Commodity Market Internationalization and Portfolio Optimization: An Empirical Study

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Neha Berlia

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India

Approved on the application of

Prof. Dr. Dr. h.c. em. Klaus Spremann

and

Prof. Dr. Andreas Grüner

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Abbreviations

ADF	AUGMENTED DICKEY FULLER
AHP	ANALYTIC HIERARCHY PROCESS
ARCH	AUTOREGRESSIVE CONDITIONAL HETEROSKEDASTICITY
BB	BRENT BLEND
BEKK	BABA-ENGLE-KRAFT-KRONER
BL	MAYA, BONNY LIGHT
CBOT	CHICAGO BOARD OF TRADE
CCC	CONSTANT CONDITIONAL CORRELATION
CME	CHICAGO MERCANTILE EXCHANGE
COMEX	COMMODITY EXCHANGE INC.
DCC	DYNAMIC CONDITIONAL CORRELATION
DF	DUBAI-FATEH
EMH	EFFICIENT MARKET HYPOTHESIS
GARCH	GENERALIZED AUTOREGRESSIVE CONDITIONAL HETEROSKEDASTICITY
GH	GREGORY AND HANSEN
GP	GOAL PROGRAMMING
ICE	INTER-CONTINENTAL EXCHANGE
IMF	INTERNATIONAL MONETARY FUND
JB	JARQUE-BERA
KPSS	KWIATKOWSKI-PHILLIPS-SCHMIDT-SHIN
LB	LJUNG BOX
LME	LONDON METAL EXCHANGE
MCGP	MULTI-CHOICE GOAL PROGRAMMING
MCX	MULTI-COMMODITY EXCHANGE
MGARCH	MULTIVARIATE GARCH
MV	MEAN-VARIANCE APPROACHES
NCDEX	NATIONAL COMMODITY & DERIVATIVES EXCHANGE
NSE	NATIONAL STOCK EXCHANGE
NYMEX	NEW YORK MERCANTILE EXCHANGE

NYSE	NEW YORK STOCK EXCHANGE
PP	PHILLIPS-PERRON
QMLE	QUASI-MAXIMUM LIKELIHOOD ESTIMATION
SD	STOCHASTIC DOMINANCE APPROACHES
SHFE	SHANGHAI FUTURES EXCHANGE
TOCOM	TOKYO COMMODITY EXCHANGE
UK	UNITED KINGDOM
USA	UNITED STATES OF AMERICA
VAR-GARCH	VECTOR AUTOREGRESSION (GARCH) MODEL
VECM	VECTOR ERROR CORRECTION MODEL
WTI	WEST TEXAS INTERMEDIATE
ZA	ZIVOT-ANDREWS

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Abstract (English)

With the growing internationalization of commodity and financial markets, researchers have increasingly focused on how price discovery and trading volumes in one market might impact/be impacted by other markets. Of particular interest have been the linkages between the markets in the developing world and those in the developed world.

The first chapter examines the process of information transmission among bullion (gold and silver) and metal (aluminum, copper and zinc) markets in India and its counterparts. We examine the transmission flow between MCX, India and its global counterparts, COMEX, LME and SHFE. The MGARCH results of volatility spillovers indicate that, in the case of bullion, MCX seems to be more dominant than COMEX, implying that it is no longer a satellite market. However, for metals LME seems to play the dominant role, followed by MCX and SHFE.

In the next chapter the research is extended to include three strategically linked oil markets of UK (ICE), India (MCX) and United States (NYMEX) exchanges. The results confirm a long-run equilibrium relationship between futures and spot prices in each market. It is found that ICE is the most dominant platform followed by NYMEX and MCX in price discovery process. Thus, MCX, an emerging market platform seems to act like a satellite market vis-à-vis international platforms. The volatility spillover results suggest that there is a long-term spillover from ICE to MCX and from MCX to NYMEX.

While the first two chapters attend to information flow between emerging markets and developed markets, the third chapter draws on this knowledge with a view to developing optimum portfolio of stock market securities representing several sectors, including bullion, metals and oil. Portfolio optimization involves determination of investment-mix such that it meets investors' aspirations, that often are multiple and vague. Conflicts of objectives and the incompleteness of available information make it almost impossible for investors to build a reliable mathematical model for representation of their preferences by considering single aspiration level for each goal. To overcome this problem, this study integrates analytic hierarchy process (AHP) and multi-choice goal programming (MCGP) as a decision aid to obtain an optimal asset allocation that better suit the preferences of investors under their needs. An empirical study is further included to illustrate the usefulness of the proposed approach in real-life applications of portfolio selection.

Abstract (Deutsch)

Mit der wachsenden Internationalisierung der Rohstoff- und Finanzmärkte hat sich die Wissenschaft zunehmend mit der Frage auseinandergesetzt, wie die Preisfindung und das Handelsvolumen in einem Markt von anderen Märkten beeinflusst werden. Von besonderem Interesse waren hierbei die Zusammenhänge zwischen den Märkten der Schwellen- und der Industrieländer.

Im ersten Kapitel der vorliegenden Arbeit wird der Prozess der Informationsübertragung zwischen den Märkten für Edel- und Industriemetalle in Indien und ihren Entsprechungen in den Industrieländern untersucht. So wird der Informationsfluss zwischen dem MCX India und seinen globalen Gegenstücken COMEX, LME und SHFE mit einem MGARCH-Modell erforscht. Die Ergebnisse der Untersuchung der Volatilitäts-Spillover deuten daraufhin, dass im Falle der Edelmetallmärkte der MCX dominanter ist als der COMEX. Dies bedeutet, dass der MCX nicht länger ein Satellitenmarkt des COMEX ist. Die Resultate der Untersuchung der Industriemetallmärkte hingegen zeigen, dass der LME die dominante Rolle innehat, gefolgt vom MCX and SHFE.

Das zweite Kapitel erweitert die Untersuchung um drei strategisch miteinander verbundene Ölmärkte an den Börsen in Grossbritannien (ICE), Indien (MCX) und den Vereinigten Staaten (NYMEX). Die Ergebnisse bestätigen eine langfristige Gleichgewichtsbeziehung zwischen Future- und Spotpreisen in jedem Markt. Weiterhin zeigt die Untersuchung, dass die ICE die dominanteste Rolle im Preisfindungsprozess spielt, gefolgt von NYMEX und MCX. Entsprechend kann die MCX als Satellitenmarkt der internationalen Handelsplätze bezeichnet werden. Die Ergebnisse der Untersuchung der Volatilitäts-Spillover legt nahe, dass es einen langfristigen Spillover von ICE zu MCX sowie von MCX zur NYMEX gibt.

Während sich die ersten beiden Kapitel mit dem Informationsfluss zwischen Schwellen- und Industrieländern befassen, wird im dritten Kapitel vor dem Hintergrund dieses Wissens ein optimales Aktienportfolio entwickelt, welches Aktien aus verschiedenen Sektoren (u.a. dem Rohstoffsektor) beinhaltet. Eine Portfoliooptimierung ist die Bestimmung eines Investmentmix, der den Zielen des Anlegers entspricht. Diese Ziele sind oftmals vielfältig und wage. Zielkonflikte sowie unvollständige Informationen machen es dem Anleger fast unmöglich ein verlässliches mathematisches Modell zu verwenden, das seine Präferenzen abbildet und die

Erreichung eines jeden Einzelziels berücksichtigt. Um dieses Problem zu lösen, wird in dieser Studie Analytic Hierarchy Process (AHP) und Multi-Choice Goal Programming (MCGP) als Entscheidungshilfe verwendet, um eine optimale Asset Allokation zu erhalten, die die Präferenzen des Investors besser berücksichtigt. In einer empirischen Studie wird zudem die Zweckmässigkeit des vorgeschlagenen Vorgehens der Portfolioselektion für die Praxis untersucht.

1. Information Transmission between International and Indian Commodities Futures Markets: An Empirical Study for Bullion and Metals

Abstract

This study examines the process of information transmission in futures prices of bullion (gold and silver) and metals (aluminum, copper and zinc) in India, represented by Multi-Commodity Exchange (MCX) and its global counterpart trading platforms, such as Commodity Exchange Inc. (COMEX), London Metal Exchange (LME) and Shanghai Futures Exchange (SHFE), for the period of 2005 to 2012. Structural breaks are identified for all sample series, which capture the impact of the recent economic crisis on global commodity markets. The price discovery results confirm that there is a long-term equilibrium relationship among the futures prices of the examined trading platforms in each commodity series, with the exception of aluminum. The MGARCH results of volatility spillovers indicate that, in the case of bullion, MCX seems to be more dominant than COMEX, implying that it is no longer a satellite market, while in the case of metals; LME seems to play the dominant role, followed by MCX and SHFE. The research contributes to the commodity market literature for emerging economies.

1.1 Introduction

A large number of studies have examined the process of information transmission by way of analyzing the price discovery and volatility spillovers for both mature and emerging commodity markets (see Ross, 1989; Tse, 1998; Thomas and Karande, 2001; Chan et al., 2004; Lee et al., 2009; Hua and Chen, 2007; Ge et al. 2008; Fung et al., 2010; Dey and Maitra, 2011; Du et al., 2011; Liu and An, 2011; Kumar and Pandey, 2011). Price discovery is defined as the process that deals with flows of information from one market to another. Volatility spillovers are the means by which the volatility in one market impacts that of another market. In recent years, strong upheavals in commodity prices, exacerbated by the global financial crisis, have attracted a great deal of attention from researchers and policymakers in examining price behavior in commodity markets, owing to their strong policy implications for market practitioners. In this study, we compare the process of information transmission in futures prices of bullion and metals in India with its global counterparts, such as the COMEX, LME and SHFE. The study is motivated by the fact that globally, due to strong demand for bullion and metals in emerging economies owing to their high economic growth, many of these economies have started setting up their own commodity exchanges and, gradually, their share in total trade has been increasing consistently. In this light, the two most promising economies are India and China, whose commodity exchanges have recorded spectacular growth in recent years and in some commodities, their trading activity is enormously large vis-à-vis their counterparts, making them two of the strongest trading platforms in the world. We specifically investigate price discovery and volatility spillovers between the Indian commodity market and international markets. The study proxies the Indian commodity market by using the data from the MCX, because it is the largest futures trading platform in the country for bullion and metals. The study focuses on India because it has one of the fastest-growing commodity markets in the world and it is competing in bullion and metals with leading global platforms such as COMEX, LME and SHFE. The Indian economy has been growing at an impressive rate of more than 9% during the last decade. Despite the fragile recovery of the United States and troubled European countries, the Indian economy still has not weakened its growth momentum and is expected to achieve a growth rate of 5.5% in 2013 and 5.7% in 2014, as projected by the International Monetary Fund (IMF, 2013). The Indian economy is also been seen as one of the largest commodity markets, augmented by high agricultural growth and increased demand for metals, bullion and energy products for industrial and domestic purposes.

In this study, we focus on bullion and metals, as these are the most actively traded commodities in India and account for 63% (38% bullion and 25% metals) of the average daily trading volume. It may be noted that agricultural commodities and energy products account for only 25% and 12% of the trading volumes, respectively, on the Indian commodity exchanges. In India, MCX is the largest trading platform for bullion, metals and energy products. In recent times, MCX has recorded the highest trading volume in gold and silver among all world-trading exchanges. The National Commodity & Derivatives Exchange (NCDEX) is the most active exchange for agricultural commodities. The criteria for selection of sample commodities from the bullion and metals category are as follows: a) India should be among the five largest producers/consumers of a given commodity; b) the Indian commodity exchange should figure among the top three trading platforms, based on trading activity for a given commodity; and c) the average daily trading volume should be 0.1 million or more in terms of respective commodity units.

The third criterion ensures that there is enough market depth for a traded commodity. All bullion and metals that satisfy either criterion (a) or (b) and, in addition, satisfy criterion (c) have been shortlisted. Five commodities have been selected: gold, silver, aluminum, copper and zinc. The commodity exchanges have been selected based on the level of trading activity exhibited for sample commodities. In the case of bullion, MCX competes with COMEX and TOCOM. Because COMEX and MCX are the two largest trading platforms in the case of bullion, they have been chosen in order to study the price discovery and volatility spillovers in futures prices. In the case of metals, LME and SHFE are two markets that compete with MCX. The LME and SHFE metals markets are relatively more developed than those of MCX. But gradually, the share of MCX is increasing and, in the case of zinc, it is almost closer to LME and SHFE. It may here be noted that we have included LME and SHFE as the proxy markets for international commodity exchange, given their international importance for metals.

The following are the major objectives of this study: a) to evaluate whether there are any structural breaks in the time series of futures prices for sample commodities; b) to examine the process of price discovery between MCX and COMEX for bullion (gold and silver) and between MCX, LME and SHFE for metals (aluminum, copper and zinc); and c) to investigate whether there are any short- and long-term volatility spillovers between MCX and COMEX for bullion and the three exchanges for metals.

The chapter comprises of six sections, including the present one: A brief review of the literature is provided in Section 1.2. Section 1.3 covers data and their sources, while methodology and estimation procedures are described in Section 1.4. In Section 1.5, we provide empirical results, followed by a summary and conclusion in the last section.

1.2 Literature Review

A large number of studies have examined the price discovery and volatility spillovers under two broad frameworks: first, within markets, examining the relationship between spot and futures (see Gagnon and Karolyi, 2006)[1]; second, between markets (futures price linkages) for an identical asset (see Hasbrouck, 1995; Lihara et al., 1996; Ding et al., 1999; Tse, 1998; Roope and Zurbruegg, 2002; Xu and Fung, 2005; among others). The early studies focused on examining the markets within—specifically, the

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[1] Gagnon and Karolyi (2006) could be a good reference in this regard.

relationship between spot and futures prices. Such an examination of information transmission between markets has helped investors identify the dominant and satellite markets to exhibit the role of dominant exchanges in the price discovery and volatility spillover of an identical asset. In this regard, Garbade and Silber's (1979) seminal study on stock market linkages could be considered the pioneer work highlighting the role of the short-run behavior of an identical asset traded in two different markets, i.e., the New York Stock Exchange (NYSE) and the regional stock exchanges, by way of emphasizing the NYSE as the dominant and the regional stock exchanges as the satellite markets. In another study, Eun and Shim (1989) examined how the information transmission could lead to dominance in the futures market. Their study concluded that the US equity market dominates the rest of the world in terms of information transmission. Later, some important studies also examined this issue in cross-country settings and with a considerably large set of assets (see King and Wadhwani, 1990; Susmel and Engle, 1994; Koutmos and Booth, 1995; Booth et al., 1996; Booth and Ciner, 1997; Booth et al., 1998; Tse, 1999; Low et al., 1999; Fung et al., 2001; among others). Here, it may be noted that most studies in literature have examined the process of information transmission in a mature markets setting and very few studies have highlighted the role of price discovery and volatility spillovers in the emerging market context, particularly the commodity market. In this regard, Fung et al. (2003) confirmed the volatility spillovers between mature (US) and emerging (China) markets for three commodities futures, i.e., copper, soybeans and wheat. Their study concluded that in the case of copper and soybeans, the US futures market played a dominant role in transmitting information to the Chinese market, while in case of wheat, both markets were found to be segmented. Hua and Chen (2007) investigated the international linkages of Chinese commodity futures markets in the case of aluminum, copper, soybean and wheat. Considering the Chicago Board of Trade (CBOT) and the LME as counterpart markets for agri and non-agri commodities, they reported that aluminum, copper and soybean futures prices were integrated with spot prices. However, they did not find such co-integration for wheat spot and futures prices. Ge et al. (2008) examined the dynamic linkages between the cotton futures markets of China and the United States. Their study reported both markets as strongly linked. Du et al. (2011) examined the important factors that impact crude oil volatility and investigated the possible linkages between crude oil volatility and agricultural commodities. Their study found evidence of volatility spillovers for sample commodities. Liu and An (2011) examined information transmission and price discovery in informationally linked markets. Using data on both synchronous and non-synchronous trading from Chinese futures/spot markets, the New York Mercantile Exchange (NYMEX), CBOT and CME Globex futures markets for copper and soybeans. Their study found evidence of bidirectional volatility spillovers between US and Chinese markets moving strongly from US to Chinese markets.

With regard to India, there are very few studies that have examined the information transmission mechanism in the Indian commodity market. As mentioned above, the empirical literature on price discovery and volatility spillovers mainly deals with developed markets such as the USA and UK. In India, significant and relevant literature on commodity market is sparse and has mainly focused on agricultural commodities (see Thomas and Karande, 2001; Naik and Jain, 2002; Kabra, 2007; Roy, 2008; Ghosh, 2009a, 2009b, 2010; Roy and Dey, 2009; Mahalik et al., 2010; Dey and Maitra, 2011). Further, the Indian literature is limited to regional exchanges and covers small samples from the period prior to the establishment of national exchanges and covers very few commodities traded on these exchanges. Pertinent to the objectives of our research, Kumar's (2004) study examined the price discovery and reported the inability of futures markets to fully incorporate information and confirmed that they are not fully efficient. In another important study, Kumar and Pandey (2011) examined the international linkages of the Indian commodity futures market with its offshore counterpart markets, i.e., CBOT, LME and NYMEX. They reported that world markets have a bigger (unidirectional) impact on Indian markets.

To summarize, in the literature on price discovery and volatility spillovers, which rests upon the process of information transmission, it is clear that while there is broad consensus on the role of information linkages across markets. The issue is still unsettled, especially in the light of the recent turbulent periods that have jolted commodity markets across the globe. Furthermore, there is very limited research on information transmission between emerging markets such as India and important international commodity exchanges; thus, the research issue needs to be empirically addressed. Futures markets in emerging countries are characterized by low liquidity and less efficient trading systems (see Tomek, 1980; Carter, 1989), making them different from the counterpart markets in mature countries. In the Indian context, prior research on the subject (see Kumar and Pandey, 2011) has used data through 2008. It may be noted that Indian commodity futures exchanges began trading only in 2004 and, hence, are of nascent origin. The period from 2009 to the present, which has been relatively unexplored, is of great importance, as it is the time when these trading platforms have achieved a higher level of trading liquidity and there may be a strengthening of international linkages. The present study attempts to fill these important research gaps by examining the information transmission between MCX (in India) and prominent international commodity exchanges for bullion and select metals using longer data periods and contemporary econometric techniques.

1.3 Methodology

1.3.1 Process of Price Discovery

At the first stage, stationarity conditions using conventional methods of unit root tests—Augmented Dickey Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS)—have been checked for all commodities under consideration, followed by structural break unit root tests, in order to identify any abnormal events during the sample period. For this purpose, the Zivot-Andrews (hereafter ZA, 1992) unit root test and the Gregory and Hansen (hereafter GH, 1996) test of co-integration with structural breaks have been employed (see Glynn et al., 2007 and Cook, 2006, for details).[2] The results of the GH test (1996) are further confirmed by the Johansen and Juselius (1992) co-integration test and the Vector Error Correction Model (VECM), as mentioned in equations (1.1) and (1.2). The bivariate co-integrated series $P_t = (F_{1,t}, F_{2,t})'$, is represented by a VECM:

$$\Delta F_{1,t} = b_1 + \beta_1 EC_{t-1} + \sum_{i=1}^{k} d_{1i}\Delta F_{1,t-i} + \sum_{i=1}^{k} g_{1i}\Delta F_{2,t-i} + \varepsilon_{1t} \tag{1.1}$$

$$\Delta F_{2,t} = b_2 + \beta_2 EC_{t-1} + \sum_{i=1}^{k} d_{2i}\Delta F_{1,t-i} + \sum_{i=1}^{k} g_{2i}\Delta F_{2,t-i} + \varepsilon_{2t} \tag{1.2}$$

Note that $EC_{t-1} = F_{1,t-1} - a - bF_{2,t-1}$ is the lagged error correction term.

Given the large number of parameters that would have to be estimated in the volatility spillover model (as discussed in subsection 1.3.2), a two-step procedure similar to that implemented by Bekaert and Harvey (1997), Ng (2000) and Baele (2005) has been considered in this study. In the first step, the VECM is estimated to obtain estimates of the shock vector for futures prices. In the second step, the first-stage residuals are used as data to check for volatility spillover between the futures prices of both markets.

[2] This study provides a detailed review of unit root tests with structural breaks.

1.3.2 Process of Volatility Spillovers

Numerous studies have investigated the process of volatility spillovers to understand the spread of shock originating from one market to another. Most studies in the literature have used different variants of GARCH models to examine the volatility spillover between markets (see Hamao et al., 1990; Lin et al., 1994; Koutmos and Booth, 1995; Booth et al., 1997; Christofi and Pericli, 1999; Engle et al., 1990). According to Chan et al. (1991), it is the volatility and not just the simple price change, that determines the flow of information from one market to another.[3]

The BEKK model is used as a benchmark to examine the volatility spillovers (see Wang, 2008). The other models, e.g., CCC (constant conditional correlation) and DCC (dynamic conditional correlation), are used to substantiate the BEKK results under the VARMA-GARCH (see Ling and McAleer, 2003) framework. We use the VARMA approach for CCC and DCC because such an approach of modeling conditional variances permits large shocks to one variable to affect the variances of other variables. Hence, this helps in substantiating BEKK results vis-à-vis CCC and DCC models to demonstrate volatility spillovers. Under this approach, the variance terms take the following form (for a 1, 1 model):

Mean equation:

$$\upsilon_{it} = \mu_{i0} + \sum_{j=1}^{5} \mu_{ij}\upsilon_{j,t-1} + \varepsilon_{it} \text{ where } \varepsilon_{it} \mid I_{it-1} \sim N(0, h_{it}), i = 1,2,3,4,5 \tag{1.3}$$

In equation (1.3), υ_{it} is the estimated residual of the sample series; ε_{it} is a random error term with conditional variance h_{it} and I_{it-1} denotes the market information at time t-1. Equation (1.4) specifies the variance equation. i=1, 2, 3, 4, 5 shows the number of sample commodities analyzed pairwise.

