on the average returns of the past 1, 6 and 12 months ranking periods. These results suggest that the strategies based on the performance of the individual commodity futures in the nearest month are more profitable in the commodity market.
4. Results of all the strategies indicate that standard deviation increases with an increase in the returns of these strategies. These outcomes are in line with the normal market perception of higher returns associated with the higher risk.
5. Sharpe ratio of all the strategies indicates that an increase in Sharpe ratio is associated with the increase in the payoffs of all the strategies. In addition, momentum, TS, IVol, MomTS and MomIVol strategies in commodity futures markets perform better with respect to their risk-adjusted return performance compared to the passive investments in equity, bond and commodity indices.
6. The comparison of mean returns, volatility and Sharpe ratio of MomTS strategy with momentum and TS strategies and MomIVol strategy with momentum and IVol strategies indicates that combined strategies such as MomTS and MomIVol perform better compared to their respective individual strategies.
7. The sub-periods analysis reveals that momentum, TS, IVol, MomTS and MomIVol strategies perform better in the earlier sub-periods of September 2006-November 2009 and December 2009-January 2013 compared to later sub-period of February

2013-April 2016. The reason for these returns could be that the commodity market was in a vicious downtrend/bear market from the year 2011 until the year 2015. On the contrary, commodity market was in bull phase from the year 2007 until the year 2009 (Sarhan, 2016). Hence, during later periods of December 2009-January 2013 and February 2013-April 2016, payoffs of these strategies have declined compared to the earlier period. It shows that profitability of these strategies is basically time-varying. Moreover, this information suggests that decreased payoffs of these strategies in the recent years were due to the reduced investment of institutional investors in the commodity market.

8. Sensitivity analysis of momentum payoffs indicates that use of distant contract and 15th of the expiry month as a rolling date to compile the futures time series are more profitable rather than the use of nearest contract and end of the month as a rolling date. It indicates that liquidity risk associated with distant maturity contract does not have any impact on the profitability of momentum strategies. This is due to the fact that liquidity risk can be easily compensated by the abnormal profit, generated due to the trading in distant maturity contract. On the contrary, sensitivity analysis of TS strategy indicates that profitability of term structure strategy is sensitive to the liquidity risk arising due to the trading in distant maturity contract and the selection of the rolling date. In addition, the profitability of TS strategies is sensitive to an impact of frequent rebalancing of long-short portfolios.
9. The abnormal performance (α) of momentum, TS, IVol, MomTS and MomIVol strategies and their sensitivity to the stock, bond and commodity indices indicates that strategies of longer holding periods are not merely a compensation for different market risk factors. It indicates that investors with a long-term investment horizon can earn abnormal returns by using these strategies in commodity futures market.
10. Sensitivity analysis of these strategies with respect to their time-varying risk indicates that profitability of momentum strategies are time-varying compared to TS, IVol, MomTS and MomIVol strategies. It indicates that the abnormal returns of these strategies for all the holding periods are not a compensation for the time-varying risk.
11. The results of transaction costs estimation for all the strategies indicate that though transaction costs reduced the magnitude of payoffs of all the strategies, they could not erode the positive returns.

12. The correlation between the returns of momentum, TS, IVol, MomTS and MomIVol strategies with the returns of stock, bond and commodity indices indicates that tactical allocation of commodity futures in a portfolio of traditional asset classes can be used as an excellent tool for portfolio diversification. In addition, these strategies can be used to earn abnormal returns by reducing the risk of the portfolios. However, the abnormal returns of these strategies and their diversification benefits lead to losing its basic inflation hedging potential.

5.3 CONCLUSIONS AND RECOMMENDATIONS

5.3.1 Conclusions

The research analyses the commodity futures as a risk management tool from the aspect of their inflation hedging potential, diversification benefits and ability to generate abnormal returns. Some of the conclusions from the study are:

1. This study empirically examines the notion identified with the inflation hedging potential of individual commodity futures under a nonlinear framework. In view of the results, it is inferred that futures of all the precious metals possess preferable inflation hedging potential in comparison to energy, industrial and agricultural products. Moreover, results have not given any evidence in favour of the inflation hedging potential of any commodities under energy sector which is against the typical market discernment and thereby contradicts the findings of earlier studies. From an investors' perspective, they can viably utilize gold, silver, copper, lead, CPO and cotton futures as a hedge against inflation. Remarkably, the inflation hedging potential of these commodities does not depend on the time horizon of investment with the exception of copper.
2. This study empirically verifies the conventional perception related to commodity futures and commodity indices as a hedge and safe haven in real market situations. The findings of the nonlinear framework confirm that individual commodity futures and commodity indices show a varying level of hedge and safe haven potential against stock and bond markets movements. The findings of MS-VAR are also justified using portfolio analysis. It confirms that outcomes of MS-VAR provide a significant guidance to investors in the construction of a diversified portfolio with enhanced risk-adjusted return performance.

