Essays on Indian Commodity Derivative Market: A Macro-Finance Perspective

Dissertation submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy in Economics of Jadavpur University, Kolkata

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2023

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Certified that the Thesis entitled ***Essays on Indian Commodity Derivative Market: A Macro-Finance Perspective*** submitted by me for the award of the degree of Doctor of Philosophy in Arts at Jadavpur University is based upon my work carried out under the supervision of Dr. Saikat Sinha Roy, Professor, Department of Economics, Jadavpur University, Kolkata, and neither this thesis nor any part of this thesis has been submitted before for any degree or diploma anywhere/elsewhere.

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Rudra Prosad Roy

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Overview

1.1 Introduction

This thesis is a collection of essays investigating into various linkages between the commodity[1] derivative[2] market and the macroeconomy in India. The literature on the commodity derivative market and that on the joint behaviour of the financial market and the macroeconomy have evolved over time, leading to an expansion of the horizon with newer dimensions. It is often argued in the literature that commodity markets have been playing a key role in transmitting shocks internationally by connecting commodity-importing countries to commodity exporters. The commodity prices provide valuable information about the behaviour of market participants, thereby revealing the market's expectations about the future financial and economic condition. These characteristics of the commodity derivative market have been attracting macroeconomists, financial economists, along with policymakers, especially the central bankers.

The derivatives market contributes fundamentally to the improvement of financial infrastructure in an economy by linking cash markets, hedgers, and speculators (Lien & Zhang 2008). In an economy, financial derivatives play different roles. First, financial derivatives products are widely used as a hedge against

[1] A commodity can be defined as "an intermediate good with a standard quality, which can be traded on competitive and liquid global international physical markets" (Clark et al. 2001).

[2] A derivative is defined as "a financial instrument whose value depends on (or derives from) the values of other, more basic underlying variables" (Hull 2002).

various types of risks (Hammoudeh & McAleer 2013). Second, the derivatives markets play an important role in price discovery (Chance & Brooks 2015). More precisely, forward and futures markets contribute to improving the predictability of asset returns as they contain information about future spot prices. Third, as against the cash market or the spot market, the derivatives market has various operational and structural characteristics that provide several advantages such as lower transaction costs, higher liquidity, and ease of short selling (Chance & Brooks 2015). Last, the presence of derivatives trading improves the efficiency of the market (Chen et al. 2005), where a market is said to be efficient if the price reveals all the available information.

By nature, commodities differ from conventional financial assets in the following ways. First, unlike other financial assets, commodity prices and price volatilities show pronounced seasonality. Second, the term structure of commodity forward price volatility is found to decline with an increase in contract horizon. This phenomenon is commonly known as "Samuelson effect" (Samuelson 1965) [3],[4]. However, the Samuelson effect may not hold if inventory is high (Fama & French 1988). Third, a number of commodities cash and futures prices, are found to be mean reverting[5],[6]. Fourth, commodity futures prices often show backwardation in which they decline with time-to-delivery. This implies that rather than deferred

[3]See, for example, Bessembinder et al. (1996), Duong & Kalev (2008), Mukherjee & Goswami (2017), among others.

[4]For Indian commodity derivative market, Gupta & Rajib (2012) find some mixed evidence. They show that for the majority of the commodities the "Samuelson effect" does not hold and thus suggests that the investors in the Indian commodity market should rely more on trading volume and open interest as determinants of price volatility and less on time-to-maturity while taking their decisions.

[5]The mean reversion theory states that after an extreme price movement, commodity prices tend to return back to the normal or average or long term level.

[6]See, Gibson & Schwartz (1990), Brennan (1989), Cortazar & Schwartz (1994), Bessembinder et al. (1995), Schwartz (1997), Schwartz & Smith (2000), among others.

ownership of a commodity or a long position in a commodity forward, immediate ownership of physical capital brings about some benefits. These said benefits expressed as a rate is called the convenience yield (Hull 2002). Fifth, commodity prices are exceedingly heteroskedastic (see, Duffie & Gray 1995, among others) and there is a positive correlation between price volatility and the degree of backwardation (see, for example, Ng & Pirrong 1994; Litzenberger & Rabinowitz 1995, among others). Sixth, the valuation of commodity contingent claims is different from the valuation of conventional financial contracts as the commodities are directly consumed and also used in the production processes as inputs. Seventh, storage is another characteristic which distinguishes commodities from other non-traditional assets. All these distinguishing characteristics of commodities influence commodity price behaviour and, in turn, its linkage with different macroeconomic indicators including output and inflation.

With storage, there is a potential for an inter-temporal shift of supply in response to relative scarcity. Moreover, on account of storage, the convenience yield plays an important role, along with the interest rate and the storage cost, in explaining the relationship between spot and forward prices. A large number of studies[7] focus on the economics of storage and the behaviour of commodity prices.

Earlier literature attempted to study the commodity market mainly from either pure macroeconomic perspective or pure finance perspective. In the traditional macroeconomic perspective, different macro-econometric approaches have been adopted to investigate into the role of commodity prices in the macroecon-

[7] See, Gustafson (1958*a*), Gustafson (1958*b*); Samuelson (1971), Lucas Jr & Prescott (1971); Williams et al. (1991), Deaton & Laroque (1992), Deaton & Laroque (1996), Lucas Jr & Prescott (1971); Chambers & Bailey (1996), Routledge et al. (2000), among others.

omy. In these studies, commodity spot prices have been primarily used. This strand of literature usually emphasizes a strong relationship between commodity spot prices, particularly crude oil prices, and different macroeconomic indicators. In these studies[8], it is commonly established that crude oil price shocks did trigger economic recessions in the Post World War II period.

A number of studies demonstrated that the "Price Puzzle", the phenomenon of rising price level following an exogenous contractionary monetary policy, may disappear if commodity prices are included in macroeconometric models (see, Sims 1992; Eichenbaum 1992, among others)[9]. As a result, commodity prices have started finding their way into empirical macroeconomic or empirical monetary models as an "information variable" (see, for example, Balke & Emery 1994; Sims 1992; Clarida et al. 2000, among others). While Sims (1992) claims that commodity prices can be used as an "information variable" or indicator of future inflation in the central bank's policy reaction function, Leeper et al. (1996) caution that the exclusion of commodity prices from the macroeconomic models can result in serious misspecification problem. However, some later studies, claim that the inclusion of commodity prices cannot resolve the prize puzzle (see, Hanson 2004, among others). Giordani (2004) argues that a commodity price index can solve a prize puzzle not because it is a good predictor of future inflation but because it contains useful information about the output gap.

The "pure finance" perspective, on the other hand, focuses on the time series behaviour of the commodity futures term structure, and is based on conven-

[8]See, Hamilton (1983), Bruno & Sachs (1985), Kilian (2008*a*), Kilian (2008*b*), Barsky & Kilian (2002), among others.

[9]The studies that intend to solve the "Price Puzzle" mainly consider structural vector autoregressive (SVAR) models.

tional views, such as the "Theory of Normal Backwardation" by Keynes (1930) and Hicks (1939) and the "Theory of Storage" by Kaldor (1939), Working (1949), and Brennan (1958). It implies that, in the absence of arbitrage, the prices of commodity futures, regardless of the period till maturity at any given time, are determined by a time-invariant linear function of a number of unobservable common state variables. In particular, earlier research has shown that the spot commodity price, the convenience yield, and the instantaneous short rate factor are three hidden common elements that affect the term structure of commodity futures. The absence of macroeconomic considerations in these latent state variables is however a major cause for concern. Consequently, it is difficult to understand these latent variables using a macroeconomic framework.

The "macro-finance" model, which combines the earlier two perspectives, has evolved in response to the growing interest in the structural relationship between interest rate term structure and the macroeconomy (see, Ang & Piazzesi 2003; Diebold et al. 2006, among others). The semi-structural central bank model (CBM) subsequently emerged, extending the "error correction" specification to the framework of the conventional macro-finance model[10] and allowing the assessment of the long-term underlying relationships between variables in the model. The macro-finance model focuses primarily — though narrowly — on the structural link between term structures connected to interest rates and the pertinent variables. Despite evidence on the impact of oil shocks on the macroeconomy, the development of the macro-finance model for the commodity futures term structure remains restricted.

[10] See, for example, Kozicki & Tinsley (2005), Dewachter et al. (2006), Dewachter & Lyrio (2006), Spencer (2008), Spencer & Liu (2010), among others.

The Context

Commodity trading in India has witnessed significant growth and transformation in recent years. This trend has been driven by globalization, regulatory reforms, and changing economic dynamics among other factors in the country. When commodity trading occurs in a deregulated environment, market participants find themselves increasingly exposed to price movements and to counterparty performance risk. As a result, a rapid increase in the volume of commodity derivatives is observed after the deregulation of commodity trading in India. Demand and prices of commodities depend largely on commodity cycles. In 2004-05, the ratio of the total value of commodities traded in the two largest commodity exchanges in India[11], to Gross Domestic Product (GDP)[12] was only 0.14. Between 2004-05 and 2011-12, this ratio increased to 1.99, followed by a sharp decline from 1.66 to 0.39 between 2012-13 and 2019-20. The ratio again increased marginally in 2019-20, followed by a decline in the volume of commodity trading in the subsequent two years on account of the Covid-19 pandemic. The ratio regained thereafter in 2022-23.

Between 2004-05 and 2011-12, the size of the Indian commodity derivative market measured in terms of the total value of commodities traded in the two largest commodity exchanges in India, namely MCX and NCDEX, went up from Rs.4.32 trillion to Rs.174.07 trillion, accounting for an average growth rate of nearly 44 per cent. Between 2004-05 and 2012-13, the number of traded contracts

[11]The Multi Commodity Exchange (MCX) and the National Commodity Derivatives Exchange (NCDEX).

[12]The GDP series considered, is at current prices and the base year is 2011-12. The data have been obtained from the database of the Ministry of Statistics and Programme Implementation, Government of India.

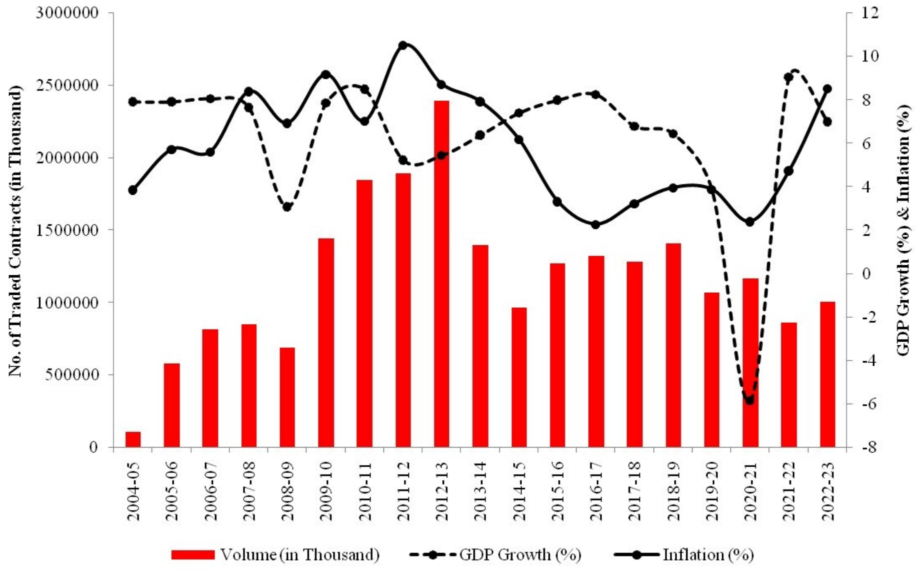
increased from 10.75 million to 239.78 million. In the succeeding years, the traded volume of commodity contracts remain relatively stable although the traded value decreased on account of a fall in prices. In 2020-21, even in the presence of the Covid-19 pandemic, the traded volume of commodity contracts increased compared to the same in the preceding year. During the pandemic years, although the prices of energy commodities and metals decreased, the same for bullions increased as investors choose to invest in safe-haven assets following the crash in equity markets. This is the primary reason behind the positive growth in the traded volume of commodity contracts and negative growth in the total value of commodity contracts traded during the Covid-19 pandemic.

Historically, commodity prices are found to be closely linked with inflation and business cycles (Bernanke 2008). Over time, in a large strand of literature[13], the inflation-hedging effectiveness properties of commodities have been extensively investigated. On the other hand, while commodity prices are important forces driving business cycles, economic growth also determines commodity price cycles. Figures 1.1 and 1.2 show synchronous movements in commodity trading and the movement in key macroeconomic indicators in India. While Figure 1.1 shows the volume of commodities traded vis-à-vis the growth rate of GDP and inflation rate[14], Figure 1.2 depicts a possible link between the growth in value of commodities traded vis-à-vis the growth rate of GDP and the inflation rate. This certainly motivates to study the relationship between movements in commodity prices and macroeconomic indicators in India.

[13]See, Erb & Harvey (2006), Gorton et al. (2013), Hoevenaars et al. (2008), Bampinas & Panagiotidis (2015), Lucey et al. (2017), Bilgin et al. (2018), Apergis et al. (2019), among others.

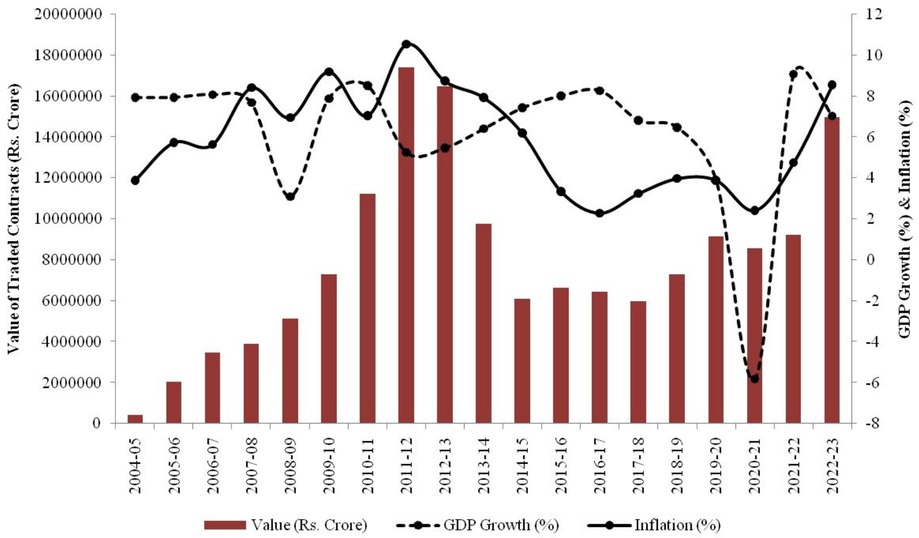
[14]The GDP growth rate (%) is calculated based on GDP at constant prices at the base year 2011-12. The inflation rate (%) is calculated from the GDP deflator series.

Figure 1.1: Volume of Commodities Traded and Macroeconomic Indicators



Note: The volume of commodities traded is the total number of contracts traded in MCX and NCDEX.

Figure 1.2: Value of Commodities Traded and Macroeconomic Indicators



Note: The value of commodities traded is the total value of contracts traded in MCX and NCDEX.

Turning to the commodity price trajectory, it can be observed that prior to the Global Financial Crisis, there was a commodity price boom, unprecedented in its magnitude and duration. The real prices of energy and metals more than doubled in five years during 2003-08, while the real price of food commodities increased 75 per cent (Erten & Ocampo 2013). The commodity boom generally results from rapid income growth, rising population and increase in demand for food[15], energy and minerals, and other commodities, especially in Asian emerging markets including China and India. This upsurge in commodity prices ended with the global economic slowdown with the easing of commodity demand. However, in the post-crisis period, commodity prices in India recovered following the commodity boom in the world economy during 2004-08 (Erten & Ocampo 2013). This is further evident from Figure 1.3, which shows the trends in nominal and real commodity price indices from the MCX commodity exchange[16].

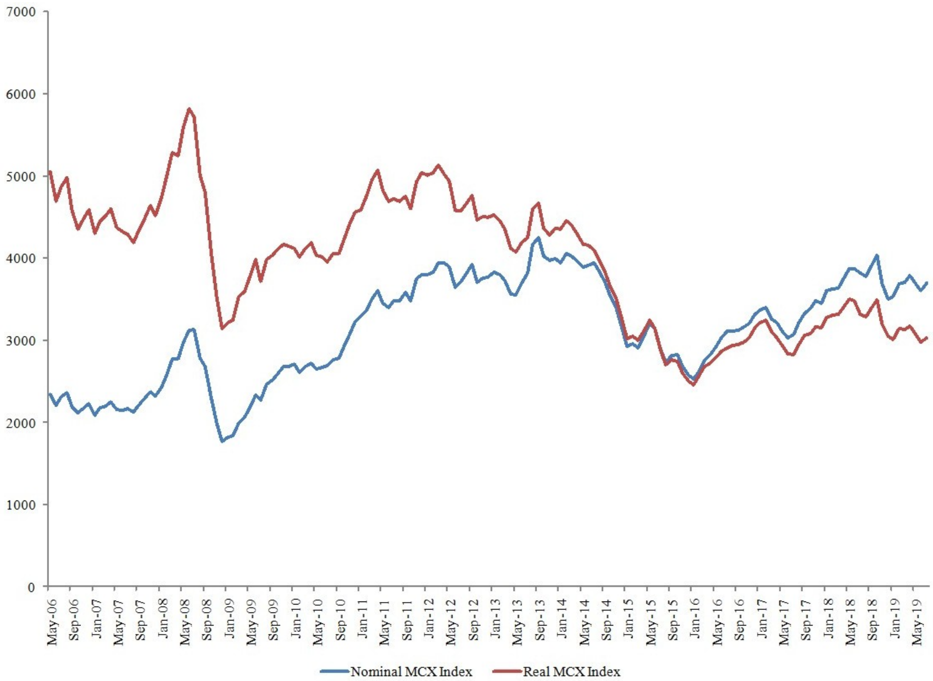
The Indian commodity futures prices index shows movements similar to the international commodity price indices, especially to the international crude oil prices since 2006. Figure 1.4 shows the co-movement between international commodity prices and Indian commodity prices, where the Brent crude oil price index and Bloomberg Commodity Index are taken as proxies of international commodity prices. For the sample period 2006 to 2019[17], the Indian commodity futures prices index is found to have a correlation of 0.55 with the Brent crude oil price index. It can be observed from Figure 1.4 that the Indian commodity price diverged from the international commodity price indices over the period. This is evident from

[15] Rapid income growth in India and China was a key factor behind the increase in food commodities after 2007 (see, for example, Krugman 2008; Wolf 2008; and Bourne & Joel 2009).

[16] The monthly real commodity price index has been obtained by deflating the nominal commodity price index by the consumer price index (CPI).

[17] Regarding discussion on the sample period, refer to Section 1.5.

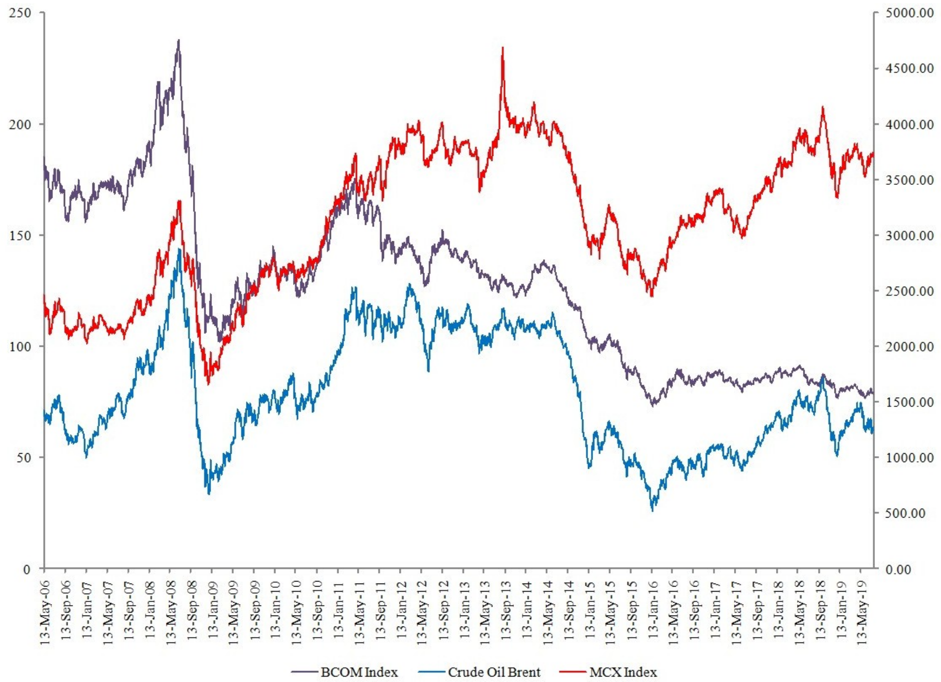
Figure 1.3: Real and Nominal MCX Commodity Prices Index



the phase-wise correlation coefficient of the two indices. The correlation coefficient between the Indian commodity futures prices index and the Bloomberg commodity price index is high at 0.89, between 2006 and 2008. However, between 2009 and 2014, the correlation coefficient lowered to 0.37, and further to -0.09 during 2014-19. The Indian commodity futures prices index shows a high correlation at 0.96 with international crude oil prices during 2006-08, followed by 0.92 and 0.90 during 2009-14 and 2014-19, respectively.

Indian commodity futures prices also show co-movement with different macroeconomic indicators. In Figure 1.5, the movement of MCX commodity price index is compared with the movements in economic growth and inflation rates being proxied by the year-on-year growth rate of the Index of Industrial Production (IIP) and year-on-year growth rate of the Consumer Price Index (CPI), respectively. It can be seen that there is a positive correlation between the inflation rate and MCX commodity price index. However, this correlation seems to become

Figure 1.4: International commodity prices Indices and Indian commodity prices Index

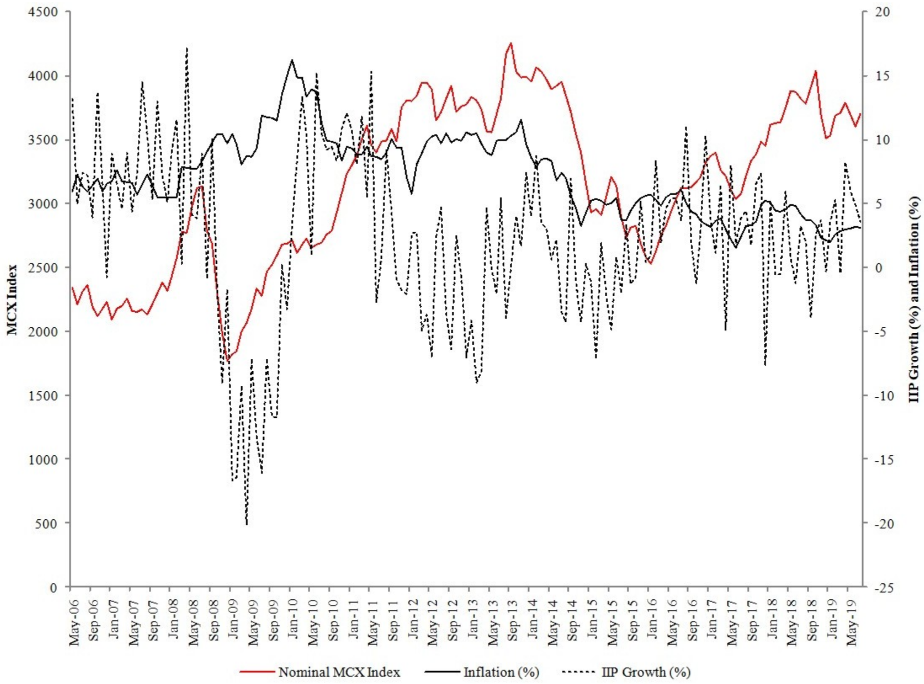


weaker since the adoption of flexible inflation targeting by the Reserve Bank of India in 2016. The relationship between IIP growth rate and MCX commodity price index is complex. It can be seen that during the Global Financial Crisis, the economic downturn in India was preceded by a fall in commodity prices. However, in the subsequent periods, the IIP growth rate and MCX commodity price index are seen to have a negative correlation possibly on account of the "cost effect"[18].

On the whole, it can be inferred that there is a one-to-one correspondence between the movements in commodity prices and macroeconomic indicators in India. It can thus be expected that any commodity market-specific shock can get transmitted to the macroeconomy in India. In this context, thus, it is important to decipher the origin of the shock in the commodity market and the transmission mechanism of shocks to different macroeconomic indicators. From the perspective

[18] As commodities are used as raw materials in the production of final goods and services, any rise in commodity prices discourages production on account of increase in input prices.

Figure 1.5: Indian Macro-Variables and Commodity Prices Index



of policymaking, the short-term fluctuations in a financial market are to a large extent on account of linkages with other financial markets. This motivates to study the nature and extent of co-movement and financial contagion in the Indian commodity derivative market. Thereafter, it is also important to examine the relationship between commodity prices and macroeconomic indicators in the short and long runs to understand the possible macroeconomic consequences of shock transmissions from the financial market to the commodity market and the rest of the macroeconomy.

1.2 Commodity Trading in India: Evolution and Policies

This section discusses, in brief, the evolution of the commodity market in India through several policy changes. Such a discussion builds an analytical perspective for the underlying linkages between the commodity derivative market and the macroeconomy in India. India has a long history of commodity futures trading. Commodity derivative markets in India are as old as those of the UK and the USA. Commodity derivatives trading in India began in 1875 with the establishment of the Cotton Trade Association in Bombay[19]. During the 1940s, India had around 300 commodity exchanges (Rajib 2015).

Restrictions in commodity trading, through policy changes, in India started in the pre-independence period. The commodity market in India was observed to grow rapidly between the First and Second World Wars. However, the Indian economy experienced a shortage of essential commodities, and since the mid-1930's the situation aggravated with the outbreak of the Second World War (Naik & Jain 2002; Bhattacharya 2007). Cotton trading was banned in 1939 and forward trading in some other commodities was also prohibited in 1943. The prohibitions in commodity trading however continued after the Second World War with necessary modifications in the Essential Supplies Temporary Powers Act, of 1946 (Bhattacharya 2007).

A number of policy changes were undertaken in the post-independence period. In the post-independence period, the Indian constitution listed the subject of future markets' under the union list and thus the regulation and the onus of development of commodity derivatives market rested with the Union Government (Srinivasan 2011). Restrictions on both the derivatives, as well as spot commodities markets, had been placed by the Forward Contracts (Regulation) Act, 1952 (Naik & Jain 2002; Bhattacharya 2007) and the Essential Commodities Act, 1955 (Bhattacharya 2007). The Forward Contracts (Regulation) Act, of 1952 provides

[19]The Chicago Board of Trade was established a decade earlier (Dasgupta 2004*b*).

the legal framework for the regulation of forward contracts in commodities and also prohibits options in commodities, and imposes several restrictions on the cash settlement of forward/future contracts. The Forward Market Commission (F.M.C.)[20], the nodal body for regulating the functioning of the futures exchanges in the country was set up in 1953 (Bhattacharya 2007), and continued till September, 2015.

The Forward Market Commission regulated the commodity future market according to the provision of the Forward Contracts (Regulation) Act, 1952. The act divided commodities into three broad categories such as prohibited, regulated and otherwise (residual commodities) (F.M.C. 2009-10). In 1955, under the Forward Contracts (Regulation) Act, futures trading in gold and silver was banned. In the early 1960s, there was a large increase in commodity futures trading leading to large pressure on inflation. Consequently, to control price volatility, the government imposed a ban on future trading (Rajib 2015) in the mid-1960s for most of the commodities except for a few minor ones (Naik & Jain 2002; Bhattacharya 2007). Future trading in molasses was banned in 1963 (Dasgupta 2004*b*) and in raw jute in 1964. The partial or complete prohibition of commodity futures trading continued in the 1960s and 1970s (Lokare 2007).

The process of liberalization was initiated with the setting up of the Dantwala Committee (1966) and it picked up, especially after the setting up of the Khusro Committee (1980) (Lokare 2007; Sahadevan 2012). Following the Khusro Committee recommendations, the government allowed future trading in potato and gur in the early 1980s and resumed trading in castor seed futures in 1985

[20] The functions of the Forward Market Commission are available in F.M.C Annual Report 2013-14.

(Naik & Jain 2002; Bhattacharya 2007). The basic objective for allowing a future market was to develop a market-driven mechanism for hedging and price risk of farmers and also to improve awareness about the value of their marketable surplus through price discovery and its dissemination (Sahadevan 2012). Later on, future trading in hessian was permitted in 1992 (F.M.C. 2009-10).

Following the economic reform in 1991, the Kabra Committee in June, 1993 recommended the opening up of futures trading in 17 selected commodity groups (Bhattacharya 2007). Since 1998, domestic entities facing commodity price risk were permitted to engage in derivatives transactions in overseas markets for risk management purposes. In 1999, the National Board of Trade was set up to offer trading in soya oil to oil industry stakeholders. In 1999, approval was given for futures trading in edible oil block and coffee, and permission for international future contracts in castor oil. In May 2001, future trading in sugar was permitted (F.M.C. 2010-11).

The process of liberalization gained momentum in 2002-03 when the central government took a series of measures to boost the commodity futures market in India. The Government of India permitted future trading in all commodities on 1 April 2003. The central government gave a mandate to four entities to set up nationwide multi-commodity exchanges and also the permitted list of commodities under the Forward Contracts (Regulation) Act was expanded. The removal of the ban on future trading for all commodities in 2003, followed the National Agricultural Policy of 2000 (Bhattacharya 2007). In the same year, recognition was granted to three multi-commodity electronic exchanges namely National Multi Commodity Exchange (NMCE), Ahmedabad (10 January 2003), Multi Commodity Exchange (MCX), Mumbai (26 September 2003), and National Commodity and Derivatives Exchange (NCDEX), Mumbai (20 November 2003). Future trading in gold and silver commenced at the NMCE, Ahmedabad, on 3 October 2003 after a ban of more than four decades. The other two exchanges namely MCX, Mumbai, and NCDEX, Mumbai, also allowed futures trading in gold and silver in 2003. (F.M.C. 2009-10).