Variance equation:

$$H_{it} = c_{ii} + \sum_{j=1}^{5} \alpha_{ij}\varepsilon^{2}_{j,t-1} + \sum_{j=1}^{5} \beta_{ij} H_{jj(t-1)} \tag{1.4}$$

This is a convenient specification that allows for volatility spillovers (see Sadorsky, 2012). c_{ii} denotes the constant terms; α denotes the ARCH terms and β denotes the GARCH terms. The coefficient α_{12}, for example, represents the short-term volatility

[3] For further details, Chan et al. (1991) could be a good reference on the need to study volatility spillovers.

spillover from one market to another (say, for example, MCX to LME), while β_{12} represents the long-term volatility spillover in the same manner as mentioned above. It may be noted that under Ling and McAleer's (2003) approach to modeling, the conditional variances allows large shocks to one variable to affect the variances of the other variables. This is a convenient specification that allows for volatility spillovers. The Engle (2002) DCC model is estimated in two steps. In the first step, GARCH parameters are estimated followed by correlations in the second step.

$$H_t = D_t R_t D_t \tag{1.5}$$

In equation (1.5), H_t is the 3×3 conditional covariance matrix, as in our case; R_t is the conditional correlation matrix and D_t is a diagonal matrix with time-varying standard deviations on the diagonal.

$$D_t = diag(h_{11t}^{1/2} \ldots\ldots h_{33t}^{1/2})$$

$$R_t = diag(q_{11t}^{-1/2} \ldots\ldots q_{33t}^{-1/2}) Q_t diag(q_{11t}^{-1/2} \ldots\ldots q_{33t}^{-1/2})$$

Where Q_t is a symmetric positive definite matrix:

$$Q_t = (1-\theta_1-\theta_2)\overline{Q} + \theta_1 \varepsilon_{t-1}\varepsilon'_{t-1} + \theta_2 Q_{t-1} \tag{1.6}$$

$\overline{Q}$ is the 3×3 unconditional correlation matrix of the standardized residuals ε_{it}; the parameters θ_1 and θ_2 are non-negative with a sum of less than unity. Under the condition of $R_t = R$ and $R_{ij} = \rho_{ij}$, equation (1.7) becomes the CCC model.

$$\rho_{ijt} = \frac{q_{ijt}}{\sqrt{q_{iit} q_{jjt}}} \tag{1.7}$$

The MGARCH models are estimated by Quasi-Maximum Likelihood Estimation (QMLE) using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm. T statistics are calculated using a robust estimate of the covariance matrix (see Sadorsky, 2012).

1.4 Data

The sample data for the daily futures prices of MCX, COMEX, LME and SHFE for five commodities, including two precious metals (gold and silver) and three non-precious metals (aluminum, copper and zinc), are retrieved from the Bloomberg database. We use the data of gold and silver traded on COMEX and aluminum, copper and zinc futures price traded on LME and SHFE as the counterpart markets for Indian futures markets. All closing prices of futures series are taken for the nearest contract to maturity. Based on the availability of the data, the sample period of each commodity is as follows: aluminum (October 26, 2005, to April 27, 2012; 1,581 observations); copper (January 4, 2005, to April 27, 2012; 1,766, observations); gold and silver (January 3, 2005, to April 30, 2012; 1,851 and 1,855 observations, respectively); and zinc (March 27, 2007, to April 27, 2012; 1,237 observations). In order to maintain parity across sample markets, all price series have been converted to US dollars after making the adjustment in terms of units of measurement.[4] For estimation purposes, all price series are further converted into natural logarithms.

1.5 Empirical Results

We examine the plot of commodity futures prices observed at sample trading platforms over the study period. In the descriptive statistics for sample commodity returns shown in Table 1.1, the mean returns of sample commodities are positive, with the exception of zinc, in all markets.[5] The highest mean daily returns are observed in the case of silver in MCX and COMEX (0.084% and 0.082%), followed by gold in MCX and COMEX (0.074% and 0.073%), respectively. The lowest average returns are found in the cases of zinc in LME (-0.038%), followed by MCX and SHFE (-0.037% and -0.035%), respectively. Mean returns for sample commodities are almost similar across competing trading platforms, with the exception of aluminum. SHFE returns in the case of aluminum are almost three and four times larger than those observed for LME and MCX. The standard deviation as a measure of volatility is highest for silver (2.432%) in MCX, followed by zinc in LME (2.395%) and MCX (2.381%). The skewness co-efficients of all metals are negative, except aluminum and zinc for MCX, highlighting the negative impacts of a series of economic crises observed in recent times, including the ongoing upheaval in Europe. All returns series are leptokurtic and violate normality, as exhibited by Jarque-Bera (JB) statistics. This is further substantiated by the results of ARCH effects, which confirm the presence of clustering in all examined commodities. The Ljung Box (LB) test further indicates autocorrelation in the sample series, especially in squared returns up to 10 lags.

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4 For example, MCX measures the futures lot in Rs/Kg terms for aluminum, copper and zinc, while LME and SHFE trade lots in USD/ton and CNY/ton terms. Similarly, the unit of trade is different among the examined markets for precious metals. Spot market data for USD/rupee currency have been downloaded from the Reserve Bank of India website and for USD/Chinese yen, the data have been extracted from the Bloomberg database.

5 Sample commodities have been calculated using the first difference of the log price series multiplied by 100.

Table 1.1: Descriptive Statistics of Sample Commodities

	Aluminum			Copper			Zinc			Gold		Silver	
	SHFE	LME	MCX	SHFE	LME	MCX	SHFE	LME	MCX	COMEX	MCX	COMEX	MCX
Mean	0.012	0.004	0.003	0.042	0.046	0.044	-0.035	-0.038	-0.037	0.073	0.074	0.082	0.084
Max.	5.184	7.522	9.388	6.630	11.507	10.767	5.819	9.651	14.170	8.625	8.721	9.237	12.196
Min.	-7.198	-10.912	-8.598	-8.824	-20.469	-19.270	-6.609	-15.886	-11.734	-7.581	-7.915	-18.387	-19.546
Std.Dev.	1.091	1.656	1.774	1.708	2.167	2.162	1.725	2.395	2.381	1.319	1.202	2.085	2.432
Skewness	-0.545	-0.182	0.311	-0.353	-0.656	-0.467	-0.409	-0.155	0.054	-0.271	-0.175	-1.415	-0.974
Kurtosis	7.847	5.577	6.249	5.025	9.858	9.318	4.078	5.564	6.454	6.815	7.961	14.674	9.047
JB	1625.983	446.264	721.082	338.274	3587.128	3001.768	94.446	343.799	615.641	1145.054	1907.949	11151.650	3119.718
Prob.	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Arch	53.769 [0.000]**	7.683 [0.000]**	16.236 [0.000]**	23.463 [0.000]**	5.386 [0.000]**	8.773 [0.000]**	6.468 [0.000]**	0.889 [0.488]	0.242 [0.943]	20.856 [0.000]**	24.903 [0.000]**	16.920 [0.000]**	35.269 [0.000]**
LB	48.437 [0.000]**	5.575 [0.849]	5.669 [0.842]	21.329 [0.018]*	9.626 [0.473]	29.811 [0.000]**	28.802 [0.001]**	2.952 [0.982]	6.582 [0.764]	17.544 [0.063]	11.896 [0.292]	8.991 [0.532]	18.331 [0.049]*
LB^2	642.600 [0.000]**	79.976 [0.000]**	221.652 [0.000]**	323.648 [0.000]**	60.430 [0.000]**	82.033 [0.000]**	49.400 [0.000]**	7.816 [0.646]	2.212 [0.994]	227.179 [0.000]**	239.137 [0.000]**	165.168 [0.000]**	259.753 [0.000]**
Obs.	1581	1581	1581	1766	1766	1766	1237	1237	1237	1851	1851	1855	1855

Note: ** denotes the level of significance at 1% and better. Values in parentheses [ ] indicate the p-values. JB=Jarque-Bera and LB= Ljung Box. LB statistics are reported up to 10 lags.

1.5.1 Tests of Stationarity and Price Discovery Process

Stationarity conditions of the sample commodity futures price series expressed in logarithmic form were tested by conventional ADF (unit root test) at the 1% level of significance. The ADF test confirms the existence of unit root at the significant level and achieves stationarity at the first difference.[6] The results of the ADF test are reconfirmed by additional tests of stationarity using PP and KPSS tests. It shall be noted that the unit root results may be suspect when the sample period under analysis may have witnessed major events (e.g., a global economic crisis such as sovereign debt defaults, currency devaluation, regulatory shocks, etc.), which are likely to create structural breaks in a particular series. In order to account for any possible regime shifts resulting from structural breaks, the ZA unit root test has been implemented on sample commodity series. The results are shown in Table 1.2. It can be observed that most of the structural breaks identified by the ZA test are during the period 2008 and 2009 highlighting the impact of the US-born global financial crisis and its aftermath. The possible reason could be a sudden fall in global demand of these commodities, due to the gloomy economic outlook of major consuming countries.

Table 1.2: Zivot-Andrews Structural Breaks Unit Root Results

Variables	At Level	Break Period
COMEX_gold	-5.223	16-07-2008
MCX_gold	-5.109	22-07-2008
COMEX_silver	-4.467	15-07-2008
MCX_silver	-4.309	15-07-2008
SHFE_alum	-5.342	25-08-2008
LME_alum	-4.255	14-07-2008
MCX_alum	-4.197	14-07-2008
SHFE_copper	-3.304	25-08-2008
LME_copper	-3.290	04-07-2008
MCX_copper	-3.322	03-07-2008
SHFE_zinc	-3.780	20-03-2009
LME_zinc	-4.304	03-03-2009
MCX_zinc	-4.265	02-03-2009
Critical Values		
1%	-5.570	
5%	-5.080	

Note: All series exhibit non-stationarity, confirming the use of co-integration with regime shifts.

6 Results of ADF, PP and KPSS unit root results are available upon request.

After the ZA test, we move to analyze the price discovery process exhibiting the lead-lag relationships between the futures prices of examined markets. Keeping in mind the importance of structural breaks, we apply the GH co-integration test with regime shifts. The GH test provides the structural break dates for sample series, as shown in Table 1.3.

Table 1.3: Gregory and Hansen Co-integration Test

Variables	t-stat	Period
MCX_gold on COMEX_gold	-10.376**	04-09-2007
COMEX_gold on MCX_gold	-10.433**	01-12-2008
MCX_silver on COMEX_silver	-7.370**	05-04-2006
COMEX_silver on MCX_silver	-7.479**	05-04-2006
SHFE_alum on LME_alum	-5.184*	24-01-2011
LME_alum on SHFE_alum	-4.734	28-04-2011
MCX_alum on LME_alum	-10.821**	29-03-2007
LME_alum on MCX_alum	-10.988**	29-03-2007
MCX_alum on SHFE_alum	-4.569	05-12-2008
SHFE_alum on MCX_alum	-4.602	09-05-2011
SHFE_copper on LME_copper	-5.823**	15-02-2006
LME_copper on SHFE_copper	-5.713**	22-08-2006
MCX_copper on LME_copper	-10.749**	01-11-2006
LME_copper on MCX_copper	-10.773**	01-11-2006
MCX_copper on SHFE_copper	-6.002**	21-08-2006
SHFE_copper on MCX_copper	-6.097**	21-08-2006
SHFE_zinc on LME_zinc	-5.139*	24-12-2008
LME_zinc on SHFE_zinc	-5.156*	24-12-2008
MCX_zinc on LME_zinc	-11.907**	16-01-2008
LME_zinc on MCX_zinc	-11.904**	18-01-2008
MCX_zinc on SHFE_zinc	-5.219**	24-12-2008
SHFE_zinc on MCX_zinc	-5.139**	24-12-2008
Significance Level Critical Values		
1%	-5.47	
5%	-4.95	

Note: ** indicates the level of significance at 1%. Like linear regression, the EG-based GH test considers dependent and independent variables.

The structural breaks identified by the GH test highlight the boom and European crisis period for the sample commodities. Despite the number of structural breaks for each commodity, the GH co-integration test indicates long-term co-integration relationships for all commodities and all trading platforms estimated pair-wise, except in case of

SHFE-MCX and LME-SHFE for aluminum. These negative results do not come as a surprise, given the abnormal return for aluminum observed at SHFE and the absence of matching structural break dates between these two pairs of platforms over the study, as shown above. The results of the GH test are further confirmed by the Johansen and Juselius (1992) test of co-integration on futures prices of five commodities (see Table 1.4). The results indicate that commodity futures prices across trading platforms, with some exceptions, are the same as those of the GH test and exhibit long-term equilibrium relationships, thus confirming an efficient price discovery process.

Table 1.4: Johansen Co-integration Results

Trace Test					**Maximum Eigen Value Test**			
Null	Alternative	Statistics	95% Critical Value		Null	Alternative	Statistics	95% Critical Value
Co-integration between SHFE_alum and LME_alum								
r=0	r>=1	16.554	20.262		r=0	r=1	12.526	15.892
r<=1	r>=2	4.028	9.165		r<=1	r=2	4.028	9.165
r<=2	r>=3				r<=2	r=3		
Co-integration between MCX_alum and LME_alum								
r=0	r>=1	94.956*	15.495		r=0	r=1	91.940*	14.265
r<=1	r>=2	3.016	3.841		r<=1	r=2	3.016	3.841
r<=2	r>=3				r<=2	r=3		
Co-integration between SHFE_alum and MCX_alum								
r=0	r>=1	23.334	25.872		r=0	r=1	18.058	19.387
r<=1	r>=2	5.276	12.518		r<=1	r=2	5.276	12.518
r<=2	r>=3				r<=2	r=3		
Co-integration between SHFE_copper and LME_copper								
r=0	r>=1	36.991*	15.495		r=0	r=1	32.761*	14.265
r<=1	r>=2	4.231*	3.841		r<=1	r=2	4.231*	3.841
r<=2	r>=3				r<=2	r=3		
Co-integration between MCX_copper and LME_copper								
r=0	r>=1	89.341*	15.495		r=0	r=1	85.046*	14.265
r<=1	r>=2	4.295*	3.841		r<=1	r=2	4.295*	3.841
r<=2	r>=3				r<=2	r=3		
Co-integration between SHFE_copper and MCX_copper								
r=0	r>=1	41.287*	15.495		r=0	r=1	36.960*	14.265
r<=1	r>=2	4.327*	3.841		r<=1	r=2	4.327*	3.841
r<=2	r>=3				r<=2	r=3		
Co-integration between SHFE_zinc and MCX_zinc								
r=0	r>=1	20.094*	15.495		r=0	r=1	15.951*	14.265
r<=1	r>=2	4.143*	3.841		r<=1	r=2	4.143*	3.841
r<=2	r>=3				r<=2	r=3		
Co-integration between MCX_zinc and LME_zinc								
r=0	r>=1	80.663*	15.495		r=0	r=1	76.719*	14.265
r<=1	r>=2	3.944*	3.841		r<=1	r=2	3.944*	3.841
r<=2	r>=3				r<=2	r=3		
Co-integration between SHFE_zinc and LME_zinc								
r=0	r>=1	19.892*	15.495		r=0	r=1	15.593*	14.265
r<=1	r>=2	4.298*	3.841		r<=1	r=2	4.298*	3.841

Trace Test					**Maximum Eigen Value Test**			
r<=2	r>=3				r<=2	r=3		
Co-integration between COMEX_gold and MCX_gold								
r=0	r>=1	64.658*	15.495		r=0	r=1	64.031*	14.265
r<=1	r>=2	0.627	3.841		r<=1	r=2	0.627	3.841
r<=2	r>=3				r<=2	r=3		
Co-integration between COMEX_silver and MCX_silver								
r=0	r>=1	49.248*	15.495		r=0	r=1	47.767*	14.265
r<=1	r>=2	1.482	3.841		r<=1	r=2	1.482	3.841
r<=2	r>=3				r<=2	r=3		

Notes: a) * indicates the level of significance at 1%, based on which order of integration is chosen; b) the lag structure is decided based on the minimum values of the Akaike information criterion.

Table 1.5: Estimated Co-efficient of the VECM

Commodity Futures	**Co-efficient**	**Commodity Futures**	**Co-efficient**	**Commodity Futures**	**Co-efficient**
$\beta_1$comex/mcx (gold)	-0.050 [-1.377]	$\beta_1$lme/mcx(copper)	-0.221** [-5.040]	$\beta_1$lme/mcx(zinc)	-0.260** [-3.787]
$\beta_2$mcx/comex (gold)	-0.080** [-2.492]	$\beta_2$mcx/lme(copper)	-0.108** [-2.084]	$\beta_2$mcx/lme(zinc)	-0.198** [-2.516]
$\beta_1$lme/mcx(alum)	-0.133** [-4.579]	$\beta_1$shfe/mcx(copper)	-0.060** [-5.723]	$\beta_1$shfe/mcx(zinc)	-0.033** [-3.480]
$\beta_2$mcx/lme(alum)	-0.127** [-3.793]	$\beta_2$mcx/shfe(copper)	0.004 [0.246]	$\beta_2$mcx/shfe(zinc)	-0.025 [-1.625]
$\beta_1$comex (silver)	- 0.028 [-1.064]	$\beta_1$shfe/lme(copper)	-0.066** [-5.125]	$\beta_1$shfe/lme(zinc)	-0.033** [-3.454]
$\beta_2$mcx(silver)	-0.050** [-2.318]	$\beta_2$lme/shfe(copper)	0.014 [0.868]	$\beta_2$lme/shfe(zinc)	-0.026 [-1.610]

Note: ** denotes the level of significance at 1% and better. Values in parentheses [ ] show t-values.

Table 1.5 shows the VECM results. The EC, which is also called as speed of adjustment coefficient β_i is shown in the table. In the case of precious metals, the co-efficient EC term is higher and more significant in the case of MCX than in the case of COMEX, implying that the futures price of COMEX leads the futures price of MCX. For futures prices of non-precious metals, there are high and significant EC terms for LME and MCX in the case of aluminum, with a higher magnitude of EC co-efficient of LME futures market than of MCX, implying that in case of aluminum, MCX leads LME in the price discovery process. In the case of copper, however, among all three markets, the EC terms are significant, with a higher magnitude of EC co-efficient in the case of LME, followed by MCX and then SHFE. This further implies that it is the SHFE followed by MCX and LME that leads in the price discovery process. Seemingly, for zinc, it is again LME that has high EC terms, followed by MCX and SHFE. In other words, SHFE leads MCX and LME in the price discovery process. To summarize, we can say that in the case of precious metals, futures prices of COMEX assimilate new market information more quickly than those of MCX do. In the case of non-precious metals, for aluminum, MCX leads LME in the price discovery process, while SHFE leads MCX and LME for copper and zinc. Based on the results, it can be inferred that, except for precious metals, futures markets of emerging countries such as China and India have started playing a prominent role in the price discovery process. The reason could be that these two economies are among the largest consumers of these metals.

1.5.2 Volatility Spillover Process

In this section, we analyze the volatility spillover effects among commodity market platforms. The estimated results are shown in Table 1.6 (Panels A and B) for precious metals and Tables 1.7–1.9 for non-precious metals. The BEKK model is used as the benchmark and its results are compared with the two restricted correlation models, CCC and DCC.

Table 1.6: MGARCH-Precious Metal Results

Panel A. Gold (COMEX-MCX)

	BEKK		CCC		DCC	
	Co-eff	**t-stat**	**Co-eff**	**t-stat**	**Co-eff**	**t-stat**
μ_1	0.004	0.198	0.009	0.468	0.010	0.596
μ_2	0.007	0.349	-0.001	-0.062	0.007	0.429
$c_{(1,1)}$	0.104	1.887*	0.011	0.657	0.015	1.255
$c_{(2,1)}$	0.010	0.212	-	-	-	-
$c_{(2,2)}$	0.092	2.243**	0.006	1.502	0.008	2.091**
$\alpha_{(1,1)}$	0.578	7.148**	0.136	2.328**	0.096	2.236**
$\alpha_{(1,2)}$	0.000	-0.004	-0.059	-1.350	0.005	0.165
$\alpha_{(2,1)}$	-0.354	-4.368**	-0.006	-0.423	0.082	2.911**
$\alpha_{(2,2)}$	0.189	2.921**	0.030	2.175**	-0.018	-0.755
$\beta_{(1,1)}$	0.859	17.416**	0.313	0.574	0.635	3.336**
$\beta_{(1,2)}$	0.050	1.135	0.671	1.137	0.289	1.562
$\beta_{(2,1)}$	0.105	1.928*	0.143	1.313	-0.079	-1.380
$\beta_{(2,2)}$	0.933	24.246**	0.843	9.012**	1.012	20.398**
$\rho_{(2,1)}$	-	-	0.880	124.118**	-	-
$\theta_{(1)}$	-	-	-	-	0.108	5.714**
$\theta_{(2)}$	-	-	-	-	0.825	30.479**

Panel B. Silver (COMEX-MCX)

	BEKK			CCC			DCC		
	Coeff	t-stat	Signif	Coeff	t-stat	Signif	Co-eff	t-stat	Signif
μ_1	0.034	1.538	0.124	0.019	0.859	0.390	0.020	0.994	0.320
μ_2	0.031	1.522	0.128	0.017	0.801	0.423	0.018	1.004	0.315
$c_{(1,1)}$	0.267	4.671**	0.000	0.032	1.758	0.079	0.027	2.073	0.038
$c_{(2,1)}$	0.164	3.257**	0.001	-	-	-	-	-	-
$c_{(2,2)}$	0.000	0.000	1.000	0.019	1.297	0.195	0.022	1.488	0.137
$\alpha_{(1,1)}$	0.107	0.623	0.533	0.127	4.949	0.000	0.084	1.959	0.050
$\alpha_{(1,2)}$	-0.316	-1.545	0.122	0.028	1.010	0.312	0.072	1.006	0.314
$\alpha_{(2,1)}$	0.290	1.293	0.196	-0.084	-0.938	0.348	-0.031	-0.284	0.776
$\alpha_{(2,2)}$	0.703	4.143**	0.000	0.301	2.626	0.009	0.238	2.182	0.029
$\beta_{(1,1)}$	1.259	8.422**	0.000	0.869	5.364	0.000	0.978	3.886	0.000
$\beta_{(1,2)}$	0.417	3.107**	0.002	-0.045	-0.291	0.771	-0.179	-0.600	0.548
$\beta_{(2,1)}$	-0.458	-2.615**	0.009	0.519	2.009	0.045	0.443	2.408	0.016
$\beta_{(2,2)}$	0.490	3.414	0.001	0.308	1.214	0.225	0.377	2.192	0.028
$\rho_{(2,1)}$	-	-	-	0.903	101.635	0.000	-	-	-
$\theta_{(1)}$	-	-	-	-	-	-	0.032	0.675	0.500
$\theta_{(2)}$	-	-	-	-	-	-	0.646	1.399	0.162

Note: models estimated using QMLE with robust (heteroskedasticity/misspecification) standard errors. In the variance equations, c denotes the constant terms, α denotes the ARCH terms and β denotes the GARCH terms. The co-efficient α_{12}, for example, represents the short-term volatility spillover from COMEX to MCX for gold and silver in Panels A and B, respectively, while β_{12} represents the long-term volatility spillover from COMEX to MCX for both panels and is interpreted in the same manner as above. * and ** denote the level of significance at 5% and above and 1% and better, respectively.