3. The overall results indicate that all the commodity futures and commodity indices possess weak hedging potential against stock and bond markets movements except for copper and zinc futures which cannot be used as a hedge against bond market movements. Hence, from the results, it is concluded that commodity futures and commodity indices can be used to diversify a portfolio of traditional asset classes.
4. The combined analysis of inflation hedging and diversification benefits of commodity futures reveals that gold and silver futures possess partial inflation hedging potential while it can be used as a weak hedge against stock and bond market movements. Hence, the gold and silver futures can be used as an alternative asset class to diversify the portfolio as well as to hedge the inflation risk. In addition, copper and cotton futures have a marginal inflation hedging potential while they can be used as a strong hedge against stock market movements. Similarly, lead and CPO possess a partial inflation hedging potential and weak hedging potential against stock market movements. However, CPO futures possess a strong hedging potential against extreme stock market movements. Hence, in addition, to the gold and silver futures, copper, cotton, CPO and lead futures can be used as an alternative asset class to diversify a portfolio and to hedge the inflation risk.
5. This study analyses the time-varying conditional profitability of five different active strategies which are designed based on the momentum, term structure and idiosyncratic volatility signals available in the Indian commodity futures market. The results indicate that the average monthly mean returns of all the active strategies i.e. momentum, TS, IVol, MomTS and MomIVol are exceptionally high compared to the average annualized return of long-only passive investment in the commodity index, Nifty stock index and CCIL bond index. Moreover, investors with a long-term investment horizon can earn a better abnormal return by using these strategies in the commodity market. In addition, the time-varying analysis of conditional beta and alpha based on the vector of macroeconomic variables suggests that abnormal performance of momentum strategies is time-varying. Conversely, the abnormal performance of TS, IVol, MomTS and MomIVol strategies are not a compensation for time-varying risk for all the holding periods.
6. In addition, the design of a combined strategy, MomIVol, by using the methodology of both momentum and IVol strategies gives the highest monthly average return among all the strategies such as momentum, TS, IVol and MomTS. Hence, it is the

major contribution of the study to the existing literature and to the real time practitioner.

7. Sensitivity analysis of momentum payoffs which uses the distant contract and 15th of the expiry month as a rolling date to compile the futures time series, indicates that exceptionally high profitability of momentum strategies can easily accommodate the liquidity risk associated with the trading in distant maturity contract. On the contrary, sensitivity analysis of TS strategy indicates that profitability of term structure strategies is sensitive to the liquidity risk which arises due to the trading in distant maturity contract, selecting the 15th of the month as a rolling date and increasing the frequency of rebalancing of long-short portfolios.
8. The estimation of net payoffs of the strategies indicates that though transaction costs reduce the magnitude of the returns, they could not erode the positive returns. Moreover, the insignificant correlation of momentum, TS, IVol, MomTS and MomIVol portfolios with the returns of stock, bond and commodity indices indicates that dynamic allocation of commodity futures in a portfolio of traditional asset classes can be used as an excellent tool for portfolio diversification.
9. Hence, from an overall analysis, it is concluded that commodity futures possess all the properties of an alternative asset class which can be used to diversify the portfolio of traditional asset classes such as stocks and bonds. In addition, the dynamic allocation of commodity futures in a portfolio is a good source of earning exceptionally high abnormal returns.

5.3.2 Recommendations

Some of the recommendations to the policy-makers that emerged from the study include:

1. The results of the study give a confirmation in favor of commodity futures as an alternative asset class. It can be included in a portfolio to generate an abnormal return by implementing the active strategies, in addition, to diversifying the portfolio. Based on the outcomes of this study, policy-makers may design a policy framework to highlight the commodity futures as an alternative asset class. It may attract financial institutions such as mutual funds, alternative investment funds, hedge funds and other financial investors to commodity derivative trading. In addition, the increased investment intensity may help in stabilizing the commodity market which has been very volatile since its inception.