With liberalization, a number of regulatory measures such as daily mark-to-market margining, time-stamping of trades, novation of contracts and creation of a trade guarantee fund, and demutualization for the new exchange, started in existing commodity exchanges in line with international best practices (Bhattacharya 2007). In 2007, the Forward Market Commission initiated a process of dissemination of futures and spot prices at various mandis, post offices, rural branches of commercial banks, and other areas frequented by participants including farmers to help them to cover their price risk in their pre-sowing and post-harvest decisions. Foreign Direct Investment (FDI) of upto 26 per cent and Foreign Institutional Investment (FII) upto 23 per cent (subject to no single investor holding more than 5 per cent) were allowed in commodity exchanges on 30 January 2008 (Economic-Survey 2007-08). The Forward Market Commission issued guidelines on setting up of new National Multi Commodity Exchanges on 14 May 2008. Under these guidelines, it prescribed the framework for the shareholding pattern of a new National Multi Commodity Exchange. The fourth national exchange namely the Indian Commodity Exchange, Gurgaon was granted recognition on 9 October 2009 (F.M.C. 2009-10).

After 2002-03, once the legal framework was in place, the government undertook several reform measures to modernize the structure of the market. Electronic trading was allowed through exchanges during post-reforms. With the help of electronic trading and the setting up of a central clearing corporation with a trade settlement guarantee, the exchanges were able to monitor and manage market risk. Commodity futures were permitted as physically settled contracts except where delivery infrastructure is underdeveloped. With these reforms trading volume across the national exchanges increased from Rs. 1294 billion in 2003 to Rs 181 trillion in 2013 (Kolamkar-Committee-Report 2014).

Even after 2003, future trading had been suspended in some commodities for sometime. To control inflation during the Global Financial Crisis, suspension in commodity futures trading was again imposed on several commodities[21] (Economic Survey, 2009-10; Kolamkar-Committee-Report 2014). Thereafter, in 2015, the Forward Market Commission did allow future trading in 113 commodities of which 24 food grains and pulses, 35 oil seeds and oils, 12 spices, 7 metals, 9 fibers and manufacturers, and 26 other commodities (F.M.C Bulletin, April-June, 2015). In September, 2015 the Forward Market Commission merged with the Securities and Exchange Board of India (SEBI) to achieve convergence of regulation of the securities and commodity markets and increase the economies of scope and scale for exchanges, financial firms, and other stakeholders (Economic-Survey 2015-16). The SEBI imposed a ban on the trading of seven agricultural commodities on 20

[21] Such as Tur (since January 23, 2007 till date), Urad (since January 23, 2007 till date), rice (since February 27, 2007 till date), wheat (since February 27, 2007 till May 14, 2009), Chana (since May 7, 2008 till November 30, 2008), Soya oil (since May 7, 2008 till November 30, 2008), Rubber (since May 7, 2008 till November 30, 2008), Potato(since May 7, 2008 till November 30, 2008), Sugar (since May 26, 2009 till September 30, 2010), and Guar seed and Guar gum (since March 27, 2012 till May 10, 2013).

December 2021 for a year on concerns over inflationary effects. The suspension then has been extended for one more year that is till 20 December 2023. On the whole, the above process of liberalization and regulatory reform in the Indian commodity market has made it more integrated with other asset markets. With liberalisation, it is important to understand commodity price movements, which have implications for several macroeconomic indicators.

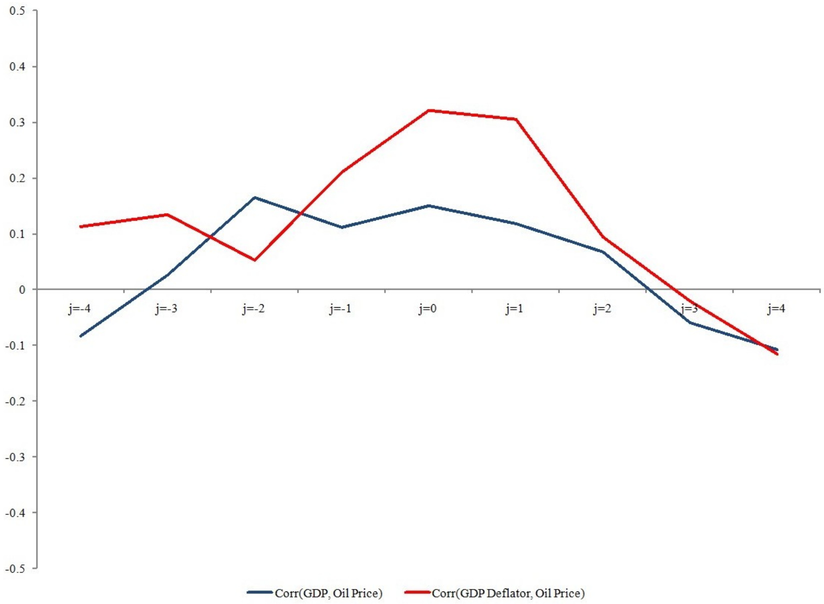
1.3 Commodity Price Movements and Macroeconomy: Certain Stylized Facts

In this section, stylized facts on the nature of the relationship between commodity prices and major Indian macroeconomic indicators is presented. The analysis in this section is carried out using both quarterly and monthly data. In the first part, quarterly international crude oil price data has been considered along with quarterly GDP and inflation data. The inflation rate has been arrived at from the GDP deflator series. In the second part, monthly MCX commodity futures price index data are considered along with monthly IIP and CPI data. For the analysis of quarterly data, the sample period considered is from 1996-97Q1 to 2022-23Q4. The starting point of the sample is chosen on the basis of the availability of quarterly GDP data. On the other hand, for the analysis of monthly data, the sample period considered is from May, 2005 to July, 2019. The starting point of the sample in this case is chosen on the basis of the availability of MCX commodity price index data.

International crude oil prices are found to be highly volatile. For instance, the standard deviation of Hodrick-Prescott (HP) filtered (logged) quarterly crude oil prices is 3.61 times larger than the Indian GDP during the chosen time period. On the other hand, the standard deviation of quarterly crude oil prices is 12.29 times larger than that of the Indian GDP deflator during the chosen time period. The dynamic correlations between the crude oil price and the aggregate variables of interest are estimated. The degree of co-movement of crude oil prices with the cycle is measured by the correlation coefficient $\rho(j)$, where $j \in \{0, \pm 1, \pm 2, \pm 3, \pm 4\}$. Information regarding whether the contemporaneous correlation coefficient, $\rho(0)$, is positive, zero, or negative indicates whether crude oil prices are procyclical, acyclical, or countercyclical, respectively. Furthermore, the cross-correlation coefficient $\rho(j)$ provides important information about whether the cycle of crude oil is leading, synchronous, or lagging the cycle of the macroeconomic indicators as $|\rho(j)|$ reaches a maximum for a negative, zero or positive j, respectively. Figure 1.6 shows the degree of cyclical correlations between crude oil price and quarterly Indian macroeconomic time series by the correlation coefficient $\rho(j)$. Figure 1.6 illustrates the nature of the dynamic correlations based on the HP filter, at lags and leads one, two, three, and four quarters.

It is observed from Figure 1.6 that international crude oil prices are leading to inflation. Following Fiorito & Kollintzas (1994) and Serletis & Shahmoradi (2005), the series can be strongly contemporaneously correlated, weakly contemporaneously correlated, and contemporaneously uncorrelated with the cycle when $0.23 \leq |\rho(0)| < 1, 0.1 \leq |\rho(0)| < 0.23, 0 \leq |\rho(0)| < 0.1$, respectively. From Figure 1.6, based on the criterion developed by Fiorito & Kollintzas (1994) and Serletis & Shahmoradi (2005), it can be observed that crude oil prices are positively contemporaneously correlated with the GDP deflator, and lead GDP deflator by one

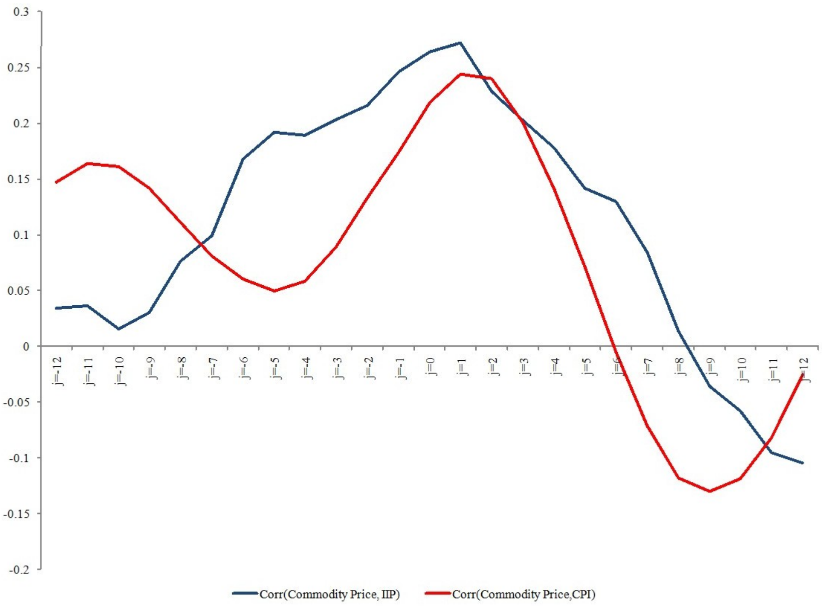
Figure 1.6: Cross Correlation with International Crude Oil Price



quarter. However, any strong correlation of crude oil prices with GDP cycles is not observed.

Apart from the relationship between international crude oil prices and macro-variables, the lead-lag relationship between the commodity futures price index and macro-variables is also reported. In this case, the degree of co-movement of commodity futures price index with the cycle has been measured by the correlation coefficient $\rho(j)$, where $j \in \{0, \pm1, \pm2, \pm3, \pm4, \ldots.., \pm12\}$. Figure 1.7 shows the degree of cyclical correlations between the commodity futures price index and monthly Indian macroeconomic time series by the correlation coefficient $\rho(j)$. Figure 1.7 reveals the magnitude of the dynamic correlations between the commodity futures price index and monthly Indian macroeconomic indicators such as IIP and CPI based on the HP filter, at lags and leads one, two, three and up to twelve months. Following the same cut-off points as Fiorito & Kollintzas (1994) and Serletis & Shahmoradi (2005) it can be inferred that the commodity futures price index is positively and contemporaneously correlated with IIP, and also leads IIP

Figure 1.7: Cross Correlation with Indian Commodity Futures Prices Index



by two months. Again, the commodity futures price index lags IIP by one month. From Figure 1.7 it can be further inferred that the commodity futures price index is positively contemporaneously correlated with CPI, and also leads CPI by two months. This shows the inflationary nature of the commodity futures prices index and commodity futures prices are procyclical.

In summary, the above stylized facts show that there is a contemporaneous as well as lead-lag relationship between commodity prices and macroeconomic indicators in India, which motivates to study the relationship in detail using different empirical and theoretical methods.

1.4 Objective of the Study and Summary of Findings

This study delves into four major issues relating to the Indian commodity derivative market. These issues, based on the existing literature and the stylized facts, include:

- an examination of the extent of co-movement and financial contagion in the Indian commodity derivative market vis-à-vis the Indian equity market;
- an exploration of the nature of the short-run and long-run relationship between commodity futures price indices and different macroeconomic indicators relevant to monetary policymaking;
- an investigation of the ability of the commodity futures prices index to forecast Indian inflation with asymmetric price changes and the presence of structural breaks;
- an analysis of the channels of transmission of crude oil price shocks to macroeconomic indicators in India in a dynamic stochastic general equilibrium framework;

Using historical daily data on returns on commodity futures and equities, in the first essay, excess co-movement and financial contagion are found in the Indian commodity derivative market. The analysis shows that the correlation between returns on commodity futures and returns on equities increases during the time of high volatility in the respective markets. The degree of financial contagion is found to increase during the time of high co-movement. The nature of financial contagion, however, is found to be non-linear. In the second essay, using the monthly data on the commodity futures price indices and different macroeconomic indicators, a significant pass-through from commodity prices to macroeconomic indicators is found. The degree of pass-through is found to vary across commodities. The relationship between commodity futures price indices and different macroeconomic indicators is found to be non-linear in both short and long runs.

In line with the results found in the second essay, the ability of the commodity futures price index to predict Indian headline inflation is found in the third essay. Using the monthly data on the composite commodity futures price index and consumer price inflation, the predictive ability of the traditional Phillips curve model is found to increase after augmentation with the inclusion of the commodity futures price index. The significant role of structural breaks and non-linearity in modelling Indian headline inflation in an augmented Phillips curve framework is also found. Significant transmission of crude oil price shocks to macroeconomic indicators is found in the fourth essay. Using a general equilibrium macroeconomic framework the effects of shocks are found to differ in the presence and absence of futures tradings. Moreover, the effects of the shocks are also found to depend on the nature of their sources.

1.5 Data

In the subsequent chapters (2, 3, and 4), different data are used. The commodity futures prices index has been used in all three chapters. Data on commodity future price indices are collected from the database of Multi Commodity Exchange (MCX). The Multi Commodity Exchange Commodity Index (MCX COMDEX) is used in empirical analysis as the Multi Commodity Exchange (MCX) is the largest commodity exchange in India. The MCX COMDEX is the only real-time commodity price index available in India. The index is designed and developed by the Research and Development Department of MCX in association with Indian Statistical Institute (ISI), Kolkata, and launched in June 2005. There are three group indices namely MCX AGRI, MCX METAL, and MCX ENERGY for agricultural commodities, metal, and energy, respectively. The MCX

COMDEX, the composite index, is a weighted average of the three group indices[22] namely MCX AGRI, MCX METAL, and MCX ENERGY.

In Chapter 2, daily data on the equity prices index is used along with the commodity futures prices index. The BSE SENSEX is used as the market-weighted stock market index. The trading hours of the commodity exchange and equity exchange differ. Following Forbes & Rigobon (2002), the rolling window approach[23] has been employed to compute the average two-day rolling returns to account for time lags between market hours. This helps to avoid bias in estimating contagion, that is nonsynchronous trading and short-term correlations arising from noise. By taking the difference of logarithms of two successive average price indices, the two-day average returns is calculated. The sample period chosen for analysis is between June 01, 2006, and March 31, 2019. The starting point is chosen solely on the basis of the availability of data on commodity future price indices in India.

In Chapters 3 and 4, the empirical estimation is carried out using monthly data for the different macroeconomic indicators such as the index of industrial production (IIP), consumer price index (CPI), and call money rate (CMR) along with the commodity futures prices index (CFP). The call money rate has been used as a proxy for short-term interest rate or instrument of monetary policy following previous studies[24] on Indian monetary policy. The consumer price in-

[22]The three group indices are computed on the basis of geometric mean. The constituents of the Index are liquid commodities traded in the Exchange. The weights of the constituents within sub-indices are assigned giving equal importance to their physical market size and their liquidity in the Exchange. The re-balancing is done annually or as and when deemed necessary by the index management team.

[23]Following Forbes & Rigobon (2002), this strategy has been used by a number of studies while estimating contagion, volatility connectedness, and volatility spillover (see, for example, Bodart & Candelon 2009; Panagiotidis et al. 2018; Yoon et al. 2019; among others).

[24]See, for example, Bhattacharya, Bhanumurthy & Mallick (2008), Mishra & Mishra (2012*a*), Mishra & Mishra (2012*b*), Mohanty & John (2015), among others.

dex (CPI) and index of industrial production (IIP) data are obtained from the database of International Financial Statistics (IFS) of the International Monetary Fund (IMF). Although IIP and CPI data are also available from the database of the Ministry of Statistics and Programme Implementation(MoSPI), Government of India, the IMF data are used in the absence of long and back-series data in the MoSPI database. Two important things are to be mentioned here. First, although a number of previous studies modelling Indian inflation have used wholesale price (WPI) inflation, consumer price inflation is considered in this study as it is more relevant from the perspective of inflation targeting in India[25]. Second, only headline inflation or CPI of all items and not the core inflation have been considered, as time-series data for the latter are not available for India. The monthly call money rate data are obtained from the Database on Indian Economy of Reserve Bank of India.

1.6 Chapter Scheme

The thesis comprises of four essays based on the four aforementioned objectives. The structure of the thesis is as follows: following this overview chapter, Chapter 2, the first essay, investigates into the non-linear nature of financial contagion in the Indian commodity derivative market vis-à-vis the equity market in India. Chapter 3, the second essay, deals with the asymmetric relationship between the macroeconomy and the commodity derivative market in India both in the short and long runs. Chapter 4, the third essay, explores the possibility of

[25] Following the recommendations of Urjit Patel Committee, the Reserve Bank of India (RBI) had adopted headline inflation measured in terms of CPI(combined) as the nominal anchor for monetary policy formulation.

forecasting inflation in India using commodity futures prices. Chapter 5, the last essay, examines the channels of transmission of different types of commodity price shocks to real and nominal macroeconomic indicators in a theoretical setup. Finally, Chapter 6 concludes the thesis with a summary of major findings and policy implications.

Chapter 2

Financial Contagion in the Indian Commodity Derivative Market: New Evidence from Quantile-on-Quantile Regression Approach

2.1 Introduction

This chapter, the first of the four essays, examines the nature and extent of financial contagion between the commodity derivative market and the equity market in India. The chapter is an extension of Roy & Sinha Roy (2017). With financial liberalization across economies since the early 1990s, asset markets globally have become more volatile (Mensi et al. 2013). In this context, it is important to study the changes in financial markets across the globe. In particular, given the volatility in asset markets, it is paramount to study the nature and extent of financial contagion between asset markets within and across countries, especially since the early 2000s. While financial contagion in a variety of asset markets including equity, bond, and currency, has been studied in the literature, studies on financial contagion in commodity derivative markets along with other asset markets are rare.

An analysis of financial contagion including commodity markets is essential mainly on account of two reasons. First, an increasing number of private and institutional investors have shown interest in investing in the oil and other commodity derivative markets in the recent period (Silvennoinen & Thorp 2013; Ohashi & Okimoto 2016), a phenomenon known as the financialization of the commodity derivative market. Second, as commodities are believed to serve as diversifiers (Abanomey & Mathur 2001; Ankrim & Hensel 1993; Anson 1999; Becker & Finnerty 2000; Georgiev 2001 and Lummer & Siegel 1993), the existence of a higher degree of co-movement between asset markets reduces the diversification benefits (Lessard 1973; Solnik 1974). Understanding the nature of financial contagion between commodity derivative markets and equity markets is therefore critical for portfolio diversification. It is only in the recent past that this aspect has been explored in the literature[1].

Historically, traditional asset classes such as stocks and bonds predominated the portfolio of investors. In the process of optimal portfolio choice, commodities are considered to be diversifiers as they are found to have a low correlation with traditional asset classes (Jensen et al. 2000; Erb & Harvey 2006; Gorton & Rouwenhorst 2006). On the other hand, investors use commodities for the purpose of hedging (Bodie & Rosansky 1980; Bodie 1983) especially during financial stress, appraising its nature of positive co-movement with inflation and hence a tendency of backwardation [2]. Further, the linkages between commodity and stock markets became important for financial agents (Silvennoinen & Thorp 2013; Dwyer et al. 2012; Vivian & Wohar 2012). Investors in the commodity market take into cognizance the volatility in equity prices alongside commodity market fluctuations and there so prevail more information on asset substitutability prevailing in the

[1] See, for example, Algieri & Leccadito (2017), Roy & Sinha Roy (2017), Ayadi et al. (2021), Chalid & Handika (2022), among others.

[2] For instance, when equity markets collapsed in the early 2000s, investors started relying more on commodity derivatives to reduce portfolio risk given a low negative correlation between stocks and commodity returns.

commodity market by comparing the dynamic volatility in the two asset markets (Choi & Hammoudeh 2010). With promotion from investment banks, commodity markets attracted huge investments and herding of index investors that in turn led to the financialization of commodity markets (Tang & Xiong 2012). Such "financialization" of commodities and thus portfolio re-balancing by index investors led to the gradual integration of commodity markets with other asset markets. Financialization resulted in increased correlation and volatility spillover between these markets (Karyotis & Alijani 2016; Adams & Glück 2015; Olson et al. 2014).

Although there exists abundant literature on the epistemology of financial crisis and hence financial contagion, any study on the effects of the same on the commodity market is however rare (Guo et al. 2011). The commodity market along with other asset markets worldwide fluctuated, with commodity prices in India experiencing a decline during the Global Financial Crisis of 2008-09. During this period, along with the rise in volatility in the commodity markets in India[3], the linkage between commodity and equity prices got strengthened (Creti et al. 2013; Roy & Sinha Roy 2017). The Indian and global commodity markets experienced large increase in prices in the first half of the 2000s, and thereafter during the Global Financial Crisis, Indian commodity prices declined by about 50 per cent (Velmurugan et al. 2010) between July 14, 2008, and December 24, 2008, following nearly 48 per cent fall in global commodity prices. A co-movement between commodity and equity prices can also be observed till 2014. After June 2014, the commodity future prices in India along with the global commodity prices experi-

[3]See Gilbert (2010) and Phillips & Yu (2011) for evidence.

enced a "great plunge" as a result of falling demand from emerging markets and underinvestment in various commodity markets (Baffes et al. 2015).

Against this backdrop and considering the aforementioned research gaps, it is vital to investigate the presence of financial contagion in the Indian commodity derivative market vis-à-vis equity markets across developed countries and emerging market economies. The present chapter attempts to examine the degree of cross-border financial contagion between the Indian commodity derivative market and equity markets. The rest of the chapter is structured as follows. Section 2.2 presents a brief review of relevant literature. Section 2.3 the econometric methodology used for the purpose of analysis. An exhaustive analysis of econometric results is presented in section 2.4. The chapter summarizes the major findings in section 2.5.

2.2 Literature Review

Theoretical studies on contagion have largely attempted to explain the different channels of contagion. In the existing literature, there are mainly four types of channels through which contagion occur which include (a) trade, (b) banks, (c) portfolio investors, and (d) wake-up calls[4]. A number of studies [5] have developed theoretical models to understand possible causes of contagion in terms of all these four channels. The theoretical literature on the third channel has been discussed here as it is found that higher exposures of commodities to common shocks are

[4]See Gandolfo & Federici (2001) for a detailed discussion on all these four channels of financial contagion.

[5]See, for example, Masson (1998), Dasgupta (2004*a*), Allen & Gale (2000), Lagunoff & Schreft (1999), King & Wadhwani (1990), Calvo (2004), Chen (1999), Calvo & Mendoza (2000), among others.

mainly driven by investors' sentiments rather than macroeconomic fundamentals (Tang & Xiong 2012). Goldstein & Pauzner (2004) have shown that the contagion occurs through a wealth effect by arguing that a decrease in the wealth of investors in one country makes investors unwilling to bear risks originating from the unknown behaviour of agents in other countries and thus withdraw their investments in the latter. This is how crisis spreads from one country to another. Kyle & Xiong (2001) also develop a model with two risky assets and three types of agents viz. noisy traders, long-term investors, and convergence traders explaining financial contagion in terms of the wealth effect. In the same line Pavlova & Rigobon (2008) discuss the role of portfolio constraints in generating contagion in stock prices across "periphery" countries as a result of wealth transfers to these countries from the "centre".

Kodres & Pritsker (2002), in the presence of multiple assets and noisy rational expectations, show financial contagion in a short period being caused by correlated information, correlated liquidity shocks, and thus cross-market rebalancing. The model, developed in the same line as King & Wadhwani (1990), shows possible transmission channel of "mistakes" from one market to another while rational agents attempt to extract information from price changes in other markets; resulting in a "contagion". Calvo (2004) develops a theoretical model to understand financial contagion in emerging market economies which takes into account asymmetric information and rational but imperfectly informed investors who react to signals emitted by informed individuals. Following the losses incurred in a crisis-affected developed market, if informed investors sell the emerging market stocks to meet their margin calls, the ill-informed investors may follow suit thereby leading to crisis in the emerging markets. Contagion has also been explained in a model of portfolio choice in the presence of imperfect information by Calvo & Mendoza (2000). The Calvo-Mendoza model shows that, with financial frictions not sufficient to produce financial contagion, information costs play an important role in the process.

Most of the empirical studies[6] on financial contagion take into consideration the equity and currency markets only. The studies on commodity markets mainly discuss the co-movement of commodities along with other assets, mainly stocks. Choi & Hammoudeh (2010), analysing the time-varying correlation between commodity prices of Brent oil, WTI oil, copper, gold, and silver, and equity prices of the S&P 500 index between 2003 and 2006, show that the correlations have increased since 2003, limiting hedging substitutability in portfolios. Filis et al. (2011), analysing time-varying correlations between oil prices and stock markets by differentiating between selected oil-importing and oil-exporting countries, show that the time-varying correlations depend on the origin of oil shocks. The response to aggregate demand-side shocks is found to be greater than supply-side shocks originating from OPEC's production cuts.

Although some recent studies discuss the evolution of correlations between commodities and financial assets in the aftermath of the Global Financial Crisis, the focus is not on the contagion effect. Studies such as by Silvennoinen & Thorp (2013), Wen et al. (2012) and Sadorsky (2014) are of the exceptions. Silvennoinen & Thorp (2013) find evidence of increased correlation during crises between 24 different commodities and equity prices index of some developed country markets.

[6]See, for example, Buyuksahin et al. (2010), Tang & Xiong (2012), Silvennoinen & Thorp (2013), Lautier & Raynaud (2012), among others.

This evidence tends to discourage investors from choosing commodities as diversifiers or safe-haven assets. Sadorsky (2014) using time-varying correlation between prices of commodities and the composite index of stock prices across emerging market economies show that correlations between commodities and equities increased during 2008 and 2009. Roy & Sinha Roy (2017) show financial contagion between the Indian commodity derivative market and the Indian equity market.

The above review of empirical literature shows some important research gaps. First, studies on financial contagion considering commodity derivative markets during the period of financial crises are rare, and those on the Indian commodity derivative market are even rarer. While some studies discuss the nature of time-varying correlation among different commodities or between some specific commodities and equities, a study on contagion in the commodity market is uncommon. Although some of the recent studies[7] have focused on Indian commodity derivative markets, none have examined the non-linear nature of cross-asset financial contagion. These gaps in the literature motivate to study the nature and extent of financial contagion in the Indian commodity derivative market considering the possible presence of non-linearities.

2.3 Methodology

Financial contagion is measured in the literature using different approaches including (a) Probability models approach, (b) Coexceedance approach, (c) Vector Autoregression (VAR) based approach, and (d) Correlation based approach. These

[7]See, Sahoo & Kumar (2009), Inoue & Hamori (2014), Chakrabarty & Sarkar (2010), Maitra & Dawar (2019), Joseph et al. (2014), Mo et al. (2018), Mohanty & Mishra (2020), among others.

four approaches have been popularized by Eichengreen et al. (1995), Eichengreen et al. (1996), Bae et al. (2003), Favero & Giavazzi (2002) and Forbes & Rigobon (2002), respectively. In the literature, financial contagion is tested mostly using the cross-market correlations. The problem of heteroskedasticity may arise on account of an increase in volatility at the time of crisis, when the cross-market dynamic correlation is required to be analysed more carefully while studying financial contagion (Forbes & Rigobon 2002). If there is no significant increase in correlation between asset returns after accounting for heteroskedasticity, then there is "no contagion, only interdependence"[8]. To calculate heteroskedasticity adjusted time-varying correlation among assets, several studies[9] use Dynamic Conditional Correlation – Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) method.

The DCC-GARCH method proposed by Engle (2002) has several advantages over other multivariate GARCH methods. Most importantly, this method adjusts for heteroskedasticity by estimating dynamic correlation coefficients of the standardized residuals (Ahmad et al. 2013). The present study has used the AR(1)-DCC-GARCH and AR(1)-ADCC-GARCH[10] methods to estimate the time-varying correlations, and thereafter linear and non-linear regression-based methods to examine the presence of financial contagion in the Indian commodity derivative market. In what follows is the discussion on the methods used for estimating time-varying conditional correlations and financial contagion.

[8] See, Forbes & Rigobon (2002), Bordo & Murshid (2001), and Basu (2002).

[9] See, for instance, Wang & Thi (2006), Cappiello et al. (2006), Cappiello et al. (2006), Hesse et al. (2008), Wang & Moore (2012), among others.

[10] Asymmetric Dynamic Conditional Correlation – Generalized Autoregressive Conditional Heteroskedasticity.

2.3.1 Estimating Financial Contagion: AR(1)-DCC-GARCH Method

In a stochastic vector process of returns of N assets $\mathbf{r_t}$ of dimension $N \times 1$, the mean equation is as follows:

$$\mathbf{r_t} = \varsigma + \boldsymbol{\mu}\mathbf{r_{t-1}} + \boldsymbol{\eta_t} \tag{2.1}$$

where $\mathbf{E}(\eta_t.\eta_t^T) = \mathbf{I_N}$ and $\eta_t = H_t^{1/2}.z_t$. The conditional variance-covariance matrix of $\mathbf{r_t}$ is an N matrix denoted by $\mathbf{H_t} = [h_{ijt}]$. The conditional covariance matrix can be decomposed into conditional standard deviations and a correlation matrix as follows:

$$\mathbf{H_t} = \mathbf{D_t R_t D_t} \tag{2.2}$$

where $\mathbf{H_t}$ is an $N \times N$ conditional covariance matrix, $\mathbf{R_t}$ is the conditional correlation matrix, and $\mathbf{D_t}$ is a diagonal matrix with time-varying standard deviations on the diagonal with $\mathbf{D_t} = diag(h_{1t}^{1/2}, h_{2t}^{1/2}, \cdots, \mathrm{h}_{nt}^{1/2})$ being the conditional standard deviation. To guarantee that $\mathbf{R_t}$ is positive definite and all the elements of $\mathbf{R_t}$ are equal or less than one, $\mathbf{R_t}$ is decomposed into

$$\mathbf{R_t} = \mathbf{Q_t^{*-1} Q_t Q_t^{*-1}} \tag{2.3}$$

where $\mathbf{Q_t}$ is a positive definite matrix defining the structure of the dynamics and $\mathbf{Q_t^{*-1}}$ rescales the elements in $\mathbf{Q_t}$ to ensure $|q_{ij}| \leq 1$. $\mathbf{Q_t^*}$ is thus the diagonal matrix consisting of the square root of diagonal elements of $\mathbf{Q_t}$ with $\mathbf{Q_t^*} = diag(q_{11t}^{1/2}, q_{22t}^{1/2}, \ldots\ldots, q_{nnt}^{1/2})$.