Table 1.7: MGARCH-Aluminum Results

Panel A: MCX-LME

Variable	MCX and LME					
	BEKK		CCC		DCC	
	Co-eff	t-stat	Co-eff	t-stat	Co-eff	t-stat
μ_1	-0.005	-0.275	-0.015	-0.670	-0.008	-0.356
μ_2	0.015	0.732	0.005	0.209	0.021	0.890
$c_{(1,1)}$	0.223	5.014**	-0.044	-0.663	0.010	1.366
$c_{(2,1)}$	0.144	4.382**	-	-	-	-
$c_{(2,2)}$	0.000	0.000	0.049	1.704	0.011	0.874
$\alpha_{(1,1)}$	0.099	1.589	0.137	2.291**	0.002	0.253
$\alpha_{(1,2)}$	-0.222	-4.839**	-0.066	-0.966	0.062	4.262**
$\alpha_{(2,1)}$	0.162	3.391**	-0.035	-1.057	0.020	1.079
$\alpha_{(2,2)}$	0.314	6.656**	0.069	2.566**	0.024	1.260
$\beta_{(1,1)}$	1.095	39.974**	-0.411	-1.511	1.214	5.632**
$\beta_{(1,2)}$	0.266	8.430**	2.065	4.820**	-0.416	-1.353
$\beta_{(2,1)}$	-0.251	-9.236**	1.334	1.015	0.595	1.264
$\beta_{(2,2)}$	0.765	40.324**	0.040	0.053	0.591	2.219**
$\rho_{(2,1)}$	-	-	0.657	22.037**	-	-
$\theta_{(1)}$	-	-	-	-	0.060	1.927*
$\theta_{(2)}$	-	-	-	-	0.188	0.319

The results of the BEKK model for precious metals, as shown in Table 1.6 (Panels A and B), indicate several instances of significant volatility spillovers. For both the short and the long-term, in the case of gold, the results confirm a unidirectional volatility spillover from MCX to COMEX, implying that the former is a more dominant trading platform than the latter. Similarly, for silver (see Table 1.6, Panel B), there is no significant volatility spillover between both markets in the short run, while in the long-term, there is a bilateral volatility spillover between COMEX and MCX futures markets, with stronger volatility moving from the latter to the former. In sum, based on price discovery and volatility spillover results, MCX seems to be the more dominant platform vis-à-vis COMEX for precious metals. This is in contrast with the price discovery results, where COMEX leads MCX in the price discovery process. In the case of non-precious metals, starting with aluminum, the results between MCX and LME (see Table 1.7, Panel A) indicate a bidirectional volatility spillover in the short and long terms, with stronger volatility moving from MCX to LME. Due to the absence of co-integration, volatility spillovers have not been studied for SHFE-MCX and SHFE-LME combinations.

Table 1.8: MGARCH-Copper Results

Panel A: MCX-LME

	BEKK		CCC		DCC	
	Co-eff	**t-stat**	**Co-eff**	**t-stat**	**Co-eff**	**t-stat**
μ_1	0.029	1.584	0.036	1.834	0.038	1.909*
μ_2	0.036	1.929*	0.036	1.718	0.042	2.187**
$c_{(1,1)}$	0.171	1.879	0.053	2.104**	0.047	3.079**
$c_{(2,1)}$	0.024	0.170	-	-	-	-
$c_{(2,2)}$	0.037	0.471	0.003	0.099	0.024	1.782
$\alpha_{(1,1)}$	0.103	2.052**	0.149	4.027**	0.131	3.127**
$\alpha_{(1,2)}$	-0.213	-4.844**	-0.002	-0.049	0.008	0.163
$\alpha_{(2,1)}$	0.219	4.627**	-0.053	-1.496	-0.012	-0.302
$\alpha_{(2,2)}$	0.290	5.729**	0.106	4.007**	0.090	3.626**
$\beta_{(1,1)}$	1.104	34.451**	0.423	2.522**	0.709	6.058**
$\beta_{(1,2)}$	0.321	6.236**	0.551	2.232**	0.164	1.119
$\beta_{(2,1)}$	-0.262	-13.298**	0.930	1.773	0.350	1.391
$\beta_{(2,2)}$	0.728	16.434**	0.290	0.896	0.655	4.076**
$\rho_{(2,1)}$	-	-	0.695	33.937**	-	-
$\theta_{(1)}$	-	-	-	-	0.039	1.344
$\theta_{(2)}$	-	-	-	-	0.905	11.180**

Panel B: MCX-SHFE

	BEKK		CCC		DCC	
	Co-eff	**t-stat**	**Co-eff**	**t-stat**	**Co-eff**	**t-stat**
μ_1	0.030	1.395	0.028	1.249	0.027	1.226
μ_2	0.014	0.653	0.015	0.841	0.014	0.766
$c_{(1,1)}$	0.198	4.765**	0.064	2.232**	0.064	2.761**
$c_{(2,1)}$	0.015	0.149	-	-	-	-
$c_{(2,2)}$	0.149	2.687**	-0.014	-0.359	-0.013	-0.330
$\alpha_{(1,1)}$	0.186	1.601	0.149	4.560**	0.150	4.468**
$\alpha_{(1,2)}$	-0.213	-1.398	-0.055	-2.161**	-0.058	-2.023**
$\alpha_{(2,1)}$	0.129	1.089	0.016	0.590	0.015	0.632
$\alpha_{(2,2)}$	0.370	4.836**	0.125	4.278**	0.126	4.744**
$\beta_{(1,1)}$	0.959	35.689**	0.456	2.911**	0.460	3.381**
$\beta_{(1,2)}$	0.069	0.755	0.856	2.425**	0.850	2.750**
$\beta_{(2,1)}$	-0.039	-0.539	1.324	1.697	1.318	1.733
$\beta_{(2,2)}$	0.901	13.870**	0.349	1.191	0.352	1.288
$\rho_{(2,1)}$	-	-	0.416	19.982**	-	-
$\theta_{(1)}$	-	-	-	-	0.000	0.228
$\theta_{(2)}$	-	-	-	-	0.925	17.018**

Panel C: SHFE- LME

	BEKK		CCC		DCC	
	Co-eff	**t-stat**	**Co-eff**	**t-stat**	**Co-eff**	**t-stat**
μ_1	0.009	0.437	0.003	0.190	0.002	0.133
μ_2	0.021	1.119	0.015	0.940	0.016	0.877
$c_{(1,1)}$	0.151	3.693**	-0.009	-0.267	-0.006	-0.314
$c_{(2,1)}$	0.041	0.862	-	-	-	-
$c_{(2,2)}$	0.117	5.170**	0.042	1.986**	0.036	2.076**
$\alpha_{(1,1)}$	0.410	5.522**	0.159	4.604**	0.159	5.069**
$\alpha_{(1,2)}$	0.031	0.389	-0.038	-1.518	-0.042	-2.252**
$\alpha_{(2,1)}$	-0.180	-1.725	-0.106	-2.785**	-0.125	-3.187**
$\alpha_{(2,2)}$	0.181	2.726**	0.143	4.870**	0.152	5.258**
$\beta_{(1,1)}$	0.885	20.441**	0.373	1.852	0.401	4.724**
$\beta_{(1,2)}$	-0.034	-1.185	0.810	2.104**	0.786	4.105**
$\beta_{(2,1)}$	0.079	1.716	0.663	2.813**	0.665	7.037**
$\beta_{(2,2)}$	0.993	49.499**	0.458	3.385**	0.480	6.766**
$\rho_{(2,1)}$	-	-	0.641	42.216**	-	-
$\theta_{(1)}$	-	-	-	-	0.027	2.095**
$\theta_{(2)}$	-	-	-	-	0.387	2.037**

Note: models estimated using QMLE with robust (heteroskedasticity/misspecification) standard errors. In the variance equations, c denotes the constant terms, α denotes the ARCH terms and β denotes the GARCH terms. The coefficient α_{12}, for example, represents the short-term volatility spillover from MCX to LME in Panel A, MCX to SHFE in Panel B and SHFE to LME in Panel C, respectively, while β_{12} represents the long-term volatility spillover in the same manner as mentioned above. * and ** denote the level of significance at 5% and above and 1% and better, respectively.

In the case of copper (see Table 1.8, Panels A to C), in the short and the long-term, there is a bidirectional volatility spillover between MCX and LME, with marginally stronger volatility spillovers moving from LME to MCX in the short-term, while in the long-term, there is a stronger volatility spillover moving from MCX to LME (see Panel A). Between MCX and SHFE and between SHFE and LME, there are no short- or long-term volatility spillovers using the BEKK model. This is in contrast with the results of the CCC and DCC models, which indicate unidirectional volatility spillovers moving from MCX to SHFE and bilateral volatility spillovers between SHFE and LME, which are stronger from LME to SHFE in the short-term and SHFE to LME in the long-term. The results imply that volatility in MCX has a strong bearing on the SHFE futures market, while there is a stronger volatility transmission from LME to SHFE (see Panels B and C).

Table 1.9: MGARCH-Zinc Results

Panel A: MCX-LME

	BEKK		**CCC**		**DCC**	
	Co-eff	**t-stat**	**Co-eff**	**t-stat**	**Co-eff**	**t-stat**
μ_1	0.021	0.694	0.032	1.427	0.028	1.105
μ_2	0.015	0.572	0.028	1.179	0.030	1.005
$c_{(1,1)}$	0.719	1.801	0.023	0.830	0.013	0.482
$c_{(2,1)}$	0.577	1.672	-	-	-	-
$c_{(2,2)}$	0.000	0.001	-0.049	-2.134**	-0.049	-2.201**
$\alpha_{(1,1)}$	-0.381	-2.088**	0.030	0.561	0.021	0.698
$\alpha_{(1,2)}$	-0.114	-0.548	-0.036	-0.658	-0.032	-0.647
$\alpha_{(2,1)}$	0.487	2.193**	0.076	1.366	0.055	1.136
$\alpha_{(2,2)}$	0.389	1.651	0.046	0.747	0.060	1.345
$\beta_{(1,1)}$	0.652	1.556	0.615	1.826*	0.702	1.723
$\beta_{(1,2)}$	-0.238	-0.727	0.469	1.117	0.383	0.741
$\beta_{(2,1)}$	-0.049	-0.237	0.969	4.486**	1.108	4.286**
$\beta_{(2,2)}$	0.918	5.434**	0.227	1.467	0.136	0.766
$\rho_{(2,1)}$	-	-	0.758	55.437**	-	-
$\theta_{(1)}$	-	-	-	-	0.011	0.462
$\theta_{(2)}$	-	-	-	-	0.821	2.067**

Panel B: MCX-SHFE

	BEKK		CCC		DCC	
	Co-eff	**t-stat**	**Co-eff**	**t-stat**	**Co-eff**	**t-stat**
μ_1	0.024	0.773	0.022	0.851	0.019	0.813
μ_2	0.027	0.979	0.008	0.332	0.011	0.485
$c_{(1,1)}$	0.119	2.676**	0.113	8.879**	0.065	2.548**
$c_{(2,1)}$	0.068	1.588	-	-	-	-
$c_{(2,2)}$	0.000	-0.002	-0.149	-10.081**	-0.109	-3.832**
$\alpha_{(1,1)}$	0.139	1.827*	0.095	4.411**	0.089	3.579**
$\alpha_{(1,2)}$	0.223	2.520**	0.018	0.685	-0.085	-2.884**
$\alpha_{(2,1)}$	-0.148	-4.055**	-0.021	-0.551	-0.032	-0.966
$\alpha_{(2,2)}$	0.153	1.950*	0.084	4.283**	0.106	4.162**
$\beta_{(1,1)}$	0.956	102.201**	0.038	2.099**	0.370	1.693
$\beta_{(1,2)}$	-0.129	-4.657**	15.547	67.199**	6.292	2.384**
$\beta_{(2,1)}$	0.126	3.795**	36.332	30.024**	17.102	3.497**
$\beta_{(2,2)}$	0.960	69.165**	-0.725	-7.769**	-0.319	-0.857
$\rho_{(2,1)}$	-	-	0.049	62.881**	-	-
$\theta_{(1)}$	-	-	-	-	0.006	3.088**
$\theta_{(2)}$	-	-	-	-	0.000	0.059

Panel C: SHFE-LME

	BEKK		CCC		DCC	
	Co-eff	**t-stat**	**Co-eff**	**t-stat**	**Co-eff**	**t-stat**
μ_1	0.024	0.805	0.034	1.418	0.030	1.076
μ_2	0.033	1.109	0.025	0.928	0.020	0.841
$c_{(1,1)}$	0.246	3.926**	0.104	1.728	0.057	0.951
$c_{(2,1)}$	-0.050	-0.721	-	-	-	-
$c_{(2,2)}$	0.000	0.000	-0.128	-1.380	-0.102	-0.978
$\alpha_{(1,1)}$	0.190	2.488**	0.092	3.625**	0.080	2.755**
$\alpha_{(1,2)}$	0.262	4.758**	0.007	0.233	-0.082	-2.409**
$\alpha_{(2,1)}$	-0.111	-1.804	-0.032	-0.804	-0.047	-1.457
$\alpha_{(2,2)}$	0.169	3.938**	0.092	3.488**	0.111	4.209**
$\beta_{(1,1)}$	0.883	29.352**	0.140	0.740	0.429	1.883*
$\beta_{(1,2)}$	0.434	15.187**	10.684	3.058**	5.213	2.094**
$\beta_{(2,1)}$	-0.451	-17.402**	25.758	3.360**	16.969	3.572**
$\beta_{(2,2)}$	0.794	32.143**	-0.565	-1.749	-0.446	-1.349
$\rho_{(2,1)}$			0.063	14.000**		
$\theta_{(1)}$					0.006	3.231**
$\theta_{(2)}$					0.000	1.670

Note: models estimated using QMLE with robust (heteroskedasticity/misspecification) standard errors. In the variance equations, c denotes the constant terms, α denotes the ARCH terms and β denotes the GARCH terms. The coefficient α_{12}, for example, represents the short-term volatility spillover from MCX to LME in Panel A, MCX to SHFE in Panel B and SHFE to LME in Panel C, respectively, while β_{12} represents the long-term volatility spillover in the same manner as mentioned above. * and ** denote the level of significance at 5% and above and 1% and better, respectively.

Last, in the case of zinc (see Table 1.9, Panels A to C), between MCX and LME, there is a unilateral volatility spillover moving from LME to MCX. In the long-term, the BEKK results indicate no evidence of volatility spillovers between either trading platforms. This is in contrast to the CCC and DCC models, which indicate a unidirectional volatility spillover from LME to MCX (see Panel A). Similarly, between MCX and SHFE, there are bilateral volatility spillovers moving strongly from MCX to SHFE in the short as well as the long-term, implying that there is stronger volatility transmission from MCX to SHFE (see Panel B). Between SHFE and LME, there is unidirectional volatility spillover from SHFE to LME; in the long-term, there is a bilateral volatility spillover moving strongly from LME to SHFE (see Panel C).

The results of the CCC model for sample commodities indicate highly positive correlations with a significance level at 1% and better. In the case of precious metals (gold and silver) (see Table 1.6, Panels A and B), the correlation co-efficients between COMEX and MCX (ρ_{21}) are 0.880 (gold) and 0.903 (silver). Similarly, for non-precious metals, in the case of aluminum, the correlation between MCX and LME (ρ_{21}) is 0.657 (see Table 1.7, Panel A). In the case of copper, the highest correlation is between MCX and LME (ρ_{21}) at 0.695, followed by SHFE and LME (ρ_{21}) at 0.641 and MCX and SHFE at 0.416 (see Table 1.8, Panels A to C). For zinc (see Table 1.9, Panels A to C), the strongest correlation is between MCX and LME (ρ_{21}) at 0.758, followed by SHFE and LME (ρ_{21}) at 0.063 and the lowest correlation is observed in the case of MCX and SHFE at 0.049. It may be noted that, among all commodities, the highest correlations are found in the case of gold and silver, implying that the trading platforms for bullion are more synchronized in terms of trade facilitation and information transmission compared to trading platforms for metals. Hence, precious metal trading exhibits stronger information transmission and, therefore, a relatively greater international character.

The results of the DCC model indicate that the estimated co-efficients on θ_1 and θ_2 for examined commodities are positive, but the level of significance varies. These estimated co-efficients sum to a value that is less than 1, implying that the dynamic conditional correlations of all commodities are mean-reverting.

Table 1.10: Diagnostic Tests for Standardized Residuals

	BEKK		CCC		DCC	
	$Q_{(20)}$	$Q_{sqr(20)}$	$Q_{(20)}$	$Q_{sqr(20)}$	$Q_{(20)}$	$Q_{sqr(20)}$
Gold (COMEX-MCX)	23.245	18.539	24.982	19.578	22.501	19.003
	[0.277]	[0.552]	[0.202]	[0.485]	[0.314]	[0.522]
Silver (COMEX-MCX)	15.258	22.179	13.646	21.256	13.864	21.447
	[0.762]	[0.331]	[0.848]	[0.382]	[0.837]	[0.371]
Aluminum (MCX-LME)	26.470	9.017	25.598	9.486	25.678	9.515
	[0.151]	[0.983]	[0.180]	[0.977]	[0.177]	[0.976]
Copper (MCX-LME)	18.751	21.473	19.393	20.415	18.214	19.565
	[0.538]	[0.370]	[0.497]	[0.432]	[0.573]	[0.485]
Copper (MCX-SHFE)	11.347	13.683	10.608	14.923]	10.416	14.402
	[0.937]	[0.846]	[0.956]	[0.781]	[0.960]	[0.810]
Copper (SHFE-LME)	18.711	18.217	18.007	19.754	17.893	19.815
	[0.541]	[0.573]	[0.587]	[0.473]	[0.595]	[0.470]
Zinc (MCX-LME)	15.716	16.171	13.434	15.315	12.917	15.089
	[0.734]	[0.706]	[0.858]	[0.758]	[0.881]	[0.771]
Zinc (MCX-SHFE)	10.815	14.055	11.084	13.986	10.464	13.307
	[0.951]	[0.828]	[0.944]	[0.831]	[0.959]	[0.864]
Zinc (SHFE-LME)	13.227	19.001	13.700	20.268	13.833	20.396
	[0.868]	[0.522]	[0.845]	[0.441]	[0.839]	[0.433]

Note: Values in parentheses are p-values.

In the diagnostic tests for the standardized residuals and their squared terms (see Table 1.10), we find no evidence of serial correlation at the 1% or even 5% level of significance and better. The results indicate no evidence of autocorrelation, even in the squared standardized residuals.

1.6 Conclusion

This study examines the process of information transmission in futures prices of bullion and metals between India, represented by MCX and its global counterparts, such as COMEX, LME and SHFE. The sample period of the study is from 2005 to 2012 (through April). We identified structural breaks for all sample futures price series. These structural breaks highlight the boom period of 2006, the US subprime crisis of 2008 and the Eurozone crisis of 2010–2011. The price discovery results confirm that there is a long-term equilibrium relationship among the futures prices of the examined trading platforms, even after accounting for the structural break in each commodity series, implying that there is informational efficiency across sample markets. Long-term equilibrium relationships, however, are not confirmed for MCX-SHFE and LME-SHFE in the case of aluminum, implying an absence of price discovery in these cases. For precious metals (gold and silver), if there is any disequilibrium in the short-term, MCX adjusts more quickly than COMEX does to restore the long-run equilibrium. In other words, the COMEX futures market leads MCX in the price discovery process. MCX impounds new market information more quickly than LME does in the case of aluminum. For copper and zinc, it is the SHFE that leads MCX and LME.

The results of volatility spillovers under the MGARCH framework indicate that, in general, there exist both short-term as well as long-term volatility spillovers between sample markets. However, in the case of gold, there is a univariate volatility spillover from MCX to COMEX, both in the short and long terms. No short-term spillover effects are observed in the case of silver; in the long-term, however, there is a bivariate spillover moving more strongly from MCX to COMEX. This implies that, while innovations in each market impact volatility; in the other market, MCX seems to play a more dominant role in the process. For aluminum, copper and zinc, unilateral short-run volatility spillovers are observed from LME to MCX, while bilateral spillovers are observed in the long-term, with MCX in the more dominant role, vis-à-vis LME, for the first two metals. Long-term volatility spillover effects seem to be absent in the case of zinc. Both MCX and LME play more important roles than SHFE plays in information transmission related to volatility. The volatility spillover results provided by the BEKK model exhibit some contradiction with the other two restricted models, CCC and DCC, for copper and zinc.