2. The findings of the study give an indication that the gold and silver futures possess all the properties of a good alternative asset class. Being the second largest gold consuming country, the consumption demand of gold is more than the investment demand in India. In India, a significant portion of household incomes spends on the purchase of gold with the intention of creating wealth. However, it has repercussions on the economy as a whole due to the increased pressure on imports and current account deficit. It has always been the prime concern of policy-makers to reduce the consumption demand for gold. Based on the results of the gold and silver futures, policy-makers may design a regulatory framework which will increase awareness among the investors and probably help to enhance the investment demand for these commodities in India.
3. The findings of the study emphasized the link among stock, bond and commodity markets and confirm the financialization of the commodity market. Based on these findings, SEBI, state governments, and other agencies may work together to develop a conducive trading environment in the commodity market for all kinds of investors.

5.4 THEORETICAL AND POLICY IMPLICATIONS

The study has a few implications which may contribute to the theoretical and practical world in a significant manner.

1. Studies conducted to examine the equilibrium relationship between individual commodity futures and inflation by incorporating the nonlinear relationship are very less. Hence, the current study enriches the existing literature by analysing the inflation hedging potential of individual commodity futures using nonlinear MS-VECM in the Indian context.
2. In addition, the previous studies have not considered the time-varying approach under the regime-specific relationship of individual commodity futures with stocks and bonds. Hence, the current study contributes to the academic world by analysing the safe haven and diversification benefits of the individual commodity futures using nonlinear MS-VAR model in the Indian context.
3. The current study augments the existing literature by assessing the possible role of time-varying conditional alpha and beta to define the payoffs of the single strategies

such as momentum, TS, IVol and the combined strategies such as MomTS and MomIVol, in commodity futures market for the Indian context.

4. The strategies for dynamic asset allocation, such as momentum, TS, IVol, MomTS and MomIVol generate exceptionally high abnormal returns compared to the abnormal returns shown in previous studies such as Erb and Harvey (2006) and Miffre and Rallis (2007). In addition, the sub-periods analysis and time-varying analysis of conditional alpha and beta indicate that the payoffs of momentum strategies are basically time-varying. Conversely, the payoffs of other strategies such as TS, IVol, MomTS and MomIVol give mixed results with respect to their time-varying performance based on different holding periods. These findings contradict the outcomes of previous studies which suggested that the payoffs of momentum and other active strategies are not merely a compensation for time-varying risk.
5. Previous studies designed a double-sort strategy which combines the methodology of both momentum and term structure strategies and triple-screen strategy which combine the methodology of momentum, term structure and idiosyncratic volatility strategies. However, there is a lack of study which combines the theoretical concepts of both momentum returns and idiosyncratic volatility to design a double-sort strategy. Hence, one of the very significant contributions of the study to the existing literature and practice is the design of a combined strategy, MomIVol which uses the methodology of both momentum and IVol strategies. The MomIVol strategy yields the highest monthly average return among all the strategies such as momentum, TS, IVol and MomTS, developed in the study.
6. Findings of this study provide a significant guidance to the investors in tactically allocating the commodity futures to their portfolio, not only to earn an exceptionally high abnormal return but also to diversify their portfolio. The current study contributes to the real time practitioner by successfully implementing the momentum, term structure and idiosyncratic volatility strategies in the Indian commodity futures market. In addition, the design of the combined strategies such as MomTS and MomIVol strategies may play an important role in the investment decision of institutional investors and professional money managers such as hedge funds and commodity pool operators. These strategies may enable them to earn exceptionally high abnormal returns and to diversify the portfolio.

5.4 FUTURE DIRECTIONS FOR RESEARCH

The study can be extended further in the following directions:

1. The current study analyses the inflation hedging and diversification benefits of commodity futures in the Indian context. The study can be extended further by performing a relative assessment of the inflation hedging potential and diversification benefits of commodity futures in other emerging nations denominated in their local currency using the framework adopted in this study.
2. This study designs five active strategies such as momentum, TS, IVol, MomTS and MomIVol using a limited cross-section of 13 highly traded commodity futures contracts of MCX. These strategies give exceptionally high abnormal returns compared to the returns yielded in the previous studies such as Erb and Harvey (2006), Miffre and Rallis (2007) and Fuertes et al. (2010). Hence, it can be taken up as a future work to investigate whether the superior profits of these active strategies are arising from data mining and are robust to an extended study period. In addition, the robustness of the high abnormal returns can be investigated further by the inclusion of expanded cross-section of commodity futures contracts for the creation of these active strategies.
3. Findings of the study indicate that the active strategies such as momentum, TS, IVol, MomTS and MomIVol give exceptionally high abnormal returns which are basically based on the historical performance of 13 commodity futures contracts. Hence, future research may be undertaken to check the consistency of these returns by using the forecasting techniques.
4. It is considered that profitability of active strategies is merely a compensation for three different risk factors. First, net profit of active strategies is negligible due to the transaction costs incurred to implement these strategies. Second, the abnormal returns in momentum strategies are merely a compensation for time-varying risk. Third, the abnormal returns of active strategies are a compensation for bearing the risks of low inventories (Gorton et al., 2013). The current study analyses the impact of transaction costs and time-varying factors on the profitability of active strategies. The study can be augmented further by evaluating the impact of inventories on the profitability of different strategies.