$\mathbf{Q_t}$ follows the dynamics in the form of

$$\mathbf{Q_t} = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 \varepsilon_{t-1}\varepsilon_{t-1}^T + \theta_2 Q_{t-1} \tag{2.4}$$

where $\bar{\mathbf{Q}}$=$Cov(\varepsilon_t.\varepsilon_t^T)$ is the unconditional covariance matrix of standardized errors and θ_1 and θ_2 are DCC parameters. θ_1 and θ_2 are scalars with the following conditions: $\theta_1 \geq 0$, $\theta_2 \geq 0$ and $\theta_1 + \theta_2 < 1$. The log-likelihood function has been estimated assuming that the error term follows the Student's t distribution.

AR(1)-ADCC-GARCH Method

The AR(1)-DCC-GARCH Method does not take into consideration asset-specific news impact parameters or asymmetries. Asymmetric Dynamic Conditional Correlation (ADCC) - Generalized Autoregressive Conditional Heteroskedasticity (GARCH) method, can be used to incorporate asymmetries. After incorporating the asymmetries, Eq.(2.4) gets modified as follows:

$$\begin{aligned}\mathbf{Q_t} &= \left(1 - {\theta_1}^T\bar{Q}\theta_1 - {\theta_2}^T\bar{Q}\theta_2 - {\theta_3}^T\bar{N}\theta_3\right) + {\theta_1}^T\varepsilon_{t-1}\varepsilon_{t-1}^T\theta_1 + {\theta_2}^T Q_{t-1}\theta_2 \\ &+ {\theta_3}^T\eta_{t-1}\eta_{t-1}^T\theta_3\end{aligned} \tag{2.5}$$

where θ_1, θ_2 and θ_3 are diagonal parameter matrixes, $\eta_t = I[\varepsilon_t < 0] \circ \varepsilon_t$ (with $\circ$ indicating the Hadamard product), $\bar{N} = E[\eta_{t t}^T]$.

2.3.2 Estimating Financial Contagion: A Linear Regression Approach

To avoid contagion tests based on apriori crisis dates that may produce biased results[11], this study uses a regression-based strategy following Chong et al.

[11]This is suggested by Dungey et al. (2005) and Pesaran & Pick (2007) among others.

(2009), Ahmad et al. (2013), Ahmad et al. (2014), and Syllignakis & Kouretas (2011). From the AR(1)-DCC-GARCH model, pair-wise time-varying conditional correlations can be obtained, and from the univariate GARCH models, a series of conditional standard deviations indicating volatility can be obtained for each asset. The conditional correlation is then regressed on conditional volatilities

$$\rho_{ij,t} = \beta_0 + \beta_1 \, h_t^{commodity} + \beta_2 \, h_t^{equity} + \epsilon_t \tag{2.6}$$

where $\rho_{ij,t}$ is the estimated pair-wise conditional correlation between the commodity returns and the returns from equities, with i and j denoting commodity and equity, respectively. The $h_t^{commodity}$ is the conditional volatility of the commodity returns at time t and $h_{i,t}^{equity}$ is that of equity returns of the i^{th} country at time t. A positive β_i (i = 1,2) obtained by estimating using least square technique and heteroskedasticity autocorrelation consistent (HAC) standard errors suggests that conditional correlation increases with volatility, thus indicating financial contagion (Ahmad et al. 2013; Ahmad et al. 2014; Syllignakis & Kouretas 2011; Roy & Sinha Roy 2017). Based on the least square estimation, the Degree of Financial Contagion (DFC) defined in terms of $\overline{R}^2$, can be written as:

$$DFC = \begin{cases} \overline{R}^2 \quad if \quad \beta_i(i = 1, 2) > 0 \\ 0 \quad if \quad \beta_i(i = 1, 2) \leq 0 \end{cases}$$

2.3.3 Estimating Financial Contagion: A Quantile-on-Quantile Regression Approach

The comprehensive relationship between the conditional correlation series and the conditional volatility series is explored using the Quantile-on-Quantile method as suggested by Sim & Zhou (2015). This method, an extension of the more widely used quantile regression, mainly shows how different quantiles of one independent variable impact different quantiles of the dependent variable. To investigate the effect of an explanatory variable on various quantiles of the result variable, standard quantile regression is first estimated.

The basic least squares method is extended by the standard quantile regression method (Koenker & Bassett Jr 1978). In contrast to the linear regression method, quantile regression looks at the effects of a variable on both the dependent variable's conditional mean and its various quantiles. This approach, compared to the least squares model, offers a more intricate connection. Additionally, Cleveland (1979) and Stone (1977) suggest the use of conventional linear regression to investigate the effects of a particular quantile of the independent variable on the dependent variable. Therefore, a combination of these two methods, namely traditional linear regression and standard quantile regression, allows researchers a better understanding of how different quantiles of the explanatory variable affect the corresponding quantiles of the outcome variable. In contrast to traditional methods like OLS and regular quantile regression, a combination of these two techniques can thus aid to better understanding of the underlying relationship.

The quantile regression method is extensively used in the finance and economics literature, given its potential to unravel the asymmetric relationship between financial and economic variables and to model the quantiles of a random variable as a function of observed variables. Moreover, the estimates of the quantile regression estimates are robust to outliers, heteroskedasticity, and skewness on the dependent variables (Xiao et al. 2019).

The quantile-on-quantile (Q-o-Q) regression approach, an improvement over the quantile regression method, is applied based on the following equation:

$$Y_t = \beta^\theta(X_t) + u_t^\theta \tag{2.7}$$

where Y_t denotes the time-varying conditional correlation between stock market returns and commodity price index returns, and X_t refers to the time-varying conditional variance of the asset returns. Here, θ denotes the θ^{th} quantile of the correlation, and u_t^θ is the error term that has a zero θ^{th} quantile.

In the absence of any prior information about the relationship between Y_t and X_t, the relationship is analysed over the θ^{th} quantile of Y_t and the τ^{th} quantile of X_t. The approximation of $\beta^\theta(.)$ around X^τ can be performed using the first order Taylor expansion such that:

$$\beta^\theta(X_t) \approx \beta^\theta(X^\tau) + \beta^{\theta'}(X^\tau)(X_t - X^\tau) \tag{2.8}$$

where $\beta^{\theta'}$ refers to the partial derivatives or marginal effect of $\beta^\theta(X_t)$ concerning X_t. Now, following Sim & Zhou (2015), $\beta^\theta(X^\tau)$ and $\beta^{\theta'(X^\tau)}$ are considered as $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$, respectively. Then the above equation can be rewritten as:

$$\beta^\theta(X_t) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(X^\tau)(X_t - X^\tau) \tag{2.9}$$

Substituting Eq. (2.8) into Eq.(2.6), the Quantile-on Quantile regression approach can be rewritten as follows:

$$Y_t = \underbrace{\beta_0(\theta,\tau) + \beta_1(\theta,\tau)(X^\tau)(X_t - X^\tau) + u_t^\theta}_{} \qquad (2.10)$$

where θ and τ are quantiles (0.05–0.95) of the dependent and independent variables, respectively. The procedure specified in the above equation gives the relationship between the τ^{th} quantile of X_t and θ^{th} quantile of Y_t, given that β_0 and β_1 are doubly indexed in θ and τ. The presence of financial contagion can be understood through a visual inspection of $\beta_1(\theta,\tau)$.

2.4 Empirical Results

This section discusses the estimation results of Quantile-on-Qauntile regression between conditional correlation and conditional volatility. As a prior, the summary statistics and results from some preliminary tests have been presented in sub-section 2.4.1. Sub-section 2.4.2 discusses the nature of co-movement among the markets chosen for the purpose of analysis. Sub-sections 2.4.3 and 2.4.4 discusses the results of financial contagion analysis using OLS regression and Quantile Regression, respectively. The results of financial contagion analysis using the Quantile-on-Quantile regression method are presented and discussed in Sub-section 2.4.5.

2.4.1 Summary Statistics and Preliminary Tests

The continuously compounded daily returns (r_{it})[12] series is used to understand the dynamic nature of the correlation between asset returns and to check the presence of financial contagion, time series properties of asset returns and certain diagnostic tests need to be carried out as prior. The summary statistics give a prior understanding of the nature of the statistical distribution of different return series used in empirical analysis. As evident from Table 2.1, investment in the equity market offers the highest average daily return while the energy commodity market offers the least. On the other hand, the average daily return from the overall commodity market is -0.0002. The highest return is obtained from investing in agricultural commodities and the least from that in energy commodities. However, energy commodities are found to be the most risky asset, as measured by a standard deviation of 1.2044 followed by equity (0.9927), agricultural commodities (0.9562), and metals (0.7178).

Further, as evident from Table 2.1, there is an asymmetry in the upside and downside potential of price changes with returns from commodity derivatives and all equities being negatively skewed. For all asset returns, kurtosis values are higher than that of a normal distribution, implying that the probability of extreme gains or losses is larger than that predicted by normal distribution. As also evident from the Jarque-Bera statistics, all asset return series show significant departure from a Gaussian distribution. From Figure A2.1 (see Appendix), the presence of volatility clustering and hence ARCH effects can be observed. Further, the ARCH-

[12]The return of an asset is the logarithmic value of the ratio of two consecutive prices and expressed as: $r_{it} = ln\left(\frac{P_{it}}{P_{i,t-1}}\right)$ where P_{it} price of the i^{th} asset at the t^{th} time period.

Table 2.1: **Summary Statistics and Preliminary Tests**

Variables → Statistics↓	Equity	COMDEX (Overall)	COMDEX (Agri)	COMDEX (Energy)	COMDEX (Metals)
Mean	0.0386	-0.0002	0.0083	-0.0076	0.0066
Median	0.0683	0.0206	0.0000	0.0128	0.0428
Maximum	9.2448	3.0590	10.0981	6.3689	3.1619
Minimum	-7.7993	-3.8660	-21.4791	-6.4417	-5.8748
Std. Dev.	0.9927	0.6737	0.9562	1.2044	0.7178
Skewness	-0.0938	-0.3967	-5.0874	-0.0374	-0.9376
Kurtosis	11.7382	5.9992	126.5628	5.5245	9.4686
Jarque-Bera	10653.43***	1342.258***	2143657***	889.574***	6325.714***
Q	902.14***	855.03***	15.286***	886.31***	741.73***
Q^2	1625.20***	613.23***	0.2253	731.83***	699.43***
ARCH-LM	286.3463***	162.1142***	0.1204	175.6391***	278.5331***
No. of Obs.	3347	3347	3347	3347	3347

Note: (i) COMDEX refers to commodity futures price index; (ii) Q and Q^2 are Ljung-Box Q statistics for return series and squared return series, respectively. ARCH-LM test shows Engle (1982) test for conditional heteroskedasticity calculated for the first lag only. (iii) *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

LM test (as proposed by Engle 1982) confirms the significant presence of ARCH effects in all the daily asset return series except the agricultural commodities. As there is no ARCH effect in the agriculture commodity index, it is excluded from the empirical analysis. These tests provide the basis for choosing a GARCH based method to estimate dynamic correlations in order to find the presence of financial contagion in the Indian commodity derivative market.

2.4.2 Co-movement and Potential for Financial Contagion

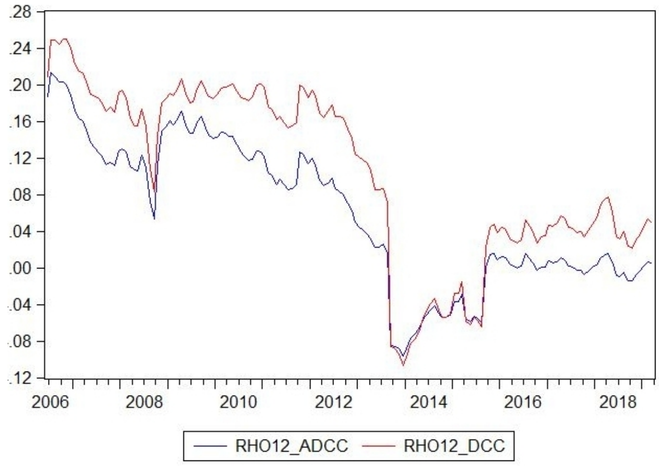
Before analysing the nature and extent of financial contagion, it is crucial to understand the pattern of co-movement of the assets returns, with excess co-movement during the crises showing contagion. The evolution of correlation or co-movement between equities and commodities aid to understand the nature of contagion (Wen et al. 2012). To analyse the co-movement of the assets, time-varying correlations are estimated using AR(1)-DCC-GJR-GARCH and AR(1)-

ADCC-GJR-GARCH methods. The GJR-GARCH model developed by Glosten et al. (1993) is chosen as the univariate GARCH model. The results of estimated AR(1)-DCC-GJR-GARCH and AR(1)-ADCC-GJR-GARCH models are given in Appendix in Tables A2.1 and A2.2, respectively. Conditional correlations, as evident from Figure 2.1, show significant variability across the sample period indicating that relying on constant conditional correlations and exogenous selection of crisis dates to test for the presence of financial contagion could be misleading.

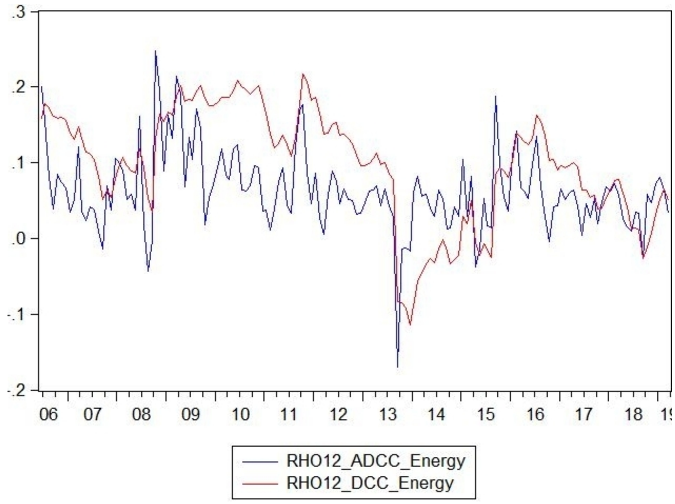
Figure 2.1(a) shows the dynamic conditional correlation between the returns from the overall commodity futures price index and the equity price index. It can be seen from the graphs that the correlation between returns from commodity derivatives and equities declined in the pre-crisis period and followed by an upward turn since the onset of the Global Financial Crisis in 2008-09. A similar pattern of correlation during the pre-crisis period has been reported in studies by Wen et al. (2012), Silvennoinen & Thorp (2013), Lombardi & Ravazzolo (2016), among others. The movements of correlations after that turnaround in 2008-09, are found to remain stable. The increased correlation between equity and commodity futures prices is seen to prevail till the end of the Eurozone crisis. The correlation is found to rise again towards the end of 2015 possibly on account of high volatility in the crude oil market during the "Great Plunge in Oil Prices" of 2014-16. These results are in tandem with the findings of Roy & Sinha Roy (2017).

Figure 2.1(b) also shows the dynamic conditional correlation between the Indian energy commodity futures price index and the equity price index. A difference is observed between the dynamic correlation for the overall commodity

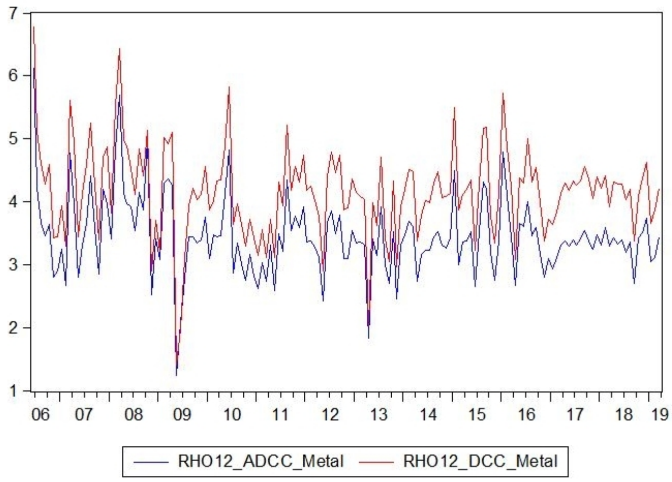
Figure 2.1: Conditional Correlation between Commodity and Equity Return



(a) Equity Prices Index and Overall Commodity Prices Index



(b) Equity Prices Index and Energy Commodity Prices Index



(c) Equity Prices Index and Metals Commodity Prices Index

Note: The dynamic correlation obtained from AR(1)-DCC-GARCH model has been shown in red, while the same obtained from AR(1)-ADCC-GARCH model has been shown in blue.

derivatives market and the energy commodity derivatives market only during the episodes of the oil price plunge of 2014-16. The degree of rise in correlations is seen to be higher in the case of energy commodities than in the case of overall commodity derivatives. It is worth mentioning that the two crisis periods, the Global financial crisis and the Great Plunge in oil prices, are different in terms of the origin of the crisis. While the large volatility in the crude oil market during the Global Financial Crisis or the Eurozone crisis was mainly on account of demand-driven factors, it is supply driven during the "Great Oil Price Plunge" period (Baffes et al. 2015). In a net oil-importing country such as India, the excess co-movement in the crude oil market is considerable during the Global Financial Crisis or the Eurozone crisis. While in case of oil-exporting countries, the evolution of the correlation between commodity derivatives and equities is mainly driven by the movement of commodity prices, the movement of correlation in the case of oil-importing countries depends upon the bearish and bullish nature of the equity markets (Wen et al. 2012).

From Figure 2.1(c) it can also be seen that the conditional correlation between returns from the metals commodity futures price index and equity prices show a similar trend as in the case of the energy commodity derivative market. However, a few observations are to be mentioned in this regard. First, although metals derivatives have a high correlation with equities even before the onset of the crisis in 2008-09, the high correlation between the energy commodities and the equities was observed only after the onset of the crisis. This finding is found to be in line with Silvennoinen & Thorp (2013). Second, it can be seen that during the Global Financial Crisis or the Eurozone crisis the rise in conditional correlation is not as notable as that in the case of energy commodities. Third, in this case, the conditional correlations fell sharply and become negative during the Oil price plunge of 2014-16. Thus it can be inferred that the evolution of the correlation between equity prices and metals prices is predominantly determined by the movement of the equity markets and not the commodity markets. The metal commodity derivative market in India is found to be clearly dominated by gold. On one hand, gold has been used by investors mainly as a safe haven asset, on the other, India being the largest consumer of gold, it is considered to be a symbol of families' wealth status and thus believed to have an important socio-cultural role (Baur & Lucey 2010). The results found are in tandem with the existing literature on gold as a safe haven asset (see Baur & McDermott 2010; Baur & Lucey 2010 among others).

2.4.3 Financial Contagion: Linear Regression Estimates

To understand the nature and extent of financial contagion between commodity futures prices and equity prices, Eq. (2.6) has been estimated using the OLS method. This shows the estimates of financial contagion around the mean. In Tables 2.2, 2.3, and 2.4, β_2 shows the increase in conditional correlation between commodity futures prices and equity prices on account of the increase in conditional volatility of equity prices. Statistically significant β_2 in Table 2.2 implies that the conditional correlation increases with an increase in conditional volatility in the Indian equity market. There is thus evidence of financial contagion in the Indian commodity derivative market. This result confirms the findings of Roy & Sinha Roy (2017). The degree of financial contagion is found to be 0.1720.

Table 2.2: Financial Contagion: Overall Commodity Derivative Market

Quantile ↓	β_0	**S.E.**	β_1	**S.E.**	β_2	**S.E.**
OLS	-0.0033	(0.0038)	0.0143	(0.0092)	0.0734***	(0.0042)
0.05	-0.0839***	(0.0080)	-0.0713***	(0.0182)	0.0879***	(0.004)
0.1	-0.0886***	(0.0052)	-0.0139	(0.0126)	0.0757***	(0.0050)
0.2	-0.0213***	(0.0067)	-0.0773***	(0.0164)	0.0912***	(0.0065)
0.25	-0.0246***	(0.0042)	-0.0449***	(0.0104)	0.0841***	(0.0046)
0.3	-0.0246***	(0.0039)	-0.0391***	(0.0095)	0.0892***	(0.0053)
0.4	-0.0270***	(0.0043)	-0.0281***	(0.0103)	0.1020***	(0.0062)
0.5	-0.0337***	(0.0077)	-0.0127	(0.0187)	0.1212***	(0.0084)
0.6	0.0066	(0.0062)	0.0254***	(0.0083)	0.0884***	(0.0044)
0.7	0.0397***	(0.0029)	0.0231***	(0.0068)	0.0716***	(0.0033)
0.75	0.0523***	(0.0053)	0.0629***	(0.0148)	0.0451***	(0.0067)
0.8	0.0656***	(0.0029)	0.0892***	(0.0089)	0.0244***	(0.0037)
0.9	0.0724***	(0.0037)	0.1343***	(0.0100)	0.0068**	(0.0033)
0.95	0.0672***	(0.0056)	0.1849***	(0.0136)	-0.0034	(0.0034)

Note: (i) S.E. is the standard error. (ii) *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

In case of the evidence on energy commodity derivative market with respect to the Indian equity market, as shown in Table 2.3, both β_1 and β_2 are statistically significant. This implies that the conditional correlation increases on account of a rise in conditional volatility either in the energy commodity derivative market or in the equity market. Therefore, financial contagion is said to be present in the Indian energy commodity derivative market. The responsiveness of conditional correlation to an increase in conditional volatility in the equity market is found to be higher than the same on account of an increase in conditional volatility in the energy commodity market. The degree of financial contagion in this case, measured in terms of the $\overline{R}^2$, is found to be 0.2003.

The presence of financial contagion in the metals commodity derivative market is observed from the results of OLS regression, presented in the first row of Table 2.4. β_1 and β_2, the two coefficients for metals futures price volatility and equity price volatility, respectively, are found to be positive and statistically signif-

Table 2.3: Financial Contagion: Energy Commodity Derivative Market

Quantile ↓	β_0	**S.E.**	β_1	**S.E.**	β_2	**S.E.**
OLS	-0.0071**	(0.0029)	0.0401***	(0.0031)	0.0414***	(0.0026)
0.05	0.0646***	(0.0047)	-0.0384***	(0.0037)	-0.0686***	(0.0122)
0.1	0.0401***	(0.0047)	-0.0246***	(0.0052)	-0.0227**	(0.0094)
0.2	0.0166***	(0.0034)	0.0021	(0.0045)	0.0079	(0.0066)
0.25	0.0139***	(0.0038)	0.0093**	(0.0044)	0.0138***	(0.0047)
0.3	0.013***	(0.0038)	0.0135***	(0.0042)	0.0184***	(0.0049)
0.4	0.0105***	(0.0038)	0.0202***	(0.0040)	0.0319***	(0.0052)
0.5	0.0035	(0.0036)	0.0275***	(0.0040)	0.0493***	(0.0047)
0.6	0.0043	(0.0038)	0.0352***	(0.0042)	0.0547***	(0.0051)
0.7	-0.0008	(0.0038)	0.0404***	(0.0038)	0.0728***	(0.0059)
0.75	-0.0044	(0.0035)	0.0433***	(0.0037)	0.0846***	(0.0046)
0.8	-0.0024	(0.0031)	0.0446***	(0.0033)	0.0878***	(0.0039)
0.9	-0.0097***	(0.0036)	0.0620***	(0.0047)	0.0969***	(0.0046)
0.95	-0.0152***	(0.0040)	0.0818***	(0.0050)	0.0966***	(0.0045)

Note: (i) S.E. is the standard error. (ii) *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

icant. This indicates the presence of financial contagion in the metals commodity derivative market in India. Unlike energy commodities, in this case, the size of β_1 coefficient is larger than the β_2 coefficient, implying a stronger influence of metals price volatility on the excess co-movement between metals and equity prices. In other words, it can be inferred that financial contagion occurs in the metals commodity derivative market mostly in times of high volatility in the commodity market. The degree of financial contagion, between metals commodity futures prices and equity prices in India, is found to be 0.0730. On the whole, the above OLS estimations do find evidence of financial contagion in the Indian commodity derivative market. In the next sub-section, the results on financial contagion are arrived at using the quantile regression method.

Table 2.4: Financial Contagion: Metals Commodity Derivative Market

Quantile ↓	β_0	S.E.	β_1	S.E.	β_2	S.E.
OLS	0.2931***	(0.0035)	0.0346***	(0.0048)	0.0308***	(0.0048)
0.05	0.3165***	-0.0094	-0.0372***	(0.0125)	-0.1122***	(0.0128)
0.1	0.3341***	(0.0096)	-0.0399***	(0.0128)	-0.0866***	(0.0136)
0.2	0.3175***	(0.0082)	-0.0123	(0.0119)	-0.0366***	(0.0111)
0.25	0.3107***	(0.0071)	0.0009	(0.0100)	-0.0209**	(0.0099)
0.3	0.3073***	(0.0066)	0.0055	(0.0093)	-0.0046	(0.0093)
0.4	0.2938***	(0.0060)	0.0225***	(0.0086)	0.0263***	(0.0086)
0.5	0.2830***	(0.0053)	0.0429***	(0.0077)	0.0453***	(0.0071)
0.6	0.2797***	(0.0054)	0.0523***	(0.0075)	0.0624***	(0.0074)
0.7	0.2711***	(0.0058)	0.0717***	(0.0090)	0.0824***	(0.0075)
0.75	0.2667***	(0.0058)	0.0814***	(0.0091)	0.0905***	(0.0077)
0.8	0.2573***	(0.0064)	0.0997***	(0.0099)	0.1001***	(0.0089)
0.9	0.2491***	(0.0055)	0.1154***	(0.0075)	0.1303***	(0.0073)
0.95	0.2541***	(0.0045)	0.1276***	(0.0063)	0.1360***	(0.0056)

Note: (i) S.E. is the standard error. (ii) *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

2.4.4 Financial Contagion: Quantile Regression Estimates

In this sub-section, on account of reseasons mentioned in section 2.3, the dependence between conditional correlation and conditional volatility is examined using the quantile regression approach. Table 2.2 presents the results of quantile regression considering the conditional correlation between the overall commodity futures price index and equity price index, and their conditional volatilities. While the OLS estimate shows that the average relationship to be positive, the quantile regression estimates show changes in the coefficients with changes in quantiles of the conditional correlation. For instance, β_1, which is the coefficient for conditional volatility of the commodity futures price index, increases with an increase in quantiles of the latter. This indicates the presence of financial contagion on account of high volatility in the commodity derivative market especially during the high co-movement regime. On the other hand, the β_2 shows an inverted U-shaped relationship between financial contagion and degree of co-movement. The coefficients imply the presence of a high degree of financial contagion around the median.

Tables 2.3 and 2.4 show the asymmetric nature of financial contagion in the energy commodity derivative market and metals commodity derivative market, respectively. The asymmetric nature of financial contagion is evident from Tables 2.3 and 2.4. From Table 2.3 it can be observed that the β_1 and β_2 coefficients increase in the higher quantiles of the correlation series. This implies the presence of stronger financial contagion during the high correlation regime. For the higher quantiles of the correlation series ($\theta = 0.5 - 0.9$), the coefficients of volatility of the equity price index are found to be stronger than that of the volatility of the energy commodity futures price index, implying a stronger contribution of equity market towards the presence of financial contagion during the high correlation regime.

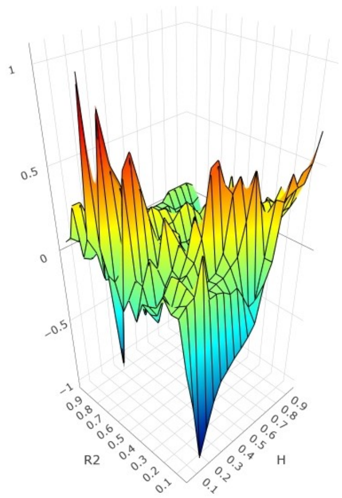
Table 2.4 shows the asymmetric relationship between conditional correlation and conditional volatilities considering the metals commodity futures price index. The significant positive impact of conditional volatilities on the conditional correlation is evident for the higher quantiles of the correlation series ($\theta = 0.4 - 0.95$). Even though in the case of the average relationship found from the OLS estimate, the effect of conditional volatility of metals is found to be stronger, the pattern changes with estimates of quantiles-varying coefficients. In the high correlation regime, the effect of conditional volatility of the equity price index is found to be relatively strong. The quantile regression estimates show an asymmetric dependence structure for the conditional correlation between commodity futures returns and equity returns on the respective conditional volatilities. Quantile-on-quantile regression estimation will result in estimates that are dependent on the asymmetric structure of conditional correlation as well as conditional volatilities.

2.4.5 Financial Contagion: Quantile-on-Quantile Regression Estimates

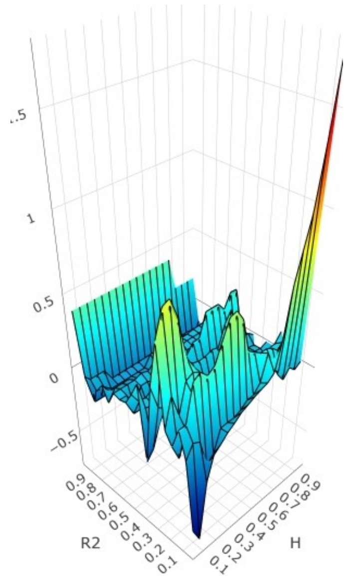
The results of quantile-on-quantile estimates, as evident from Figure 2.2, indicate that the impact of conditional volatility on the conditional correlation between commodity futures returns and equity returns varies across different quantiles of dependent and independent variables. Figure 2.2(a) shows the effect of conditional volatility of the overall commodity derivative market on the conditional correlation, whereas Figure 2.2(b) shows the effect of conditional volatility of the equity market on the conditional correlation. The results shown in Figures 2.2(a) and 2.2(b) are similar to those obtained from the quantile regression. Financial contagion between the overall commodity derivative market and equity market on account of high volatility in the commodity market is found during the high correlation regime From Figures 2.2(a) and 2.2(b), it is also observed that during the low-correlation and low-volatility regime, there is no evidence of financial contagion. Therefore, in a tranquil period, commodity derivatives can be used as diversifiers by the investors holding equities in their portfolios.