Our empirical results have strong economic implications for market players and regulators, as well as academicians working on international financial integration literature. For precious metals, while COMEX tends to play a lead role in the price discovery process, the volatility-related information transmission in the long run seems to be stronger from MCX to COMEX. Thus, in contrast to the findings of Kumar and Pandey (2011), COMEX does not seem to be a fully dominant platform in the overall information transmission process. In other words, MCX, an emerging market platform, may not qualify as a pure satellite market. For non-precious metals, the emerging market platforms in China (SHFE) and India (MCX) seem to be more dominant than the mature market platforms are, both in price discovery as well as in the volatility spillover process. Thus, the emerging market platforms have achieved their due importance, given the high level of demand for these metals in the fast-growing manufacturing industry. The recent global economic crisis has impacted all economies, but the western economies have fared worse compared to their emerging counterparts. Hence, the center of gravity of the world economy has gradually been shifting from west to east and it is likely that the emerging market platforms may perform leadership roles in information transmission for all other commodities, including precious metals, in the near future.

Our results highlight the role of emerging commodity market platforms in the international information transmission process. Hence, policy makers in emerging markets such as India should facilitate necessary institutional and fiscal architecture, as well as regulatory reforms, so that their commodity market trading platforms can achieve greater liquidity and efficiency in order to achieve a relatively more dominant position in the international information transmission process.

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2. An Examination of Price Discovery and Volatility Spillovers of Crude Oil in Globally Linked Commodity Markets

Abstract

This chapter examines the price discovery and volatility spillovers between spot and futures as well as futures prices of three strategically linked oil markets viz., Inter-Continental Exchange (ICE), MCX and NYMEX from 05 February 2006 to 15 October 2012. The results confirm a long-run equilibrium relationship between futures and spot prices in each market; futures prices lead spot prices in the price discovery process. Analyzing futures prices, we find that ICE is the most dominant platform, followed by NYMEX and MCX in price discovery process. Thus MCX, an emerging market platform, seems to act like a satellite market vis-à-vis international platforms. The volatility spillover results suggest that there is a long-term spillover from ICE to MCX and from MCX to NYMEX. The volatility information seems to flow from NYMEX to ICE. The GARCH-CCC & DCC model results confirm both cross-market and within market co-movements which become weak during the crisis period and tend to become stronger during the stable period. The study provides relevant implications for policy makers and market traders. The outcome of this study contributes to commodity market literature, especially relating to information transmission between strategically linked markets.

2.1 Introduction

Since the early 1970s, the frequent upheavals in the energy market, especially the price of crude oil, have always been an issue of great concern for academics, regulators and policy makers owing to its adverse impact on the macroeconomic fundamentals of the global economy. In this regard, an important issue that has garnered a great deal of attention from researchers and policy makers is the market behavior of energy markets—particularly crude oils with respect to their price discovery and volatility spillover potentials (Lean et al., 2010). In recent years, particularly after the global economic crisis of 2008, there have been significant changes in the energy markets worldwide, particularly for crude oil. In the literature, studies have considered several factors, such as globalization, changing economic dynamics, international relations and global politics, war, technological innovations and developments in energy markets and the recent financial crisis. These have shifted the economic and political focus from the west to east. Moreover such factors have increased volatility in the energy market environment that have led market players to hedge the investment risk using derivatives such as futures and options for energy products (Nomikos and Andriosopoulos, 2012). In the international commodity market, the crude oil market is characterized as an umbrella market because of a large variety of products, such as West Texas Intermediate (WTI); Brent Blend (BB); Maya, Bonny Light (BL) and Dubai-Fateh (DF). Among these crude oils, WTI and BB are considered as light and sweet crude oil because of their higher API gravity index[7] compared to others (Kaufmann and Ullman, 2009). Hence, WTI and BB are widely used for domestic and industrial purposes. In both mature and emerging markets, WTI and BB are also highly traded crude oil on their trading platforms. In terms of recent trends, WTI is being taken as a benchmark for price determination in the crude oil industry.

Taking the above discussion as a starting point, this chapter attempts to investigate the price discovery and volatility spillovers between futures and spot prices and between futures prices of WTI traded on three commodity trading platforms viz., NYMEX, ICE and MCX. It may be noted that NYMEX and ICE are two principal platforms for oil trading at a global level and hence compete with each other for a price leadership role in the crude oil market. MCX is the major commodity exchange in India. India is a fast emerging, trillion-dollar economy for which crude oil is an important item in the import bill. Hence, MCX in our case represents an emerging market platform, which shall help us in understanding the information transmission process between mature and emerging economies relating to an international commodity like crude oil. In futures markets, a market is characterized as dominant market when it assimilates all the new information rapidly in its price and has stronger volatility spillovers to other markets (Hong, 2001). Under the efficient market hypothesis (EMH), it is assumed that all the publicly available information must be incorporated into the price for traded assets with no possibility of speculation and arbitrage. But in a technology-driven, complex financial system, it is often observed that the process of information transmission is not as symmetrical as it is understood to be (Kaufmann and Ullman, 2009). Therefore, this motivates researchers and policy makers to investigate the energy market platforms with respect to their price discovery and volatility spillover potential. In literature, price discovery implies a lead-lag relationship between futures and spot prices in a market and between futures prices in two different markets (Tse,

7 American Petroleum Institute (API) gravity index is a measure of how light or heavy a petroleum product relative to water. See Kaufmann and Ullman (2009) for more details.

1999). Under the co-integration framework, it implies the establishment of a long-run equilibrium relationship. In the event of any departures from equilibrium due to exogenous shocks, price discovery also takes into account the speed of adjustment of a market towards equilibrium price. Econometrically, such a process is called an error correction mechanism (see, Zhong et al., 2004; Rittler, 2012). Besides price discovery, a volatility spillover also plays an important role in information transmission, as it highlights the process through which volatility in one market affects that of another market (Chan et al., 1991). The present study is particularly important in light of the increasing integration of global commodity markets that has generated interest for understanding the volatility spillovers from one market to another. Volatility spillovers are usually attributed to the cross-market hedging and changes in commonly available information, which may simultaneously impact the expectations of various participants across markets (Engle et al., 1990). More specifically, volatility spillovers examine information assimilation in two different ways: firstly, in terms of own-volatility spillovers under lagged innovations (information) and secondly in terms of its own lagged volatility spillovers. Spillovers under lagged innovations are referred to as clustering effects under the ARCH framework and lagged spillovers of an asset itself is referred to as volatility persistence under the GARCH framework—Such effects have strong implications for market participants since they highlight the assimilation of information rather than just the information contained in the price (Hong, 2001; Gagnon and Karolyi, 2006; Nekhili and Naeem, 2009). One can also use volatility spillovers to measure the spillover of past information and lagged volatility of an asset/market on another asset/market this is referred to as cross volatility spillover effects (Gagnon and Karolyi, 2006). Such effects have also practical implications as cross volatility spillovers help in characterizing the commodity market as a dominant or a satellite trading platform (see, Karmakar, 2009; Mahalik et al., 2010; Du et al., 2011; Liu and An, 2011; Arouria et al., 2012, among others).

This chapter examines the process of how volatility in the oil futures prices changes across markets. Since oil prices in examined countries play an important role in driving economic growth among sample commodity exchanges, it is crucial for market participants to understand the volatility spillovers process across these exchanges and their dominance in oil trading. In particular, the study empirically examines the first and the second moment properties of oil futures traded on the three sample exchanges. Much of the research to date has focused on the interaction between the cash and the futures tiers of the crude oil market. The present study tries to answer the following research questions: Firstly, between NYMEX and ICE, the two leading international trading platforms for oil futures contracts, which is the dominant trading platform for crude oil trading (WTI) globally? Secondly, between these mature trading platforms and an emerging market trading platform such as MCX, what is the information transmission process? To address these questions, the objectives of this study are:

(i). to examine the lead-lag relationship between spot and futures prices and between futures prices of sample markets;

(ii). to investigate the volatility spillovers among sample markets to ascertain the dominant and satellite platforms.

The chapter comprises six sections, including the present one: A brief review of the literature is provided in Section 2.2. Section 2.3 covers data and their sources, while methodology and estimation procedures are described in Section 2.4. In Section 2.5, we provide empirical results, followed by a summary and conclusion in the last section.

2.2 Literature Review

In this section, the primary focus is on information linkages among strategically located markets. Prior research has focused mainly on financial markets; comparatively less attention has paid to the commodity and foreign exchange markets (see Koutmos and Booth, 1995; Hamao et al., 1990; Hong, 2001). There have been notable studies relating to energy products (see Antoniou and Foster, 1992; Ng and Pirrong, 1996; Tse and Booth, 1997; Lin and Tamvakis, 2001; Ewing et al., 2002; Hammoudeh et al., 2003; Lanza et al., 2006; Malik and Hammoudeh, 2007; Mu, 2007; Hammoudeh and Yuan, 2008; Kaufmann and Ullman, 2009; Bekiros and Diks, 2008; Nomikos and Andriosopoulos, 2012; Arouri et al., 2012; Ji and Fan, 2012). So far, none have examined price discovery and volatility spillovers by taking into account the recent changes in the international economic dynamics and strong upheavals in energy products, particularly crude oil.

The study of Tse and Booth (1997) examines the information transmission between New York heating oil futures and London gas oil futures and reports that the former is a more dominant market than the later. Lin and Tamvakis (2001) examine the spillover effects between NYMEX and London's International Petroleum Exchange (IPE) crude oil futures markets and report that there is a stronger volatility spillover from NYMEX to IPE when traded in different hours. Using Dynamic Conditional Correlations (DCC – GARCH), Lanza et al. (2006) examine the daily returns on WTI oil forward and futures prices. Similar to our study, they reports dramatic aberrations in time-varying conditional correlations with the magnitude being negative to zero. Spargoli and Zagaglia (2007) examine the co-movement between futures markets for crude oil traded on NYMEX and ICE. Using the structural BEKK-GARCH model they find that during the turmoil period, NYMEX reacts more quickly than ICE. This further implies that NYMEX assimilates new information more quickly than ICE. Bekiros and Diks (2008) examine the relationship between futures and spot prices of WTI under different time intervals by applying linear and nonlinear causal relationships analyzing two sample periods, namely PI, which spans 1991 to 1999 and PII (1999 to 2007). They highlight the weaknesses related with first moment relationships (lead-lag relationships) with the use of a nonlinear causality test. Based on the linear causality results, the study reports bi-directional Granger causality between spot and futures prices in both periods, whereas the nonlinear causality results indicate the uni-directional causal relationship from spot to futures prices only in PII. Kaufmann and Ullman (2009) examine the unified nature of global oil market by investigating the causal relationships among prices for crude oils from Africa, Europe, Middle East and North America on both spot and futures markets and include different variants of crude oil, such as WTI, BB, Maya, Bonny Light and Dubai–Fateh. They report a weak relationship between futures and spot prices and also reports that spot prices of Dubai-Fateh lead other spot and futures prices; while among other crude oil futures and spot prices, WTI leads other exchanges and contracts. However, studies have also examined the information transmission of oil under different dimensions by linking oil with metals and stock markets. In this regard, Lean et al., (2010) examine the market efficiency of oil futures and spot prices of WTI by applying both mean-variance (MV) and stochastic dominance (SD) approaches and report no evidence of any MV and SD relationships between the examined series and conclude that spot and futures do not dominate one another. Hence, there is no arbitrage opportunity between futures and spot markets.

Arouria et al. (2012) examine the impact of oil price fluctuations on European equity markets by analyzing volatility spillovers and hedging effectiveness. Based on the results of Vector Autoregression (VAR-GARCH) model, they find a strong evidence of significant volatility spillovers between oil price and sector stock returns. In the Indian context, Goyal and Tripathi (2012) examine the lead-lag relationship between spot and futures of crude oil by applying mutual and across-exchange causality tests. Using the data of US WTI crude oil spot prices, UK Brent spot and MCX WTI spot, they find an evidence of price discovery in mature exchanges, where spot prices lead futures prices under the VECM framework and further report reverse causality from emerging to mature exchanges. Ewing and Malik (2013) examine the volatility transmission between gold and oil futures by taking into account a structural break. Using uni-variate and bi-variate GARCH models, they find a strong evidence of significant volatility transmission between gold and oil returns after taking into account structural breaks in variance. By and large the findings of recent studies as mentioned above are not in line with present work. To summarize, we can say that while there is a broad consensus on the role of information linkages across markets, the issue is still unsettled, especially in light of the recent turbulent periods, which have jolted the commodity markets across the globe, especially the crude oil prices taking a northward trend. Moreover, the futures markets in emerging countries are characterized by low liquidity and less efficient trading systems (Tomek, 1980; Carter, 1989), making them different from the counterpart markets in mature countries. Under emerging market frameworks, this is the first attempt to examine price discovery and volatility spillovers by taking into account a more recent period, which has still been unexplored in cross-market frameworks; it is of great importance as it is the time when these trading platforms have achieved a higher level of trading liquidity and there may be strengthening of international linkages in terms of energy products.

2.3 Methodology

2.3.1 Process of Price Discovery and Co-Integration

In the first stage, a stationarity condition using conventional methods of unit root tests viz., ADF, PP and KPSS have been used to check for stationarity for all sample series. Following Zhong et al. (2004) and Hou and Li (2013), we apply Johansen and Juselius (1992) to exhibit the long-run relationship followed by VECM, as mentioned in equations (2.1) and (2.2). The bivariate co-integrated series $P_t = (F_t, S_t)'$, :

$$\Delta F_t = \alpha_1 + \beta_1 EC_{t-1} + \sum_{i=1}^{k} d_{1i} \Delta F_{t-i} + \sum_{i=1}^{k} g_{1i} \Delta S_{t-i} + \varepsilon_{1t} \tag{2.1}$$

$$\Delta S_t = \alpha_2 + \beta_2 EC_{t-1} + \sum_{i=1}^{k} d_{2i} \Delta F_{t-i} + \sum_{i=1}^{k} g_{2i} \Delta S_{t-i} + \varepsilon_{2t} \tag{2.2}$$

Note that $EC_{t-1} = F_{t-1} - a - bS_{t-1}$ is the lagged error correction (EC) term.

The error correction model of the bivariate co-integrated series $P_t = (F_{1,t}, F_{2,t})'$, is represented using the following VECM:

$$\Delta F_{1,t} = b_1 + \beta_1 EC_{t-1} + \sum_{i=1}^{k} d_{1i} \Delta F_{1,t-i} + \sum_{i=1}^{k} g_{1i} \Delta F_{2,t-i} + \varepsilon_{1t} \tag{2.3}$$

$$\Delta F_{2,t} = b_2 + \beta_2 EC_{t-1} + \sum_{i=1}^{k} d_{2i} \Delta F_{1,t-i} + \sum_{i=1}^{k} g_{2i} \Delta F_{2,t-i} + \varepsilon_{2t} \tag{2.4}$$

Where, $EC_{t-1} = F_{1,t-1} - a - bF_{2,t-1}$ is the lagged EC term.

Given the large number of parameters that would have to be estimated in the spillover model (discussed in subsection in 2.3.2), a two-step procedure similar to that implemented by Bekaert and Harvey (1997), Tse (1999), Ng (2000) and Rittler (2012) has been considered in this study. In the first step, a VECM is estimated to obtain the residuals. In the second step, first-stage residuals are used to estimate volatility spillovers between spot and futures prices and between the futures prices of both markets.

2.3.2 Process of Volatility Spillovers

It is the volatility that determines the flow of information from one market to another and not just a simple price change (Chan et al., 1991).[8] Numerous studies have investigated the process of volatility spillovers to exhibit the spread of news from one market that affects the volatility spillover process of another market. The important studies in the existing literature are of Hamao et al. (1990), Koutmos and Booth (1995) and Lin et al. (1994) for the US, UK and Japanese stock markets and Booth et al. (1997) and Christofi and Pericli (1999). Engle et al. (1990) introduced the GARCH models to examine the volatility spillovers. Most studies in the literature have used different variants of GARCH models to study volatility spillovers between markets.

[8] For further details, Chan et al. (1991) could be a good reference on the need to study the volatility spillovers.

Keeping in view the above-mentioned literature, we employ the GARCH-BEKK (Baba et al. 1990) model to model the volatility spillover dynamics between futures and spot prices and between futures prices of ICE, MCX and NYMEX. In addition to the BEKK model, CCC and DCC models are employed to infer upon the constant and time-varying correlation patterns of the sample oil price series under consideration. A brief description of each model is mentioned below.

GARCH (BEKK) Model

The BEKK model is the most natural way to deal with the multivariate matrix operations. In this study, the model is implemented on the standardized residuals obtained from the VECM of the series under the following specification.

Mean equation:

$$\upsilon_{it} = \mu_{i0} + \sum_{j=1}^{2} \mu_{ij} \upsilon_{j,t-1} + \varepsilon_{it} \text{ where } \varepsilon_{it} \mid I_{it-1} \sim N(0, h_{it}), i = 1, 2 \quad (2.5)$$

In equation (2.5), υ_{it} is the estimated residual of the sample series; ε_{it} is a random error term with conditional variance h_{it}; I_{it-1} denotes the market information at time *t*-1. Equation (2.5) specifies the variance equation *i*=1, 2 denotes the bivariate model. The BEKK parameterization of multivariate GARCH model is written in the following manner:

$$H_{t+1} = C'C + A'\varepsilon_t \varepsilon_t' A + B' H_t B \quad (2.6)$$

Where the individual elements of C, A and B matrices for equation (2.6) are mentioned below:

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}, \ B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \text{and}\, C = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$$

The off-diagonal elements of matrix A (a_{12} and a_{21}) represent the short-term volatility spillover (ARCH effect) from market 1 to another market 2. The off-diagonal elements of matrix B (b_{12} and b_{21}) represent the long-term volatility spillover (GARCH effect) in the same manner as mentioned above.

CCC-GARCH and DCC-GARCH Models

The Engle's (2002) DCC model is estimated in two steps. In the first step, GARCH parameters are estimated followed by correlations in the second step:

$$\mathrm{H_t} = \mathrm{D_t R_t D_t} \tag{2.7}$$

In equation (2.7), H_t is a 2×2 conditional covariance matrix as in our case; R_t is a conditional correlation matrix and D_t is a diagonal matrix with time-varying standard deviations on the diagonal.

$$D_t = diag({h_{11t}}^{1/2}, {h_{22t}}^{1/2})$$

$$R_t = diag({q_{11t}}^{-1/2}, {q_{22t}}^{-1/2}) Q_t diag({q_{11t}}^{-1/2}, {q_{22t}}^{-1/2})$$

Where Q_t is a symmetric positive definite matrix:

$$Q_t = (1-\theta_1-\theta_2)\overline{Q} + \theta_1 \varepsilon_{t-1} \varepsilon'_{t-1} + \theta_2 Q_{t-1} \tag{2.8}$$

$\overline{Q}$ is the 2×2 unconditional correlation matrix of the standardized residuals ε_{it}. The parameters θ_1 and θ_2 are non-negative with a sum of less than unity. Under the condition of $R_t = R$ and $R_{ij} = \rho_{ij}$ equation (2.9) becomes the CCC model.

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \tag{2.9}$$

The MGARCH models are estimated by QMLE using the BFGS algorithm. T statistics are calculated using a robust estimate of the covariance matrix (see Sadorsky, 2012).

2.4 Data

The sample data for the daily spot and futures prices of NYMEX, ICE and MCX for WTI have been retrieved from the Bloomberg database. All closing prices of futures series are taken for the nearest contract to maturity (see Zhong et al., 2004). The sample period of the study is 05 February 2006 to 15 October 2012 (1727 observations). To maintain parity across the sample markets, the price series are taken in USD terms.[9] For estimation purposes, all price series have further been converted

[9] Previous day observation is used in case of missing observations assuming that the data were unavailable because of national holidays or any other reasons. Two days rolling average to account for time synchronization of different markets lying in different time zones has not been considered in this study due to a severe autocorrelation problem as highlighted by (Chiang, Jeon and Li, 2007).

into natural logarithms. The sample series under investigation are denoted as follows: ICE, NYMEX and MCX denote the futures prices of WTI crude oil traded on ICE, NYMEX and MCX platforms; MCXSPOT denotes the spot price of MCX and SPOT denotes the spot prices of ICE and NYMEX.

2.5 Empirical Results

The time-series graphs of actual WTI crude oil prices clearly shows the evidence of similar movement in prices, implying that there is not much scope of arbitration in the oil market and the relevant market information is intercepted by each sample market immediately (see Fig. 2.1).