5.6 SUMMARY

Commodity derivative trading has witnessed a significant growth in India over the last decade. This is in tune with the investors' demand for alternative investment as a risk management tool. Commodities are considered as an excellent risk management tool since investors are looking towards the creation of long-short trading strategies. These strategies help them to obtain an alternative investment exposure and also to reduce volatility and earn a reliable income. However, commodity derivative trading in India has to move a long way to reach the level of other developed countries. There is a need to design a robust regulatory framework to develop an integrated commodity market which protects the interest of both investors and hedgers. This is an ongoing process of developing a transparent and fair procedure of trading in commodity futures contract to enhance the credibility of derivative trading among investors and hedgers.

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Appendix 1

Table 1: Unit Root Test Statistics

	Level Series			First Difference		
	ADF Test	KPSS Test	Zivot Andrews Test	ADF Test	KPSS Test	Zivot Andrews Test
Gold	-0.975	1.14*	-3.65	-12.89*	0.271	-13.45*
Silver	-1.71	0.708**	-3.13	-11.46*	0.174	-12.25*
Copper	-1.79	0.603**	-3.85	-8.82*	0.068	-9.75*
Zinc	-2.04	0.194**	-2.62	-11.13*	0.171	-12.11*
Aluminium	-2.60	0.135**	-5.62	-9.39*	0.048	-9.89*
Nickel	-2.64	0.359***	-5.24	-9.36*	0.116	-10.39*
Lead	-2.49	0.536**	-3.59	-9.90*	0.089	-10.94*
Crude Oil	-2.20	0.391***	-4.69	-8.20*	0.091	-5.69*
Natural Gas	-2.53	0.609**	-4.32	-10.75*	0.049	-11.02*
Cardamom	-2.93	0.459***	-4.65	-9.07*	0.309	-8.62*
Mentha Oil	-2.26	0.522**	-3.46	-9.48*	0.099	-10.42*
CPO	-1.71	0.508**	-4.75	-8.00*	0.093	-8.35*
Cotton	-2.08	0.261***	-4.82	-7.90*	0.085	-8.50*
MCXMETAL	-1.48	0.954*	-3.21	-11.45*	0.148	-12.11*
MCXENERGY	-2.34	0.302***	-4.57	-7.77*	0.079	-8.00*
MCXAGRI	-1.91	0.551**	-3.54	-12.05*	0.124	-12.74*
WPI (All Commodities)	-1.02	1.25*	-4.15	-6.21*	0.334	-5.71*

(***Source:*** *Secondary Data Analysis*)