While Figure 2.2(c) shows the effect of conditional volatility of the energy commodity derivative market on the conditional correlation, Figure 2.2(d) shows the effect of conditional volatility of the equity market on the conditional correlation between returns on energy commodities and returns on equities. Figure 2.2(c) shows that there is no evidence of financial contagion with respect to the rise in volatility in the energy commodity derivative market. However, Figure

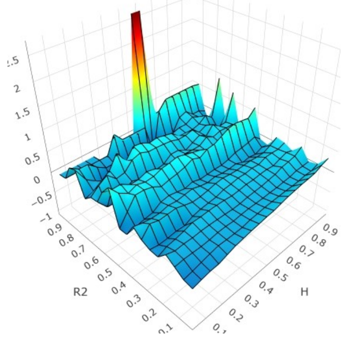
Figure 2.2: Asymmetric Financial Contagion



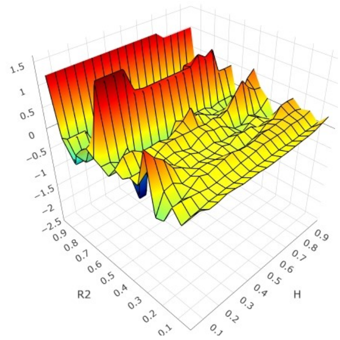
(a) $\beta_1(\theta, \tau)$ **Equity**



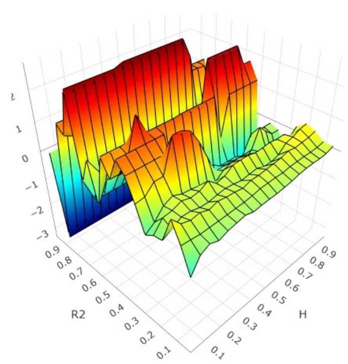
(b) $\beta_1(\theta, \tau)$ **CFP(Overall)**



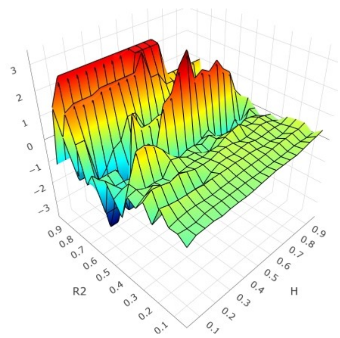
(c) $\beta_1(\theta, \tau)$ **Equity**



(d) $\beta_1(\theta, \tau)$ **CFP(Energy)**



(e) $\beta_1(\theta, \tau)$ **Equity**



(f) $\beta_1(\theta, \tau)$ **CFP(Metals)**

2.2(d) shows strong evidence of financial contagion when the correlation between energy commodities and equities is very high. The nature of financial contagion between the metals commodity derivative market and equity market is also found to be heterogeneous across quantiles and is presented in Figures 2.2(e) and 2.2(f). From Figure 2.2(e) it can be observed that financial contagion on account of the rise in volatility in the metals commodity derivative market occurs only during the high correlation regime. Similarly, the financial contagion on account of the rise in volatility in the equity market occurs only during the high correlation regime as can be observed from Figure 2.2(f). The contribution of the volatility of the equity market to financial contagion is found to be relatively stronger.

In summary, it is found that dependence between the commodity derivative market and the Indian stock markets exists, but asymmetric, and is right-tailed. Dependence in a high correlation regime is particularly strong. Moreover, dependence is significantly positive at the higher quantiles. Additionally, changes in the dependence of each type of commodity are heterogeneous across quantiles. On the whole, the results from the Quantile-on-Quantile regression show that there is financial contagion in the Indian commodity derivative market vis-à-vis the Indian equity market, and that contagion is non-linear in nature. This is found across all types of commodities considered.

2.5 Summary of Findings

Volatility in returns in the Indian commodity derivative market during different crisis periods indicates that with various shocks there is a possibility of financial contagion across different types of commodities. This essay attempts to find the presence of financial contagion between the Indian commodity derivative market and the Indian equity markets. Substantial evidence of financial contagion is found. This chapter in a sense, is an extension of Roy & Sinha Roy (2017) as it shows financial contagion in the Indian commodity derivative market considering different types of commodities such as energy and metals. The asymmetric nature of financial contagion in the Indian commodity derivative market is also observed in this essay. The Indian commodity derivative market shows evidence of financial contagion vis-à-vis the domestic equity market and the degree of financial contagion is found to vary across quantiles.

The presence of financial contagion is also verified with respect to extreme events in the equity markets as well as in the commodity derivative markets. The presence of financial contagion in the Indian commodity derivative market creates a possibility of shocks and volatility transmission from traditional asset markets to the commodity derivative market. These shocks may further get transmitted to the macroeconomy and pose challenges for the policymakers if there is a close linkage between commodity prices and different macroeconomic indicators. Extending this analysis, the linkage between the Indian commodity derivative market and the macroeconomy is examined in Chapters 3 and 4. The possible transmission channels for different types of commodity market-specific shocks to the real variables are studied in Chapter 5.

Appendix to Chapter 2

Figure A2.1: Time Pattern of Commodity and Equity Returns

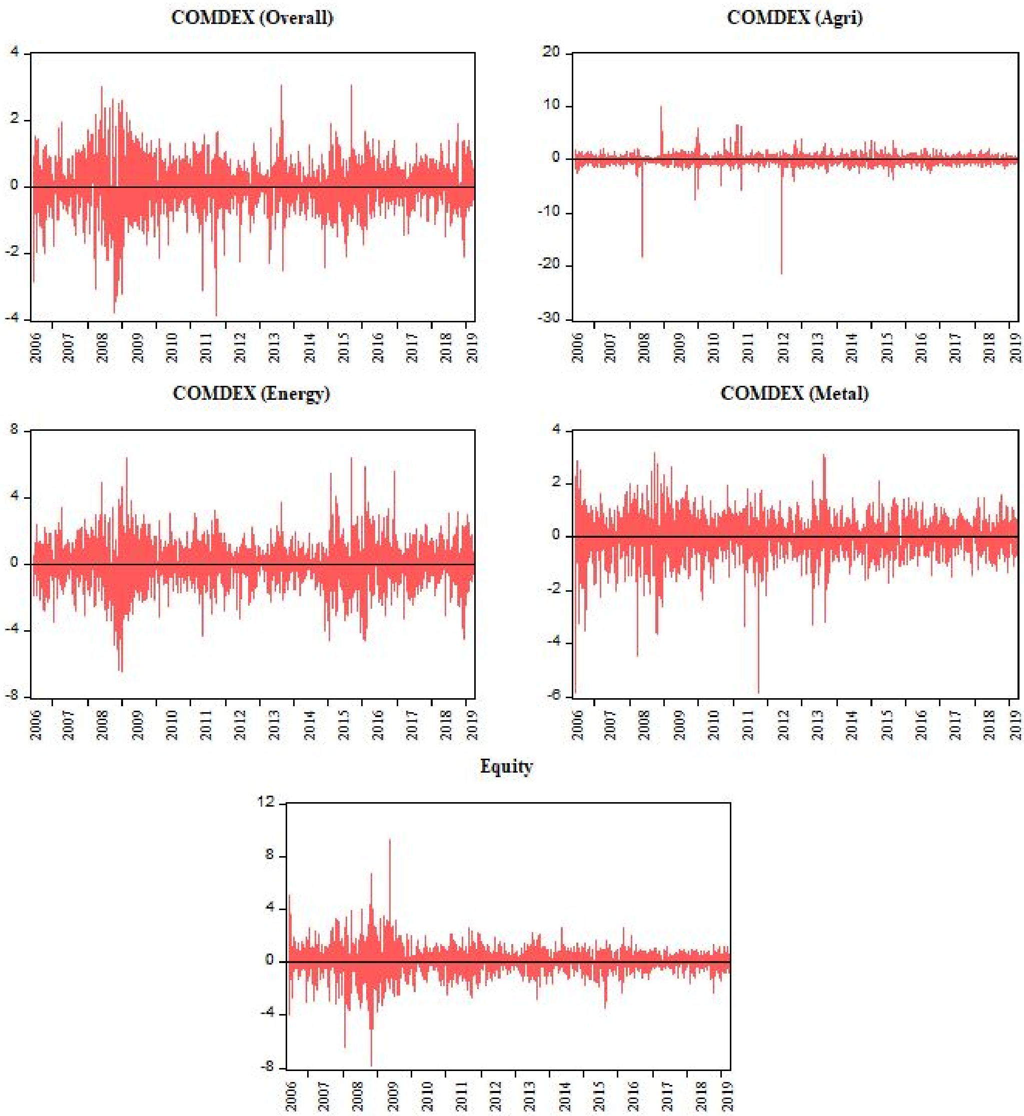


Table A2.1 : AR(1)-DCC-GJR-GARCH(1,1) Estimation Results

Commodity →	CFP(Overall)		CFP(Energy)		CFP(Metals)	
Parameter ↓	Coef.	SE.	Coef.	SE.	Coef.	SE.
ς_1	0.0047	(0.0079)	0.0022	(0.0133)	0.0085	(0.0092)
μ_1	0.5194***	(0.0144)	0.5170***	(0.0142)	0.4913***	(0.0132)
ς_2	0.0188**	(0.0083)	0.0194**	(0.0089)	0.0254***	(0.0079)
μ_2	0.5300***	(0.0143)	0.5294***	(0.0137)	0.4927***	(0.0130)
ζ_1	0.0058***	(0.0010)	0.0089***	(0.0018)	0.0241***	(0.0018)
ζ_2	0.0092***	(0.0012)	0.0088***	(0.0011)	0.0088***	(0.0014)
α_1	0.0652***	(0.0049)	0.0419***	(0.0033)	0.0327***	(0.0066)
α_2	0.0392***	(0.0080)	0.0409***	(0.0033)	0.0406***	(0.003)
β_1	0.9005***	(0.0044)	0.9242***	(0.0035)	0.8427***	(0.0031)
β_2	0.8762***	(0.0033)	0.8760***	(0.0052)	0.8831***	(0.0042)
γ_1	0.0338***	(0.0117)	0.0550***	(0.0099)	0.2010***	(0.0112)
γ_2	0.1444***	(0.0162)	0.1431***	(0.0102)	0.1334***	(0.0070)
θ_1	0.0037**	(0.0015)	0.0053***	(0.0016)	0.0787***	(0.0092)
θ_2	0.9958***	(0.0019)	0.9939***	(0.0021)	0.8470***	(0.0215)
t	10.9053***	(1.0396)	11.0002***	(1.1005)	10.2606***	(0.9647)

Note: (i) S.E. stands for standard error; (ii) Coefficients in the univariate GARCH model with subscript 1 and 2 are for commodity and equity markets, respectively; (iii) *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

Table A2.2 : AR(1)-ADCC-GJR-GARCH(1,1) Estimation Results

Commodity →	CFP(Overall)		CFP(Energy)		CFP(Metals)	
Parameter ↓	Coef.	SE.	Coef.	SE.	Coef.	SE.
ς_1	0.0048	(0.0080)	0.0022	(0.0133)	0.0082	(0.0093)
μ_1	0.5201***	(0.0152)	0.5171***	(0.0142)	0.4919***	(0.0131)
ς_2	0.0192**	(0.0087)	0.0196**	(0.0085)	0.0246***	(0.0077)
μ_2	0.5295***	(0.0146)	0.5296***	(0.0143)	0.4961***	(0.0131)
ζ_1	0.0058***	(0.0009)	0.0087***	(0.0017)	0.0231***	(0.0032)
ζ_2	0.0092***	(0.0019)	0.0087***	(0.0012)	0.0085***	(0.0011)
α_1	0.0654***	(0.0051)	0.0415***	(0.0022)	0.0303***	(0.0115)
α_2	0.0386***	(0.0094)	0.0409***	(0.0035)	0.0392***	(0.0034)
β_1	0.8999***	(0.0031)	0.9243***	(0.0066)	0.8417***	(0.0106)
β_2	0.8758***	(0.0124)	0.8755***	(0.0075)	0.8813***	(0.0059)
γ_1	0.0334***	(0.0110)	0.0556***	(0.0105)	0.1991***	(0.0221)
γ_2	0.1446***	(0.0205)	0.1433***	(0.0117)	0.1331***	(0.0102)
θ_1	0.0025*	(0.0014)	0.0225***	(0.0068)	0.0577***	(0.0079)
θ_2	0.9954***	(0.0025)	0.9239***	(0.0205)	0.7869***	(0.0193)
θ_3	0.0015**	(0.0008)	0.0232***	(0.0083)	0.1410***	(0.0179)
t	10.9543***	(1.0744)	11.086***	(1.1142)	10.2299***	(1.0340)

Note: (i) S.E. stands for standard error; (ii) Coefficients in the univariate GARCH model with subscript 1 and 2 are for commodity and equity markets, respectively; (iii) *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

Chapter 3

Commodity Futures Prices Pass-through and Monetary Policy in India: Does Asymmetry Matter?[1]

3.1 Introduction

This essay explores the nature and extent of commodity futures price pass-through to various macroeconomic indicators relevant to monetary policy in India. The stylized facts, presented in Chapter 1, show that the commodity futures prices and macroeconomic indicators are contemporaneously and successively correlated. In Chapter 2, the non-linear nature of financial contagion has been found in the Indian commodity derivative market vis-a-vis the equity market. These evidences show the possibility of a spillover of volatility as a result of any financial market-specific shock, from the equity market to the commodity market. It is now crucial to examine whether there is any possibility of transmission of such shocks to the Indian macroeconomy. This essay investigates into the nature of the relationship between commodity futures prices and macroeconomic indicators, both in the long and short runs, if any.

While predicting movements of macroeconomic indicators is of prime importance from the point of view of monetary policymaking, it has become more challenging in an era of recurrent financial crises and frequent commodity price

[1] A version of this Chapter is published as Roy, R. P., Sinha Roy, S. (2022). Commodity futures prices pass-through and monetary policy in India: Does asymmetry matter? *The Journal of Economic Asymmetries*, 25, e00229. doi: https://doi.org/10.1016/j.jeca.2021.e00229

shocks. In such an exercise to predict the movement of macroeconomic indicators, the selection of true predictors and an unerring methodology are imperative. The rising volatility in traditional/conventional as well as non-traditional/non-conventional assets (such as commodities) prices has encouraged discussion on whether monetary policy authorities are required to respond to asset market signals. Even though some studies[2] have argued against monetary policy responses to asset price fluctuations, some others[3] have argued in favour of considering asset prices signals in monetary policymaking. While Bernanke & Gertler (2000) argue that monetary policy needs to respond to asset prices changes only when the latter signals change in expected inflation, Cecchetti et al. (2000) claim that along with responding to inflation, policy instruments responding to movements in asset prices, reduce the likelihood of formation of asset price bubbles and thus output-volatility. This is especially important when the central bank practices flexible inflation targeting, in which a positive weightage is assigned to stabilization of output along with maintaining low and stable inflation.

The expanding macro-finance literature shows that central banks across countries are assigning increasing credence to the association between commodity prices and macro fundamentals in their respective aim to control inflation using monetary policy. Studies have found close linkages between commodity futures prices and consumer prices, with movements in the former inducing fluctuations in the latter. This is mainly on account of two reasons. First, as commodities are being used as raw materials in the production of manufactured goods, changes

[2]See, Fuhrer & Moore (1992), Bernanke & Gertler (2000), Bernanke & Gertler (2001), among others.

[3]See, for example, Cecchetti et al. (2000), Cecchetti et al. (2002), among others.

in commodity prices reflect supply shocks to production and have an impact on pricing decisions of firms (Garner 1989; Marquis & Cunningham 1990). Second, as commodity prices are mainly determined in the derivatives markets, they reflect the future state of the economy (Kilian 2009; Ciner 2011; Hu & Xiong 2017; and Sockin & Xiong 2015) and are found to react to demand and supply shocks promptly (Kugler 1991; Bhar & Hamori 2008). Hence, with increasing participation, rising speculative activities, financialization and globalization of commodity markets, it has become imperative for the monetary policy authorities to understand the relationship between commodity futures prices and consumer prices especially when stability in the general price level is the prime objective of the central bank.

Expectations of consumers, producers, and investors about future economic performances often trigger inflation. In an "overheated economy", if speculators expect demand for a commodity to rise, they take more long positions resulting in a rise in the price of that commodity and thus, in the general price level. Arguing in the same line, Sockin & Xiong (2015) show that in the presence of informational frictions, a rise in commodity futures prices can have both cost and informational effects. The impact of changes in commodity futures prices on the general price level depends upon the relative strength of the "informational effect" and the "cost effect". If the former is stronger than the latter, an increase in commodity futures price incentivizes higher production on one hand and dampens price rise on the other. On the contrary, if the cost effect is found to be dominant, a rise in commodity futures prices leads to a surge in the general price level. While studying the relationship between commodity price indices and core consumer price inflation, Blomberg & Harris (1995) find that although there was a positive relationship between the two during the 1970s and early 1980s, a rise in commodity price indices had a negative effect on inflation during the late 1980s and early 1990s. Hence, they conclude that commodity price indices lost their predictive power. However, this changing relationship can be explained through the cost and the informational effects.

The impacts of commodity prices on inflation through these two aforesaid effects can be better understood if the relationship is studied considering the possible presence of non-linearities. Some studies have examined the non-linear relationship between international crude oil prices and inflation (Salisu et al. 2017; Salisu & Isah 2018; Lacheheb & Sirag 2019). Since, in these studies, spot prices have been considered, a rise in crude oil prices having only cost effect is found to increase the general price level, and a decrease in crude oil prices lowers the production costs and thus results in a fall in the general price level. The present chapter contributes to the literature by examining the commodity futures prices and inflation relationship considering non-linearities that allow us to identify the cost effect as well as the informational effect. The rest of this chapter is structured as follows: Section 3.2 discusses the relevant literature, while Section 3.3 provides the detailed empirical methodology used. Empirical results and discussions are presented in Section 3.4. Finally, Section 3.5 concludes the chapter.

3.2 Literature Review

A number of studies have argued that commodity prices could be used as a leading indicator of inflation in managing monetary policy (Olivera 1970; Garner 1989; Marquis & Cunningham 1990; Christiano et al. 1996; Awokuse & Yang 2003), as commodity prices induce inflation (Breeden 1980; Erb & Harvey 2006; Gorton & Rouwenhorst 2006; Bhar & Hamori 2008; Cologni & Manera 2008; Bekaert & Wang 2010) apart from impacting real economic activity (Garner 1989; Awokuse & Yang 2003). Garner (1989), using monthly U.S. data, claims that the commodity price index can be used as information variables in order to improve the forecasts of inflation. Sephton (1991), using a different methodology, shows that the results of Garner (1989) are robust. Marquis & Cunningham (1990) also argue in favour of incorporating commodity prices in policy design when commodity prices and CPI are co-integrated. However, Kugler (1991) finds that consumer prices and commodity prices only follow a common trend, but do not move proportionately over the long-run. Nonetheless, given the relationship between commodity prices and general price level, the former can be a leading indicator of inflation or an intermediate target for monetary policy.

Most of the aforementioned studies[4] examine the relationship between commodity prices and macroeconomic indicators for industrialized countries. Only a few studies attempt to understand the commodity futures price-inflation relationship for emerging markets. For instance, Tule et al. (2019) explore the role of agricultural commodity futures prices in predicting inflation in Nigeria. There

[4]See, for example, Garner (1989), Sephton (1991), Marquis & Cunningham (1990), and Cody & Mills (1991), among others.

are some studies on crude oil price pass-through to inflation in developed countries (see, for example, Hooker 2002; Tiwari et al. 2019, among others), and for developing countries as well.

Many studies, on the other hand, examine the crude oil price-inflation relationship for emerging market economies. Salisu et al. (2017), investigating the relationship between crude oil prices and inflation in a number of countries including emerging economies, show that there is a significant difference in predicting the power of crude oil prices for the oil-exporting and oil-importing countries. In the same line, Tule et al. (2020) show that considering supply-side factors such as crude oil prices, an augmented Phillips curve type model can predict inflation better for Nigeria. Similarly, Mandal et al. (2012) find strong non-linear crude oil price pass-through to inflation in India, the impact of the crude oil price on industrial production is however found to be smaller.

This relationship between commodity price and inflation is required to be studied separately for emerging market economies as it is found that the relationship has become weaker over time for developed countries, while that for the emerging economies have become gradually stronger (Dedeoğlu & Kaya 2014). Cunado & De Gracia (2005) show that oil price pass-through to inflation is limited only in the short-run for several Asian economics. Dedeoğlu & Kaya (2014) find that the relationship between crude oil prices and inflation has become stronger over time in Turkey. On the contrary, Chen et al. (2020) show that the effects of oil price shocks on Chinese inflation are time-varying in nature and decrease along the price chain. Sarwar et al. (2020) show that the crude oil price pass-through is more to non-food inflation rather than to food price inflation in Pakistan.

A number of studies have empirically established the non-linear relationship between crude oil price shocks and inflation (see, for example, Hamilton 1996; Mork 1989; Mory 1993, among others). Some recent studies, such as by Sek (2017) and Sarwar et al. (2020) have examined the non-linearities in pass-through of crude oil prices applying Nonlinear Autoregressive Distributed Lag (NARDL) estimation strategy. However, no studies hitherto have examined the non-linear pass-through from commodity futures prices to macroeconomic indicators. While studying the pass-through of commodity futures prices to inflation and other macroeconomic indicators, it is essential to consider asymmetries as commodity prices exhibit cycles (Erten & Ocampo 2013). The informational effect and cost effect may thus work differently during the commodity price boom and bust. The analyses in the present chapter attempt to find some insight into this non-linear relationship between commodity futures prices and macroeconomic indicators in India.

Modelling inflation in emerging market economies is a challenging task. Although there are some recent studies[5] on modelling inflation in India, there is hardly any study examining the relationship between commodity futures prices and macroeconomic indicators such as inflation, industrial output, and rate of interest. This is important to study, as commodity derivative markets in emerging market economies including India have been liberalized in the recent past (see Chapter 1) and these economies have witnessed phenomenal growth in commodity trading.

[5]See, for example, Mishra & Mishra (2012*a*), Mishra & Mishra (2012*b*), Kapur (2013), Mohanty & John (2015), Balakrishnan & Parameswaran (2021), Raj et al. (2019), Jithin & Suresh (2020), among others.

In the recent past, the Reserve Bank of India (RBI) has adopted 'flexible inflation targeting' as the monetary policy strategy[6], and hence inflation forecasts have become more important in conducting and formulating monetary policy[7]. Thus, one of the key requirements is to set up a model or find a methodology for inflation forecasting and also to select a number of predictors capable of predicting future inflation accurately. Against this backdrop, this chapter empirically investigates into the relationship between commodity futures price index and macroeconomic indicators relevant to monetary policymaking. More precisely, in the present chapter, the long-run relationship between the commodity futures price index and macroeconomic indicators (such as industrial production, inflation, and interest rate) is examined. The corresponding short-run relationship is also being looked into.

3.3 Empirical Methodology

As macroeconomic, monetary, and price variables in particular, are mostly nonstationary in nature, cointegration and error correction based method has been employed in the present chapter in order to examine the role of commodity futures prices in monetary policymaking in India, following a large number of previous studies [8]. In theoretical and applied econometric literature, cointegration as a method has become popular to study the long-run relationship between

[6] Ray (2013) has detailed the phases of monetary policy in India. In June 2016, the Reserve Bank of India (RBI) adopted the flexible inflation targeting framework of monetary policy with the primary objective of maintaining price stability without neglecting output stability.

[7] The flexible inflation targeting is when along with a positive weight on stabilization of output, the conditional inflation forecast has been gradually adjusted towards the inflation target, as against the strict inflation targeting with low and stable inflation together with a zero weight on output stabilization (Svensson 1999).

[8] See, for example, Garner (1989), Sephton (1991). Marquis & Cunningham (1990), Cody & Mills (1991), Hua (1998), among others.

non-stationary series as well as re-parameterizing them to the error correction model (ECM) for studying short-run dynamics[9]. The Autoregressive Distributed Lag (ARDL) method is used instead of Johansen & Juselius (1990) cointegration method especially when one cointegrating vector exists. More precisely, ARDL based cointegration methodology has been applied for examining a long-run relationship irrespective of whether the variables in consideration are I(0) or I(1). The ARDL-based method has advantages over other methods mainly on account of i) its flexibility in terms of the order of integration of variables involved (Nusair 2016); and ii) its applicability in case of small samples (Romilly et al. 2001).

To investigate the presence of asymmetric effects in the short-run and long-run relationships between commodity futures price indices and macroeconomic indicators, the Non-linear Autoregressive Distributed Lag (NARDL) approach, developed by Shin et al. (2014), is used in this chapter. The NARDL approach consists of a dynamic error correction representation and thus enables one to study the pattern of asymmetric pass-through of commodity futures prices both in the short-run and in the long-run. The method allows one to test for cointegration and asymmetric nonlinearity in a single equation (Romilly et al. 2001). In other words, the NARDL approach can accommodate a combination of persistent and stationary variables in a coherent manner (Greenwood-Nimmo & Shin 2013). Furthermore, the model is linear in parameters and can be estimated using the ordinary least square technique.

[9] The journey started with Granger (1981), followed by Engle & Granger (1987), Autoregressive Distributed Lag (ARDL) cointegration method of Pesaran et al. (1995) and Pesaran et al. (2001) bounds tests, and Johansen & Juselius (1990).

The NARDL model which rests on an asymmetric long-run relationship, takes the following form:

$$y_t = \beta^+ \mathbf{x_t^+} + \beta^- \mathbf{x_t^-} + u_t \tag{3.1}$$

where $\mathbf{x_t}$ is $k \times 1$ vector of regressors. The regressors are defined as sum of two partial sum processes of positive and negative changes as follows:

$$\mathbf{x_t} = \mathbf{x_0} + \mathbf{x_t^+} + \mathbf{x_t^-}$$

where $\mathbf{x_0}$ is the initial value, $\mathbf{x_t^+} = \sum_{j=t}^{t} \Delta\mathbf{x_j^+} = \sum_{j=t}^{t} max(\Delta\mathbf{x_j}, 0)$ and $\mathbf{x_t^-} = \sum_{j=t}^{t} \Delta\mathbf{x_j^-} = \sum_{j=t}^{t} min(\Delta\mathbf{x_j}, 0)$. The NARDL(p,q) model defined in Eq. (3.1) is then written as

$$\boldsymbol{y_t = \sum_{j=1}^{p} \phi_j y_{t-j} + \sum_{j=1}^{q} (\theta_j^{+'} x_{t-j}^{+} + \theta_j^{-'} x_{t-j}^{-}) + \varepsilon_t} \tag{3.2}$$

where ϕ_j are the autoregressive parameters, θ_j^+ and θ_j^- contain the asymmetric distributed-lag parameters, and ε_t is an i.i.d process with mean zero and homoskedastic variance σ_ε^2. In order to understand the short-run effects, the error correction model associated with Eq. (3.2) is

$$\Delta y_t = \rho y_{t-1} + \theta^{+'} x_{t-1}^{+} + \theta^{-'} x_{t-1}^{-} + \sum_{j=1}^{p-1} \gamma_j \Delta y_{t-j} + \sum_{j=1}^{q-1} (\varphi_j^{+'} \Delta x_{t-j}^{+} + \varphi_j^{-'} \Delta x_{t-j}^{-})$$
$$+ \varepsilon_t \tag{3.3}$$

where $\rho = \sum_{j=1}^{p} \phi_j - 1, \gamma_j = -\sum_{i=j+1}^{p} \phi_i$ for $j = 1, 2, ..., p-1$, $\boldsymbol{\theta}^+ = \sum_{j=0}^{q} \boldsymbol{\theta}_j^+$,

$\boldsymbol{\theta}^- = \sum_{j=0}^{q} \boldsymbol{\theta_j^-}$, $\boldsymbol{\varphi_0^+} = \boldsymbol{\theta_0^+}$, $\boldsymbol{\varphi_0^-} = \boldsymbol{\theta_0^-}$, $\boldsymbol{\varphi_j^+} = -\sum_{i=j+1}^{q} \theta_j^+$, $\boldsymbol{\varphi_j^-} = -\sum_{i=j+1}^{q} \theta_j^-$,$j = 1, 2, ..., q-1$. The two asymmetric long-run parameters are then defined as $\boldsymbol{\beta}^+ = -\boldsymbol{\theta}^+/\boldsymbol{\rho}$ and $\boldsymbol{\beta}^- = -\boldsymbol{\theta}^-/\boldsymbol{\rho}$. The conditional nonlinear error correction model associated with Eq. (3.3) is then as follows:

$$\Delta y_t = \rho y_{t-1} + \boldsymbol{\theta}^{+\prime} \boldsymbol{x_{t-1}^+} + \boldsymbol{\theta}^{-\prime} \boldsymbol{x_{t-1}^-} + \sum_{j=1}^{p-1} \gamma_j \Delta y_{t-j} + \sum_{j=0}^{q-1} (\boldsymbol{\pi_j^{+\prime}} \boldsymbol{\Delta x_{t-j}^+} + \boldsymbol{\pi_j^{-\prime}} \boldsymbol{\Delta x_{t-j}^-})$$
$$+ e_t \tag{3.4}$$

where $\Delta \boldsymbol{x_t} = \sum_{j=1}^{q-1} \boldsymbol{\Pi_j} \Delta \boldsymbol{x_{t-j}} + \boldsymbol{v_t}$ is a marginal data generating process and $\varepsilon_t = \omega'(\Delta \boldsymbol{x_t} - \sum_{j=1}^{q-1} \boldsymbol{\Pi_j} \Delta \boldsymbol{x_{t-j}}) + e_t$. Here, $\boldsymbol{\pi_0^+} = \boldsymbol{\theta_0^+} + \boldsymbol{\omega}$, $\boldsymbol{\pi_0^-} = \boldsymbol{\theta_0^-} + \boldsymbol{\omega}$, $\boldsymbol{\pi_j^+} = \boldsymbol{\varphi_j^+}$ $-\boldsymbol{\omega' \Pi_j}$, and $\boldsymbol{\pi_j^-} = \boldsymbol{\varphi_j^-} - \boldsymbol{\omega' \Pi_j}$ for $j = 1, 2, ..., q-1$.

The empirical estimation of the NARDL method involves certain steps, which are similar to the estimation of the linear ARDL model. However, the former requires some additional steps such as testing the presence of short-run and long-run asymmetries. The first step necessitates estimation of the error correction model described in Eq. (3.4) using standard OLS technique. The second step is the tests for presence of a cointegrating relationship. Here, two tests proposed by Banerjee et al. (1998) and Pesaran et al. (2001), are carried out. The cointegration test procedure proposed by Banerjee et al. (1998) tests the hypothesis $H_0 : \rho = 0$ against $H_1 : \rho < 0$ and reports the test statistics t_{BDM}. The other cointegration test procedure proposed by Pesaran et al. (2001) tests the hypothesis $H_0 : \theta^+ = \theta^- = 0$ against $H_1 : \theta^+ \neq \theta^- \neq 0$ and reports the test statistics F_{PSS}. The bounds test procedure proposed by Pesaran et al. (2001)

allows to test the long-run relationship in the presence of asymmetries which may exhibit complex inter-dependencies, and thereby has distinct advantages.