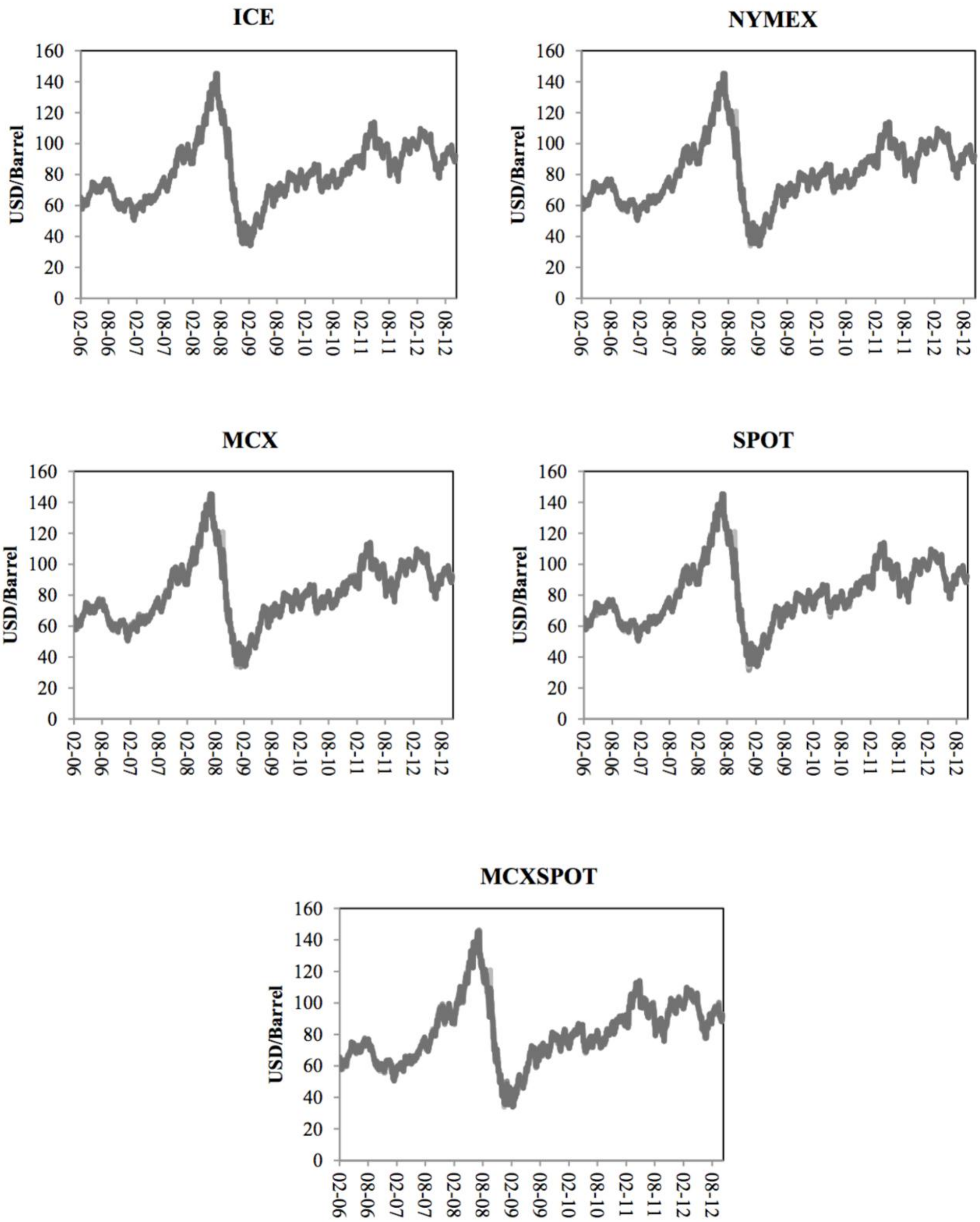

Figure 2.1: Time-series plots of ICE, NYMEX, MCX, SPOT and MCXSPOT

Besides this, we have also plotted the continuously compounded daily returns graphs of all sample markets. It appears that clustering in each market is more prominent during June 2008 to August 2009 and during April 2011 to June 2011 (see Fig. 2.2).

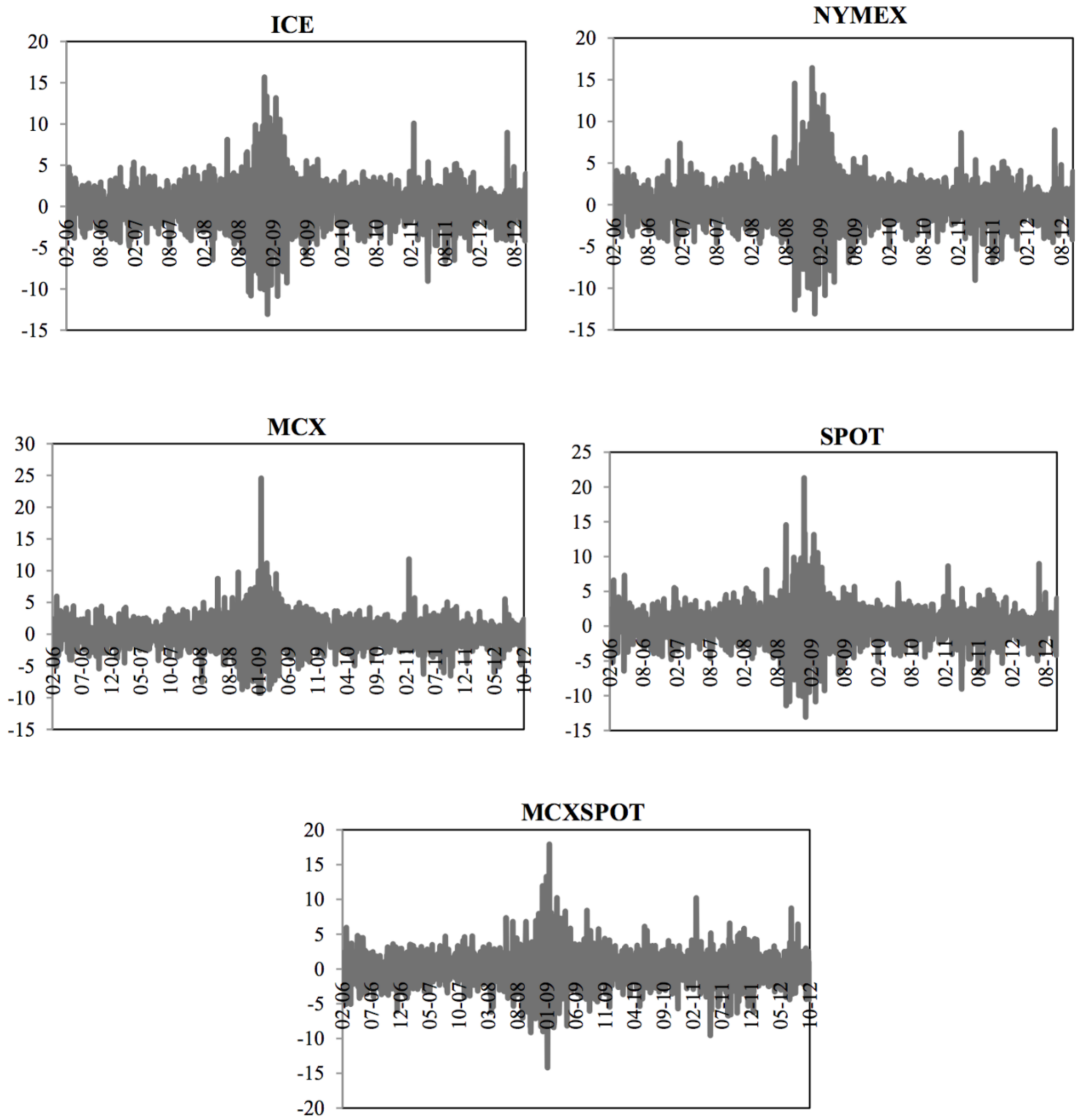

Figure 2.2: Time-series plot of daily returns of ICE, NYMEX, SPOT, MCX and MCXSPOT

While the first clustering period can be attributed to the global economic crisis and its aftermath, the second period is related to the intensified phase of the Eurozone crisis. The return behavior of each market appears to be similar, as it has been observed in the case of actual prices. But it would be interesting to see how the behavior of these markets changes in terms of their price discovery under the first moment condition and volatility spillovers in the second moment condition. The descriptive statistics of sample oil futures and spot series are shown in Table 2.1.[10] The mean returns of WTI crude oil appear to be almost the same across all markets. The highest mean daily returns are observed in the case of NYMEX and SPOT, which is 0.021% and lowest in case of ICE, MCX and MCXSPOT, which is 0.020%. The standard deviation as a

[10] Sample oil prices series have been calculated using the first difference of the log price series multiplied by 100.

measure of volatility is highest for SPOT (2.559%) and NYMEX (2.538%), followed by ICE (2.477%) and MCXSPOT (2.437%). Strikingly, the lowest volatile market appears to be of MCX, which has a volatility of 2.252%. However, this low volatility may be an outcome of lower information flows owing to less trading volume coupled with relatively greater price regulations in an emerging market like India.

Table 2.1: Descriptive Statistics of Sample Commodities

	Futures Returns			Spot Returns	
	ICE	MCX	NYMEX	MCXSPOT	SPOT
Mean	0.020	0.020	0.021	0.020	0.021
Max.	15.659	24.532	16.410	17.915	21.277
Min.	-13.065	-9.301	-13.065	-14.196	-13.065
Std.Dev.	2.477	2.252	2.538	2.437	2.559
Skewness	0.063	0.725	0.134	0.172	0.307
Kurtosis	7.453	13.421	7.972	7.346	9.308
JB	1427.781	7965.404	1783.879	1367.761	2890.642
Prob.	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Arch	48.814 [0.000]**	14.955 [0.000]**	45.048 [0.000]**	33.858 [0.000]**	57.608 [0.000]**
LB	17.459 [0.064]	11.928 [0.289]	24.554 [0.006]**	29.0469 [0.001]**	30.376 [0.000]**
LB^2	1106.96 [0.000]**	239.081 [0.000]**	1038.05 [0.000]**	587.742 [0.000]**	798.412 [0.000]**
Obs.	1727	1727	1727	1727	1727

Note: ** denotes level of significance at 1% and better. Values in parentheses [ ] indicate the p-values. JB = Jarque Bera and LB = Ljung Box. LB statistics are reported up to 10 lags.

On the whole, the risk-returns relationship is positive for all sample series under consideration. The volatility measures are more than a hundred times larger than the mean values. All returns series exhibit a positive skewness and are also leptokurtic. This automatically leads to the violation of the normality assumption as exhibited by the Jarque-Bera (JB) statistics. The results imply that all the sample markets are not informationally efficient. There is also strong evidence of volatility clustering in sample series, indicating the need for a greater analysis of the second moment. The Ljung-Box (LB) test confirms no autocorrelation in the level of sample series up to 10 lags, with the exception of NYMEX, MCXSPOT and SPOT, while all variables indicate significant autocorrelation in squared terms.

2.5.1 Tests of Stationarity and Price Discovery Process

Stationarity conditions of the oil futures-spot price series expressed in logarithmic form are tested by conventional ADF, PP and KPSS tests (see Table 2.2).

Table 2.2: Unit Root Results

	ADF		PP		KPSS	
Variables	**Level**	**First Difference**	**Level**	**First Difference**	**Level**	**First Difference**
Futures prices						
ICE	-2.213	-43.971**	-2.061	-44.082**	0.202	0.060**
MCX	-2.045	-41.899**	-2.029	-41.900**	0.204	0.061**
NYMEX	-2.259	-43.947**	-2.088	-44.110**	0.201	0.060**
Spot prices						
MCXSPOT	-2.181	-44.173**	-2.047	-44.252**	0.202	0.061
SPOT	-2.258	-43.496**	-2.213	-43.503**	0.201	0.055
Critical Values						
1%	-3.963				0.216	
5%	-3.412				0.146	
10%	-3.128				0.119	

Note: ** indicates the level of significance at 1% and better.

All the unit root tests clearly confirm the existence of a unit root at level and exhibit stationarity at first difference for all oil price series. Table 2.3 shows the results of Johansen and Juselius (1992) test of co-integration and indicates that all sample oil price series exhibit a long-run relationship, confirming the strong informational linkages between spot and futures as well as between futures prices of the examined sample trading platforms.

Table 2.3: Johansen Co-integration Results

Trace Test					**Maximum Eigen Value Test**			
Null	Alternative	Statistics	95% Critical Value		Null	Alternative	Statistics	95% Critical Value
Co-integration between ICE and SPOT								
r=0	r>=1	317.806**	25.872		r=0	r=1	313.19**	19.387
r<=1	r>=2	4.614	12.518		r<=1	r=2	4.614	12.518
r<=2	r>=3				r<=2	r=3		

Co-integration between MCX and MCXSPOT								
r=0	r>=1	258.953**	25.872		r=0	r=1	254.78**	19.387
r<=1	r>=2	4.167	12.518		r<=1	r=2	4.167	12.518
r<=2	r>=3				r<=2	r=3		
Co-integration between NYMEX and SPOT								
r=0	r>=1	278.88**	25.872		r=0	r=1	274.09**	19.387
r<=1	r>=2	4.782	12.517		r<=1	r=2	4.782	12.517
r<=2	r>=3				r<=2	r=3		
Co-integration between ICE and NYMEX								
r=0	r>=1	252.167**	15.494		r=0	r=1	248.64**	14.264
r<=1	r>=2	3.517	3.841		r<=1	r=2	3.517	3.841
r<=2	r>=3				r<=2	r=3		
Co-integration between ICE and MCX								
r=0	r>=1	150.53**	25.872		r=0	r=1	146.94**	19.387
r<=1	r>=2	3.596	12.517		r<=1	r=2	3.596	12.517
r<=2	r>=3				r<=2	r=3		
Co-integration between NYMEX and MCX								
r=0	r>=1	167.92**	25.872		r=0	r=1	164.36**	19.387
r<=1	r>=2	3.558	12.517		r<=1	r=2	3.558	12.517
r<=2	r>=3				r<=2	r=3		

Notes: a) * indicates level of significance at 1%, based of which order of integration is chosen.
b) The lag structure is decided based on the minimum values of the Akaike information criterion.

Table 2.4 shows the VECM results. The EC, which is also called the speed of adjustment co-efficient β_i, is shown in the table. The results indicate that between spot and futures prices of all sample markets, the speed of adjustment co-efficient β_2 appears to be greater in spot than in the futures market, indicating that when the co-integrated series is in disequilibrium in the short-run, it is the spot price (cash market) that makes a greater adjustment than the futures price (futures market) to restore the equilibrium. In other words, futures price leads the spot price in the price discovery process. From an investment strategy perspective, the significantly negative EC term for spot series implies that spot prices are over-valued in most sample markets. However, only in the case of NYMEX spot positive numbers are reported implying that the spot prices in these markets are relatively undervalued. The information provides market traders an incentive to sell/short-sell oil in spot and buy oil futures and exercise lending options to make arbitrage profits. Such an arbitrage process could be the reason for a long-run equilibrium relationship between spot and futures prices in these markets as confirmed by the co-integration results. The causality test reconfirms our findings of an observable bilateral causality between all sample futures and spot prices, which is stronger from the former to the latter. In sum, oil futures prices help in the discovery of oil spot prices.

In the cross-market analysis, a long-run equilibrium relationship is confirmed between futures prices of all sample markets; there are significant EC terms for all futures series with the exception of ICE/NYMEX, thereby implying that any departures from the equilibrium are significant. Based on the magnitude of EC co-efficient and its statistical significance, it can be therefore inferred that among all three futures markets, it is the ICE that leads NYMEX and MCX futures markets in price discovery process. In other words, ICE futures prices assimilate new information quicker than NYMEX and MCX. Strikingly, in the case of NYMEX and MCX futures prices, speed of adjustment is by and large the same, indicating that MCX is efficiently getting integrated with global trading platforms in the case of oil. From a global investor's perspective, it seems that the ICE futures is relatively over-valued owing their representation by a considerably negative coefficient. Hence, the arbitrage process may involve selling ICE futures and buying NYMEX futures to reap short-term profits. Moreover, the causality tests provide a reconfirmation that ICE seems to be a dominant platform in the crude oil price discovery process, followed by NYMEX and then MCX.

Table 2.4: Estimated Co-efficient of the VECM

Commodity	Co-efficient	Commodity	Co-efficient
$\beta_{1(ice/spot)}$	-0.048	$\beta_{2(spot/ice)}$	-0.35
	[-0.893]		[-6.367]**
$\beta_{1(mcx/mcxspot)}$	-0.102	$\beta_{2(mcxspot/mcx)}$	-0.499
	[-1.869]		[-11.242]**
$\beta_{1(nymex/spot)}$	0.285	$\beta_{2(spot/nymex)}$	-0.767
	[2.918]**		[-7.959]**
$\beta_{1(ice/nymex)}$	-0.133	$\beta_{2(nymex/ice)}$	-0.834
	[-1.091]		[-6.959]**
$\beta_{1(ice/mcx)}$	-0.146	$\beta_{2(mcx/ice)}$	-0.333
	[-2.068]**		[-5.436]**
$\beta_{1(nymex/mcx)}$	-0.257	$\beta_{2(mcx/nymex)}$	-0.244
	[-4.072]**		[-4.472]**

Note: values in parentheses [ ] show t-values. ** denotes the level of significance at 1% and better.

The price discovery results of VECM are further substantiated by the Granger causality results (see Table 2.5). The results indicate a bidirectional causal relationship between spot and futures prices of sample oil markets with stronger causality moving from futures to spot, indicating that futures price leads the spot price in the price discovery process. However, among three oil trading platforms prices analyzed pairwise, it appears that ICE strongly Granger causes NYMEX and MCX as the magnitude of F-statistics of ICE is found to be higher than of MCX and NYMEX. Between NYMEX and MCX, NYMEX has a stronger Granger causality to MCX, implying that in the international oil market, ICE futures prices assimilate new market information faster than NYMEX and MCX for price discovery.

Table 2.5: Granger Causality Results

Null Hypothesis:			F-Statistic	Prob.
ICE	$\nrightarrow$	SPOT	22.131**	[0.000]
SPOT	$\nrightarrow$	ICE	6.195**	[0.000]
MCXSPOT	$\nrightarrow$	MCX	4.071**	[0.003]
MCX	$\nrightarrow$	MCXSPOT	323.977**	[0.000]
SPOT	$\nrightarrow$	NYMEX	6.777**	[0.000]
NYMEX	$\nrightarrow$	SPOT	21.704**	[0.000]
MCX	$\nrightarrow$	ICE	2.077**	[0.043]
ICE	$\nrightarrow$	MCX	37.700**	[0.000]
NYMEX	$\nrightarrow$	ICE	6.464**	[0.000]
ICE	$\nrightarrow$	NYMEX	27.671**	[0.000]
MCX	$\nrightarrow$	NYMEX	4.258**	[0.000]
NYMEX	$\nrightarrow$	MCX	28.902**	[0.000]

Note: $\nrightarrow$ shows null hypothesis does not Granger Cause. Values in parentheses are p-values. ** denotes the level of significance at 5% and better.

2.5.2 Volatility Spillovers Process

The estimated results of GARCH-BEKK model to examine the volatility spillovers among sample countries are shown in Table 2.6 (Panel A to F). The volatility spillover results between ICE futures and its SPOT, shown in Panel (A), confirm that there is an ARCH effect only in the case of SPOT. This implies that past innovations of SPOT prices have a significant and positive impact on the current SPOT volatility. Turning to cross-volatility spillover effects in the short-run, the results indicate that there are bilateral volatility spillovers between ICE and SPOT prices, with a stronger volatility spillover moving from ICE futures to SPOT. It may be noted that in the case of ICE, the past innovations in spot prices positively impact the current futures price volatility, while in the case from futures to spot it is exactly the opposite. With respect to long-term effects of ICE futures and spot, the results indicate that there is a strong evidence of volatility persistence, implying that there is a observable GARCH effect in the case of futures and spot. This further means that the past volatility of current futures/spot prices impacts the current volatility futures/spot significantly. Surprisingly, volatility persistence appears to be stronger in futures compared to spot. Turning to cross-market long-term volatility spillovers, the results indicate that there are bilateral volatility spillovers between spot and futures with stronger volatility spillover moving from futures to spot. It may here be noted that unlike the short-term, the past volatility of SPOT impacts the current volatility of futures (ICE) negatively, while impacting futures price volatility and spot price volatility positively.

Similarly, in the case of MCX in the short-run, the spillover results indicate that there is no ARCH effect in futures and spot prices. While there is a unilateral volatility spillover moving from futures to spot, the spillover appears to be negative, implying that the past innovations in the futures market impact the current spot market inversely in the short-term. With respect to long-term spillovers, the results indicate strong evidence of volatility persistence in the case of futures and spot prices. The results imply that the past volatility of futures and spot impact their current futures and spot considerably. Strikingly, there appears to be no long-term cross-market volatility spillovers between spot and futures prices in the case of MCX. With respect to NYMEX (see Panel C), the results indicate that there is a positive short-term clustering in the case of SPOT prices. Surprisingly, there is no cross-market spillover, implying that in the short-term, it is only the SPOT market that bears the impact of past innovations in the market. Turning to long-term volatility spillovers, the results indicate no evidence of volatility persistence. However, there is a negative volatility spillover moving from futures to spot, while the inverse is not found.

In sum, we confirm a bilateral volatility spillover between ICE futures and spot in both futures as well as spot in the long-run, which is stronger from the former to the latter. Further, a unilateral volatility spillover from futures to spot is confirmed for MCX in the short-term and for NYMEX only in the long-term. Thus, the oil futures seem to have a destabilizing effect on spot prices, which should be of concern to policy makers and regulators.

With respect to futures markets volatility spillovers involving futures prices, we start with ICE and NYMEX results. We find that there are no significant own as well as cross-market spillovers in the short-term (see Panel D). The long-term volatility spillover results show high volatility persistence in the case of both ICE and NYMEX. This implies that the past volatility of ICE and NYMEX impact their current volatility considerably. With respect to cross-market spillovers, the results indicate only a one-way volatility spillover moving from NYMEX to ICE. This is in contrast to price discovery results, particularly the Granger causality results which indicate ICE as the lead market. The results of volatility spillovers have strong implications as it indicates that the past volatility of NYMEX impacts current volatility of ICE futures prices. However, the results of ICE and MCX (see Panel E) indicate that in the short-term, there is a strong evidence of volatility clustering in both ICE and MCX futures prices. The results of short-term cross-market volatility spillovers indicate that there is a one-way spillover moving from MCX to ICE. In the long-term, the results indicate that there is a strong evidence of high volatility persistence in the case of ICE and MCX, implying that there are significant impacts of past volatility on current volatility for ICE and MCX futures prices. Turning to cross-market volatility spillovers, the results indicate that there is a unilateral volatility spillover moving from ICE to MCX. The long-term results are in line with price discovery results indicating the dominance of ICE over MCX. Lastly, we analyze the spillover results for MCX and NYMEX. The results indicate that in the short-run, own volatility spillovers are high for MCX while for NYMEX this is not the case. With respect to short-term cross-market volatility spillovers, the results indicate negative and unilateral volatility spillovers moving from NYMEX to MCX. The negative volatility spillover co-efficient shows that the past innovations of NYMEX indicate the current volatility of MCX significantly. Turning to long-term results, it appears that there is strong evidence of volatility persistence in both markets, implying that there is an impact of past volatility of futures prices on the current volatility of futures prices. With respect to cross-market volatility, the results indicate that there is a unilateral volatility spillover moving from MCX to NYMEX. The results imply that in contrast to the short-term, in the long-term, past volatility of MCX appears to have a stronger impact on the current volatility of NYMEX.