** shows the significance level at 1%, ** at 5% and ***at 10% level of significance.*

Table 2: Lag Length Selection Criterion

Models	Information Criterion	Lag		
		1	2	3
Gold-WPI	AIC	-909.59	**-904.72**	-891.17
	SIC	-844.78	**-853.15**	-832.72
	HQ	-894.34	**-899.92**	-867.59
Silver-WPI	AIC	-701.76	**-697.75**	-682.76
	SIC	-663.94	**-676.18**	-624.31
	HQ	-686.51	**-699.95**	659.18
Copper-WPI	AIC	**-951.68**	-953.47	949.19
	SIC	**-920.74**	-908.77	-890.74
	HQ	**-939.20**	-935.44	-925.61
Aluminium-WPI	AIC	**-1105.49**	-1106.71	-1102.47
	SIC	**-1074.55**	-1062.02	-1044.02
	HQ	**-1093.01**	-1088.68	-1078.89
Zinc-WPI	AIC	**-711.60**	-717.40	-713.08
	SIC	**-680.66**	-672.71	-654.63
	HQ	**-699.12**	-699.38	-689.50
Nickel-WPI	AIC	-929.46	**-939.83**	-925.17
	SIC	-873.08	**-889.20**	-867.79
	HQ	-917.18	**-919.38**	-901.99
Lead-WPI	AIC	-891.91	-895.82	**-891.38**
	SIC	-862.05	-852.68	**-874.98**
	HQ	-879.83	-878.37	**-868.57**
Crude Oil-WPI	AIC	-499.37	**-495.10**	-500.19
	SIC	-468.43	**-487.41**	-441.75
	HQ	-486.89	**-497.08**	-476.62
Natural Gas-WPI	AIC	**-740.49**	-740.50	-734.03
	SIC	**-709.63**	-695.92	-675.73
	HQ	**-728.04**	-722.51	-710.51
Cardamom-WPI	AIC	**-542.79**	-541.05	-539.16
	SIC	**-511.84**	-496.36	-480.71
	HQ	**-530.30**	-523.02	-515.58
Mentha Oil-WPI	AIC	**-659.22**	-657.81	-661.32
	SIC	**-628.28**	-613.12	-602.87
	HQ	**-646.74**	-639.78	-637.74
CPO-WPI	AIC	-802.81	**-798.52**	-797.31
	SIC	-773.97	**-787.81**	-742.84
	HQ	-791.12	**-795.64**	-775.23
Cotton-WPI	AIC	-539.96	-548.68	**-541.86**
	SIC	-516.33	-514.55	**-533.87**
	HQ	-530.39	-534.86	**-557.63**
MCXMETAL-WPI	AIC	**-1182.30**	-1190.19	-1187.17
	SIC	**-1151.36**	-1145.50	-1128.72
	HQ	**-1169.82**	-1172.17	-1163.59
MCXENERGY-WPI	AIC	**-1113.10**	-1113.65	-1113.08
	SIC	**-1082.16**	-1068.95	-1054.64
	HQ	**-1100.62**	-1095.62	-1089.51
MCXAGRI-WPI	AIC	**-1120.10**	-1117.09	-1112.80
	SIC	**-1089.16**	-1072.32	-1054.36
	HQ	**-1107.63**	-1098.98	-1089.23

(***Source:*** *Secondary Data Analysis*)

Notes: Numbers in bold indicate the selected lag order for the respective model.

Table 3: BDS Statistics of Linear VECM of the Models

Models		BDS Statistic	Probability
Gold-WPI	Gold	0.011	0.079
	WPI	0.003	0.496
Silver-WPI	Silver	0.023	0.562
	WPI	0.029	0.354
Copper-WPI	Copper	-0.0009	0.006
	WPI	0.033	0.00
Nickel-WPI	Nickel	0.012	0.174
	WPI	0.036	0.087
Lead-WPI	Lead	0.003	0.528
	WPI	0.053	0.326
Crude oil-WPI	Crude oil	0.012	0.561
	WPI	0.021	0.852
CPO-WPI	CPO	0.005	0.284
	WPI	0.008	0.240
Cotton-WPI	Cotton	-0.009	0.415
	WPI	-0.007	0.520

*(**Source:** Secondary Data Analysis)*

Table 4: Unit Root Test Results

	Level Series			First Difference		
	ADF Test	KPSS Test	Zivot Andrews Test	ADF Test	KPSS Test	Zivot Andrews Test
Gold	-0.975	1.14*	-3.65	-12.89*	0.271	-13.45*
Silver	-1.71	0.708**	-3.13	-11.46*	0.174	-12.25*
Copper	-1.79	0.603**	-3.85	-8.82*	0.068	-9.75*
Zinc	-2.04	0.194**	-2.62	-11.13*	0.171	-12.11*
Aluminium	-2.60	0.135**	-5.62	-9.39*	0.048	-9.89*
Nickel	-2.64	0.359***	-5.24	-9.36*	0.116	-10.39*
Lead	-2.49	0.536**	-3.59	-9.90*	0.089	-10.94*
Crude Oil	-2.20	0.391***	-4.69	-8.20*	0.091	-5.69*
Natural Gas	-2.53	0.609**	-4.32	-10.75*	0.049	-11.02*
Cardamom	-2.93	0.459***	-4.65	-9.07*	0.309	-8.62*
Mentha Oil	-2.26	0.522**	-3.46	-9.48*	0.099	-10.42*
CPO	-1.71	0.508**	-4.75	-8.00*	0.093	-8.35*
Cotton	-2.08	0.261***	-4.82	-7.90*	0.085	-8.50*
MCXMETAL	-1.48	0.954*	-3.21	-11.45*	0.148	-12.11*
MCXENERGY	-2.34	0.302***	-4.57	-7.77*	0.079	-8.00*
MCXAGRI	-1.91	0.551**	-3.54	-12.05*	0.124	-12.74*
Nifty Stock Index	-1.32	1.03*	-3.41	-10.16*	0.046	11.23*
CCIL Bond Index	0.251	1.26*	-4.21	-7.53*	0.036	-7.84*

*(**Source:** Secondary Data Analysis)*

* shows the significance level at 1%, ** at 5% and *** at 10% level of significance.