The third step involves the testing for presence of long-run and short-run asymmetries. To check the presence of long-run asymmetry, the null hypothesis $H_0 : \beta^+ = \beta^-$ has been tested using the standard Wald test procedure. Then, the presence of short-run asymmetry can be examined by testing the null hypothesis $\sum_{i=0}^{q-1} \pi_i^+ = \sum_{i=0}^{q-1} \pi_i^-$. The fourth and the last step is to estimate the asymmetric cumulative dynamic multiplier effect as follows:

$$m_h^+ = \sum_{j=0}^{h} \frac{\delta y_{t+j}}{\delta x_t^+}$$
$$m_h^- = \sum_{j=0}^{h} \frac{\delta y_{t+j}}{\delta x_t^-}$$

where m_h^+ (m_h^-) is the dynamic multiplier effect of x_t^+ (x_t^-) on y_t. It is to be noted that as $h \to \infty$, $m_h^+ \to \beta^+$ and $m_h^- \to \beta^-$. The graphical representation of dynamic multipliers of positive and negative changes in predictors helps one to understand the asymmetric adjustment patterns of explained variables. Following Shin et al. (2014), the confidence intervals for the dynamic multipliers have been estimated by a non-parametric bootstrap technique.

3.4 Empirical Results

This section presents the preliminary test results and the results of NARDL analysis. The empirical estimation is carried out using monthly data of commodity futures prices and macroeconomic indicators as discussed in Chapter 1.

3.4.1 Unit Root Test

Before estimating the NARDL model, unit root tests are required to be carried out. Macroeconomic and financial variables often exhibit trending behaviour or non-stationarity in the mean. Statistically, the variables used in this chapter are checked for (non)stationarity using unit root tests. The Augmented-Dicky-Fuller(ADF) (Dickey & Fuller 1979), Philips-Perron (PP) (Phillips & Perron 1988), Dickey-Fuller Test With GLS Detrending (DFGLS) (Elliott et al. 1996), and Ng-Perron (NP) (Ng & Perron 2001) unit root tests have been used. The DFGLS test for unit root suggested by Elliott et al. (1996) is used as GLS local detrending results in substantial gains in power over the standard ADF unit root tests. On the other hand, the Ng & Perron (2001) test modifies the Phillips (1987) and Phillips & Perron (1988) tests in a number of ways in order to increase the test's size and power.

Table 3.1 reports the unit root test results of variables used in the analysis both at the level and at first difference. The unit root test results reveal that all the variables except CMR and CFP(Energy) are I(1) at the usual significance level. The CMR and CFP(Energy) are found to be I(0). These results are important for ARDL based cointegration bounds tests. From Table 3.1, it is also clear that none of the variables are I(2), and thus the NARDL method can be applied.

3.4.2 Causality Test

As a prior to the NARDL analysis, a causality test is carried out in order to understand whether commodity futures prices can at all be used as predictors of

Table 3.1: Unit Root Test

Statistics →	ADF	PP	DF-GLS	Ng-Perron			
Variable↓				MZ_α	MZ_t	MSB	MP_T
			(at level)				
IIP	-1.6549	-1.9412	0.8343	0.9093	1.0438	1.1479	88.1858
CPI	-2.0523	-2.1214	0.8400	0.8589	0.7980	0.9290	59.5602
CMR	-3.1320**	-3.7360***	-2.8655***	-13.1794**	-2.5613**	0.1943**	1.8816**
CFP(Agri)	-1.7483	-1.6047	-0.5315	-1.1454	-0.5210	0.4549	13.7969
CFP(Energy)	-3.0258**	-2.5359	-2.7107***	-15.8802***	-2.8133***	0.1772**	1.5602***
CFP(Metals)	-1.4528	-1.6582	0.3211	0.3821	0.3359	0.8789	48.9099
CFP(Overall)	-1.9414	-1.9991	-0.6154	-1.3529	-0.6473	0.4784	13.8643
			(at first difference)				
IIP	-3.0215**	-20.5223***	-3.0175***	-7.6615*	-1.9279*	0.2516**	3.3095**
CPI	-3.6565***	-10.3745***	-0.9968	-1.4435	-0.8362	0.5793	16.6602
CMR	-8.2300***	-18.8898***	-8.0294***	-118.3300***	-7.6917***	0.0650***	0.2074***
CFP(Agri)	-8.6043***	-9.7113***	-4.4314***	-28.6918***	-3.7834***	0.1319***	0.8674***
CFP(Energy)	-6.3700***	-9.0091***	-5.0359***	-38.9016***	-4.3643***	0.1122***	0.7610***
CFP(Metals)	-2.9916***	-10.7340***	-0.9090***	-0.8843***	-0.5965***	0.6745***	23.6514***
CFP(Overall)	-5.2795***	-8.4426***	-2.3790**	-9.8217**	-2.1586**	0.21978***	2.7228***

Note: (i) As symbolized in the table, IIP, CPI, CMR and CFP stand for index of industrial production, consumer price index, call money rate and commodity future prices, respectively. (ii) The Akaike information criterion (AIC) has been used for the purpose of appropriate lag selection. (iii) *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

macroeconomic indicators relevant to monetary policy. Following Awokuse & Yang (2003), Bhar & Hamori (2008), and many other studies, the Toda & Yamamoto (1995) lag-augmented vector autoregression (henceforth T&Y LA-VAR or T&Y in short) based causality test procedure is applied. The T&Y procedure is performed directly on the estimated coefficients of VAR in levels. At first, a VAR(k) model is estimated. The correct order of VAR, k, is then augmented by the maximal order of integration, say $dmax$; and then the VAR of order $k + dmax$ has been estimated ignoring the coefficients of the last $dmax$ vector. The T&Y procedure uses a modified Wald (MWALD) test for causality, as the same shuns the problems of ordinary Granger Causality test by ignoring the order of integration (Zapata & Rambaldi 1997; Wolde-Rufael 2004). The MWALD test statistic follows an asymptotic chi-squared distribution with k degrees of freedom.

The first step of the T&Y causality test is to determine the order of integration, $dmax$, of the variables used in the empirical analysis. From Table 3.1, it

Table 3.2: MWALD test Statistics from VAR (1) ($dmax = 1$)

Explained Variable → **Explanatory Variable ↓**	**IIP**	**CPI**	**CMR**
CFP(**Agri**)	2.1706	0.0176	1.2705
CFP^{+}(**Agri**)	5.0598**	0.0275	0.1752
CFP^{-}(**Agri**)	0.8100	0.2086	2.5503
CFP(**Energy**)	12.4025***	4.0155**	6.1865**
CFP^{+}(**Energy**)	11.2035***	0.0866	0.7339
CFP^{-}(**Energy**)	15.2387***	5.0344**	6.7094***
CFP(**Metals**)	5.5666**	6.5827**	5.1110**
CFP^{+}(**Metals**)	1.0857	4.3781**	1.8379
CFP^{-}(**Metals**)	4.3379**	9.4333***	9.9591***
CFP(**Overall**)	12.0472***	5.2855**	6.2472**
CFP^{+}(**Overall**)	7.2115***	7.9311***	2.1539
CFP^{-}(**Overall**)	12.2480***	4.7116**	6.2696**

Note: As symbolized in the table, IIP, CPI, CMR and CFP stand for the index of industrial production, consumer price index, call money rate and commodity futures price index, respectively. *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

can be re-iterated that except for CFP(energy) and CMR, all other variables are I(1). The CMR being I(0), the *dmax* of the variables included in the T&Y test is considered to be one. To determine the optimal lag length of the VAR model, Schwarz Information Criterion and Hannan-Quin Information Criterion are used. The last step of the T&Y causality analysis is to determine the maximum lag length, which is determined by the likelihood ratio test in this case.

The results of the causality test in the T&Y procedure, based on MWALD test statistics from VAR(1), using four different commodity futures price indices, viz. CFP(Overall), CFP(Agri.), CFP(Energy), and CFP(Metals), are reported in Table 3.2. The Chi-squared statistics show that the CPI is caused by CFP(Overall), CFP(Energy), and CFP(Metals); indicating that commodity futures prices explain the future path of inflation in India. Further, the significance of both positive and negative commodity price changes in the case of CFP(Overall) and CFP(Metals), is indicative of an asymmetric relationship between commodity prices and inflation. Further, the MWALD test statistics imply that CFP(Overall), CFP(Energy) and CFP(Metals) can significantly predict industrial production or economic activity in India. The result strongly establishes the informational role of commodity futures prices in the process of monetary policy formulation in India. In order to check whether the central bank responds to commodity futures price changes, the CMR is also used as the explained variable and it is found that negative changes in CFP(Energy) and CFP(Metals) significantly cause changes in CMR.

3.4.3 NARDL Estimation Results

Cointegration Test

As detailed in Section 3.3, bounds tests for cointegration are used as an empirical strategy. The results of the two bounds tests statistics for cointegration, viz. F_{PSS} and t_{BDM}, between the macroeconomic variables such as IIP, CPI, CMR, and the commodity futures price indices are presented in Table 3.3. The linear ARDL model is the benchmark one, in which the F_{PSS} statistics show that the null hypothesis of no cointegration can be rejected only in a few cases. The results thus indicate weak evidence of the presence of any linear or symmetric long-run relationship between commodity futures prices and macroeconomic variables in India. On the contrary, the F_{PSS} and t_{BDM} test statistics for the NARDL model are found to exceed the upper bound critical values at the conventional significance levels, thus indicating the presence of an asymmetric long-run relationship between the aforementioned variables. It is to be mentioned that the cointegrating relationship between commodity prices and consumer prices index is found to be stronger in the linear model rather than in the non-linear model.

The existence of cointegrating relationship among the impulses brings about how industrial production and consumer prices respond to positive and negative shocks in commodity futures prices. These results thus contradict the findings of Kugler (1991).

Table 3.3: Bounds tests for cointegration in the ARDL and NARDL models

Method →	ARDL		NARDL	
Statistics →	t_{BDM}	F_{PSS}	t_{BDM}	F_{PSS}
Explained Variable →	**IIP**			
CFP(Agri)	-0.7813	1.2746	-3.5703**	3.6382**
CFP (Energy)	-1.9048	10.9140***	-2.5948**	11.9984***
CFP(Metals)	1.0460	3.3255	-4.1620***	10.0674***
CFP(Overall)	-0.0167	8.9646***	-4.0770**	8.6271***
Explained Variable →	**CPI**			
CFP(Agri)	-3.5437**	60.0638***	-1.3343	3.9682**
CFP (Energy)	-2.2675	5.6397***	-2.2884	3.4591*
CFP(Metals)	-2.5988	6.2842***	-2.5948	5.7531***
CFP(Overall)	-2.6508	6.1657***	-3.2678*	4.5718**
Explained Variable →	**CMR**			
CFP(Agri)	-2.4348	2.3427	-4.1679***	7.4394***
CFP (Energy)	-3.7212**	7.0090***	-3.2750*	5.1504***
CFP(Metals)	-2.8784	3.2721	-3.1813	4.2849**
CFP(Overall)	-3.3596**	5.3413**	-3.3328*	5.4237***

Note: As symbolized in the table, IIP, CPI, CMR and CFP stand for index of industrial production, consumer price index, call money rate and commodity futures price index, respectively. *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

From the results presented in Table 3.2, it is also evident that the relationship between commodity futures prices and macroeconomic variables is not linear in nature, and thus an asymmetric specification is required to be considered. On the other hand, although the cointegrating relationship between the rate of interest and the commodity futures prices is found to be existent in the NARDL models, there is evidence of linear cointegrating relationship in case of energy and overall commodity futures prices indices.

Test for Asymmetry

Having found the existence of an asymmetric cointegrating relationship between commodity futures prices and macroeconomic variables, it is now important to test for the presence of asymmetry in both the long and short runs. The Wald statistics for the tests of long-run and short-run asymmetries between commodity futures price indices and macroeconomic variables from the NARDL estimates are reported in Table 3.4. The symmetry test statistics suggest the existence of an asymmetric relationship between CFP and IIP in the long-run as well as in the short-run. Thus, it implies that in general positive and negative changes in the commodity futures prices indices under consideration have a differential impact on the production decision of firms. This is on account of differential impacts of informational and cost effects during the rise and fall in commodity futures prices. In the case of the relationship between CPI and CFP, the null hypothesis of long-run symmetry can be rejected in the case of the energy index and the metals index, whereas the null hypothesis of short-run symmetry can be rejected in the case of the agricultural index and the energy index. The symmetry test statistics also suggest that the asymmetric relationship between CFP and CMR prevails only in the long-run (except in the case of CFP (Energy)). The instrument used by the central bank is thus found to respond differently to positive and negative changes in commodity prices.

To summarize, the results on symmetry test suggest that a NARDL method, which allows both long-run as well as short-run asymmetries, is best suited for studying the dynamic relationship between the commodity futures prices indices

Table 3.4: Wald tests for long-run and short-run asymmetry

Test →	Long-run asymmetry			Short-run asymmetry		
Null Hypothesis →	$(\boldsymbol{H_0} : \boldsymbol{\beta^+ = \beta^-})$			$(\boldsymbol{H_0} : \sum_{j=1}^{q-1} \boldsymbol{\pi_j^+} = \sum_{j=1}^{q-1} \boldsymbol{\pi_j^-})$		
Explained Variable →	**IIP**	**CPI**	**CMR**	**IIP**	**CPI**	**CMR**
CFP(Agri)	13.1151***	0.7954	10.6142***	4.4294**	8.3288***	13.0088***
CFP (Energy)	4.5106**	3.6985**	0.8716	18.4673***	3.0138*	1.3395
CFP(Metals)	20.5332***	3.7824**	7.0720***	7.8138***	-	0.2869
CFP(Overall)	17.3306***	1.5923	6.0186**	11.1279***	2.5506	0.0393

Note: As symbolized in the table, IIP, CPI, CMR and CFP stand for index of industrial production, consumer price index, call money rate and commodity futures price index, respectively. *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

and macroeconomic indicators. In other words, neglecting the presence of non-linearity while modelling the relationship between the commodity futures prices indices and macroeconomic indicators may lead to model misspecification and inappropriate inferences.

Long-run and Short-run Coefficients

Having ascertained that the asymmetric cointegrated relationship exists, it is important to examine for long-run and short-run effects of asymmetric changes in commodity futures prices indices on macroeconomic variables such as industrial production, consumer prices, and rate of interest. The estimated coefficients presented in Tables 3.5, 3.6, and 3.7 show that the adjustment (ρ) is immediate in case of the index of industrial production (between -0.09 and -0.38) and interest rate (between -0.14 and -0.23) and relatively sluggish in case of consumer price index (between -0.02 and -0.22). Statistically significant estimated parameters, θ_+ and θ_- evince the presence of long-run pass-through of commodity futures prices. On the other hand, $\sum_{j=0}^{q-1} \pi_j^+$ and $\sum_{j=0}^{q-1} \pi_j^-$ indicate the presence of significant pass-through of commodity futures prices in the short-run.

From Table 3.5, it can be seen that θ^+ is significant in all cases except for energy commodities. Thus, in the long-run, a rise in commodity futures prices

Table 3.5: Asymmetric Effects of Commodity Futures Price Changes on Industrial Production

Explained Variable →	Index of Industrial Production			
Explanatory Variable →	CFP(Agri)	CFP(Energy)	CFP(Metals)	CFP(Overall)
Long-run Coefficients				
ρ	-0.2237***	-0.0922**	-0.3832***	-0.2477***
	(0.0627)	(0.0355)	(0.0921)	(0.0608)
θ_{+}	0.0570***	-0.0042	0.0843***	0.0465**
	(0.0205)	(0.0092)	(0.0309)	(0.0215)
θ^{-}	0.0112	-0.0159**	-0.0216	-0.0170
	(0.0119)	(0.0071)	(0.0152)	(0.0124)
Short-run Coefficients				
$\sum_{j=0}^{q-1} \pi_j^{+}$	0.2649**	-	-	
$\sum_{j=0}^{q-1} \pi_j^{-}$	-	0.2282***	0.3859***	0.3459***
Diagnostic Tests				
F_{BG}	1.0312	0.3422	0.1073	1.4904
F_{BPG}	1.6989	0.9071	1.4661	1.3535
$\overline{R}^2$	0.3724	0.3173	0.3990	0.3783

Note: (i) As symbolized in the table, CFP stand for commodity futures prices. The notation for the estimated coefficients relates to Eq. 3.4. (ii) The F_{BG} and F_{BPG} are the Breusch–Godfrey serial correlation test and the Breusch-Pagan-Godfrey heteroskedasticity test statistics, respectively. (iii) The heteroskedasticity and autocorrelation consistent (HAC) standard errors have been reported. (iv) The Akaike information criterion (AIC) has been used for the purpose of appropriate model selection. (v) *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

is found to have a significant positive impact on industrial production, indicating that the informational effect plays a stronger role than the cost effect. On the other hand, a fall in future prices of energy commodities is seen to have a negative impact on industrial production in the long-run. A rise (fall) in commodity futures prices can have a positive (negative) informational effect and negative (positive) cost effect on industrial production. The information effect indicates that a stronger future economy measured in terms of a rise in commodity prices induces higher production. On the other hand, as commodities are used as raw materials, a rise in their prices forces producers to produce less through cost effects. The observed statistically significant aggregated short-run coefficients indicate the presence of pass-through of commodity futures prices in the short-run. It can be seen that a negative change in commodity futures prices having a positive and stronger impact on industrial production. This suggests that in the short run, the cost effect dominates the information effect in the transmission mechanism. These results are in line with Awokuse & Yang (2003), and are believed to have significance in the process of monetary policy in India considering the importance of stabilization of output in flexible inflation targeting.

Table 3.6: Asymmetric Effects of Commodity Futures Price Changes on Inflation

Explained Variable →	**Consumer Price Index**			
Explanatory Variable →	**CFP(Agri)**	**CFP(Energy)**	**CFP(Metals)**	**CFP(Overall)**
Long-run Coefficients				
ρ	-0.0204	-0.2204**	-0.0327**	-0.0437***
	(0.0153)	(0.0096)	(0.0126)	(0.0134)
θ^{+}	0.0090*	0.0094**	0.0127***	0.0242***
	(0.0048)	(0.0037)	(0.0048)	(0.0066)
θ^{-}	0.0041	0.0048*	0.0012	0.0100**
	(0.0035)	(0.0026)	(0.0043)	(0.0044)
Short-run Coefficients				
$\sum_{j=0}^{q-1} \pi_j^{+}$	0.0967**	-	-	-0.0190
$\sum_{j=0}^{q-1} \pi_j^{-}$	-0.0844**	-0.0481	-	-0.1590***
Diagnostic Tests				
F_{BG}	0.1878	0.8639	0.8382	1.6197
F_{BPG}	1.5726	0.8266	1.3901	1.4005
$\overline{R}^2$	0.1769	0.1951	0.1246	0.2735

Note: (i) As symbolized in the table, CFP stand for commodity futures prices. The notation for the estimated coefficients relates to Eq. 3.4. (ii) The F_{BG} and F_{BPG} are the Breusch–Godfrey serial correlation test and the Breusch-Pagan-Godfrey heteroskedasticity test statistics, respectively. (iii) The heteroskedasticity and autocorrelation consistent (HAC) standard errors have been reported. (iv) The Akaike information criterion (AIC) has been used for the purpose of appropriate model selection. (v) *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

In Table 3.6, significant long-run and short-run coefficients indicate the presence of commodity price pass-through to consumer prices. It can be seen that in the case of agriculture and metals commodities, for the long-run cointegrated relationship between commodity futures price indices and consumer price index, only the coefficient of positive changes in commodity futures prices is found to have statistical significance, indicating the predominance of informational effect over the cost effect. In the case of energy and overall commodity prices indices, both positive and negative changes in prices are found to have a significant and positive impact on consumer prices. However, in these two cases, the coefficients of positive commodity futures price changes are found to be higher than that of negative price changes. The coefficient of positive price changes is found to be the maximum in the case of metals (0.0127), which are largely used in the production of manufactured goods. From the aggregated short-run coefficients, the cost effect is found to dominate over the informational effects. These results certainly reassure the informational role of commodity futures prices in monetary policy making as suggested in the literature by Awokuse & Yang (2003), Bhar & Hamori (2008), among others.

As suggested by Cody & Mills (1991) and Awokuse & Yang (2003), to understand whether the monetary policy authorities did use the information contained in commodity futures prices, one has to study the explanatory power of commodity futures prices in predicting policy instruments such as interest rates. Besides, since the partial sum series of commodity futures prices are used as explanatory variables, the results are also likely to suggest whether the central bank is responding asymmetrically to the price signals. The results reported in Table 3.7 show that the long-run coefficients of both positive and negative changes in commodity futures prices are statistically significant and distinguishable.

Table 3.7: Asymmetric Effects of Commodity Futures Price Changes on Interest Rate

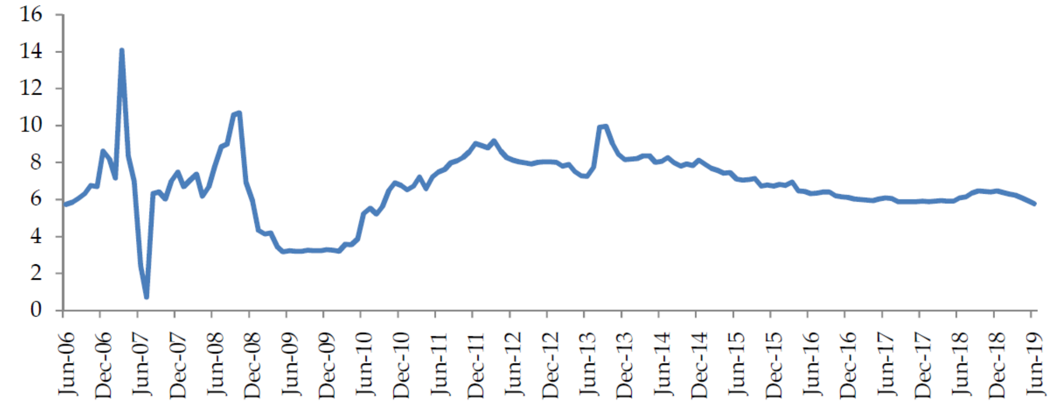
Explained Variable →	Call Money Rate			
Explanatory Variable →	CFP(Agri)	CFP(Energy)	CFP(Metals)	CFP(Overall)
Long-run Coefficients				
ρ	-0.1359***	-0.1839***	-0.2288***	-0.2121***
	(0.0326)	(0.0561)	(0.0719)	(0.0637)
θ^{+}	0.8387***	1.1966***	1.6589**	2.0163***
	(0.2797)	(0.3925)	(0.7103)	(0.6235)
θ^{-}	1.1088***	1.1483***	2.4338**	2.3522***
	(0.3394)	(0.3834)	(0.9744)	(0.7263)
Short-run Coefficients				
$\sum_{j=0}^{q-1} \pi_j^{+}$	-	-	-3.1464	-
$\sum_{j=0}^{q-1} \pi_j^{-}$	-23.8488***	3.5452	-5.2314	1.3466
Diagnostic Tests				
F_{BG}	15.5108***	51.0923***	75.7298***	59.4684***
F_{BPG}	1.3671	10.6767***	10.5550***	17.3117***
$\overline{R}^2$	0.5164	0.3128	0.3013	0.3652

Note: (i) As symbolized in the table, CFP stand for commodity futures prices. The notation for the estimated coefficients relates to Eq. 3.4. (ii) The F_{BG} and F_{BPG} are the Breusch–Godfrey serial correlation test and the Breusch-Pagan-Godfrey heteroskedasticity test statistics, respectively. (iii) The heteroskedasticity and autocorrelation consistent (HAC) standard errors have been reported. (iv) The Akaike information criterion (AIC) has been used for the purpose of appropriate model selection. (v) *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

This finding is apposite as the results presented in Tables 3.5 and 3.6 corroborates the importance of asymmetric commodity price changes in monetary policymaking. In case of short run, the presence of dominance of cost effect is seen only in case of the agricultural commodities. It is to be mentioned in this regard that even after using the heteroskedasticity and autocorrelation consistent (HAC) standard errors as suggested by Newey & West (1987), the residuals show a significant presence of autocorrelation and heteroskedasticity. This is mainly on account of the fact that the data series on call money rate [10] in India show large

[10]Unlike other proxies for the rate of interest variable, the call money rate in India is used as the proxy for a nominal rate of interest for which a long historical data series is available, and as it is mentioned earlier that a number of studies in the literature have used the same for the purpose of analysis.

Figure 3.1: Call Money Rate in India



fluctuations in March, 2007 and July, 2007 during the pre-global financial crisis period. This is shown in Figure 3.1.

Relevance of Results vis-à-vis the Existing Literature

There are a number of studies[11] examining commodity prices-inflation relationships considering asymmetric price changes. In the present chapter, cointegration and error correction analyses have been done considering non-linearities following Sek (2017), Lacheheb & Sirag (2019), Sarwar et al. (2020) and Husaini & Lean (2021). Further, the relationship between commodity futures prices and macroeconomic indicators has been examined by considering asymmetric changes in the former. This is a new attempt to analyse the long-run and short-run relationships between commodity futures prices and macroeconomic indicators relevant for monetary policymaking in an emerging market economy, considering the possible presence of asymmetric price changes in commodity futures prices, that has helped in distinguishing the informational and cost effects of commodity futures price changes. The cointegration analysis in this chapter, showing stronger

[11]See, for example, Salisu et al. (2017), Tule et al. (2019), Tule et al. (2020), Sarwar et al. (2020), among others.

long-run relationship between commodity prices and inflation, contradicts the findings of Cunado & De Gracia (2005) which show only a short-run relationship between oil prices and economic activities for a number of Asian emerging market economies.

The evidence of a strong relationship between commodity prices and inflation for an emerging market economy like India as found in this chapter supports the findings of Dedeoğlu & Kaya (2014), which show a strong relationship between oil prices and inflation in Turkey employing a VAR model, and thus the results are inherently for the short-run. On the contrary, in the present chapter long-run relationship between energy commodity futures prices and inflation is found to exist in India. The results found in this chapter also support the results from Lacheheb & Sirag (2019), in which a significant relationship between a rise in oil prices and inflation is found to exist.

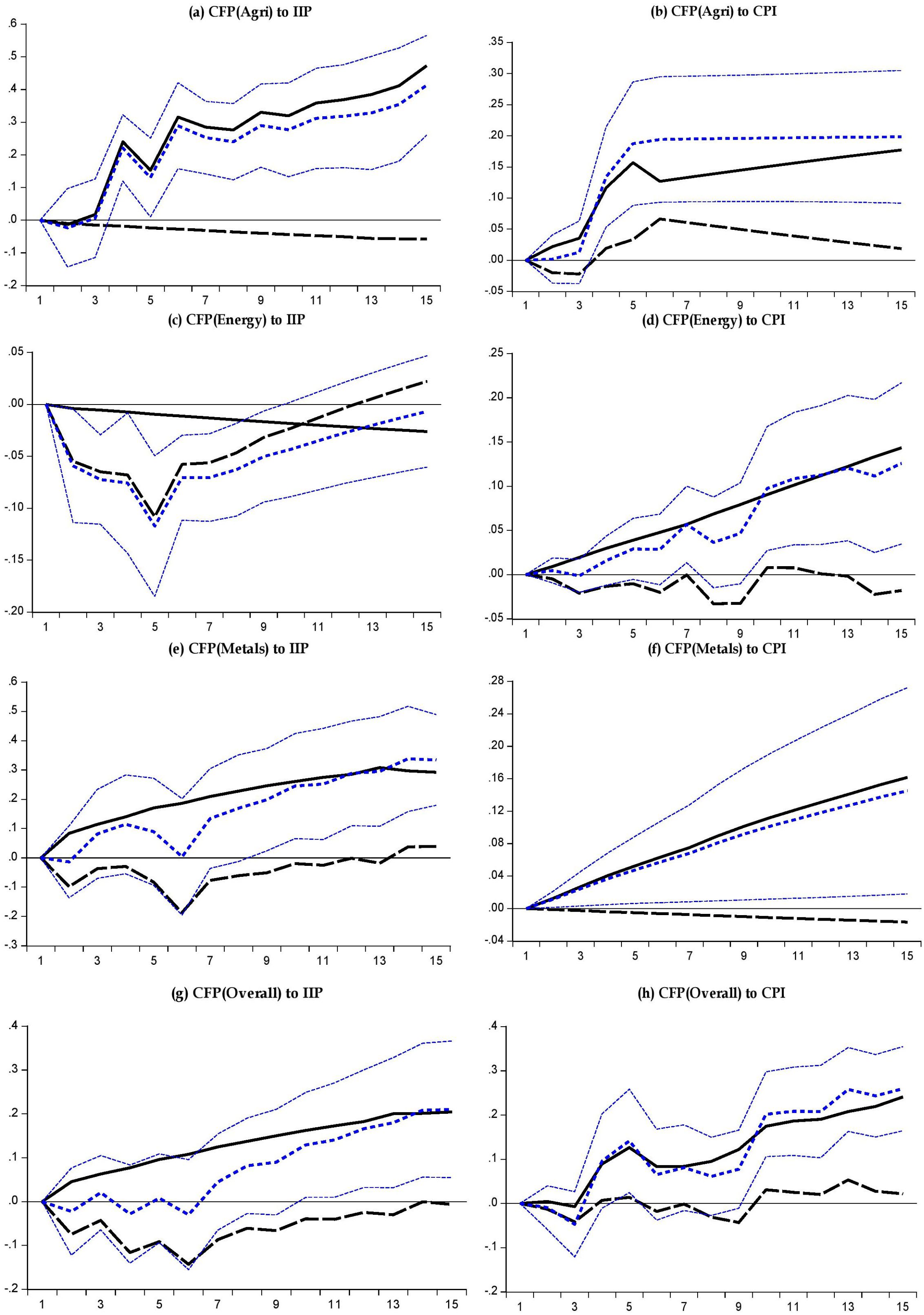
Such long-run and short-run relationships between oil prices and inflation are found using a NARDL framework. Using the same NARDL framework, Husaini & Lean (2021) study the effects of changes in oil prices on producer price inflation and consumer price inflation for emerging market economies in Asia. This chapter employing the NARDL method, shows the effect of asymmetric price changes in commodity futures prices on macroeconomic indicators. This helps in distinguishing the informational and cost effects of commodity futures price changes as documented for a number of industrialized countries.