To summarize, we can say that the volatility spillover results are more or less in line with price discovery results. Turning to cross-market volatility spillover, there is a case of unilateral volatility spillover in each market, implying that the information flow across markets is not symmetric. However, there is also a substantial finding of the evidence of strong volatility persistence in most of the sample markets. This implies that own volatility spillover is stronger than the cross-market spillovers. The possible explanation could be due to domestic reasons, such as longer trading hours, presence of more noise traders than value traders and regulatory regimes, which could have strong bearing on the market. However, the spot and futures market results indicate that it is the futures price that assimilates new information quicker than the spot prices in each sample market with the exception of MCX. Turning to cross-market volatility spillovers, the results indicate that between ICE and NYMEX, the volatility spillover of NYMEX appears to have a stronger effect on ICE. Similarly, in the case of ICE and MCX, the spillover impact of MCX is stronger in the short-term, while in the long-term ICE dominates MCX. Additionally, MCX futures price volatility impacts NYMEX futures price volatility. Also, NYMEX seems to be the dominant market vis-à-vis ICE, while the latter is a more dominant platform in the price discovery process.

Turning to constant and time-varying dynamic conditional correlations, the results of CCC model suggest that there is strong correlation between each pair of markets. But based on the magnitude of correlations, it appears that the correlation is high between NYMEX and its SPOT (0.974) and is significant followed by ICE and its SPOT (0.934) and MCX and its MCXSPOT (0.544). With respect to cross-market correlations, the results indicate the high correlation between ICE and NYMEX (0.954) followed by ICE and MCX (0.839) and MCX and NYMEX (0.807). The CCC model provides interesting results. MCX futures exhibit greater association with the international counterpart exchanges then its local spot market. This implies that emerging market platforms like MCX exhibit a greater integration with international markets than at the domestic level. This may be due to the nature of oil as an international commodity and the possible market microstructure differences between futures and spot markets, making the former more informationally linked to each other than to their cash counterpart. Turning to DCC results, the estimated coefficients of $\theta(1)$ and $\theta(2)$ are high in each case except ICE in case of SPOT and MCX in case of MCXSPOT.

Table 2.6: MGARCH Results

Panel A. ICE-SPOT

Variables	BEKK		CCC		DCC	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
μ_1	0.032	[0.951]	0.062	[2.248] *	0.053	[2.097] *
μ_2	0.032	[1.093]	0.061	[2.409] *	0.051	[2.218] *
$c_{(1,1)}$	0.037	[1.259]	0.039	[2.505] *	0.037	[2.175] *
$c_{(2,1)}$	-0.133	[-1.884]				
$c_{(2,2)}$	0.001	[0.002]	0.047	[2.285] *	0.042	[2.021] *
$\alpha_{(1,1)}$	-0.105	[-1.339]	0.079	[3.248] *	0.086	[2.013] *
$\alpha_{(1,2)}$	-0.656	[-6.492]*				
$\alpha_{(2,1)}$	0.215	[2.705] *				
$\alpha_{(2,2)}$	0.584	[5.191] *	0.107	[2.682] *	0.108	[2.213] *
$\beta_{(1,1)}$	1.186	[53.072] *	0.869	[22.399] *	0.855	[13.571] *
$\beta_{(1,2)}$	0.647	[5.021] *				
$\beta_{(2,1)}$	-0.212	[-9.201] *				
$\beta_{(2,2)}$	0.325	[2.394] *	0.832	[14.318] *	0.822	[11.065] *
$\rho_{(2,1)}$			0.934	[78.323] *		
$\theta_{(1)}$					0.019	[0.884]
$\theta_{(2)}$					0.565	[8.372] *
Log likelihood	-2459.49		-2618.61		-2596.76	

Panel B. MCX-SPOT

Variables	BEKK		CCC		DCC	
	Coeff	t-Stat	Coeff	t-Stat	Coeff	t-Stat
μ_1	0.030	[1.379]	0.039	[1.693]	0.037	[1.521]
μ_2	0.027	[1.283]	0.036	[1.651]	0.041	[1.777]
$c_{(1,1)}$	0.123	[1.827]	0.021	[3.32] *	0.021	[3.523] *
$c_{(2,1)}$	-0.135	[-1.613]				
$c_{(2,2)}$	0.013	[0.143]	0.034	[1.759]	0.033	[2.265] *
$\alpha_{(1,1)}$	0.185	[1.510]	0.056	[4.22] *	0.059	[4.587] *
$\alpha_{(1,2)}$	-0.219	[-2.034]*				
$\alpha_{(2,1)}$	0.031	[0.353]				
$\alpha_{(2,2)}$	0.224	[1.885]	0.102	[2.44] *	0.108	[3.443] *
$\beta_{(1,1)}$	0.971	[23.27] *	0.919	[59.14] *	0.918	[56.56] *
$\beta_{(1,2)}$	0.104	[1.679]				
$\beta_{(2,1)}$	-0.002	[-0.064]				
$\beta_{(2,2)}$	0.909	[14.27] *	0.862	[15.48] *	0.861	[21.31] *
$\rho_{(2,1)}$			0.544	[27.56] *		
$\theta_{(1)}$					0.056	[4.10] *
$\theta_{(2)}$					0.399	[1.877]
Log likelihood	-4198.67		-4200.06		-4192.02	

Panel C. NYMEX-SPOT

Variables	BEKK		CCC		DCC	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
μ_1	0.021	[0.539]	0.021	[0.529]	0.026	[0.977]
μ_2	0.025	[0.724]	0.023	[0.537]	0.029	[1.024]
$c_{(1,1)}$	0.932	[20.510]*	0.074	[2.638]*	0.040	[3.047]*
$c_{(2,1)}$	0.927	[23.319]*				
$c_{(2,2)}$	0.000	[-0.006]	0.077	[2.511]*	0.042	[2.858]*
$\alpha_{(1,1)}$	0.318	[1.281]	0.285	[3.372]*	0.189	[6.397]*
$\alpha_{(1,2)}$	-0.408	[-1.291]				
$\alpha_{(2,1)}$	0.029	[0.132]				
$\alpha_{(2,2)}$	0.641	[2.389]*	0.301	[3.633]*	0.190	[5.036]*
$\beta_{(1,1)}$	-0.493	[-1.541]	0.666	[11.52]*	0.728	[35.35]*
$\beta_{(1,2)}$	-1.139	[-3.069]*				
$\beta_{(2,1)}$	0.489	[0.912]				
$\beta_{(2,2)}$	1.087	[1.783]	0.651	[10.315]*	0.721	[23.17]*
$\rho_{(2,1)}$			0.974	[252.50]*		
$\theta_{(1)}$					0.083	[1.250]
$\theta_{(2)}$					0.640	[0.000]
Log likelihood	-1527.9		-1896.8		-1929.4	

Panel D. ICE-NYMEX

Variables	BEKK		CCC		DCC	
	Coeff	**t-stats**	**Coeff**	**t-stats**	**Coeff**	**t-stats**
μ_1	0.000	[0.010]	0.086	[2.671] *	0.004	[2.525] *
μ_2	0.003	[0.092]	0.084	[2.595] *	0.006	[1.995]*
$c_{(1,1)}$	0.119	[1.006]	0.028	[1.749]	0.026	[92.4] *
$c_{(2,1)}$	-0.069	[-0.919]				
$c_{(2,2)}$	0.000	[0.000]	0.029	[1.631]	0.027	[207.8] *
$\alpha_{(1,1)}$	0.061	[0.537]	0.072	[1.646]	0.063	[215.2] *
$\alpha_{(1,2)}$	-0.072	[-0.652]				
$\alpha_{(2,1)}$	-0.046	[-0.448]				
$\alpha_{(2,2)}$	-0.111	[-0.970]	0.084	[1.616]	0.076	[985.2] *
$\beta_{(1,1)}$	-0.650	[-2.662]*	0.891	[19.15] *	0.891	[816.8] *
$\beta_{(1,2)}$	-0.367	[-0.829]				
$\beta_{(2,1)}$	1.586	[7.305] *				
$\beta_{(2,2)}$	1.324	[3.144] *	0.878	[15.50] *	0.875	[142.1] *
$\rho_{(2,1)}$			0.954	[77.86] *		
$\theta_{(1)}$					0.041	[-0.048]
$\theta_{(2)}$					0.959	[2.210] *
Log likelihood	-2270.08		-2341.50		-2234.50	

Panel E. ICE-MCX

Variables	**BEKK**		**CCC**		**DCC**	
	Coeff	**t-stat**	**Coeff**	**t-stat**	**Coeff**	**t-stat**
μ_1	0.038	[2.032]*	0.045	[1.970]	0.046	[1.896]
μ_2	0.023	[1.234]	0.045	[1.799]	0.037	[1.424]
$c_{(1,1)}$	0.198	[5.142]*	0.012	[1.807]	0.019	[2.46] *
$c_{(2,1)}$	0.062	[1.287]				
$c_{(2,2)}$	0.000	[0.000]	0.014	[2.593] *	0.016	[2.788] *
$\alpha_{(1,1)}$	0.470	[5.091] *	0.058	[2.839] *	0.087	[4.401] *
$\alpha_{(1,2)}$	0.051	[0.476]				
$\alpha_{(2,1)}$	0.215	[2.896] *				
$\alpha_{(2,2)}$	0.190	[2.355] *	0.058	[2.890] *	0.079	[4.77] *
$\beta_{(1,1)}$	0.901	[19.20] *	0.926	[32.76] *	0.890	[35.9] *
$\beta_{(1,2)}$	0.104	[2.152] *				
$\beta_{(2,1)}$	0.032	[0.535]				
$\beta_{(2,2)}$	0.897	[21.40] *	0.925	[41.37] *	0.903	[52.51] *
$\rho_{(2,1)}$			0.839	[66.80] *		
$\theta_{(1)}$					0.058	[3.23] *
$\theta_{(2)}$					0.927	[40.12] *
Log likelihood	-3285.44		-3359.80		-3307.27	

Panel F. NYMEX-MCX

Variables	BEKK		CCC		DCC	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
μ_1	0.027	[1.429]	0.058	[2.104] *	0.034	[1.388]
μ_2	0.035	[2.051]*	0.055	[2.548] *	0.032	[1.380]
$c_{(1,1)}$	0.084	[2.106] *	0.016	[2.129] *	0.017	[2.208] *
$c_{(2,1)}$	0.231	[8.418] *				
$c_{(2,2)}$	0.000	[-0.001]	0.015	[2.058] *	0.022	[2.076] *
$\alpha_{(1,1)}$	0.155	[1.655]	0.050	[3.158] *	0.079	[3.881] *
$\alpha_{(1,2)}$	-0.272	[-4.25] *				
$\alpha_{(2,1)}$	-0.002	[-0.013]				
$\alpha_{(2,2)}$	0.589	[7.342] *	0.060	[2.787] *	0.099	[3.262] *
$\beta_{(1,1)}$	0.909	[26.29] *	0.929	[50.24] *	0.905	[46.91] *
$\beta_{(1,2)}$	0.062	[1.097]				
$\beta_{(2,1)}$	0.089	[2.034] *				
$\beta_{(2,2)}$	0.839	[16.58] *	0.919	[34.21] *	0.878	[26.47] *
$\rho_{(2,1)}$			0.807	[55.29] *		
$\theta_{(1)}$					0.097	[2.481] *
$\theta_{(2)}$					0.877	[18.45] *
Log likelihood	-3392.56		-3496.68		-3433.39	

Note: Models estimated using QMLE with robust (heteroskedasticity/misspecification) standard errors. μ_i denotes the mean equation coefficients. In the variance equations, c denotes the constant terms, α denotes the ARCH terms and β denotes the GARCH terms. The coefficient α_{12} for example can be interpreted as the short-term volatility spillover moving from ICE futures to its SPOT in Panel, rest of the panels are also interpreted in the same manner, respectively. While, β_{12} represents the long-term volatility spillover from ICE to SPOT for is interpreted in the same manner as above. * denotes the level of significance at 5% and better for panels A to F, respectively.

2.5.3 Dynamic Conditional Correlations

Fig. 2.3 shows the time-varying DCCs. The results between futures and spot prices of sample markets indicate an evidence of volatility clustering in each case. However, there appears to be stronger volatility clustering in the case of MCX. For the DCC patterns in the case of ICE and SPOT, the magnitude of correlation coefficients are high (0.90), indicating a strong evidence of co-movement. Similar DCC patterns are also seen in the case of NYMEX and SPOT. In the case of MCX, the DCCs are high and range from 0.10 to 0.80. DCCs of within markets indicate that until 2008 there was not much variation in correlations. However, there appears to be a strong variation in correlations around October 2008 then it further shoots up around June 2009. Seemingly, there is again a fall in correlation around October 2010 then it went up again afterwards, indicating a strong impact of the global financial crisis and Eurozone turmoil. Turning to cross-market volatility spillovers, there is not much variation in DCC in the case of ICE and NYMEX, but there are apparent ups and downs in DCC for ICE and MCX and for NYMEX and MCX. The magnitudes of DCC among the three pairs range from 0.20 to 0.90. The correlation patterns of ICE and NYMEX are in tandem within market correlations. The correlation patterns for ICE and MCX and for MCX and NYMEX reached low values around March 2007, October 2008 and October 2010, but there is a sudden jump in the magnitude of correlation co-efficients such that it reaches up to 0.90. This implies that during crisis period, DCCs are generally lower and increase significantly afterwards. The possible reasons could be because of a sudden fall in demand during the crisis period. This could have caused economies to be bottomed out and demands to be resurged thereby leading to a closer co-movement between alternative oil markets (see Sadorsky, 2012). Given in June 2012 to October 2012, there is again a drop in DCC, as can be observed from the graph. To conclude, one can say that there is a clear trend in the DCC patterns of examined markets during a crisis event and normally the correlations appear to be higher afterwards. Finally, the diagnostic tests find that for the standardized residuals and its squared values it exhibit no evidence of serial correlation at the 1% level across all the models applied (see Table 2.7).

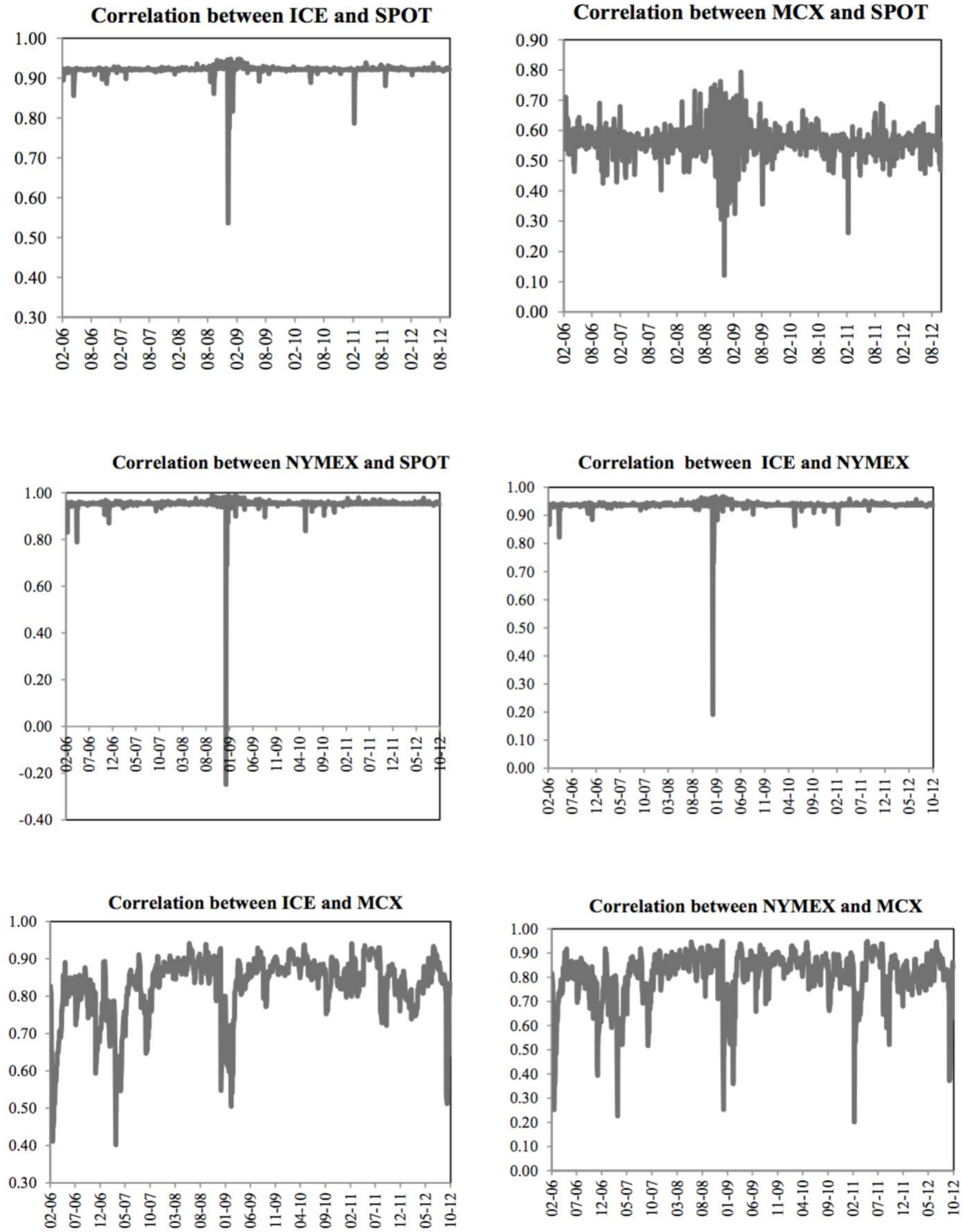

Figure 2.3: Time –varying conditional correlations from the DCC model

Table 2.7: Diagnostic Tests for Standardized Residuals

	BEKK		CCC		DCC	
	$Q_{(20)}$	$Q_{sqr(20)}$	$Q_{(20)}$	$Q_{sqr(20)}$	$Q_{(20)}$	$Q_{sqr(20)}$
ICE/SPOT	24.818	24.365	27.179	24.995	27.449	25.141
	[0.209]	[0.227]	[0.130]	[0.202]	[0.123]	[0.196]
ICE/NYMEX	23.836	28.986	25.222	28.706	25.502	28.781
	[0.250]	[0.088]	[0.193]	[0.094]	[0.183]	[0.092]
ICE/MCX	31.081	23.874	28.183	21.664	28.347	21.365
	[0.054]	[0.248]	[0.105]	[0.359]	[0.101]	[0.376]
MCX/SPOT	18.018	21.008	17.685	19.667	17.651	19.569
	[0.586]	[0.480]	[0.608]	[0.620]	[0.610]	[0.620]
NYMEX/MCX	23.470	26.219	19.869	32.436	19.446	32.973
	[0.266]	[0.131]	[0.466]	[0.039]	[0.493]	[0.034]
NYMEX/SPOT	26.614	30.618	19.431	15.623	19.313	15.413
	[0.113]	[0.080]	[0.494]	[0.740]	[0.502]	[0.752]

2.6 Conclusion

This chapter examines the price discovery and volatility spillovers between spot and futures and between futures prices of three markets viz., ICE, MCX and NYMEX. The results confirm the existence of price discovery between spot and futures and among sample futures markets. Between spot and futures, the futures price leads the spot price in price discovery process, implying that futures prices assimilate new market information faster than spot in all sample markets. This result is in contrast to the findings of Goyal and Tripathi (2012). In the results of futures prices of the three markets analyzed pairwise, we find that ICE is a more dominant market, followed by NYMEX and MCX in terms of price discovery. Causality test results further confirm a two-way information transmission between spot and futures markets exists, which is stronger from the former to the later. Between futures markets, two-way information linkages exist which are stronger from ICE to NYMEX, ICE to MCX and NYMEX to MCX. The volatility spillover results indicate that it is the futures price that assimilates new information quicker than spot in each sample market with the exception of MCX. Turning to cross-market volatility spillovers, the results show that between ICE and NYMEX, the volatility spillover of NYMEX appears to have a stronger effect on ICE. Similarly in the case of ICE and NYMEX, the spillover impact of MCX is stronger in the short-term, while in the long-term ICE dominates MCX. Apparently, between NYMEX and MCX, in the short-term, NYMEX has a stronger spillover than MCX, while in the long-term there are opposite results. It may be noted that in terms of volatility spillovers, NYMEX appears to be the dominant market, while ICE and MCX appear to be equally competing markets, which is in line with the findings of Spargoli and Zagaglia (2007). The CCC model results show a strong co-movement between ICE futures, NYMEX futures and their spot platforms. Interestingly, for MCX, the cross-market association (between futures prices) seems to be much stronger than within market association (between spot and futures), thus implying that emerging market platforms for oil are more integrated with their international exchanges than with domestic spot markets. The DCC results confirm that there are stronger cross-market associations; however, weaker within market associations during economic crisis periods. These within market associations seem to become stronger for stable periods.

The research has strong implications for policy makers as well as market traders. The mature market trading platforms like ICE and NYMEX seem to be dominant with regard to information dissemination on oil trading vis-à-vis emerging market platforms like MCX, which clearly appears to be a satellite market. ICE seems to play a leadership role in the international oil price discovery process. Hence, a price quote of ICE for WTI crude should be used as a pricing benchmark by world economies, including India. As expected, futures markets for oil seem to be more informationally efficient than the spot market. From a risk management perspective NYMEX seems to take the lead in the information transmission relating to return volatility. Furthermore, since international futures prices seem to be more correlated with each other than with the corresponding spot prices; this confirms the international nature of oil as a commodity. Finally, oil market integration seems to be stronger during stable phases than during crisis periods, which may have policy implications for global oil trade.