Table 5: Lag Length Selection Criterion

Models	Information Criterion	Lags			
		0	1	2	3
Nifty-Bond-Gold	AIC	50.11	41.46	41.54	41.56
	SIC	50.18	41.75	42.05	42.29
	HQ	50.14	41.58	41.75	41.86
Nifty-Bond-Silver	AIC	52.27	43.89	44.01	44.02
	SIC	52.34	44.19	44.53	44.75
	HQ	52.29	44.01	44.22	44.32
Nifty-Bond-Copper	AIC	41.72	33.52	33.63	33.60
	SIC	41.79	33.82	34.14	34.33
	HQ	41.75	33.64	33.83	33.89
Nifty-Bond-Aluminium	AIC	38.20	30.77	30.84	30.88
	SIC	38.28	31.07	31.35	31.61
	HQ	38.23	30.89	31.05	31.18
Nifty-Bond-Zinc	AIC	39.00	31.33	31.43	31.47
	SIC	39.07	31.62	31.95	32.19
	HQ	39.03	31.45	31.64	31.76
Nifty-Bond-Nickel	AIC	43.12	36.08	36.23	36.31
	SIC	43.19	36.39	36.76	37.07
	HQ	43.15	36.21	36.45	36.62
Nifty-Bond-Lead	AIC	30.24	24.51	24.57	24.56
	SIC	30.29	24.67	24.83	24.94
	HQ	30.26	24.57	24.67	24.72
Nifty-Bond-Crude Oil	AIC	47.53	38.98	39.01	39.00
	SIC	47.60	39.28	39.52	39.74
	HQ	47.56	39.11	39.22	39.30
Nifty-Bond-Natural Gas	AIC	41.63	34.16	34.27	34.29
	SIC	41.70	34.45	34.78	35.03
	HQ	41.66	34.28	34.48	34.48
Nifty-Bond-Cardamom	AIC	44.39	36.89	37.01	37.05
	SIC	44.47	37.19	37.52	37.78
	HQ	44.43	37.02	37.22	37.34
Nifty-Bond-Mentha Oil	AIC	44.91	37.23	37.28	37.32
	SIC	44.98	37.52	37.79	38.05
	HQ	44.94	37.34	37.49	37.61
Nifty-Bond-CPO	AIC	41.29	33.17	33.29	33.45
	SIC	41.38	33.52	33.86	34.30
	HQ	41.33	33.31	33.53	33.79
Nifty-Bond-Cotton	AIC	46.71	39.91	39.98	40.03
	SIC	46.83	40.36	40.78	41.18
	HQ	46.75	40.08	40.29	40.47
Nifty-Bond-MCXMETAL	AIC	46.62	37.99	38.08	38.08
	SIC	46.69	38.28	38.59	38.80
	HQ	46.65	38.11	38.29	38.37
Nifty-Bond-MCXENERGY	AIC	46.67	38.27	38.25	38.25
	SIC	46.74	38.56	38.77	38.99
	HQ	46.70	38.39	38.46	38.55
Nifty-Bond-MCXAGRI	AIC	45.59	37.37	37.49	37.57
	SIC	45.66	37.66	38.01	38.31
	HQ	45.62	37.49	37.71	37.84

(***Source:*** *Secondary Data Analysis*)