In the present chapter, strong evidence of the presence of informational effects of commodity futures price changes has been found, and thus results obtained support the findings of Awokuse & Yang (2003), Bhar & Hamori (2008) etc. The relationship between agriculture commodity prices and inflation found in this chapter also supports the results of Tule et al. (2020). The relationship is found to be stronger in the short-run rather than in the long-run. Although, Mandal et al. (2012) have found international crude oil price pass-through to industrial output and inflation mainly in the short-run, the findings in this chapter show pass-through of domestic energy commodity futures prices to inflation and industrial output are found especially in the long-run. However, in the same line as Mandal et al. (2012), the pass-through effect is found to be more profound in case of inflation rather than industrial output.

3.4.4 Dynamic Multipliers

Following Shin et al. (2014), the asymmetric cumulative dynamic multipliers of commodity futures price changes have been calculated. The results presented in Tables 3.5 and 3.6 determine the shape of the cumulative dynamic multipliers presented in Figure 3.2, which complement the analysis of the asymmetric effects of commodity futures prices on industrial production and consumer prices. These multipliers show the pattern of adjustment of the index of industrial production and consumer price index to their new long-run equilibrium following a positive or negative unitary shock in commodity futures price indices. While, Figures 3.2(a), 3.2(c), 3.2(e), and 3.2(g) present the adjustments of industrial production to positive and negative unitary commodity price shocks, Figures 3.2(b), 3.2(d), 3.2(f), and 3.2(h) depict analogous adjustments of consumer prices. The figures show significant dynamic effects of positive price shocks in the case of agri-

Figure 3.2: Cumulative Dynamic Multipliers



Note: The solid (dashed) black line is the cumulative dynamic multiplier with respect to a 1% positive (negative) change in the commodity futures price, while the heavy dashed blue line plots the difference between the two. The light dashed blue lines report the two standard error confidence intervals for the difference line computed by stochastic simulation. The horizontal axis represents time intervals, while the vertical axis is in percentage points.

cultural and metal commodities, negative price shocks in the case of the energy commodity futures price index, and both positive and negative price shocks in the overall commodity price index to industrial production in the long-run. However, only stronger positive commodity price shocks to consumer prices are evident. As evident from the figure that after a negative commodity futures prices shock, the industrial production takes nearly 4-5 months to retrogress and converges with the long-run coefficients that vary between 0.05 to 0.08 (see Table 3.5). The transmission is relatively slow in the case of consumer prices (as also can be seen in Table 3.6). It can be observed from the figure that an increase in futures prices of agricultural commodities and metals takes about 5-6 months to be fully transferred to the level of consumer prices and converges with the respective long-run coefficients. On the other hand, an increase in futures prices of energy commodities and metals takes more time to be completely transmitted to consumer prices. Asymmetric impact on inflation and output can thus be observed in response to commodity futures price shocks.

3.5 Summary of Findings

Inflation targeting has been espoused as the policy objective in the monetary policy framework by the central banks in many developed countries since the 1990s and in many emerging market economies since the 2000s. As the success of inflation targeting largely depends on the prediction of the future path of inflation, a large number of studies started exploring different determinants of inflation. In this regard, one strand of literature has examined the relationship between commodity prices and inflation and shows the informational role of commodity futures prices in monetary policy-making. However, such efforts in case of emerging market economies including India are rare. This chapter explores whether commodity futures prices explain trends in inflation and other macroeconomic indicators in India.

This chapter has a number of key results and thus contributes to the existing literature in several ways. First, there is a nonlinear relationship between commodity futures prices and macroeconomic indicators both in long and short runs. Second, using the nonlinear model, the cost effect and the informational effect of commodity futures price changes on industrial production and inflation are distinguished. This ascertains the informational role of commodity futures prices for an emerging market economy like India. Third, the use of commodity futures price indices at the disaggregated level helps in distinguishing the observed relationship separately in cases of agricultural commodities, energy commodities, and metals. The relationship between commodity prices and industrial production is found to be stronger in the case of agricultural commodities and metals that are mostly used as raw materials in industrial production. On the contrary, in case of inflation, energy prices are found to play a stronger role. Last, but not of least importance, while examining the relationship between commodity futures prices and rate of interest it is found that there is a significant presence of asymmetric pass-through.

Chapter 4

Forecasting Indian Inflation using Commodity Futures Prices: The Role of Asymmetries and Structural Breaks

4.1 Introduction

In this essay, an attempt is made to forecast Indian inflation using commodity futures prices. Like many other developed and emerging market economies, India has adopted the flexible inflation-targeting framework for the purpose of monetary policy. Thereupon, forecasting inflation accurately has become imperative. For that purpose, it is essential to select appropriate predictors of Indian inflation. As evident from Chapter 1, there is a lead-lag correlation between commodity futures prices and macroeconomic indicators in India. A strong correlation is found especially with inflation. Furthermore, in Chapter 3, commodity futures price pass-through to inflation is evident both in the short-run as well as in the long-run. This essay further extends the observed relationship in Chapter 3 by examining the role of domestic commodity futures prices in predicting Indian inflation in a Phillips curve framework.

Maintaining low and stable inflation is one of the key objectives of monetary policy, irrespective of whether the central bank is practising inflation targeting or otherwise. In the inflation targeting framework, a central bank first estimates and announces a projected or “target” inflation rate. Further, it attempts to control the actual inflation towards that target using monetary policy tools such as interest rates. Since the 1990s most of the central banks across countries have adopted either inflation targeting or flexible inflation targeting which has made inflation the key economic indicators that the central banks monitor and evaluate while drawing the monetary policy. Flexible inflation targeting, as against strict inflation targeting or the "inflation nutter", is the strategy to stabilize inflation around the inflation target along with stabilizing the real economy[1]. Since, it is recognized that the effectiveness of monetary policy involves significant lags, it is optimal for the central banks to be forward-looking in monetary policymaking. In other words, the monetary authorities have to set the policy tools anticipating the future in terms of economic growth and inflation. Hence, achieving low and stable inflation is contingent upon the near-accurate prediction of inflation. However, predicting inflation is also difficult in emerging market economies mainly on account of recurrent supply shocks and dominance of volatile components such as food and fuel items in consumer baskets that are used while estimating different price indices. As emerging market economies have increasingly embraced inflation targeting during the last two decades as their monetary policy framework, for the monetary policy authorities it has become extremely important to forecast inflation accurately.

The Phillips curve framework has been extensively used in the literature to forecast inflation. Apart from the demand-side factors, supply-side factors are also found to determine inflation. The supply-side factors play a crucial role in

[1]See King (1997) for a detailed discussion.

modelling inflation through the Phillips curve framework, as the demand-side determinants of inflation may produce less desirable results if important supply-side factors are ignored[2]. Augmenting the Phillips curve framework by incorporating the supply side factors along with the demand side factors and inflation expectations is termed the 'triangle model of inflation' (Gordon & Stock 1998). In a 'triangle model of inflation', it is assumed that inflation depends on inertia (in inflation), apart from demand-side and supply-side factors (Kapur 2013). However, it is difficult to find out an approximate single proxy for the supply-side factors. Commodity prices (mainly crude oil prices) are considered to be an important supply-side factor, and their movements certainly capture the supply shocks. In recent times, crude oil prices have been extensively used as a proxy for supply-side factors in modelling inflation.

The present chapter thus offers an alternative to crude oil prices in modelling inflation in India. In this chapter, it is hypothesized that the inclusion of the domestic commodity futures price index instead of international crude oil price in the Phillips curve is likely to improve the forecasting performance. The chapter thus evaluates the forecasting performance of the domestic commodity futures price index based augmented Phillips curve with that of the traditional Phillips curve and international crude oil price based augmented Phillips curve.

With financialization, commodities have emerged as a new asset class. In the recent past, the rise in the volatility in traditional as well as non-traditional assets[3] (such as commodities) prices has encouraged researchers to discuss whether

[2]See Chen et al. (2014) and studies cited therein for a detailed discussion.

[3]The difference between traditional asset class and the alternative or non-traditional asset class is discussed in detail in Wilcox et al. (2013).

monetary policymakers are required to respond to asset market signals or not. Even though some studies [4] have argued against responding to asset price movements, some others [5] have argued in favour of including asset prices in monetary policy-making. While Fuhrer & Moore (1992) argue that monetary policy should respond to changes in asset prices only when the latter signals change in expected inflation, Cecchetti et al. (2000) claim that along with responding to inflation, policy instruments responding to asset price movements, reduce the likelihood of formation of asset price bubbles, and thus output-volatility. While some studies have observed the exchange rate pass-through to inflation[6], studies explaining the role of commodity prices (domestic or global) in explaining Indian inflation are rare. As observed earlier, inflation dynamics in India like in many other emerging market economies and unlike in many developed economies, is complex, forecasting Indian inflation using a macroeconomic model is even more challenging[7].

While incorporating highly volatile asset prices into macroeconomic modelling, some inherent macroeconomic and statistical properties such as non-linearity, structural breaks, heteroskedasticity, and endogeneity need to be controlled for. Ignoring the presence of structural breaks in a Data Generating Process of economic variables such as inflation invalidates the modern econometric testing procedure and produces misleading results (Junttila 2001). To understand the possible pres-

[4]See, for example, Fuhrer & Moore (1992), Bernanke & Gertler (2000), Bernanke & Gertler (2001), among others.

[5]See, for example, Cecchetti et al. (2000), Cecchetti et al. (2002), among others.

[6]See, for example, Bhattacharya, Patnaik & Shah (2008), Khundrakpam (2008), Kapur & Behera (2012), among others.

[7]A number of studies looking into the efficiency in the Indian commodity market (see, for example, Goyal et al. 2012, Inoue & Hamori 2014, Joseph et al. 2014, Inani 2018, Junior et al. 2020, Pradhan et al. 2021, among others) find a strong relationship between futures and spot prices. This establishes the possibility that commodity futures prices can predict inflation, as the latter has a close linkage with the spot prices.

ence of structural breaks in Indian inflation, it is important to discuss the changes in monetary policy in India.

Inflation and Monetary Policy in India

The trajectory of inflation in India is found to have evolved through many phases and alongside there are many changes in monetary policy in India. To conceptualize, the Reserve Bank of India (RBI) adopted flexible inflation targeting in June 2016 with the prime objective of price stability defined in terms of targeting CPI inflation. Even though there are various contending theories explaining inflation in India, the RBI uses monetary policy in a bid to manage inflation. It is thus important to understand the history of monetary policy in India[8]. The history of monetary policy in post-independence India can be broadly divided into four phases. In the first phase (1951-85), the monetary policy can be described as one of 'controlled expansion', and was mainly guided by the broader parameters of planning. In the second phase (1986-1998), the RBI switched over to the monetary targeting framework with the objective of price stability along with providing adequate credit to the productive sectors of the economy. Keeping the basic objective of monetary policy intact but with a significant change in the operating procedure, the RBI formally shifted to a "multiple indicator approach" in April 1998. This phase continued till mid-2016, when the RBI formally adopted the "flexible inflation targeting" framework with the primary objective of maintaining price stability along with economic growth.

[8]For a detailed discussion see Ray (2013) and Mohan & Ray (2019).

India's inflation varied over phases of monetary policy regimes. In Figure 4.1, different phases of consumer price inflation in India can be observed between 2006 and 2019. To account for structural shifts in the inflation series, following Bai & Perron (1998), Bai & Perron (2003), multiple break-point test has been carried out[9]. With changing inflation trajectory, drivers of inflation change. In India, rise in inflation rate is found to be caused by both global and domestic predictors in addition to standard demand and supply side predictors (Mohanty & John 2015). In the first phase (January, 2006 - July, 2007), a low and stable inflation regime is observed; which was mainly on account of the tightening of expansionary fiscal policy after the introduction of Fiscal Responsibility and Budget Management (FRBM) rules in 2004. In the pre-Global Financial Crisis (GFC) period with a rise in global commodity prices and crude oil prices, consumer price inflation in India increased mainly on account of rising fuel price inflation and its pass-through to other goods and services. Post GFC and the resulting contagion in commodity markets and other global financial markets, the producer price inflation and consumer price inflation rates in India showed considerable divergence. The consumer price inflation during this period (August, 2008 - July, 2010) remained at near double digits. This was mainly on account of rising input costs and a rise in inflation expectations as a result of low monetary policy credibility at the time of persistent food and fuel price shocks. In the subsequent period (August, 2010 - December, 2013), the European debt crisis did not impact on the stability of consumer price inflation, but it remained stable. Declining aggregate demand resulting from pass-through of depreciating exchange rate following the

[9] The four breakpoints are found to be August, 2008, August, 2010, January, 2014, and September, 2016.

Figure 4.1: Consumer Price Inflation Trajectory in India

taper tantrum, increase in key policy rates since January 2014 and the "Great Plunge in Crude Oil Prices" since mid-2014 led to lowering of consumer price inflation and remained stable until mid-2016.

In June 2016, the Government of India amended RBI Act, and finally, India formally adopted flexible inflation targeting with a target of 4.0 per cent with upper and lower bounds of 6.0 per cent and 2.0 per cent, respectively, in August 2016. India experienced a phase of disinflation thereafter. However, consumer price inflation in India again rose since June 2017 mainly on account of rising crude oil prices. Thus, commodity prices and exchange rate movements are found to be critical in determining Indian inflation (Mohanty & John 2015). The rest of this chapter is structured as follows: Section 4.2 discusses the relevant literature, while Section 4.3 provides some theoretical support for using commodity prices in predicting inflation in India. The detailed empirical methodology is discussed in Section 4.4. Empirical results and discussions are presented in Section 4.5. Finally, Section 4.6 concludes the Chapter.

4.2 Literature Review

The theoretical studies claim that the commodity market comprises information concerning the future strength of the global economy (Kilian 2009, Hu & Xiong 2013, and Sockin & Xiong 2015). As commodity prices are mostly determined in derivatives markets, they respond promptly to demand and supply shocks (Kugler 1991). With commodities being largely used in production, their prices reflecting production costs, any change in commodity price reflects a supply shocks that may affect the production and pricing decisions of firms (Marquis & Cunningham 1990). Inflation is found to be triggered to a great extent by expectations of consumers, producers, and investors about future economic performances. It is commonly argued that in an "overheated economy," if the speculators expect the demand for a commodity to increase, with long positions by speculators, the price for that commodity increases leading to higher consumer prices. Developing a theoretical model, Sockin & Xiong (2015) argue that in presence of informational frictions, commodity futures prices can have both a usual cost effect and an informational effect. A rise in commodity futures prices signals a stronger economy in the future; and thus leads to higher demand and hence, higher prices.

Although commodity prices and consumer price index may not be cointegrated (Baillie 1989, Boughton & Branson 1988, Garner 1989), the information contained in commodity prices may be of use for forecasting commodity prices (Pecchenino 1992). Fischer (1977) and Gray (1976) suggest that for the monetary authorities, it is crucial to understand whether the rise in inflation is on account of changes in demand side or supply side predictors. Therefore, one may argue that it is essential for the monetary policy authorities understand to the commodity price–consumer price relationship in trying to predict the inflation trajectory in an economy.

With recurring attention to inflation targeting, a large number of studies have focused on examining the role of commodity prices in determining current and future inflation. In this context, the use of the demand-side factors based Phillips curve framework in predicting inflation has been found to be predominant in the literature. Subsequently, studies have included supply-side variables including commodity prices as a predictor of current and future inflation. As found in the literature, commodity price indices appear to lead the consumer price index (CPI), and thus may be used to signal inflationary expectations and produce better inflation forecasts. Some of the earlier studies have used commodity price indices as indicators of monetary policy[10], while recent studies have also examined the impact of crude-oil prices on inflation[11], and some others have studied the ability of commodity price aggregates or crude-oil price in predicting inflation[12].

As discussed in Chapter 3, a number of studies have argued in favour of using commodity prices as a leading indicator of inflation in managing monetary policy. Based on the evidence on the relationship between commodity prices and inflation, some recent studies have examined the performance of different macroeconomic models in predicting inflation. Considering small commodity-exporting countries that are practising inflation targeting, Chen et al. (2014) show that the

[10]See, for example, Angell (1987), Whitt (1988), DeFina (1988), Garner (1989), Furlong et al. (1996), Boughton & Branson (1988), Hall (1982), Baillie (1989), among others.

[11]See for example Bashar et al. (2013), Dedeoğlu & Kaya (2014), Bec & De Gaye (2016), Pal & Mitra (2017), among others.

[12]See, for instance, Gospodinov & Ng (2013), Chen et al. (2014), Salisu & Isah (2018), Salisu et al. (2018), Gospodinov (2016), among others.

commodity price indices, especially at the disaggregated level, can be used to predict consumer price or producer price inflation. Gospodinov & Ng (2013) provide pieces of evidence that leading principal components from convenience yields of commodities to have predictive power for inflation in G7 countries. In the same line, Gospodinov (2016) argues in favour of using convenience yields-based models for forecasting U.S. core inflation. Balcilar et al. (2017) test whether the inclusion of precious metal prices, while controlling for conditional correlation, can significantly improve the inflation forecasting for South Africa.

Salisu et al. (2018) claim that augmenting the traditional demand-side Phillips curve model with supply-side predictors such as crude-oil price can outperform the traditional Phillips curve-based model in predicting both headline and core inflation for the OECD countries. Salisu & Isah (2018) also find pieces of evidence that a multi-predictor model considering both the demand and supply side predictors with asymmetric changes can produce an improved forecast for U.S. inflation. Tule et al. (2019) and Tule et al. (2020) also argue on similar lines for the Nigerian economy. However, Fasanya & Awodimila (2020) find more nuanced results using different predictors in augmented models.

From the literature discussed above it can be seen that although there are numerous studies on inflation forecasting, no unique framework has been followed. The studies that augment the Phillips curve framework with the inclusion of supply-side variables, mostly consider the international crude oil price or international commodity price index. No studies, so far, have considered augmenting the Phillips curve framework with the commodity futures index. In addition, among the studies discussed above, there is a uniformity in terms of the use of asymmetric changes in prices and hence, the inclusion of structural breaks. While Chen et al. (2014) and Tule et al. (2019) have considered structural breaks while forecasting inflation; only Salisu & Isah (2018) and Fasanya & Awodimila (2020) have considered non-linearities or asymmetric price changes. The present chapter attempts to address these gaps in the literature.

4.3 Theoretical Understanding

In this section, a simple analytical model has been developed extending the framework of Kawai (1983) and Bond (1984). The model is developed following the assumptions in Kawai (1983) and Bond (1984), with certain modifications. The model considers the economy in the short run in the sense that interest rate shocks do not lead to changes in other macroeconomic indicators (such as the level of economic activity). Although Bond (1984) assumes the supply of the commodity to be exogenous, the present chapter follows the version of Kawai (1983) in making the supply of commodities endogenous. The commodity considered in the theoretical model is assumed to be completely standardized. A futures contract is assumed to be settled by the actual delivery of the commodity, and the futures market reopens every period, and delivery takes place only once in each period. In the present chapter, departing from Bond (1984), the production and inventory demands for commodities have been considered.

Production Demand for Commodities

The final good, which is used for the purpose of consumption and investment, is produced by firms using the constant elasticity of substitution (CES) production function of the following type:

$$Y_t = A_t \left[(1-\omega)^{\frac{1}{\rho}} V_t^{\frac{\rho-1}{\rho}} + \omega^{\frac{1}{\rho}} C_t^{\frac{\rho-1}{\rho}} \right] \tag{4.1}$$

with V_t being the value-added input which represents all other goods and services except the commodity in consideration (C_t) used in the production of the final good, Y_t. $\omega \in [0, 1]$ is the share of the commodity used in the production of the final good Y_t, and ρ is the elasticity of substitution between the two inputs. It is assumed that the producer buys the commodity from the futures market in the $t-1$ period at a price F_{t-1}, takes delivery in the t^{th} period, and uses it as a raw material to produce the final good, Y_t. The final good is then sold to the market at a price of P_t, a weighted index of the prices charged by all the producers. The profit-maximizing firms then demand the commodity as follows:

$$C_t^{PD} = \frac{\omega Y_t}{A_t \left[(1-\omega) \left(\frac{F_{t-1}}{P_t} \right)^{\rho-1} + \omega \right]^{\frac{\rho}{1-\rho}}} \tag{4.2}$$

where A_t denotes technological progress. Since the model structure is linear in nature, without loss of generality, the production demand for a commodity can simply be expressed as a linear function of final output produced, Y_t, one period ahead futures prices, F_{t-1}, and the general price level, P_t.

$$C_t^{PD} = \alpha Y_t - \beta F_{t-1} + \gamma P_t \tag{4.3}$$

Inventory Demand for Commodities

The second type of demand for the commodity is for the purpose of stock-holding. The demand for stock-holding is determined on the basis of the marginal returns of the financial assets. The inventory dealer enters into a forward contract at time t to deliver the commodity at time $t+1$ at a futures contract price F_t. The marginal return from the hedged stock is then defined as follows:

$$R(f)'_t = F_t - S_t - h \tag{4.4}$$

where h is the marginal cost of inventory holding [13]. As the model assumes that all stocks are hedged, the stockist compares the marginal returns from holding commodities to alternative forms of investment. If it is assumed that the transaction costs in the financial securities market are negligible, then the inventory demand for the commodity can be specified as follows:

$$C_t^{ID} = I_0 + \zeta[R(f)'_t - r_t];\ \zeta > 0$$

or

$$C_t^{ID} = I_0 + \zeta[F_t - S_t - h - r_t];\ \zeta > 0 \tag{4.5}$$

where r_t is the one-period rate of interest on financial security.

[13] Here, a quadratic cost function is assumed following Kawai (1983).

Supply of Commodities

Following Kawai (1983), it is assumed that the commodity producer can enter into a contract at time t to deliver the commodity in time $t+1$ at a known contract price F_t. Using a quadratic cost function, the optimum level of the commodity supplied can be written as follows:

$$X_t = \eta F_t \tag{4.6}$$

Demand for Futures Contract

The demand for futures contracts is defined by speculators' activities. The speculators demand the futures contracts on the basis of the expected profit margin or the difference between the expected spot price of period $t+1$ and the futures price at period t. The demand for futures contracts is defined as:

$$G_t = \mu(E_t S_{t+1} - F_t);\ \mu > 0 \tag{4.7}$$

where $E_t S_{t+1}$ is the expectation about S_{t+1} at period t and conditional on information available at time t.

Supply of Futures Contract

Since it is assumed that all stocks are hedged, the supply of futures contracts by the inventory dealers, B_t is equal to the inventory demanded.

$$B_t = C_t^{I^D} \tag{4.8}$$

Market Equilibrium Conditions

The market is said to be in equilibrium when the demand and supply of commodities and the demand and supply of futures contracts will simultaneously be in balance. Then the commodity market equilibrium condition is given by

$$C_t^{PD} + C_t^{ID} = C_{t-1}^{I} + X_t \tag{4.9}$$

where C_{t-1}^{I} is the carry-over of inventory from the period $t-1$. On the other hand, the futures market is in equilibrium when the following condition is satisfied.

$$B_t = G_t \tag{4.10}$$

Determination of Price Equation

Solving equations (4.9) and (4.10) along with equations (4.1) to (4.8), the general price level can be found as follows:

$$P_t = \frac{\mu}{\gamma}F_t + \frac{(\beta+\eta)}{\gamma}F_{t-1} - \frac{\mu}{\gamma}E_t S_{t+1} - \frac{\alpha}{\gamma}Y_t + \frac{1}{\gamma}C_{t-1}^{I} \tag{4.11}$$

Equation (4.11) thus shows that the commodity futures price at time t and $t-1$ have a positive impact on the general price level or the price index for all commodities taken together. This indicates a positive link between inflation and commodity futures price levels and inflation. This forms the basis of an empirical exercise that follows.

4.4 Empirical Methodology

The Feasible Quasi Generalized Least Square (FQGLS) method, as proposed by Westerlund & Narayan (2012) and Westerlund & Narayan (2015) is employed as an estimation strategy, to capture any possible presence of endogeneity, persistence, and conditional heteroskedasticity effects in the forecasting model. A large number of studies have already used this method to predict stock returns and exchange rates [14] A number of studies have used time series methods such as Autoregressive Moving Average (ARMA)[15] or Vector Autoregssion (VAR) based methods[16] or Time Varying VAR[17]. The FQGLS method has many advantages over the existing methods as it simultaneously captures potential endogeneity, persistence and conditional heteroskedasticity. This is more important when high-frequency financial variables are used as predictors in regression[18]. Various studies[19] use the FQGLS method as an estimation strategy to forecast inflation. A large number of studies[20] have used the Phillips curve framework to model Indian inflation. The present chapter employs the FQGLS method on the augmented Phillips curve-based model being augmented by the commodity futures price index. The following sub-sections explain the FQGLS method in detail.

[14] See, for example, Sharma & Thuraisamy (2013), Narayan & Bannigidadmath (2015), Bannigidadmath & Narayan (2016), Phan et al. (2015).

[15] See, for example, Stoviček (2007), Nyoni & Nathaniel (2018), Zhang et al. (2020), among others.

[16] See, for example, Kenny et al. (1998), Uko & Nkoro (2012), Öğünç et al. (2013), Clements & Galvão (2013); Giannone et al. (2014), among others.

[17] See, for example, Ruch et al. (2020), Barnett et al. (2014), among others.

[18] See Salisu & Isah (2018) for a detailed discussion on the advantages of the FQGLS method.

[19] For instance, Salisu & Isah (2018), Salisu et al. 2018, Tule et al. 2019, Tule et al. 2020, among others.

[20] See, for example, Dholakia (1990), Kapur & Patra (2003), Srinivasan et al. (2006), Dua & Gaur (2010), Paul (2009), Patra & Kapur (2012), Patra & Ray (2010), Singh et al. (2011), Mazumder (2011), among others.

4.4.1 Estimation Approach

For the predictability tests, Feasible Quasi Generalized Least Square (FQGLS) method a la Westerlund & Narayan (2015) is applied. The principal advantage of this method over other methods is that it takes into account the persistence, endogeneity, and heteroskedasticity features of the data. A predictive regression model for Indian inflation can be of the following form:

$$\pi_t = \alpha + \beta x_{t-1} + \epsilon_{\pi,t} \tag{4.12}$$

where π_t is the inflation and x_t is a potential predictor variable. The error term $\epsilon_{\pi,t}$ has a zero mean and variance $\sigma^2_{\epsilon_{\pi,t}}$. The predictability test can be performed with the null hypothesis $H_0 : \beta = 0$. The predictor in Eq. (4.12) follows a first-order autoregressive process:

$$x_t = \mu(1 - \rho) + \rho x_{t-1} + \epsilon_{x,t} \tag{4.13}$$

where $|\rho| \leq 1$ and the error term $\epsilon_{x,t}$ has a zero mean and variance $\sigma^2_{\epsilon_{x,t}}$. In the presence of an endogenous predictor variable, the null hypothesis of no predictability will be biased.

The endogeneity effect is being tested following the Westerlund & Narayan (2015) technique of modelling the error terms, which is as:

$$\epsilon_{\pi,t} = \gamma \epsilon_{x,t} + \eta_t \tag{4.14}$$

where the error term η_t has a zero mean and variance $\sigma^2_{\eta t}$. The $\epsilon_{x,t}$ and η_t are assumed to be uncorrelated. Now, to remove the effect of endogeneity, Eq. (4.13) and Eq. (4.14) can be substituted in equation (4.12) as:

$$\pi_t = \theta + \beta x_{t-1} + \gamma(x_t - \rho x_{t-1}) + \eta_t \tag{4.15}$$

where $\theta = \alpha - \gamma\mu(1-\rho)$. Following Westerlund & Narayan (2015), a bias-adjusted OLS estimator for β, as suggested by Lewellen (2004), can be used in order to correct for any inherent bias in β. The Eq. (4.15) can then be rewritten as:

$$\pi_t = \theta + \beta^{adj} x_{t-1} + \gamma(x_t - \rho x_{t-1}) + \eta_t \tag{4.16}$$

where $\beta^{adj} = \beta - \gamma(\rho - \rho_0)$ and ρ_0 is a guess for ρ. Westerlund & Narayan (2015) propose $\rho = 1 + \frac{c}{T}$ where $c \leq 0$ is a drift parameter that measures the degree of persistency in x_t.

The last issue to deal with in the estimation, in addition to endogeneity and persistence effects, is conditional heteroskedasticity. Westerlund & Narayan (2015) suggest using the following variance equation for η_t to model heteroskedasticity.

$$var(\eta_t|I_{t-1}) = \sigma^2_{\eta_t} = \Psi_0 + \Sigma^q_{k=1}\Psi_k\eta^2_{t-k} \tag{4.17}$$

where I_{t-1} is is the all information available at time t-1 and it is assumed that $\Psi_0 > 0$, $\Psi_k \geq 0, (k = 1, 2, \ldots, q)$ and $\Sigma^q_{k=1}\Psi_k < 1$. The FQGLS estimator assumes that the regression error η_t follows an autoregressive conditional heteroskedasticity (ARCH) structure and thus the $\frac{1}{\sigma^2_{\eta_t}}$ is to be used as weights. Then, the FQGLS-based t-statistics for testing the null hypothesis $H_0 : \beta = 0$ for the predictability test takes the following form:

$$t_{FQGLS} = \frac{\sum_{q_m+2}^{T} \hat{\tau_t^2} x_{t-1}^d \pi_t^d}{\sqrt{\sum_{q_m+2}^{T} \hat{\tau_t^2} (x_{t-1}^d)^2}} \tag{4.18}$$

where $\tau_t = 1/\sigma\eta_t$, $x_t^d = x_t - \sum_{s=2}^{T} x_t/T$ and $\pi_t^d = \pi_t - \sum_{s=2}^{T} \pi_t/T$.