The futures market volatility does have some destabilizing implications for spot prices, thus indicating that crude prices may be affected by speculative activity besides the demand-supply fundamentals and tax regimes. Therefore, the market trades may exploit any departures from equilibrium in the short-run by developing appropriate arbitrage strategies.

The present study contributes to commodity market literature, especially that which deals with information linkages between mature and emerging market platforms and focuses on the little explored area of information linkages between mature and emerging market platforms. The study is particularly relevant, given the strategic importance of oil in the global economy.

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3. Asset Portfolio Optimization using Analytical Hierarchy Process and Multi-choice Goal Programming

Abstract

Drawing on our understanding of market linkages, in the present chapter, a model of portfolio optimization is developed. Real-life portfolio selection problems seem complex in nature. In fact, the conflicts of objectives and the incompleteness of available information make it almost impossible for investors to build a reliable mathematical model to represent their preferences by considering a single aspiration level for each goal. Also, in some situations, investors want to make a decision about a problem, with a goal that can be achieved from specific aspiration levels (i.e., one goal mapping many aspiration levels). To overcome this difficulty, the present study integrates analytic hierarchy process (AHP) and multi-choice goal programming (MCGP) as a decision aid to obtain an optimal asset allocation that better suits the preferences of investors, according to their needs. This study obtains weights from the AHP and implements them for each goal using MCGP for the asset allocation problem. According to the function of multi-aspiration provided by MCGP, investors can set multi-aspirations for each goal to find the optimal asset allocation. The advantage of the proposed integrated AHP-MCGP approach is that it allows investors to indicate multiple aspiration levels for each goal. A real-life portfolio selection problem is considered to validate the usefulness of the proposed approach.

3.1 Introduction

The asset portfolio selection involves obtaining optimal proportions of the assets to construct a portfolio that respects investor preferences. Portfolio selection as a field of study began with the Markowitz model (1952), in which return is quantified as the mean and risk as the variance. Konno and Yamazaki (1991) used absolute deviation and Speranza (1993) used semi-absolute deviation to measure risk in portfolio selection. All these formulations are based on the assumption that investors have complete information for decision making. However, in reality, the information is often incomplete and hence decisions are made with uncertainty. Moreover, financial markets are also affected by the vagueness and ambiguity associated with the use of linguistic expressions (Sheen, 2005) such as “high risk,” “low profit,” and “low liquidity” by investors and investment experts. Portfolio selection formulations have benefited greatly from the fuzzy set theory (FST) (Zadeh, 1965) in terms of integrating quantitative and qualitative information, the subjective preferences of the investors and the knowledge of the experts.

A review of the literature on the applications of FST in portfolio selection shows that a variety of approaches are being used. Ammar (2008) discussed the fuzzy portfolio optimization problem within a convex quadratic programming framework. Bilbao-Terol et al. (2006) applied fuzzy compromise programming to portfolio selection. Chen and Huang (2009) presented a portfolio selection model with fuzzy returns and risks. Fei (2007) studied optimal consumption and portfolio choice under the conditions of ambiguity and anticipation. Hasuike et al. (2009) considered portfolio selection models involving probabilistic future returns with ambiguous expected returns assumed as random fuzzy variables. Huang (2007a, 2007b) proposed portfolio selection models that involved stochastic return rates with fuzzy information and return rates containing both randomness and fuzziness. A new definition of risk was used by Huang (2008) for portfolio selection in a fuzzy environment. Jana et al. (2009) studied the multiobjective possibilistic model of portfolio selection considering transaction cost and using entropy for portfolio diversification. Li and Xu (2009) proposed a portfolio selection model in a hybrid uncertain environment considering the return of each asset as a fuzzy random variable. Lin and Liu (2008) developed portfolio selection models with minimum transaction lots using a fuzzy multiobjective decision-making approach. Qin et al. (2009) presented portfolio selection models in which cross-entropy was used to define diversity and solved these models in a fuzzy environment. Tiryaki and Ahlatcioglu (2009) used a fuzzy analytic hierarchy process in portfolio selection to provide both ranking and weighting information to the investors. Vercher et al. (2007) studied fuzzy portfolio selection models to minimize the downside risk constrained by a given expected return. Vercher (2008) proposed models for portfolio selection in which returns on the assets were considered fuzzy numbers and obtained optimal portfolios using semi-infinite programming in a soft framework. Zhang et al. (2007) proposed portfolio selection models that were based on lower and upper possibilistic means and possibilistic variances, respectively. Zhang (2007) discussed portfolio selection problem using upper and lower possibilistic means and variances for bounded assets while considering uncertain returns of the risky assets as fuzzy numbers. Zhang et al. (2009) used interval-valued possibilistic means and possibilistic variance in portfolio selection.

The aforementioned studies of portfolio selection considered return and risk as the two fundamental factors that govern investors' choice. However, it is often found that not all the information relevant to portfolio selection can be captured in terms of only return and risk. Other considerations/criteria might be of equal, if not greater, importance to investors. By considering these in the portfolio selection model, it may be possible to obtain portfolios in which the deficit on account of the return and risk criteria is more than compensated by portfolio performance on other criteria, resulting in greater overall satisfaction for investors. There are studies that consider criteria other than return and risk, e.g., Ehrgott et al. (2004), Fang et al. (2006), Gupta et al. (2008, 2010, 2011, 2012).

A common limitation of all the studies reviewed thus far is that they were based on a single aspiration level for each objective. However, in real-life investments, investors are interested in indicating multiple aspiration levels. In our view, portfolio selection models can be substantially improved by incorporating multiple aspiration levels for each goal (i.e., one goal mapping multiple aspiration levels). By allowing investors to indicate multiple aspiration levels, we can avoid underestimations in decision making. For example, setting multiple aspiration levels for financial goals can avoid neglecting the still suitable assets that may be omitted due to the strict single aspiration level. To the best of our knowledge, there is no research on incorporating multiple aspiration levels into portfolio selection.

The purpose of this chapter is to incorporate multiple aspiration levels into portfolio selection. It may be noted that aspirations pertaining to financial investments are rooted, inter alia, in expectations about the real sectors underlying the financial assets. Implicit is the assumption that the dynamics of the markets for the real sectors are imputed in the behavior of the assets representing them. Thus, the risk-return measures of the assets and the portfolio constructed from them broadly capture our understanding of commodity markets and their linkages. Toward this aim, an integrated method of analytical hierarchy process and multi-choice goal programming (AHP-MCGP) is proposed to solve portfolio selection problems. First, AHP is used to calculate the relative weight of the four criteria, namely, short-term return, long-term return, risk and liquidity, for a given investor type. Then, using these relative weights for each goal and considering realistic constraints regarding the portfolio selection, a MCGP model is formulated and solved to obtain optimal asset allocation. A brief discussion of the goals follows.

For portfolio return, we consider short-term return (average performance of the asset during a 12-month period) and long-term return (average performance of the asset during a 36-month period). This is done in order to capture the subjective preferences of the investors for portfolio return. For a given expected return, the investor penalizes negative semi-absolute deviation, which is defined as portfolio risk. Liquidity is considered in terms of the probability of conversion of an investment into cash (turnover) without any significant loss in value.

Some advantages of the proposed integrated AHP-MCGP approach are as follows:

1. The AHP-MCGP allows investors to set multiple financial goals corresponding to their requirements.
2. Each financial goal can be cut to multiple aspiration levels to better suit human perceptions such as "the more the better" or "the less the better." With the flexibility of this function, AHP-MCGP will help to find the asset allocation that is closest to the investor's requirements.
3. AHP-MCGP is more realistic, compact and easily implemented in decision making as a simple mathematical problem.

The chapter is organized as follows. In Section 3.2, we present a multiobjective programming model of portfolio selection. In Section 3.3, we describe our research methodology. In Section 3.4, a real-life portfolio selection problem is considered to show the effectiveness and applicability of the proposed methodology. This section also includes a discussion of the results obtained. Finally, in Section 3.5, we present our concluding observations.

3.2 The Portfolio Selection Problem

In this section, we formulate a portfolio selection problem as an optimization problem with multiple objectives. We assume that investors allocate their wealth among n assets offering random rates of return. We introduce some notation as follows:

r_i : the expected return of the i-th asset,

x_i : the proportion of total funds invested in the i-th asset,

y_i : the binary variable indicating whether the i-th asset is contained in the portfolio or not, i.e.,

$$y_i = \begin{cases} 1, & \text{if } i\text{-th asset is contained in the portfolio} \\ 0, & \text{otherwise} \end{cases}$$

r_i^{12} : the average 12-month performance of the i-th asset,

r_i^{36} : the average 36-month performance of the i-th asset,

r_{it} : the historical return of the i-th asset over the past period t,

u_i : the maximal fraction of the capital budget allocated to the i-th asset,

l_i : the minimal fraction of the capital budget allocated to the i-th asset.

3.2.1 Objectives

- **Short-term return**

The short-term return of the portfolio is expressed as follows:

$$f_1(x) = \sum_{i=1}^{n} r_i^{12} x_i,$$

where $r_i^{12} = \dfrac{1}{12}\sum_{i=1}^{12} r_{it}$, $i = 1,2,\ldots,n$.

- **Long-term return**

The long-term return of the portfolio is expressed as follows:

$$f_2(x) = \sum_{i=1}^{n} r_i^{36} x_i,$$

where $r_i^{36} = \dfrac{1}{36}\sum_{i=1}^{36} r_{it}$, $i = 1,2,\ldots,n$.

- **Risk**

The semi-absolute deviation of return of the portfolio below the expected return over the past period t , $t = 1,2,\ldots,T$ can be expressed as

$$w_t(x) = \left| \min\left\{ 0, \sum_{i=1}^{n} (r_{it} - r_i)x_i \right\} \right| = \frac{\left| \sum_{i=1}^{n} (r_{it} - r_i)x_i \right| + \sum_{i=1}^{n} (r_i - r_{it})x_i}{2} .$$

Therefore, the expected semi-absolute deviation of return of the portfolio $x = (x_1, x_2, ..., x_n)$ below the expected return becomes

$$f_3(x) = w(x) = \frac{1}{T}\sum_{t=1}^{T} w_t(x) = \sum_{t=1}^{T} \frac{\left| \sum_{i=1}^{n} (r_{it} - r_i)x_i \right| + \sum_{i=1}^{n} (r_i - r_{it})x_i}{2T} .$$

We use $w(x)$ to measure portfolio risk.

- **Liquidity**

For any asset, liquidity may be measured with the help of the turnover rate defined as the ratio between the average stock traded on the market and the tradable stock (shares held by public) of that asset (Gupta et al., 2008). The liquidity of the portfolio is expressed as follows:

$$f_4(x) = \sum_{i=1}^{n} L_i x_i$$

3.2.2 Constraints

- Capital budget constraint on the assets:

$$\sum_{i=1}^{n} x_i = 1 .$$

- Maximal fraction of the capital that can be invested in a single asset:

$$x_i \le u_i y_i ,\ i = 1, 2, ..., n .$$

- Minimal fraction of the capital that can be invested in a single asset:

$$x_i \ge l_i y_i ,\ i = 1, 2, ..., n .$$

The maximal and minimal fractions of the capital budget allocated to the various assets in the portfolio depend on a number of factors. For example, one may consider price/value relative of the asset vis-à-vis the average of the price/value of all the assets in the chosen portfolio, the minimal lot size that can be traded on the market, the past behavior of the price/volume of the asset, information available about the issuer of the asset and trends in the industry of which it is a part. In other words, investors refer to a host of fundamental and technical analysis factors affecting the company and the industry. Because investors differ in their interpretations of the available information, they may allocate the same overall capital budget differently. The constraints corresponding to lower bounds l_i and upper bounds u_i on the investment in individual assets $(0 \le l_i, u_i \le 1, l_i \le u_i, \forall i)$ are included to avoid a large number of very small investments (lower bounds) and, at the same time, to ensure a sufficient diversification of the investment (upper bounds) (Gupta et al., 2008, 2010).

- Number of assets held in a portfolio:

$$\sum_{i=1}^{n} y_i = h$$

where h is the number of assets that the investor chooses to include in the portfolio. Of all the assets from a given set, the investor would pick up the ones that are likely to yield the desired satisfaction of his preferences. It is not necessary that all the assets from a given set are configured into the portfolio. Investors differ with respect to the number of assets that they can effectively manage in a portfolio (Gupta et al., 2008, 2010).

- No short selling of assets:

$$x_i \ge 0, \quad i = 1, 2, \ldots, n.$$

3.2.3 The Decision Problem

The constrained multiobjective portfolio selection problem is formulated as follows:

$$\text{(P1)} \qquad \max f_1(x) = \sum_{i=1}^{n} r_i^{12} x_i$$

$$\max f_2(x) = \sum_{i=1}^{n} r_i^{36} x_i$$

$$\min f_3(x) = w(x) = \sum_{t=1}^{T} \frac{\left| \sum_{i=1}^{n} (r_{it} - r_i) x_i \right| + \sum_{i=1}^{n} (r_i - r_{it}) x_i}{2T}$$

$$\max f_4(x) = \sum_{i=1}^{n} L_i x_i$$

subject to $$\sum_{i=1}^{n} x_i = 1, \tag{3.1}$$

$$\sum_{i=1}^{n} y_i = h, \tag{3.2}$$

$$x_i \le u_i y_i, \quad i = 1,2,...,n, \tag{3.3}$$

$$x_i \ge l_i y_i, \quad i = 1,2,...,n, \tag{3.4}$$

$$x_i \ge 0, \quad i = 1,2,...,n, \tag{3.5}$$

$$y_i \in \{0,1\}, \quad i = 1,2,...,n. \tag{3.6}$$

In order to eliminate the absolute-valued function in (P1), we transform the problem into the following form:

(P2) $$\max f_1(x) = \sum_{i=1}^{n} r_i^{12} x_i$$

$$\max f_2(x) = \sum_{i=1}^{n} r_i^{36} x_i$$

$$\min f_3(p) = w(p) = \frac{1}{T} \sum_{t=1}^{T} p_t$$

$$\max f_4(x) = \sum_{i=1}^{n} L_i x_i$$

subject to $$p_t + \sum_{i=1}^{n} (r_{it} - r_i) x_i \ge 0, \quad t = 1,2,...,T,$$

$$p_t \ge 0, \quad t = 1,2,...,T,$$

and Constraints (3.1)-(3.6).

The problem (P2) is a multiobjective linear programming problem. There are several efficient methods to solve this problem.

3.3 The Proposed Integrated AHP-MCGP Method

This study integrates AHP and MCGP as a new method to solve the problem of asset allocation. The AHP method with a pair-wise comparison technique is used to measure the relative weights of each goal. Using these weights as coefficients of the goals in the objective function of MCGP, we can easily obtain the optimal asset allocation. First of all, we use AHP approach to obtain the relative weights of each goal. Second, the MCGP method is utilized to obtain the optimal asset allocation.

3.3.1 Modeling Relative Weights of Goals via AHP

We measure the relative weight of each goal per investor preferences using AHP. The first step in the process of AHP is to define the various asset allocation goals. Second, the opinions of investors are collected by face-to-face interviews and then their judgment is drawn up into a matrix of pair-wise comparisons between individual asset allocation goals using a nine-point (1-9) scale. Third, the normalization of the geometric mean method is used to determine the relative weight of each goal. Finally, the consistency of the matrix is checked by calculating the Consistency Ratio (Saaty, 2000).

3.3.2 Portfolio Selection Model based on Multi-choice Goal Programming

Here, we formulate a multiobjective portfolio selection problem based on multiple aspiration levels of investors to determine a satisfying portfolio selection strategy. We assume that investors indicate multiple aspiration levels.

- **Multi-choice goal programming**

Goal programming (GP) is an analytical multiple objective decision-making approach designed to address decision-making problems in which targets have been assigned to all attributes and where the decision-makers are interested in minimizing the non-achievement of a particular goal (Liao, 2009). GP was first introduced by Charnes and Cooper (1961) and was further developed using various types of methods, such as Lexicographic GP, Weighted GP and MINMAX GP. (Romero, 2001). GP can be expressed as follows:

$$\min \quad \sum_{i=1}^{n} w_i (d_i^+ + d_i^-)$$

$$\text{subject to} \quad f_i(x) - d_i^+ + d_i^- = g_i, \quad i = 1, 2, \ldots, n,$$

$$d_i^+, d_i^- \geq 0, \quad i = 1, 2, \ldots, n,$$

$$x \in F,$$

where w_i is the weight attached to the i-th goal; F is a feasible set; x is an element of F ; $f_i(x)$ is the linear function of the i-th goal; g_i is the aspiration level of the i-th goal; d_i^+ and d_+^- are the positive and negative deviation attached to the i-th goal $| f_i(x) - g_i |$.The above model is a multiple goal model.

Although GP is capable of handling decision problems involving multiple goals, if these goals can be achieved from some aspiration levels, it becomes a MCGP problem (Chang, 2007). The MCGP allows the decision-maker to set multi-choice aspiration levels for each goal to avoid the underestimation of the decision. The rapid development of MCGP has led to an enormous diversity in models and methods. However, few studies have explored using MCGP to address real-life problems, such as supplier selection and location selection, that involve conflicts of criteria. In fact, the conflicts between criteria and the incompleteness of information make it very difficult for decision-makers to build a reliable mathematical model for the representation of their preference.

According to Chang (2007), a MCGP problem can be stated in the following model:

$$\min \sum_{i=1}^{n} w_i \mid f_i(x) - g_{i1} \text{ or } g_{i2} \text{ or } \ldots \text{or } g_{im} \mid$$

subject to $x \in F$ (F is a feasible set)

where g_{ij} $(i = 1, 2, \ldots, n; j = 1, 2, \ldots., m)$ is the j-th aspiration level of the i-th goal, $g_{ij-1} \leq g_{ij} \leq g_{ij+1}$; all other variables are defined as in GP.

The MCGP can be expressed by the following mixed binary achievement function:

$$\min \quad \sum_{i=1}^{n} w_i \left(d_i^+ + d_i^- \right)$$

subject to $f_i(x) - d_i^+ + d_i^- = \sum_{j=1}^{m} g_{ij} S_{ij}(B)$, $i = 1,2,...,n,$ (3.7)

$d_i^+, d_i^- \geq 0,\ i = 1,2,...,n,$

$x \in F$ (F is a feasible set),

where $S_{ij}(B)$ represents a function of binary serial number attached to multi-choice aspiration levels, g_{ij}; other variables are defined as in GP. The above model involves multiplicative terms of binary variables on the right-hand side of equation (3.7), which makes it difficult to implement when the problem size gets large and it is not easily understood by industrial participants.

In order to solve the problem of multiplicative terms of binary variables on the right-hand side of equation (3.7), a new idea of upper $(g_{i,\max})$ and lower $(g_{i,\min})$ bounds of the i-th aspiration level, y_i, was introduced by Chang (2008), where y_i is the continuous variable $g_{i,\min} \leq y_i \leq g_{i,\max}$. In other words, Chang (2008) employed a continuous variable, y_i, with a range of interval values to replace multiplicative terms of the binary variable, $\sum_{j=1}^{m} g_{ij} S_{ij}$, with a range of discrete values on the right-hand side of equation (3.7). The MCGP can be reformulated as the following two alternative MCGP-achievement functions (Chang, 2008):

The first case, "the more the better," is formulated as

$$\min \quad \sum_{i=1}^{n} w_i(d_i^+ + d_i^-) + \alpha_i(e_i^+ + e_i^-)$$

subject to $f_i(x) - d_i^+ + d_i^- = y_i$, $i = 1,2,...,n,$ (3.8)

$y_i - e_i^+ + e_i^- = g_{i,\max}$, $i = 1,2,...,n,$ (3.9)

$g_{i,\min} \leq y_i \leq g_{i,\max},$

$d_i^+, d_i^-, e_i^+, e_i^-,\ i = 1,2,...,n,$

$x \in F$ (F is a feasible set),

where d_i^+ and d_i^- are the positive and negative deviations attached to the i-th goal $|f_i(x)-y_i|$ in equation (3.8); e_i^+ and e_i^- are the positive and negative deviations attached to $|y_i - g_{i,\max}|$ in equation (3.9); α_i is the weight attached to the sum of the deviation of $|y_i - g_{i,\max}|$; all other variables are defined as in MCGP.

The second case, "the less the better," is formulated as

$$\min \quad \sum_{i=1}^{n} w_i(d_i^+ + d_i^-) + \alpha_i(e_i^+ + e_i^-)$$

$$\text{subject to} \quad f_i(x) - d_i^+ + d_i^- = y_i, \; i = 1,2,\ldots,n, \tag{3.10}$$

$$y_i - e_i^+ + e_i^- = g_{i,\min}, \; i = 1,2,\ldots,n, \tag{3.11}$$

$$g_{i,\min} \le y_i \le g_{i,\max},$$

$$d_i^+, d_i^-, e_i^+, e_i^-, \; i = 1,2,\ldots,n,$$

$$x \in F \quad (F \text{ is a feasible set}),$$

where d_i^+ and d_i^- are the positive and negative deviations attached to the i-th goal $|f_i(x)-y_i|$ in equation (3.10); e_i^+ and e_i^- are the positive and negative deviations attached to $|y_i - g_{i,\min}|$ in equation (3.11); α_i is the weight attached to the sum of the deviation of $|y_i - g_{i,\min}|$; all other variables are defined as in MCGP.