Table 6: BDS Statistics of Linear VAR estimated for the Models

Models		BDS Statistics	Probability
Nifty-Bond-Gold	Nifty	0.009	0.042
	Bond	0.048	0.00
	Gold	0.007	0.024
Nifty-Bond-Silver	Nifty	0.009	0.065
	Bond	0.042	0.00
	Silver	0.009	0.017
Nifty-Bond-Copper	Nifty	0.003	0.02
	Bond	0.042	0.00
	Copper	0.012	0.014
Nifty-Bond-Aluminium	Nifty	0.010	0.035
	Bond	0.039	0.00
	Aluminium	0.006	0.087
Nifty-Bond-Zinc	Nifty	0.010	0.039
	Bond	0.056	0.00
	Zinc	-0.002	0.064
Nifty-Bond-Nickel	Nifty	0.010	0.064
	Bond	0.036	0.00
	Nickel	0.007	0.034
Nifty-Bond-Lead	Nifty	0.014	0.011
	Bond	0.052	0.00
	Lead	0.016	0.013
Nifty-Bond-Crude Oil	Nifty	0.009	0.063
	Bond	0.027	0.002
	Crude Oil	0.004	0.027
Nifty-Bond-Natural Gas	Nifty	0.009	0.042
	Bond	0.044	0.00
	Natural Gas	0.008	0.079
Nifty-Bond-Cardamom	Nifty	0.010	0.033
	Bond	0.047	0.00
	Cardamom	0.017	0.001
Nifty-Bond-Mentha Oil	Nifty	0.010	0.038
	Bond	0.049	0.00
	Mentha Oil	0.016	0.01
Nifty-Bond-CPO	Nifty	-0.0008	0.087
	Bond	0.038	0.00
	CPO	0.002	0.088
Nifty-Bond-Cotton	Nifty	0.003	0.065
	Bond	0.005	0.069
	Cotton	-0.018	0.051
Nifty-Bond-MCXMETAL	Nifty	0.010	0.045
	Bond	0.037	0.00
	MCXMETAL	0.001	0.075
Nifty-Bond-MCXENERGY	Nifty	0.010	0.040
	Bond	0.024	0.003
	MCXENERGY	0.009	0.016
Nifty-Bond-MCXAGRI	Nifty	0.009	0.074
	Bond	0.044	0.00
	MCXAGRI	-0.002	0.082

*(**Source:** Secondary Data Analysis)*

Table 7: Regime Selection for all the Models

	VAR (1)			MSIAH(2)VAR(1)			MSIAH(3)VAR(1)		
	AIC	SIC	HQ	AIC	SIC	HQ	AIC	SIC	HQ
Nifty-Bond-Gold	-1155.78	-1086.59	-1128.23	-1263.74	-1116.70	-1205.24	-1326.19	-1094.03	-1233.82
Nifty-Bond-Silver	-1040.55	-971.37	-1012.99	-1196.57	-1049.53	-1138.06	-1198.77	-966.60	-1106.39
Nifty-Bond-Copper	-1102.49	-1033.30	-1074.94	-1273.37	-1135.33	-1214.87	-1269.58	-1122.33	-1287.25
Nifty-Bond-Zinc	-1071.85	-1002.66	-1044.29	-1147.59	-1009.55	-1089.09	-1241.21	-1000.05	-1148.84
Nifty-Bond-Aluminium	-1148.49	-1079.31	-1120.94	-1320.54	-1173.51	-1262.04	-1319.54	-1087.38	-1227.17
Nifty-Bond-Lead	-924.11	-857.09	-897.30	-1073.34	-970.74	-1016.36	-1065.25	-968.24	-1022.56
Nifty-Bond-Nickel	-918.69	-851.88	-891.88	-1128.24	-983.53	-1070.54	-1170.97	-942.49	-1079.87
Nifty-Bond-Crude Oil	-1056.97	-987.78	-1029.41	-1210.32	-1063.28	-1151.82	-1217.89	-985.73	-1125.52
Nifty-Bond-Natural Gas	-955.49	-886.46	-927.99	-1041.44	-894.73	-983.05	-1067.94	-836.29	-975.74
Nifty-Bond-Cardamom	-966.42	-897.24	-938.87	-1080.87	-933.83	-1022.37	-1137.77	-905.61	-1045.40
Nifty-Bond-CPO	-855.83	-790.85	-829.74	-944.90	-806.51	-889.41	-979.76	-761.25	-892.14
Nifty-Bond-Mentha Oil	-991.08	-921.90	-963.53	-1151.54	-1004.51	-1093.05	-1166.25	-934.09	-1073.88
Nifty-Bond-Cotton	-619.50	-564.95	-597.34	-677.79	-590.46	-630.15	-678.87	-589.23	-645.25
Nifty-Bond-MCXENERGY	-1068.42	-999.23	-1040.86	-1220.63	-1073.60	-1162.13	-1230.38	-998.22	-1138.01
Nifty-Bond-MCXMETAL	-1161.66	-1092.48	-1134.12	-1327.12	-1180.09	-1268.62	-1325.18	-1093.03	-1232.82
Nifty-Bond-MCXAGRI	-1099.67	-1030.48	-1072.12	-1288.28	-1141.25	-1229.78	-1243.78	-1011.63	-1151.42

(***Source:*** *Secondary Data Analysis*)