Linear Models

Following are the single-predictor and multiple-predictor models estimated for Indian inflation with symmetric price changes:

$$\pi_t = \theta_Y + \beta_Y Y_{t-1} + \gamma_Y (Y_t - \rho_Y Y_{t-1}) + \eta_{Y,t} \tag{4.19a}$$

$$\pi_t = \theta_O + \beta_O P_{t-1}^O + \gamma_O (P_t^O - \rho_O P_{t-1}^O) + \eta_{O,t} \tag{4.19b}$$

$$\pi_t = \theta_C + \beta_C P_{t-1}^C + \gamma_C (P_t^C - \rho_C P_{t-1}^C) + \eta_{C,t} \tag{4.19c}$$

$$\pi_t = \theta_{Y,O} + \beta_Y Y_{t-1} + \gamma_Y (Y_t - \rho_Y Y_{t-1}) + \beta_O P_{t-1}^O + \gamma_O (P_t^O - \rho_O P_{t-1}^O) + \eta_{Y,O,t} \tag{4.19d}$$

$$\pi_t = \theta_{Y,C} + \beta_Y Y_{t-1} + \gamma_Y (Y_t - \rho_Y Y_{t-1}) + \beta_C P_{t-1}^C + \gamma_C (P_t^C - \rho_C P_{t-1}^C) + \eta_{Y,C,t} \tag{4.19e}$$

where, Y, P^O, and P^C are output, crude oil price, and commodity price index, respectively. Equation (4.19a) can be denoted as the traditional Phillips curve model.

Non-Linear Models

To check for the asymmetric effect of crude oil and commodity price changes, prices change is then decomposed into positive (P^+) and negative (P^-) changes. Following Shin et al. (2014), Nusair (2016), Van Hoang et al. (2016), Salisu & Isah (2018), and Salisu et al. (2018), the P^+ and P^- are computed as positive and negative partial sum decomposition of price changes as follows:

$$P_t = P_0 + P_t^+ + P_t^-$$

where $P^+ = \Sigma_{j=1}^{t}\Delta P_j^+ = \Sigma_{j=1}^{t} max(\Delta P_j^+, 0)$ and $P^- = \Sigma_{j=1}^{t}\Delta P_j^- = \Sigma_{j=1}^{t} min(\Delta P_j^-, 0)$ Incorporating the asymmetric price changes, the single-predictor and multiple-predictor models estimated for Indian inflation are as follows:

$$\pi_t = \theta_{O^a} + \beta_{O^+} P_{t-1}^{O+} + \beta_{O^-} P_{t-1}^{O-} + \gamma_{O^+}(P_t^{O^+} - \rho_{O^+} P_{t-1}^{O+}) + \gamma_{O^-}(P_t^{O^-} - \rho_{O^-} P_{t-1}^{O-}) + \eta_{O^a,t}; \tag{4.20a}$$

$$\pi_t = \theta_{C^a} + \beta_{C^+} P_{t-1}^{C+} + \beta_{C^-} P_{t-1}^{C-} + \gamma_{C^+}(P_t^{C^+} - \rho_{C^+} P_{t-1}^{C+}) + \gamma_{C^-}(P_t^{C^-} - \rho_{C^-} P_{t-1}^{C-}) + \eta_{C^a,t}; \tag{4.20b}$$

$$\pi_t = \theta_{(O,Y)^a} + \beta_Y Y_{t-1} + \gamma_Y(Y_t - \rho_Y Y_{t-1}) + \beta_{O^+} P_{t-1}^{O+} + \beta_{O^-} P_{t-1}^{O-} + \gamma_{O^+}(P_t^{O^+} - \rho_{O^+} P_{t-1}^{O+}) + \gamma_{O^-}(P_t^{O^-} - \rho_{O^-} P_{t-1}^{O-}) + \eta_{(O,Y)^a,t}; \tag{4.20c}$$

$$\pi_t = \theta_{(C,Y)^a} + \beta_Y Y_{t-1} + \gamma_Y(Y_t - \rho_Y Y_{t-1}) + \beta_{C^+} P_{t-1}^{C+} + \beta_{C^-} P_{t-1}^{C-} + \gamma_{C^+}(P_t^{C^+} - \rho_{C^+} P_{t-1}^{C+}) + \gamma_{C^-}(P_t^{C^-} - \rho_{C^-} P_{t-1}^{C-}) + \eta_{(C,Y)^a,t}; \tag{4.20d}$$

where P^{o^+}, P^{o^-}, P^{c^+}, and P^{c^+} are positive crude oil price changes, negative crude oil price changes, positive commodity price changes and negative commodity price changes, respectively. Equations (4.19b), (4.19c), (4.20a) and (4.20b) are purely supply-side models. Equations (4.19d), (4.19e), (4.20c) and (4.20d) are the multiple-predictor models involving both the demand and supply predictors. Following Salisu & Isah (2018), and Salisu et al. (2018), the multiple-predictor models have been estimated with a price-output combination. Equations (4.19d) and (4.20c) involve the crude oil price-output combination, whereas equations (4.19e) and (4.20d) involve the commodity price index-output combination.

4.4.2 Forecasting Approach

The forecast analysis has been done for both in-sample and out-of-sample periods. In order to check the robustness of forecast performance, a number of studies have put stress on selecting multiple out-of-sample periods (see, for example, Bossaerts & Hillion 1999, Goyal & Welch 2003, Brennan & Xia 2005, and Ang & Bekaert 2007). The inflation forecasting in India as practised by the RBI involves now-casting, short-term projections of 12 months and medium-term projections of 24 months (Raj et al. 2019). Hence, three out-of-sample forecast horizons of 3 months (very short-term), 12 months (short-term), and 24 months (medium-term) are considered. In addition, the rolling window approach has been adopted to produce the forecast results [21].

For evaluation of the forecast performance of the aforementioned models, three tests namely, the Campbell-Thompson test, the Diebold-Mariano test, and

[21] This follows Rapach et al. (2010), Narayan & Bannigidadmath (2015), Bannigidadmath & Narayan (2016), Salisu & Isah (2018), and Salisu et al. (2018).

the Clark-West test, have been adopted. The Campbell-Thompson test (following Campbell & Thompson 2008) is computed as follows:

$$OR^2 = 1 - (MSE_u/MSE_r) \tag{4.21}$$

where MSE_r and MSE_u are the mean square error(MSE) of the prediction from the restricted and unrestricted models, respectively. A positive OR^2 implies that the unrestricted model outperforms the restricted model and vice-versa. The second test following Diebold & Mariano (2002) has been applied to compare the forecast performance of the restricted and unrestricted models. The loss difference between the two forecasts; from restricted and unrestricted models, can be defined as follows:

$$d_t = g(e_{r,t}) - g(e_{u,t})$$

where $e_{i,t} = (\hat{\pi}_t^i - \pi_t)$; i=r,u and the loss function is defined as the squared-error loss function. To test the equal forecast accuracy of the two forecasts, the null hypothesis $H_0 : E(d_t) = 0$ has been tested. Under the null hypothesis, the D-M statistics is defined as:

$$D = \frac{\overline{d}}{\sqrt{\frac{1}{T}V(d)}} \sim N(0,1) \tag{4.22}$$

where $\overline{d} = \frac{1}{T}\Sigma_{t=1}^{T}[g(e_{r,t}) - g(e_{u,t})]$ is the sample mean loss function and $V(d)$ is the unconditional variance of d. Last, but not of least importance, the Clark & West (2007) test involves computing the equation

$$f_t = (\pi - \hat{\pi_t^r})^2 - [(\pi - \hat{\pi_t^u})^2 - (\hat{\pi_t^r} - \hat{\pi_t^u})^2] \tag{4.23}$$

where $(\pi - \hat{\pi_t^r})^2$ and $(\pi - \hat{\pi_t^u})^2$ are squared errors from the restricted and unrestricted models, respectively. To test the equality of forecast performance of restricted and unrestricted models on the basis of the C-W test, the f_t is regressed on a constant, and the resulting t-statistics are reported.

4.5 Empirical Results

This section presents the results obtained from the FQGLS estimation and different tests that have been used to evaluate forecasting performances of different models used.

4.5.1 Preliminary Analysis

For the forecasting exercise, the in-sample forecast horizon covers the time period from June 2006 to June 2017. Monthly historical data have been used instead of quarterly data; as used in the earlier Chapter 3, as the former allows for a higher number of observations. Since core inflation data are not available for India, this chapter relies only on headline inflation[22]. The beginning of the sample is dictated by the availability of data on commodity futures price index[23]. The three out-of-sample forecast horizons cover the time period July 2017 to September 2017 (three months), July 2017 to June 2018 (twelve months), and July 2017 to June 2019 (twenty-four months). The 12-month year-on-year inflation has been

[22]Some previous studies have attempted to estimate wholesale price core inflation for India (see, for example, Mohanty et al. 2000, Das et al. 2009, Raj & Misra 2011, Ball et al. 2016, among others.). However, this chapter has only attempted to forecast headline inflation mainly on account of the following reasons. First, headline inflation is more volatile as compared to core inflation (Ball et al. 2016) and thus forecasting headline inflation is relatively more challenging. Second, from the point of view of inflation targeting, forecasting headline inflation is more relevant.

[23]The data for commodity futures prices indices are available only after May 13, 2005, and hence June 2006 is taken as the starting month of the sample.

calculated as $\pi_t = ln(CPI_t) - ln(CPI_{t-12})$. Similar results have been found even if inflation rates are computed as $\pi_t = \frac{(CPI_t - CPI_{t-12})}{CPI_{t-12}}$.

Table 4.1: Serial Correlation and Heteroskedasticity Tests

	Autocorrelation (Q-statistics)				ARCH LM (F- Statistics)			
	Q(1)	**Q(3)**	**Q(6)**	**Q(12)**	**ARCH(1)**	**ARCH(3)**	**ARCH(6)**	**ARCH(12)**
Y	140.53***	410.11***	755.96***	1344.20***	117.1917***	130.2707***	125.0962***	130.4126***
P^O	149.52***	391.21***	623.12***	857.06***	117.4947***	121.0199***	119.9761***	116.1302***
P^{O+}	153.21***	441.90***	830.12***	1459.00***	155.2470***	153.5257***	150.5067***	144.5024***
P^{O-}	153.68***	444.41***	841.33***	1501.90***	154.4026***	152.9791***	149.9739***	144.0820***
P^C	151.95***	420.03***	723.06***	1103.60***	132.6330***	135.0915***	133.3267***	130.0630***
P^{C+}	153.65***	445.01***	841.50***	1497.30***	155.3151***	153.5037***	150.4985***	144.4690***
P^{C-}	153.42***	442.88***	836.38***	1487.00***	154.2716***	152.7516***	149.7673***	143.7958***

Note: As symbolized in the table, Y, P^O and P^C stand for output, crude oil price and commodity future prices, respectively. ***, ** and * denote 1%, 5% and 10% levels of significance, respectively.

Prior to applying the FQGLS method, it is important to check whether there is evidence of autocorrelation, heteroskedasticity and endogeneity. The presence of autocorrelation and conditional heteroskedasticity in the predictor series have been checked, and the results are reported in Table 4.1. Using Ljung & Box (1978) and Engle (1982) ARCH-LM test, the presence of serial dependence and conditional heteroskedasticity in all the predictor series are found. Both the tests have been carried out using lag lengths k = 1, 3, 6, and 12. The null hypotheses of no autocorrelation and ARCH effects are rejected even after the increase in lag length. On the other hand, it is crucial to test for the presence of persistence and endogeneity of the predictors. The AR(1) model is estimated for each of the predictors and the estimated persistence coefficients are presented in Table 4.2. The coefficients are statistically significant for each of the predictors and most of the coefficients are very close to unity.

To test for endogeneity, Eq. (4.14) is estimated using each of the predictors. The results are presented in Table 4.2. In this case, there is no evidence of the presence of endogeneity when inflation is used as the explained variable.

However, the presence of endogeneity is evident when the CPI series is used as the explained variable[24], [25]. The FQGLS method can be applied even when there is no issue of endogeneity (see, for example, Fasanya & Awodimila 2020). The above results certainly reinforce the choice of FQGLS estimator to correct for the possible presence of persistence and heteroskedasticity in this analysis.

Table 4.2: Tests for Endogeneity and Persistence of the Predictors

Test → Variables ↓	Persistence Test	Endogeneity Test
Y	0.9449***	-0.0220
P^{O}	0.9652***	0.0073
P^{O+}	0.9974***	-0.0690
P^{O-}	0.9984***	0.0033
P^{C}	0.9763***	-0.0088
P^{C+}	0.9954***	-0.0453
P^{C-}	0.9956***	0.0183

Note: As symbolized in the table, Y, P^O, and P^C stand for output, crude oil price, and commodity future prices, respectively. ***, ** and * denote 1%, 5% and 10% levels of significance, respectively.

4.5.2 Predictability Test

Prior to evaluating the forecast performance of alternate models, it is important to discuss the results of the predictability tests carried out using the different model predictors, viz. index of industrial production (IIP), crude oil price (OP), and commodity futures prices (CFP). The FQGLS statistics for both the single predictor (restricted) and multiple predictor (unrestricted) models of Indian inflation considering symmetric and asymmetric price changes along with the presence of structural breaks are presented in Tables 4.3 and 4.4, respectively. In the case of models with structural breaks (both with symmetric and asymmet-

[24]The results are not reported. However, the same may be obtained upon request.

[25]Although some studies have attempted to forecast CPI instead of inflation, it is chosen to forecast the inflation series following a large number of studies. This is believed to have computational benefits for the monetary authority.

ric price changes), all the predictors are observed to be statistically significant. This indicates that both the demand-side and supply-side predictors used in the Phillips curve framework can significantly predict Indian inflation individually and jointly. The predictability tests show that both in the single-predictor and multiple-predictor models commodity futures prices are found to have a positive effect on inflation. These empirical findings support the relationship found in the theoretical model developed in Section 4.3. The results also support the findings of a number of earlier studies (including Chen et al. 2014, Bec & De Gaye 2016, and Gelos & Ustyugova 2017, among others) that commodity prices and output can significantly predict inflation.

Table 4.3: Predictability Test: Symmetric Price Change with Structural Breaks

	Single Predictor Model			Multiple Predictor Model	
Coefficient↓	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
β_Y	0.0940***			0.0943***	0.0714***
	(0.0161)			(0.0164)	(0.0159)
β_{PO}		0.0103***		0.0141***	
		(0.0024)		(0.0026)	0.0380***
β_{PC}			0.0390***		(0.0058)
			(0.0055)		

Note: As symbolized in the table, Y, P^O and P^C stand for output, crude oil price and commodity futures prices, respectively. Standard errors are mentioned in parentheses. ***, ** and * denote 1%, 5% and 10% levels of significance, respectively.

In models considering asymmetric price changes, it is found that the estimates of both negative and positive changes in crude oil and in commodity futures prices are statistically significant (see Table 4.4). These results thus suggest that non-linearity plays an important role in the case of commodity futures prices and inflation relationship, and support the findings of Chapter 3. The asymmetric responses of inflation to crude oil price and commodity price changes are found to be robust across single and multiple predictor models. Contrary to findings of

Table 4.4: Predictability Test: Asymmetric Price Change with Structural Breaks

	Single Predictor Model			Multiple Predictor Model	
Coefficient↓	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
β_Y	0.0940***			0.0422*	0.0389*
	(0.0161)			(0.0231)	(0.0211)
β_{PO+}		0.0251***		0.0220***	
		(0.0034)		(0.0040)	
β_{PO-}		0.0102***		0.0112***	
		(0.0026)		(0.0027)	
β_{PC+}			0.0475***		0.0450***
			(0.0061)		(0.0068)
β_{PC-}			0.0258***		0.0293***
			(0.0063)		(0.0067)

Note: As symbolized in the table, Y, P^O and P^C stand for output, crude oil price and commodity future prices, respectively. Standard errors are mentioned in parentheses. ***, ** and * denote 1%, 5% and 10% levels of significance, respectively.

Salisu & Isah (2018), it is found that both the positive and negative commodity price and crude oil price changes have a positive impact on inflation. Moreover, the results show that positive price changes have a greater impact on inflation than negative price changes. These results can be explained, following Sockin & Xiong (2015), in terms of cost and information effects. The information effect has a positive influence on inflation; while the cost effect has a positive impact on inflation in case of positive price changes and a negative impact in case of negative price changes. If the information effect is stronger than the negative cost effect, then on balance there is a positive impact on inflation

4.5.3 Unbiasedness of Forecasting Models

Prior to evaluating the forecast performance of different models, it is important to check whether the different models that have been estimated, produce unbiased forecasts or not. To do so, the Mincer & Zarnowitz (1969) regression technique has been used. In the present case, the Mincer-Zarnowitz regression takes the following form:

$$\pi_t = \alpha + \beta\hat{\pi}_t + \epsilon_t \tag{4.24}$$

where π_t and $\hat{\pi}_t$ are actual inflation and forecasted inflation, respectively. The forecasts are said to be unbiased if and only if $\alpha = 0$ and $\beta = 1$. For each of the inflation forecasts obtained from the twenty models estimated, Eq. (4.24) has been estimated and a Wald test is carried out with a null hypothesis $H_0 : \alpha = 0$ & $\beta = 1$. The Chi-square test statistics are reported in Tables A4.1 and A4.2 (see Appendix). It can be observed that for each of the models used for the purpose of evaluating inflation forecasts, the null hypothesis is accepted and thus is said to be unbiased in nature. Thus, there is no reason to prefer one model over another at least on account of biasedness.

4.5.4 In-sample Forecast Performance Evaluation

Having found that crude oil price, commodity futures prices, and output significantly predict Indian inflation, it is then necessary to evaluate the forecast performance of both the single-predictor and multiple-predictor models taking into account the aforementioned predictors separately and together. In this section, the in-sample forecast evaluation results have been discussed. Here, the results of models with structural breaks have been discussed. The results are discussed in four parts. First, the in-sample forecast performances of the traditional demand-side Phillips curve model and the supply-side Phillips curve model are compared. Second, the forecast performance of two single predictor supply-side Phillips curve models is discussed. The motivation here is to examine whether the commodity futures price-based model performs better than the crude oil price-based supply-side model in predicting Indian inflation. Third, the commodity futures price-based single predictor model is compared with the multiple predictors model are compared. The rationale for this is to study whether the forecast performance is more accurate if the traditional demand-side Phillips curve model is augmented with supply-side predictors such as commodity futures prices. Last, the forecast performance of commodity futures prices based augmented Phillips curve model is compared with the crude oil price-based multiple-predictor model.

Table 4.5: In Sample Forecast Evaluation: Symmetric Price Changes with Structural Breaks

	Single Predictor Model			**Multiple Predictor Model**	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
			C-T Test Statistics		
AR	0.6260	0.6026	0.6290	0.6412	0.6564
Model 1 (Y)		-0.0625	0.0079	0.0406	0.0812
Model 2 (P^O)			0.0663	0.0971	0.1353
Model 3 (P^C)				0.0329	0.0739
Model 4 (Y, P^O)					0.0423
			D-M Test Statistics		
AR	6.9253***	7.2930***	7.4435***	7.0319***	7.1450***
Model 1 (Y)		-1.3185	0.1699	1.6033	2.8289***
Model 2 (P^O)			3.4851***	1.9698**	2.8071***
Model 3 (P^C)				0.7163	1.7728*
Model 4 (Y, P^O)					2.5284**
			C-W Test Statistics		
AR	12.1578***	11.0292***	11.2198***	12.3075***	12.3324***
Model 1 (Y)		0.2634*	0.5152***	0.3349***	0.5039***
Model 2 (P^O)			0.3144***	0.7732***	0.8856***
Model 3 (P^C)				0.4483***	0.4746***
Model 4 (Y, P^O)					0.1430***

Note: As symbolized in the table, Y, P^O and P^C stand for output, crude oil price and commodity future prices, respectively. Restricted models are shown in rows while unrestricted models are shown in columns. ***, ** and * denote 1%, 5% and 10% levels of significance, respectively.

Demand-side vs. Supply-side (Single-predictor Models)

The Campbell and Thompson (C-T) test, the Diebold and Mariano (D-M) test, and the Clark and West (C-W) test results are reported in Table 4.5 and Table 4.6. Here the demand-side Phillips curve model (Model 1) is compared with the commodity futures price-based supply-side Phillips curve model (Model

3). While the former is treated as the restricted model, the latter is treated as the unrestricted one. As mentioned earlier, a positive C-T statistic, a positive and significant D-M statistic and C-W statistic indicate that the unrestricted model outperforms the restricted model. Starting with the models considering symmetric price changes, it is found that all three statistics are positive and the C-W test statistic is positive and statistically significant (see Table 4.5). For models with asymmetric price changes, the results show that the C-T test statistic is positive and the D-M and C-W test statistics are positive and significant (see Table 4.6). These results reveal that the commodity futures prices-based supply-side Phillips curve model gives a better in-sample forecast of Indian inflation than the traditional Phillips curve model.

Crude Oil Prices vs. Commodity Futures Prices (Single-predictor Models)

Further, the in-sample forecast performance of two supply-side models (Models 2 and 3) are compared. While Model 2 considers crude oil price as the only predictor, Model 3 considers the commodity futures price index as the predictor of inflation. As evident from all the three test statistics reported in Table 4.5, it can be seen that in the case of models with symmetric price changes, the commodity futures price-based supply-side model (Model 3) performs better than the crude oil price-based single-predictor model (Model 2) in predicting Indian inflation.

With the C-T test statistic being positive and the D-M and C-W test statistics being positive and significant, the commodity futures price-based supply-side model predicts Indian inflation better than the crude oil price-based supply-side Phillips curve model. From Table 4.6 it can also be observed that for the models with asymmetric price changes also, the commodity futures price-based model predicts Indian inflation better than the crude oil price-based single-predictor model. These results certainly confirm the findings of Salisu & Isah (2018), Salisu et al. (2018), among others. This is on account of the fact that the spot crude oil price changes have only cost effects while commodity futures price changes have both cost as well as information effects.

Table 4.6: In Sample Forecast Evaluation: Asymmetric Price Changes with Structural Breaks))

	Single Predictor Model			Multiple Predictor Model	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
C-T Test Statistics					
AR	0.6260	0.6402	0.6519	0.6504	0.6612
Model 1 (Y)		0.0381	0.0692	0.0652	0.0941
Model 2 (P^{O+}, P^{O-})			0.0324	0.0282	0.0583
Model 3 (P^{C+}, P^{C-})				-0.0043	0.0268
Model 4 (Y, P^{O+}, P^{O-})					0.0309
D-M Test Statistics					
AR	6.9253***	7.4555***	7.4599***	7.2658***	7.2704***
Model 1 (Y)		0.8880	1.6598*	2.0684**	2.8118***
Model 2 (P^{O+}, P^{O-})			1.7073*	1.1877	1.6885*
Model 3 (P^{C+}, P^{C-})				-0.1635	1.220
Model 4 (Y, P^{O+}, P^{O-})					1.4843
C-W Test Statistics					
AR	12.1578***	11.7649***	11.7994***	12.3032***	12.3873***
Model 1 (Y)		0.5635***	0.6491***	0.5139***	0.6156***
Model 2 (P^{O+}, P^{O-})			0.1109**	0.1269*	0.2379**
Model 3 (P^{C+}, P^{C-})				0.1206*	0.1274*
Model 4 (Y, P^{O+}, P^{O-})					0.1025**

Note: As symbolized in the table, Y, P^O, and P^C stand for output, crude oil price, and commodity future prices, respectively. Restricted models are shown in rows while unrestricted models are shown in columns. ***, ** and * denote 1%, 5% and 10% levels of significance, respectively.

Single predictor vs. Multiple predictors Models

The multiple predictors model (Model 5) has been compared with three single predictor models, Model 1, Model 2, and Model 3. For models with symmetric price changes, comparing Model 5 with Model 1, the results in Table 4.5 show that not only all the three test statistics are positive but the D-M and C-W test statistics are also statistically significant. This implies that the commodity futures price based multiple predictors model outperforms the demand-side Phillips curve model in predicting Indian inflation. The same is found even when asymmetry in price changes is allowed for (see Table 4.6). On the other hand, comparing the commodity price-based multiple predictors model with the crude oil price-based single-predictor model, it is observed that in case of the in-sample forecast, the former outperforms the latter (see Table 4.5). The results do not alter even after allowing for asymmetric price changes (see Table 4.6). Further, comparing the commodity price-based multiple predictors model with the commodity price-based single predictor model, it is observed that in case of in-sample forecast, the former outperforms the latter (see Table 4.5). This is the case even if asymmetric price changes are considered (see Table 4.6).

The above findings thus indicate that augmenting the traditional demand-side Phillips curve model with symmetric or asymmetric commodity futures price changes can lead to more accurate in-sample forecast for inflation. This implies that the augmented Phillips curve model containing commodity futures prices can be used instead of the crude oil price-based supply-side Phillips curve model in forecasting Indian inflation.

Crude Oil Prices vs. Commodity Futures Prices (multiple predictor Models)

Turning to the main hypothesis of the chapter, the in-sample forecast performance of the crude oil price based augmented Phillips curve model (Model 4) is compared with that of the commodity futures price based augmented Phillips curve model (Model 5). With symmetric price changes, while the C-T test statistics are positive, D-M and the C-W test statistics are positive and statistically significant (see Table 4.5). On the other hand, for asymmetric price changes, all the three statistics are positive and the C-W test statistic is significant (see Table 4.6). These results suggest that augmenting the traditional demand-side Phillips curve with commodity futures prices instead of crude oil prices increases the accuracy of the inflation forecast in India. This chapter contributes to the literature as it shows that the commodity futures price based augmented Phillips curve model can produce better inflation forecast in comparison with the crude oil prices based augmented Philips curve model.

4.5.5 Out-of-sample Forecast Performance Evaluation

After assessing the in-sample forecast performance of different single-predictor and multiple-predictor models, an evaluation of the out-of-sample forecast performances of these models is in order. However, the inflation forecasting framework of the Reserve Bank of India considers only short-term projections of 12 months and medium-term projections of 24 months (Raj et al. 2019). Following the same, in the present analysis, results for three forecast horizons (h) of three months (h=3), twelve months (h=12), and twenty-four months (h=24) have been reported in

Table 4.7. Similar out-of-sample forecasts with asymmetric price changes are reported in Table 4.8. Table 4.10 shows a comparison of forecast results based on symmetric and asymmetric price changes.

For out-of-sample forecasts with very short forecast horizons (h=3) in the presence of both symmetric and asymmetric price changes, the commodity futures price-based single predictor model outperforms other single predictor models in predicting inflation in India. On the other hand, for short-term forecasting (that is with h=12) with both the symmetric as well as asymmetric price changes, commodity futures price-based supply-side models perform better than other single predictor models in predicting Indian retail inflation. In the case of medium-term forecasting (h=24), it can be inferred that if the commodity futures price-based supply-side model is used instead of the demand-side model for the purpose of forecasting Indian inflation, asymmetric price changes need to be considered.

For a very short-term inflation forecasting (h=3), in terms of C-T test, D-M test, and C-W test statistics, it is found that the commodity futures price-based single predictor model is a better alternative compared to the crude oil price-based single predictor as well as demand side models (see Table 4.7 and Table 4.8). This is true even in the case of short-term inflation forecasting with h=12 (See Table 4.9 and Table 4.10). In the case of medium-term forecasting, the asymmetric crude oil price-based supply-side Phillips curve model is found to predict Indian inflation better than the commodity futures price-based Phillips curve model (see Table 4.8). Further, the commodity futures price-based multiple predictors model not only outperforms the demand-side model but also the oil price-based or commodity price-based single predictor supply-side models (see Table 4.7). The results

Table 4.7: Out of sample Forecast Evaluation: Symmetric Price Changes with Structural Breaks

	Single Predictor Model			Multiple Predictor Model	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Forecast Horizon (h) = 3					
C-T Test Statistics					
AR	0.6317	0.6077	0.6344	0.6468	0.6618
Model 1 (Y)		-0.0651	0.0073	0.0412	0.0819
Model 2 (P^O)			0.0679	0.0997	0.1380
Model 3 (P^C)				0.0341	0.0751
Model 4 (Y, P^O)					0.0425
D-M Test Statistics					
AR	7.1782***	7.5572***	7.7107***	7.2864***	7.4007***
Model 1 (Y)		-1.3772	0.1571	1.6298	2.8590***
Model 2 (P^O)			3.5899***	2.0356**	2.8785***
Model 3 (P^C)				0.7444	1.8094*
Model 4 (Y, P^O)					2.5415**
C-W Test Statistics					
AR	12.7780***	11.5835***	11.8305***	13.0138***	13.0490***
Model 1 (Y)		0.2368*	0.4969***	0.3476***	0.5152***
Model 2 (P^O)			0.3263***	0.8116***	0.9249***
Model 3 (P^C)				0.4685***	0.4969***
Model 4 (Y, P^O)					0.1413***
Forecast Horizon (h) = 12					
C-T Test Statistics					
AR	0.6300	0.6057	0.6316	0.6479	0.6602
Model 1 (Y)		-0.0656	0.0044	0.0484	0.0818
Model 2 (P^O)			0.0657	0.1070	0.1383
Model 3 (P^C)				0.0441	0.0777
Model 4 (Y, P^O)					0.0351
D-M Test Statistics					
AR	7.3515***	7.7287***	7.8797***	7.4834***	7.5795***
Model 1 (Y)		-1.4412	0.0991	1.9723**	2.9638***
Model 2 (P^O)			3.6076***	2.2546**	2.9978***
Model 3 (P^C)				0.9944	1.9491*
Model 4 (Y, P^O)					2.1062**
C-W Test Statistics					
AR	13.3441***	12.2281***	12.4588***	13.5716***	13.6176***
Model 1 (Y)		0.2218*	0.4642***	0.3261***	0.4821***
Model 2 (P^O)			0.3044***	0.7711***	0.8735***
Model 3 (P^C)				0.4506***	0.4732***
Model 4 (Y, P^O)					0.1314***
Forecast Horizon (h) = 24					
C-T Test Statistics					
AR	0.5269	0.4943	0.5220	0.5588	0.5624
Model 1 (Y)		-0.0689	-0.0104	0.0674	0.0749
Model 2 (P^O)			0.0548	0.1276	0.1345
Model 3 (P^C)				0.0770	0.0844
Model 4 (Y, P^O)					0.0080
D-M Test Statistics					
AR	6.2965***	6.3324***	6.5835***	6.6316***	6.6407***
Model 1 (Y)		-2.2500**	-0.3558	3.5684***	4.1006***
Model 2 (P^O)			4.7657***	3.6341***	4.2153***
Model 3 (P^C)				2.4086**	3.1186***
Model 4 (Y, P^O)					0.6849
C-W Test Statistics					
AR	12.8387***	11.8005***	11.9892***	13.0158***	13.0517***
Model 1 (Y)		0.1173	0.3732***	0.3190***	0.4597***
Model 2 (P^O)			0.3163***	0.8360***	0.9265***
Model 3 (P^C)				0.5017***	0.5183***
Model 4 (Y, P^O)					0.1179***

Note: As symbolized in the table, Y, P^O, and P^C stand for output, crude oil price, and commodity future prices, respectively. Restricted models are shown in rows while unrestricted models are shown in columns. ***, ** and * denote 1%, 5% and 10% levels of significance, respectively.