Based on the above discussion, we formulate the multi-choice portfolio selection problem as

$$\text{(P3)} \quad \min w_1(d_1^- + e_1^-) + w_2(d_2^- + e_2^-) + w_3(d_3^+ + e_3^+) + w_4(d_4^- + e_4^-)$$

$$\text{subject to} \quad \sum_{i=1}^{n} r_i^{12} x_i - d_1^+ + d_1^- = y_1, \tag{3.12}$$

$$y_1 - e_1^+ + e_1^- = r_{\max}^{12}, \tag{3.13}$$

$$r_{\min}^{12} \le y_1 \le r_{\max}^{12},$$

$$\sum_{i=1}^{n} r_i^{36} x_i - d_2^+ + d_2^- = y_2, \tag{3.14}$$

$$y_2 - e_2^+ + e_2^- = r_{\max}^{36}, \tag{3.15}$$

$$r_{\min}^{36} \le y_2 \le r_{\max}^{36},$$

$$\sum_{t=1}^{T} \frac{\left|\sum_{i=1}^{n}(r_{it} - r_i)x_i\right| + \sum_{i=1}^{n}(r_i - r_{it})x_i}{2T} - d_3^+ + d_3^- = y_3, \tag{3.16}$$

$$y_3 - e_3^+ + e_3^- = r_{\min}^{risk}, \tag{3.17}$$

$$r_{\min}^{risk} \le y_3 \le r_{\max}^{risk},$$

$$\sum_{i=1}^{n} L_i x_i - d_4^+ + d_4^- = y_4, \tag{3.18}$$

$$y_4 - e_4^+ + e_4^- = L_{\max}, \tag{3.19}$$

$$L_{\min} \le y_4 \le L_{\max},$$

$$d_1^+, d_1^-, d_2^+, d_2^-, d_3^+, d_3^-, d_4^+, d_4^-, e_1^+, e_1^-, e_2^+, e_2^-, e_3^+, e_3^-, e_4^+, e_4^-,$$

and Constraints (3.1)-(3.6),

where d_1^+ and d_1^- are the positive and negative deviations attached to the short-term return goal $\left|\sum_{i=1}^{n} r_i^{12} x_i - y_1\right|$ in equation (3.12); e_1^+ and e_1^- are the positive and negative deviations attached to $|\, y_1 - r_{\max}^{12} \,|$ in equation (3.13); w_1 is the weight attached to the sum of the deviation of $\left|\sum_{i=1}^{n} r_i^{12} x_i - y_1\right|$ and $|\, y_1 - r_{\max}^{12} \,|$, d_2^+ and d_2^- are the positive and negative deviations attached to the long-term return goal $\left|\sum_{i=1}^{n} r_i^{36} x_i - y_2\right|$ in equation (3.14); e_2^+ and e_2^- are the positive and negative deviations attached to $|\, y_2 - r_{\max}^{36} \,|$ in equation (3.15); w_2 is the weight attached to the sum of the deviation of $\left|\sum_{i=1}^{n} r_i^{36} x_i - y_2\right|$ and $|\, y_2 - r_{\max}^{36} \,|$; d_3^+ and d_3^- are the positive and negative deviations attached to the risk goal $\left|\sum_{t=1}^{T}\frac{\left|\sum_{i=1}^{n}(r_{it}-r_i)x_i\right|+\sum_{i=1}^{n}(r_i-r_{it})x_i}{2T}-y_3\right|$ in equation (3.16); e_3^+ and e_3^- are the positive and negative deviations attached to $|\, y_3 - r_{\min}^{risk}\,|$ in equation (3.17); w_3 is the weight attached to the sum of the deviation of $\left|\sum_{t=1}^{T}\frac{\left|\sum_{i=1}^{n}(r_{it}-r_i)x_i\right|+\sum_{i=1}^{n}(r_i-r_{it})x_i}{2T}-y_3\right|$ and $|\, y_3 - r_{\min}^{risk}\,|$; d_4^+ and d_4^- are the positive and negative deviations attached to the liquidity goal $\left|\sum_{i=1}^{n}Lx_i - y_4\right|$ in equation (3.18); e_4^+ and e_4^- are the positive and negative deviations attached to $|\, y_4 - L_{\max}\,|$ in equation (3.19); w_4 is the weight attached to the sum of the deviation $\left|\sum_{i=1}^{n}L_i x_i - y_4\right|$ and $|\, y_4 - L_{\max}\,|$.

It may be noted that the values of $r_{\min}^{12}, r_{\max}^{12}$, $r_{\min}^{36}, r_{\max}^{36}$, $r_{\min}^{risk}, r_{\max}^{risk}$ and $L_{\min}$, $L_{\max}$ may be given by the decision-maker based on his/her experience or may be obtained by solving the following single goal portfolio problem as follows:

$$r_{\min}^{12} = \min\sum_{i=1}^{n} r_i^{12}x_i, \text{ subject to Constraints (3.1)-(3.6).} \tag{3.20}$$

$$r_{\max}^{12} = \max\sum_{i=1}^{n} r_i^{12}x_i, \text{ subject to Constraints (3.1)-(3.6).} \tag{3.21}$$

$$r_{\min}^{36} = \min\sum_{i=1}^{n} r_i^{36}x_i, \text{ subject to Constraints (3.1)-(3.6).} \tag{3.22}$$

$$r_{\max}^{36} = \max\sum_{i=1}^{n} r_i^{36}x_i, \text{ subject to Constraints (3.1)-(3.6).} \tag{3.23}$$

$$r_{\min}^{risk} = \min\sum_{t=1}^{T}\frac{\left|\sum_{i=1}^{n}(r_{it}-r_i)x_i\right|+\sum_{i=1}^{n}(r_i-r_{it})x_i}{2T}, \text{ subject to Constraints(3.1)-(3.6).} \tag{3.24}$$

$$r_{\max}^{risk} = \max \sum_{t=1}^{T} \frac{\left| \sum_{i=1}^{n} (r_{it} - r_i) x_i \right| + \sum_{i=1}^{n} (r_i - r_{it}) x_i}{2T}, \text{ subject to Constraints (3.1)-(3.6).} \quad (3.25)$$

$$L_{\min} = \min \sum_{t=1}^{T} L_i x_i, \text{ subject to Constraints (3.1)-(3.6).} \quad (3.26)$$

$$L_{\max} = \max \sum_{t=1}^{T} L_i x_i, \text{ subject to Constraints (3.1)-(3.6).} \quad (3.27)$$

It is important to mention that, in order to solve the models proposed in equation (3. 24) and equation (3. 25), we eliminate the absolute-valued function on the same line as discussed in Section 3.2.3.

3.3.3 Research Framework

Fig. 1 illustrates the detailed procedure of the proposed integrated AHP-MCGP approach for the portfolio selection problem.

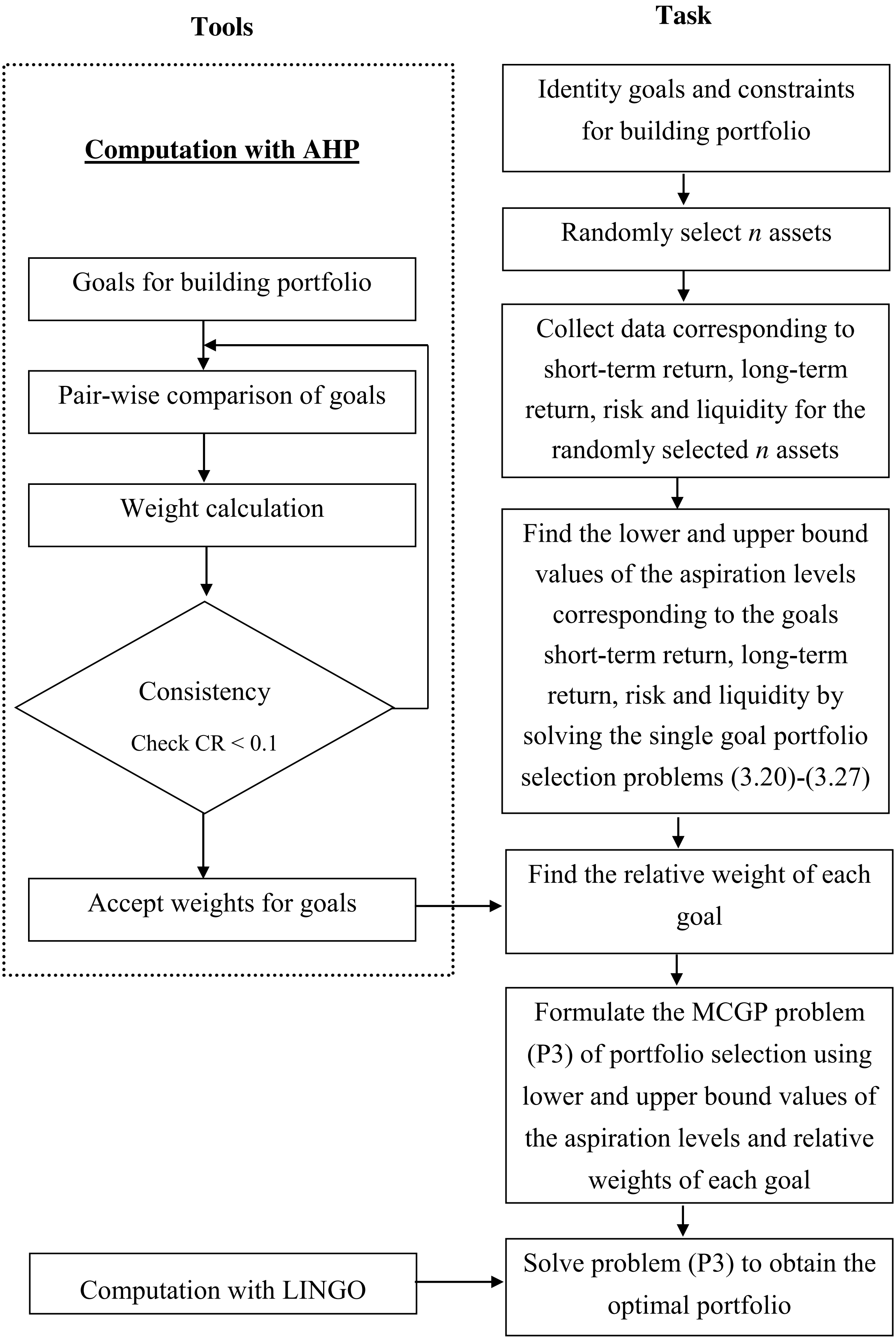

Figure 3.1: An integrated AHP-MCGP procedure for portfolio selection

3.4 Numerical Illustration: Results and Analysis

To demonstrate the usefulness of the proposed AHP-MCGP approach for portfolio selection, a real-life empirical study done for the imaginary investor on the data set extracted from the National Stock Exchange (NSE), Mumbai, India, is provided here. We have selected 20 assets listed on the NSE to form a population from which we attempt to construct portfolios.

3.4.1 Calculation of AHP Weights

In the AHP computation, we consider three types of investors, namely, return seekers, safety seekers and liquidity seekers. The reason for considering three types of investors is based on the understanding of investor behavior provided by Gupta et al. (2010). The relative weights of the four criteria, i.e., short-term return, long-term return, risk and liquidity, for the three types of investors are provided in Tables 3.1-3.3. Because the value of CR is less than 0.1 for all the three cases, the judgments are acceptable.

Table 3.1: Pair-wise Comparison Matrix of the Four Criteria for Return Seekers

	Short-term return	Long-term return	Risk	Liquidity	Weights
Short-term return	1	0.5	2	3	0.27714
Long-term return	2	1	3	4	0.46582
Risk	0.5	0.33333	1	2	0.16107
Liquidity	0.33333	0.25	0.5	1	0.09597

CI = 0.01316, RI = 0.89, CR = 0.01479

Table 3.2: Pair-wise Comparison Matrix of the Four Criteria for Safety Seekers

	Short-term return	Long-term return	Risk	Liquidity	Weights
Short-term return	1	0.5	0.33333	2	0.17067
Long-term return	2	1	0.5	2	0.25962
Risk	3	2	1	3	0.44952
Liquidity	0.5	0.5	0.33333	1	0.12019

CI = 0.02778, RI = 0.89, CR = 0.03121

Table 3.3: Pair-wise Comparison Matrix of the Four Criteria for Liquidity Seekers

	Short-term return	Long-term return	Risk	Liquidity	Weights
Short-term return	1	0.5	1	0.5	0.16468
Long-term return	2	1	1	0.5	0.23413
Risk	1	1	1	0.33333	0.17460
Liquidity	2	2	3	1	0.42659

CI = 0.02822, RI = 0.89, CR = 0.03171

3.4.2 Asset Allocation

The 20 financial assets form the population from which we attempt to construct a portfolio comprising 8 assets. The reason for constructing a portfolio of 8 assets is based on the understanding of investor behavior provided a survey that shows that portfolio diversification by investors lies in the narrow range of 3-10 assets (Gupta et al., 2005). Table 3.4 provides the data corresponding to expected short-term return, expected long-term return, risk and liquidity. It may be noted that the average returns used in this study are the average of the averages, that is, the average monthly returns. The monthly returns are based on the daily returns. We use the average 36-month performance of the asset as the expected return in the calculations. Liquidity of the assets is measured using the respective turnover rates.

Using the data given in Table 3.4, we solve the single goal portfolio problems (3.20)-(3.27) to obtain the lower bound value $r_{\min}^{12}$ and upper bound value $r_{\max}^{12}$ for the short-term return goal; the lower bound value $r_{\min}^{36}$ and upper bound value $r_{\max}^{36}$ for the long-term return goal; the lower bound value $r_{\min}^{risk}$ and upper bound value $r_{\max}^{risk}$ for the risk goal; and the lower bound value $L_{\min}$ and upper bound value $L_{\max}$ for the liquidity goal. Table 3.5 presents the computational results

Table 3.4: Input Data of Assets

Data	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
Expected short-term	0.17377	0.16111	0.20249	0.09481	0.35012	0.28332	0.14264	0.17333	0.08511	019311
Expected long-term	0.19278	0.21366	0.21711	0.19819	0.40086	0.30831	0.27858	0.27477	017133	017985
Risk	0.13233	0.15847	0.17308	0.17779	0.26506	0.23237	0.21806	0.19649	017385	0.12945
Liquidity	0.00040	0.00051	0.00070	0.00078	0.00228	0.00140	0.00508	0.00500	0.00078	0.00037

Data	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20
Expected short-term	0.24057	0.15152	0.12064	0.32033	0.08501	0.06110	0.27495	0.18855	0.18030	0.39583
Expected long-term	0.29892	0.29428	0.26969	0.34734	0.23776	0.27098	0.30107	0.29633	0.36700	0.30120
Risk	0.19205	0.20298	0.16236	0.24781	0.20088	0.18182	0.17323	0.17112	0.21188	0.16652
Liquidity	0.00040	0.00056	0.00113	0.00123	0.00103	0.00204	0.00072	0.00064	0.00064	0.00051

Table 3.5: The Lower-Upper Bound Solution Payoff Matrix

	$r^{12}_{\min}$	$r^{12}_{\max}$
Short-term return	0.07583	0.34449
	$r^{36}_{\min}$	$r^{36}_{\max}$
Long-term return	0.18228	0.36896
	$r^{risk}_{\min}$	$r^{risk}_{\max}$
Risk	0.0837161	0.24493
	$L_{\min}$	$L_{\max}$
Liquidity	0.00041	0.00418

We now present the computational results.

- **Case 1 for return seekers**

We incorporate the relative weights and lower and upper bound values of the four criteria, i.e., short-term return, long-term return, risk and liquidity, from Table 3.1 and Table 3.5, respectively, into the model (P3) to identify the optimal allocation. For this purpose, the model is coded and solved using LINGO 12.0 software (Schrage, 2006) on a Pentium dual-core 1.40 GHz computer with 3 GB RAM. The computational result is summarized in Table 3.6. Table 3.7 presents the proportions of the assets in the obtained portfolio.

- **Case 2 for safety seekers**

We incorporate the relative weights and lower and upper bound values of the four criteria from Table 3.2 and Table 3.5, respectively, into the model (P3) to identify the optimal allocation. The computational result is summarized in Table 3.6. Table 3.7 presents the proportions of the assets in the obtained portfolio.

- **Case 3 for liquidity seekers**

We incorporate the relative weights and lower and upper bound values of the four criteria from Table 3.3 and Table 3.5, respectively, into the model (P3) to identify the optimal allocation. The computational result is summarized in Table 3.6. Table 3.7 presents the proportions of the assets in the obtained portfolio.

Table 3.6: Summary Results of Portfolio Selection for Case 1, Case 2 and Case 3

Cases	Objective values																			
	Short-term return	Long-term return	Risk	Liquidity	d_1^+	d_1^-	d_2^+	d_2^-	d_3^+	d_3^-	d_4^+	d_4^-	e_1^+	e_1^-	e_2^+	e_2^-	e_3^+	e_3^-	e_4^+	e_4^-
Case 1	0.34097	0.34800	0.22706	0.00136	0	0.003523	0	0.02097	0.014334	0	0	0.00282	0	0	0	0	0	0	0	0
Case 2	0.33956	0.34201	0.21930	0.00128	0	0.00493	0	0.01269	0.13558	0	0	0.00290	0	0	0	0	0	0	0	0
Case 1	0.24767	0.32364	0.22003	0.00183	0	0.09682	0	0.04532	0.13631	0	0	0.00235	0	0	0	0	0	0	0	0

Table 3.7: The Proportions of the Assets in Obtained Portfolios for Case 1, Case 2 and Case 3

	Assets									
	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
Case 1	0	0	0.02	0	0.35	0.025	0	0	0	0
Case 2	0	0	0.02	0	0.34431	0	0	0	0	0.026
Case3	0	0	0.02	0	0.4	0	0	0	0	0
	Assets									
	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20
Case 1	0.04	0	0	0.27862	0	0	0.023	0	0.01	0.25338
Case 2	0.04	0	0	0.21351	0	0	0.03218	0	0.024	0.3
Case 3	0.04	0	0	0.19585	0	0.27915	0.023	0.032	0.01	0

A comparison of the solutions for the three cases listed in Table 3.6 highlights that, if investors are return seekers, they will obtain a higher level of expected return in comparison to liquidity seekers and safety seekers, but this finding supposes a higher risk level. If investors are safety seekers, they will obtain a lower level of risk in comparison to liquidity seekers and return seekers, but this finding supposes accepting a medium level of expected return. If investors are liquidity seekers, they will obtain a higher level of liquidity in comparison to return seekers and safety seekers, but this finding supposes a lower return level.

The previous analysis of the various decision situations from the standpoint of investor preferences demonstrates that the portfolio selection models developed in this chapter discriminate between investor types. Thus, it is possible to construct portfolios with reference to the diversity of investor preferences.

3.5 Conclusion

In real-life portfolio selection, problems are complex in nature. In fact, the conflicts of objectives and the incompleteness of available information make it almost impossible for investors to build a reliable mathematical model for representation of their preferences by considering a single aspiration level for each goal. Also, in some situations, investors would like to make a decision on the problem, with a goal that can be achieved from some specific aspiration levels (i.e., one goal mapping many aspiration levels). In order to overcome this problem, the present study developed the AHP-MCGP method to assist investors in finding an optimal asset allocation according to their preferences in terms of the aspiration levels. Using AHP, we have measured the relative weights of the four criteria, namely, short-term return, long-term return, risk and liquidity, for a given investor type. These relative weights are then implemented into each goal using MCGP for the portfolio selection problem. With different investment purposes, investors can set multiple aspiration levels for each financial goal using MCGP to find the most suitable asset allocation.

Compared with previous methods, the main advantage of the proposed method is that it not only provides flexibility to the investors to describe their preferences, but it also can set multiple goals with multiple aspiration levels corresponding to the investors' requirements. Setting multiple aspiration levels for financial goals can avoid neglecting the still suitable assets that may be omitted due to the strict single aspiration level. The flexibility of incorporating multiple aspiration levels into portfolio selection problems can be viewed as a decision aid to help investors achieve better asset allocations.

The findings of this chapter highlights the ability of the proposed portfolio selection approach in yielding optimal portfolios based on the understanding of commodity markets and their linkages.

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Curriculum Vitae (CV)

Education:

2010-2013	**UNIVERSITY OF ST. GALLEN** Doctoral Studies in *Finance*	**ST GALLEN, SWITZERLAND**
2008-2010	**UNIVERSITY OF ST. GALLEN** Masters in *Banking and Finance*	**ST GALLEN, SWITZERLAND**
2004-2008	**STANFORD UNIVERSITY** Bachelor of Science degree *in Economics*	**STANFORD, CALIFORNIA**

Experience:

From 2013	**APEEJAY STYA GROUP** Member Management Board	**NEW DELHI, INDIA**
Summers' 2011, 2012	**APEEJAY STYA GROUP** Financial Analyst	**NEW DELHI, INDIA**
Summer 2008	**APEEJAY EDUCATION SOCIETY** Primary Field Auditor	**NEW DELHI, INDIA**
Summer 2007	**INVESTMENT BANK – ING VYASA** Financial Analyst – Emerging Corporate Department	**NEW DELHI, INDIA**
2005-2008	**STANFORD UNIVERSITY** Research Assistant – Dept. of Psychology / Dept. of Economics	**STANFORD, CALIFORNIA**
Summers' 2005- 2006	**MARTIN AND HARRIS LTD** System Analyst	**NEW DELHI, INDIA**

Publications:

Savani, K., Markus, H. R., Naidu, N. V. R., Kumar, S., & Berlia, N. (2010). What counts as a choice? US Americans are more likely than Indians to construe actions as choices. *Psychological Science*, 21 (3), 391-398.

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Sehgal, S., Berlia, N., & Ahmad, W. (2013). An Examination of Price Discovery and Volatility Spillovers of Crude Oil in Globally Linked Commodity Markets. *International Journal of Economics and Finance*, *5* (5), 15.

Personal:

Fluent in Hindi and English. Won national awards in India for horse riding (Dressage and show jumping) as well as won awards in the United States in Equestrian Championships as a part of Stanford Equestrian Team. Won national award in Indian Instrument Sarod in year 2002, 2003, 2005. Enjoy playing Tennis.