Table 8: RCM Statistics of all the Models

Models	RCM Statistics
Nifty-Bond-Gold	12.00
Nifty-Bond-Silver	9.77
Nifty-Bond-Copper	9.37
Nifty-Bond-Zinc	11.36
Nifty-Bond-Aluminium	7.51
Nifty-Bond-Nickel	1.77E+12
Nifty-Bond-Lead	8.63
Nifty-Bond-Crude Oil	6.26
Nifty-Bond-Natural Gas	9.37
Nifty-Bond-Cardamom	0.00008
Nifty-Bond-Mentha Oil	0.00078
Nifty-Bond-CPO	0.743
Nifty-Bond-Cotton	2.40
Nifty-Bond-MCXMETAL	12.89
Nifty-Bond-MCXENERGY	15.79
Nifty-Bond-MCXAGRI	13.23

(***Source:*** *Secondary Data Analysis*)

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List of Publications based on Ph.D. Research Work

[To be filled-in by the Research Scholar and to be enclosed with Thesis Submission Form]

SI.NO	Title of the paper	Authors (in the same order as in the paper, Underline the Research Scholar's name)	Name of the Journal/Conference Symposium, Vol., No., Pages	Month & year of Publication	Category*
1	An Empirical Investigation of Dynamism of Interrelationship in Gold, Silver, Bond and Stock from the Lens of Conventional Wisdom: An Indian perspective	Ritika Jaiswal, Rashmi Uchil	2nd India International Bullion Summit (IIBS), India Bullion and Jewellers Association ltd (IBJA) Mumbai, October 04-06, 2014	October, 2014	Conference[3]
2	Analysis of Dynamic Interrelationship of Gold, Bond and Stock through the lens of Conventional Wisdom: An Indian perspective	Ritika Jaiswal, Rashmi Uchil	International Conference on Frontiers of Infrastructure Finance (ICFIF 2014), Indian Institute of Technology Kharagpur, November 13-15, 2014	November, 2014	Conference[3]
3	An Empirical Analysis of Inflation Hedging Potential of Commodity Futures using the Markov-Switching Model and Vector Error Correction Model	Ritika Jaiswal, Rashmi Uchil	Third PAN-IIM World Management Conference, Indian Institute of Management Indore, December 16-18, 2015.	December, 2015	Conference[3]
4	Markov-Switching Approach to Analyse the Inflation Hedging Potential of Copper and Gold Futures	Ritika Jaiswal, Rashmi Uchil	IOSR Journal of Economics and Finance (IOSR-JEF)	January 2016	Journal[1]
5	Analysis of Hedge and Safe Haven Role of Gold and Silver Futures: A Regime Switching Approach	Ritika Jaiswal, Rashmi Uchil	52nd Annual Conference of the Indian Econometric Society (TIES), Indian Institute of Management Kozhikode, January 4-6, 2016	January, 2016	Conference[3]
6	An Analysis of Gold Futures as an Alternative Asset: Evidence from	Ritika Jaiswal, Rashmi Uchil	The 2016 International Conference on Contemporary eConomics and FinanCial	December, 2016	Conference[3]

	India		governanCe, Bali, Indonesia.		
7	An Analysis of Gold Futures as an Alternative Asset: Evidence from India	Ritika Jaiswal, Rashmi Uchil	International Journal of Economics and Financial Issues (IJEFI) (Accepted for Publication)	January, 2017	Journal[1]
8	An Analysis of Diversification Benefits of Commodity Futures using Markov Regime-Switching Approach	Ritika Jaiswal, Rashmi Uchil	Afro-Asian Journal of Finance and Accounting (In forthcoming articles) http://www.inderscience.com/info/ingeneral/forthcoming.php?jcode=aajfa	April, 2017	Journal[1]
9	An Empirical Analysis of Inflation Hedging Potential of Commodity Futures: A Regime Switching Approach	Ritika Jaiswal, Rashmi Uchil	Indore Management Journal (Accepted for Publication)	June 2017	Journal[1]
10	An Analysis of Commodity Futures as an Inflation Hedge using Regime-Switching Framework	Ritika Jaiswal, Rashmi Uchil	Journal of Indian Business Research (Under Revision)	June 2017	Journal[1]
11	An Analysis of Time-Varying Conditional Profitability of Momentum Strategies in Commodity Futures Market	Ritika Jaiswal, Rashmi Uchil	Journal of Commodity Market (Under Review)	June 2017	Journal[1]

*Category 1: Journal paper, full paper reviewed 2: Journal paper, Abstract reviewed
3: Conference/Symposium paper, full paper reviewed 4: Conference/Symposium paper, abstract reviewed
5: others (including papers in Workshops, NITK Research Bulletins, Short notes, etc.)
(If the paper has been accepted for publication but yet to be published, the supporting documents must be attached.)

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