Table 4.8: Out of Sample Forecast Evaluation: Asymmetric Price Changes with Structural Breaks

	Single Predictor Model			Multiple Predictor Model	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Forecast Horizon (h) = 3					
C-T Test Statistics					
AR	0.6317	0.6456	0.6572	0.6558	0.6664
Model 1 (Y)		0.0379	0.0694	0.0655	0.0944
Model 2 (P^{O+}, P^{O-})			0.0327	0.0287	0.0587
Model 3 (P^{C+}, P^{C-})				-0.0042	0.0269
Model 4 (Y, P^{O+}, P^{O-})					0.0309
D-M Test Statistics					
AR	7.1782***	7.7216***	7.7247***	7.5253***	7.5282***
Model 1 (Y)		0.8846	1.6663*	2.0805**	2.8224***
Model 2 (P^{O+}, P^{O-})			1.7319*	1.2133	1.7063*
Model 3 (P^{C+}, P^{C-})				-0.1582	1.1289
Model 4 (Y, P^{O+}, P^{O-})					1.4848
C-W Test Statistics					
AR	12.7780***	12.4215***	12.4723***	13.0013***	13.1057***
Model 1 (Y)		0.5554***	0.6429***	0.5191***	0.6235***
Model 2 (P^{O+}, P^{O-})			0.1120**	0.1353**	0.2485***
Model 3 (P^{C+}, P^{C-})				0.1251*	0.1359**
Model 4 (Y, P^{O+}, P^{O-})					0.1037**
Forecast Horizon (h) = 12					
C-T Test Statistics					
AR	0.6300	0.6429	0.6515	0.6541	0.6622
Model 1 (Y)		0.0348	0.0583	0.0651	0.0872
Model 2 (P^{O+}, P^{O-})			0.0243	0.0314	0.0542
Model 3 (P^{C+}, P^{C-})				0.0072	0.0307
Model 4 (Y, P^{O+}, P^{O-})					0.0236
D-M Test Statistics					
AR	7.3516***	7.8896***	7.8691***	7.7015***	7.6856***
Model 1 (Y)		0.8455	1.4515	2.1376***	2.6909***
Model 2 (P^{O+}, P^{O-})			1.3226	1.3797	1.6502*
Model 3 (P^{C+}, P^{C-})				0.2827	1.3613
Model 4 (Y, P^{O+}, P^{O-})					1.1661
C-W Test Statistics					
AR	13.3441***	13.0281***	13.1068***	13.5795***	13.6940***
Model 1 (Y)		0.5191***	0.6015***	0.4857***	0.5832***
Model 2 (P^{O+}, P^{O-})			0.1055**	0.1306**	0.2363***
Model 3 (P^{C+}, P^{C-})				0.1227*	0.1314**
Model 4 (Y, P^{O+}, P^{O-})					0.0974**
Forecast Horizon (h) = 24					
C-T Test Statistics					
AR	0.5269	0.5566	0.5502	0.5683	0.5646
Model 1 (Y)		0.0627	0.0492	0.0875	0.0796
Model 2 (P^{O+}, P^{O-})			-0.0144	0.0264	0.0181
Model 3 (P^{C+}, P^{C-})				0.0403	0.0321
Model 4 (Y, P^{O+}, P^{O-})					-0.0086
D-M Test Statistics					
AR	6.2965***	6.9793***	6.7952***	6.8734***	6.7429***
Model 1 (Y)		2.0368**	1.9299*	3.5029***	3.6876***
Model 2 (P^{O+}, P^{O-})			-0.0970	1.7602*	0.8092
Model 3 (P^{C+}, P^{C-})				2.0332**	2.2434**
Model 4 (Y, P^{O+}, P^{O-})					-0.5536
C-W Test Statistics					
AR	12.8387***	12.4772***	12.5703***	12.9954***	13.1113***
Model 1 (Y)		0.5865***	0.5990***	0.5424***	0.5951***
Model 2 (P^{O+}, P^{O-})			0.0475	0.1125*	0.1818**
Model 3 (P^{C+}, P^{C-})				0.1601**	0.1354**
Model 4 (Y, P^{O+}, P^{O-})					0.0604

Note: As symbolized in the table, Y, P^O, and P^C stand for output, crude oil price, and commodity future prices, respectively. Restricted models are shown in rows while unrestricted models are shown in columns. ***, ** and * denote 1%, 5% and 10% levels of significance, respectively.

are found to be robust in the sense that the same outcome is observed even when asymmetry in price changes is allowed (see Table 4.8). Moreover, in the case of short-term (h=12) and medium-term (h=24) inflation forecasting, the commodity futures price based augmented Phillips curve model (Model 5) is found to perform better than the traditional Phillips curve model (model 1), the oil price based single predictor supply side model (Model 2) or the commodity futures price based single predictor supply side model (both with and without asymmetric price changes) (see Table 4.7 and Table 4.8).

The above findings thus indicate that augmenting the traditional demand-side Phillips curve with symmetric or asymmetric commodity price changes can improve the out-of-sample forecast performance. Moreover, while comparing the commodity price-based multiple predictor model with the crude oil price-based single predictor model, the test statistics get reduced when asymmetric price changes are allowed. This certainly implies that the asymmetry matters more for extremely volatile crude oil prices than for commodity futures prices. Lastly, comparing the out-of-sample forecast performance of two multiple-predictor models for a very short-term forecast (h=3) horizon, the symmetric commodity futures price-based multiple-predictor model (Model 5) is found to forecast inflation better than the symmetric crude oil price change based multiple-predictor model (Model 4) (see Table 4.7). Considering the models with asymmetric price changes, the results are found to be unaltered for h=3 and h=12. The exception to this pattern is when the forecasting horizon is medium-term (h=24) with asymmetric price changes. On the whole, the in-sample and out-of-sample forecasts show that augmenting the traditional demand-side Phillips curve with asymmetric commodity price changes can produce a better inflation forecast in India.

4.5.6 Symmetric vs. Asymmetric Models

As discussed earlier, in this chapter linear as well as non-linear models have been considered. In non-linear models asymmetric price changes are being considered; whereas only symmetric price changes have been considered in linear models. In what follows is a comparison of the forecast performances of models of symmetric price changes with that of asymmetric price changes. Like previous cases, the forecast performances are being evaluated on the basis of the C-T test, D-M test, and C-W test. The results are presented in Table 4.9 and Table 4.10, which show the results of in-sample forecast performances and out-of-sample forecast performance, respectively. From the table, it can be seen that model 5 performs the best when asymmetric price changes have been considered. This model outperforms all the models with symmetric price changes in terms of all the three test statistics. On the other hand, the augmented Phillips curve model with asymmetric oil price changes (Model 4) fails to outperform the augmented Phillips curve model with symmetric commodity price changes (Model 5). This supports the results presented and analysed in an earlier section. The results are the same if one considers the out-of-sample forecast of very short periods and short periods (h=3) (see Table 4.10). Lastly, in the case of medium-term forecasts (h=24), the models with asymmetric price changes are found to perform better than the models with only symmetric price changes.

On the whole, the in-sample forecast results show that the commodity futures price based augmented Phillips curve model is a better choice than the crude oil price based augmented Phillips curve model while predicting Indian inflation. Furthermore, the out-of-sample forecast results show that the commodity futures price based augmented Phillips curve model can produce a better prediction for Indian inflation than the crude oil price based augmented Phillips curve model at least in the very short-run and short-run. In both exercises, it is found that while forecasting Indian headline inflation, it is important to consider asymmetric price changes. More precisely, when the augmented Phillips curve model is used for the purpose of forecasting Indian inflation, augmentation is required to be done using asymmetric commodity futures price changes instead of changes in symmetric commodity futures prices.

Table 4.9: Symmetric vs. Asymmetric Models (In Sample Forecast)

	Model 2 (P^{O+}, P^{O-})	**Model 3** (P^{C+}, P^{C-})	**Model 4** (Y, P^{O+}, P^{O-})	**Model 5** (Y, P^{C+}, P^{C-})
		C-T Test Statistics		
Model 2 (P^O)	0.0947	0.1240	0.1202	0.1474
Model 3 (P^C)	0.0304	0.0618	0.0577	0.0869
Model 4 (Y, P^O)	-0.0026	0.0298	0.0256	0.0558
Model 5 (Y, P^C)	-0.0470	-0.0131	-0.0174	0.0141
		D-M Test Statistics		
Model 2 (P^O)	3.0485***	3.7947***	2.9525***	3.2794***
Model 3 (P^C)	1.3895	2.9112***	1.7129*	2.3789**
Model 4 (Y, P^O)	0.0017	0.7685	1.1847	2.0581**
Model 5 (Y, P^C)	-1.0163	-0.2874	-0.6121	1.0809
		C-W Test Statistics		
Model 2 (P^O)	0.5265***	0.6295***	0.6487***	0.7729***
Model 3 (P^C)	0.2303***	0.2765***	0.3434***	0.4021***
Model 4 (Y, P^O)	0.1803*	0.2834***	0.1426**	0.2574***
Model 5 (Y, P^C)	0.0486	0.0845	0.0322	0.0752**

Note: As symbolized in the table, Y, P^O, and P^C stand for output, crude oil price, and commodity future prices, respectively. Restricted models are shown in rows while unrestricted models are shown in columns. ***, ** and * denote 1%, 5% and 10% levels of significance, respectively.

Table 4.10: Symmetric vs. Asymmetric Models (Out of Sample Forecast)

	Model 2 $(P^{O}+, P^{O}-)$	Model 3 $(P^{C}+, P^{C}-)$	Model 4 $(Y, P^{O}+, P^{O}-)$	Model 5 $(Y, P^{C}+, P^{C}-)$
Forecast Horizon (h) = 3				
C-T Test Statistics				
Model 2 (P^O)	0.0966	0.1262	0.1226	0.1497
Model 3 (P^C)	0.0308	0.0625	0.0586	0.0877
Model 4 (Y, P^O)	-0.0034	0.0294	0.0254	0.0555
Model 5 (Y, P^C)	-0.0480	-0.0137	-0.0179	0.0136
D-M Test Statistics				
Model 2 (P^O)	3.1253***	3.8783***	3.0241***	3.3443***
Model 3 (P^C)	1.4081	2.9499***	1.7417*	2.4057**
Model 4 (Y, P^O)	-0.0185	0.7585	1.1726	2.0476**
Model 5 (Y, P^C)	-1.0437	-0.3075	-0.6357	1.0460
C-W Test Statistics				
Model 2 (P^O)	0.5247***	0.6297***	0.6480***	0.7741***
Model 3 (P^C)	0.2268***	0.2745***	0.3398***	0.4001***
Model 4 (Y, P^O)	0.1746*	0.2765***	0.1389**	0.2523***
Model 5 (Y, P^C)	0.0463	0.0814	0.0307	0.0726**
Forecast Horizon (h) = 12				
C-T Test Statistics				
Model 2 (P^O)	0.0943	0.1163	0.1227	0.1434
Model 3 (P^C)	0.0305	0.0541	0.0609	0.0831
Model 4 (Y, P^O)	-0.0142	0.0104	0.0176	0.0408
Model 5 (Y, P^C)	-0.0511	-0.0256	-0.0182	0.0058
D-M Test Statistics				
Model 2 (P^O)	3.1600***	3.6943***	3.1345***	3.3294***
Model 3 (P^C)	1.4480	2.6468***	1.8733*	2.3808**
Model 4 (Y, P^O)	-0.2757	0.3061	0.8477	1.5135
Model 5 (Y, P^C)	-1.1665	-0.6711	-0.6823	0.5440
C-W Test Statistics				
Model 2 (P^O)	0.4990***	0.5808***	0.6260***	0.7290***
Model 3 (P^C)	0.2164***	0.2456***	0.3335***	0.3754***
Model 4 $(Y, P^O$**P**$)$	0.1452	0.2310**	0.1167**	0.2140***
Model 5 (Y, P^C)	0.0344	0.0547	0.0270	0.0547
Forecast Horizon (h) = 24				
C-T Test Statistics				
Model 2 (P^O)	0.1231	0.1104	0.1463	0.1389
Model 3 (P^C)	0.0723	0.0589	0.0969	0.0891
Model 4 (Y, P^O)	-0.0051	-0.0196	0.0214	0.0130
Model 5 (Y, P^C)	-0.0132	-0.0279	0.0136	0.0051
D-M Test Statistics				
Model 2 (P^O)	4.3496***	4.8203***	4.3896***	4.5065***
Model 3 (P^C)	3.0693***	3.7033***	3.3346***	3.5381***
Model 4 (Y, P^O)	-0.0912	-0.6176	1.4666	0.8519
Model 5 (Y, P^C)	-0.3792	-1.1834	0.9112	0.7777
C-W Test Statistics				
Model 2 (P^O)	0.7602***	0.7192***	0.9035***	0.9099***
Model 3 (P^C)	0.4219***	0.3378***	0.5548***	0.5092***
Model 4 (Y, P^O)	0.1524*	0.1343	0.1464***	0.1625**
Model 5 (Y, P^C)	0.0970	0.0146	0.1112*	0.0601*

Note: As symbolized in the table, Y, P^O and P^C stand for output, crude oil price and commodity future prices, respectively. Restricted models are shown in rows while unrestricted models are shown in columns. ***, ** and * denote 1%, 5% and 10% levels of significance, respectively.

4.6 Summary of Findings

In the present chapter, a theoretical model is developed extending the framework of Kawai (1983) and Bond (1984). The forecasting accuracy of the traditional demand–side Phillips curve model is examined while augmenting the model with the commodity futures price index. For that purpose, monthly CPI and commodity futures prices index data are used. The multiple predictors augmented Phillips curve is estimated using the Feasible Quasi Generalized Least Squares (FQGLS) estimation technique developed by Westerlund & Narayan (2015). Using different tests for forecasting accuracy both the in-sample and out-of-sample predictability of the augmented Phillips curve model are examined. For the out-of-sample forecasting evaluation, the rolling-window approach has been used. The results strongly suggest in favour of complementing the traditional Phillips curve-based inflation model for the Indian economy with the supply-side predictors such as commodity futures prices. In addition, it is also found that demand-side or supply-side predictors based models perform poorly in comparison to multiple predictor models that consider both the demand and supply-side predictors.

Both in the theoretical model and in the empirical analysis, the present chapter finds a positive relationship between commodity futures prices and inflation. While, on one hand, the results of this chapter strongly support the views of some earlier studies in augmenting the Philips curve model with supply-side factors to produce better inflation forecast, the results, it is also found that augmentation with commodity futures prices has stronger predictive power than crude oil prices in forecasting inflation. The chapter also takes into consideration possible non-linearities as advocated by Shin et al. (2014). In order to accommodate the changes in monetary policy regimes and changes in inflation, the present chapter also considers the possible presence of structural breaks in headline inflation. The results strongly advocate that while modelling Indian inflation, especially for the purpose of forecasting, it is imperative to take into account the asymmetric commodity futures price changes, and structural breaks in inflation; and at the same time control for the possible presence of persistence, heteroskedasticity, and endogeneity. The results are thus important, especially for monetary policymaking. To sum up this chapter, along with validating the argument in favour of using commodity prices in inflation modelling in India, also proposes that domestic commodity futures price aggregates or domestic commodity futures price indices are better predictors of Indian headline inflation in comparison to international crude oil prices.

Appendix to Chapter 4

Table A4.1: Mincer and Zarnowitz Test (Symmetric Price Changes with Structural Breaks)

	Single predictor Model			Multi predictor Model	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
			In Sample		
α	-0.0007	-0.0050	-0.0053	-0.0027	-0.0021
	(0.0051)	(0.0060)	(0.0054)	(0.0048)	(0.0044)
β	0.9916***	1.0466***	1.0620***	1.0137***	1.0147***
	(0.0720)	(0.0915)	(0.0810)	(0.0677)	(0.0636)
χ^2	0.7328	2.5752	1.6776	1.7178	0.8284
	(0.6932)	(0.2759)	(0.4322)	(0.4236)	(0.6608)
			Out of Sample; h=3		
α	-0.0005	-0.0043	-0.0047	-0.0023	-0.0018
	(0.0045)	(0.0053)	(0.0047)	(0.0042)	(0.0039)
β	0.9901***	1.0390***	1.0545***	1.0095***	1.0117***
	(0.0663)	(0.0838)	(0.0744)	(0.0621)	(0.0586)
χ^2	0.7370	2.7080	1.7728	1.7728	0.8509
	(0.6918)	(0.2582)	(0.4121)	(0.4121)	(0.6535)
			Out of Sample; h=12		
α	-0.0003	-0.0035	-0.0039	-0.0017	-0.0014
	(0.0040)	(0.0047)	(0.0042)	(0.0037)	(0.0035)
β	0.9873***	1.0298***	1.0464***	1.0037***	1.0077***
	(0.0617)	(0.0784)	(0.0697)	(0.0579)	(0.0547)
χ^2	0.7357	2.5419	1.7034	1.7545	0.8447
	(0.6922)	(0.2806)	(0.4267)	(0.4159)	(0.6555)
			Out of Sample; h=24		
α	-0.0001	-0.0032	-0.0037	-0.0015	-0.0013
	(0.0039)	(0.0047)	(0.0041)	(0.0036)	(0.0034)
β	0.9863***	1.0272***	1.0443***	1.002***	1.0065***
	(0.0607)	(0.0774)	(0.0688)	(0.0571)	(0.0539)
χ^2	0.7343	2.4937	1.6924	1.7447	0.8425
	(0.6927)	(0.2874)	(0.4291)	(0.4180)	(0.6562)

Note: The values reported in parentheses are standard errors while ***, ** and * denote 1%, 5% and 10% levels of significance, respectively.

Table A4.2: Mincer and Zarnowitz Test (Asymmetric Price Changes with Structural Breaks)

	Single predictor Model			Multi predictor Model	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
			In Sample		
α	-0.0007	-0.0041	-0.0038	-0.0026	-0.0019
	(0.0051)	(0.0052)	(0.0046)	(0.0048)	(0.0043)
β	0.9916***	1.0464***	1.0478***	1.0218***	1.0178***
	(0.0720)	(0.0741)	(0.0686)	(0.0675)	(0.0620)
χ^2	0.7328	0.9370	0.8250	0.7652	0.3912
	(0.6932)	(0.6260)	(0.6620)	(0.6821)	(0.8223)
			Out of Sample; h=3		
α	-0.0005	-0.0036	-0.0033	-0.0023	-0.0016
	(0.0045)	(0.0045)	(0.0041)	(0.0043)	(0.0038)
β	0.9901***	1.0407***	1.0429***	1.0180***	1.0153***
	(0.0663)	(0.0675)	(0.0631)	(0.0617)	(0.0571)
χ^2	0.7370	0.9900	0.8632	0.7921	0.4019
	(0.6918)	(0.6096)	(0.6495)	(0.6730)	(0.8180)
			Out of Sample; h=12		
α	-0.0003	-0.0030	-0.0029	-0.0018	-0.0013
	(0.0040)	(0.0040)	(0.0036)	(0.0037)	(0.0034)
β	0.9873***	1.0344***	1.0378***	1.0134***	1.0123***
	(0.0617)	(0.0626)	(0.0592)	(0.0571)	(0.0533)
χ^2	0.7357	0.9900	0.8534	0.7924	0.4004
	(0.6922)	(0.6096)	(0.6527)	(0.6729)	(0.8186)
			Out of Sample; h=24		
α	-0.0001	-0.0028	-0.0027	-0.0016	-0.0012
	(0.0039)	(0.0039)	(0.0035)	(0.0036)	(0.0033)
β	0.9863***	1.0327***	1.0365***	1.0120***	1.0114***
	(0.0607)	(0.0615)	(0.0583)	(0.0561)	(0.0525)
χ^2	0.7343	0.9933	0.8533	0.7931	0.4003
	(0.6927)	(0.6086)	(0.6527)	(0.6726)	(0.8186)

Note: The values reported in parentheses are standard errors while ***, ** and * denote 1%, 5% and 10% levels of significance, respectively.

Chapter 5

Consequences of Crude Oil Price Shocks and Role of Derivatives: A Dynamic Stochastic General Equilibrium Analysis for India

5.1 Introduction

In this chapter, a simple New Keynesian (NK) Dynamic Stochastic General Equilibrium (DSGE) model has been developed for India, to decipher the effects of crude oil price shocks in the presence of crude oil storage and crude oil derivatives trading. Rise in world prices of crude oil is a cause for concern as it has a cost-push effect on inflation. Starting with the first global oil shock in 1973 to the latest rise in international crude oil prices following the Russia-Ukraine conflict in early 2022, a large empirical literature has emerged examining the macroeconomic impacts of crude oil price shocks[1]. A number of recent studies[2] also point out that the relationship between crude oil prices and macroeconomic indicators depends on the underlying origins of the oil price shocks. India is a large crude oil importing country and repeated global crude oil price shocks are likely to impact the macroeconomy of India in a significant way. Moreover, in Chapters 3 and 4, a strong relationship between commodity prices and macroeconomic indicators has been found. Identifying and quantifying possible sources of crude oil price fluctua-

[1] For a survey of literature on this issue, see Chapters 3 and 4.

[2] See, for example, Kilian (2008*a*), Kilian (2008*b*), Kilian (2009), Peersman & Van Robays (2009), Du et al. (2010), among others.

tions are of prime importance. While the relationship is studied using a theoretical framework, it is important to identify the possible sources and channels through which oil price shocks get transmitted to the rest of the economy. Quantification of the impact of oil shocks assumes importance while providing recommendations for policymaking, especially to the central banks. In a novel attempt, this chapter examines the changes in the nature of the macroeconomic impacts of various crude oil price shocks in India, in the presence of crude oil derivatives trading.

A large number of studies[3] have empirically examined the relationship between oil prices and macroeconomic indicators since 1973, after the first oil embargo[4]. The two pioneering studies examining the macroeconomic impacts of crude oil price shock are Darby (1982) and Hamilton (1983) on the US economy. Hamilton's proposition of a linear impact of crude oil price shocks has later been extended to non-linear models by Mork (1989), Mory (1993), Hamilton (1996), and Lee et al. (1995), wherein the asymmetric responses of macroeconomic indicators to the upward and downward movements of crude oil price have been examined[5]. Various other studies[6] investigate the relationship between crude oil price and macroeconomic indicators for developed countries. Although the studies that examine the nexus between oil price and macroeconomic indicators mainly

[3]See, for instance, Hamilton (1983), Zhang (2008), Cologni & Manera (2009), Kilian (2008*a*), Berument et al. (2010), Hamilton (2011), Kilian & Vigfusson (2011), Kilian & Vigfusson (2017), Kilian & Zhou (2022), and many others.

[4]For a detailed review of the literature see Jones & Leiby (1996), Jones et al. (2004), Rafiq et al. (2009).

[5]Some other researchers have also found weakening relationship between oil price and macroeconomic indicators (see, for example, Hooker 1996, Naccache 2010, among others).

[6]See, for example, Burbidge & Harrison (1984), Gisser & Goodwin (1986), Mork et al. (1994), Lee et al. (2001), Guo et al. (2005), Roeger (2005), Lardic & Mignon (2006), Cologni & Manera (2008), Jiménez-Rodríguez & Sánchez (2005), Jiménez-Rodríguez (2008), Katircioglu et al. (2015), Lorusso & Pieroni (2018), Charfeddine et al. (2020), and Herrera & Rangaraju (2020) among others.

focus on the oil-importing developed countries, some recent studies have examined this relationship for developing countries[7].

The impact of crude oil price shocks on macroeconomy in the India, a crude oil importing and inflation-targeting small open developing economy, has been analysed in the literature[8]. In general, these studies arrive at the same conclusion that oil shocks are inflationary for the Indian economy. Rakshit (2005) suggests that the pass-through of an oil price increase leads to a rise in the general price level as a consequence of an increase in marginal costs in the final goods-producing sector, where oil is used as an input. In response, the conservative central bank may go for monetary tightening in a bid to neutralize the cost-push effect of the oil price shock on the price level but with a cost in terms of further losses in output and employment. However, the shocks have a 'feedback effect', and hence evidence of bidirectional causality is found by Bhattacharya & Bhattacharyya (2001). Deheri & Ramachandran (2023) show the asymmetric response of macroeconomic indicators including industrial output growth, inflation rates, and exchange rates to crude oil price shocks.

The empirical studies discussed so far rely on macroeconometric models that mostly use different types of Vector Autoregression (VAR), Vector Error-Correction (VEC), and Autoregressive Distributive Lag (ARDL) frameworks to

[7]Such as Indonesia (Baek 2021; Baek & Yoon 2022) the Philippines (Raguindin & Reyes 2005), Malaysia (Ahmed & Wadud 2011) Venezuela (Elanshasy et al. 2005; Su et al. 2020), Nigeria (Akpan 2009; Iwayemi & Fowowe 2011), Iran (Farzanegan & Markwardt 2009; Davari & Kamalian 2018), Thailand (Rafiq et al. 2009), Tunisia (Jbir & Zouari-Ghorbel 2009) and China (Du et al. 2010; Tang et al. 2010; Ju et al. 2014; Zhao et al. 2016; Kim et al. 2017; Cross & Nguyen 2017; Wen et al. 2019; Chen et al. 2020).

[8]See, for instance, Bhattacharya & Bhattacharyya (2001), Kumar (2009), Rakshit (2005), Rakshit (2011), Bhanumurthy et al. (2012), Ghosh & Kanjilal (2014), Cunado et al. (2015), Gupta & Goyal (2015), Varghese (2017), Bhat et al. (2018), Nasir et al. (2018), Sreenu (2018), Khan et al. (2019), Ahmed et al. (2019), Deheri & Ramachandran (2023), among others.

test the (non)linear relationship. As these studies estimate the relationship considering only a few variables and therefore tend to be misspecified (Paetz & Gupta 2016), resulting in divergence from the true magnitude of the effects of crude oil price shocks (Gupta & Sun 2020). It is often argued that unless the effects of crude oil price shocks are studied in a general equilibrium setup, the effects could be overestimated (Hou et al. 2016). Furthermore, since these approaches are atheoretical and non-structural, they suffer from the Lucas Jr (1976) critique.

The use of a theoretical framework helps one to identify the origin of oil price shocks and their differential impacts on macroeconomic indicators. On top of that, while studying the effects of crude oil price shock on the real economy, it is important to identify the nature and sources of these shocks, especially for designing the macroeconomic policies in response to changes in oil prices (Kilian 2009). Although, mostly, there is evidence of a decline in real GDP growth and a spike in inflation following an exogenous crude oil supply shock, the uncertainty about the future oil supplies can also have an impact on the real economy (Kilian 2008*a*). While studies (Hamilton 2003, Kilian 2008*a*, and Kilian 2008*b*) show the impacts of actual exogenous variation in crude oil supply, Kilian (2009) shows that there can be precautionary demand for crude oil as well. Therefore, to study the relationship between oil prices and real variables, micro-founded general equilibrium model can be of use.

While there is a large body of literature empirically examining the differential impacts of crude oil price shocks, only a few studies[9] attempt a theoretical

[9]See, for example, Buiter & Purvis (1980), Rotemberg & Woodford (1996), Finn (2000), Leduc & Sill (2004), Nakov & Pescatori (2010), Unalmis et al. (2009), An & Kang (2011), Unalmis et al. (2012), Hou et al. (2016), Tumen et al. (2016), Balke & Brown (2018), Aminu (2019), Chan & Dong (2022), among others.

understanding of the reason underlying such macroeconomic impacts. Rotemberg & Woodford (1996), considering an imperfectly competitive market in a model that involves implicit collusion in the product market, explain the negative effect of crude oil price shock on output and real wages better than a stochastic growth model that considers a perfectly competitive product market. In contrast, Finn (2000) shows that a general equilibrium model with a competitive setup can also explain the recessionary consequences of crude oil price shocks. The study shows that the mechanism through which an increase in oil price induces a contraction in economic activity is very similar to an adverse technology shock. Leduc & Sill (2004), in a calibrated general equilibrium setup, examine the consequences of oil price shocks on the economy and the role of monetary policy to offset the negative impact on output. Considering different policy objectives of the central banks, the study shows that the contractionary impact of crude oil price shock is minimum when the central bank targets prices.

However, Leduc & Sill (2004) and many such theoretical studies[10] examining the transmission of oil price shock assume that oil price is exogenously determined [11]. When oil price is assumed to be exogenously determined, it implies by construction that all oil price shocks are alike and the macroeconomic impacts and policy implications of crude oil price movements are independent of the fundamental causes of oil price shocks (Nakov & Pescatori 2010). Another strand of literature has been examining the effects of oil price shocks assuming that oil price is endogenous and determined through interactions of supply and demand

[10] See, for instance, Kim & Loungani (1992), Carlstrom & Fuerst (2006), De Walque et al. (2005), among others.

[11] In these studies the oil price is assumed to follow an AR(1) process.

for crude oil. This demand for crude oil includes precautionary demand for oil inventory alongside production demand for crude oil (see, for example, Unalmis et al. 2012; Olovsson 2019; Tumen et al. 2016, among others). Olovsson (2019) finds that an increase in demand for oil inventory holding is the most important reason for a large increase in oil prices. With the inclusion of oil inventory holding in the model, it is possible to distinguish the effects of crude oil price increase on account of supply disruptions from the same on account of increasing precautionary demand for crude oil following negative news about future oil supply and high uncertainty about the future price of crude oil (Cross et al. 2022). Kilian (2009) argues that changes in precautionary demand for crude oil can have immediate and potentially large effects on crude oil prices and on other real and nominal variables even when actual crude oil production may not change. The precautionary oil demand is however different from the speculative demand for crude oil (Cross et al. 2022), where the latter shock occurs following buyers' anticipation about future demand and supply conditions [12].

In this regard, a few studies[13] distinguish the effects of crude oil price changes arising out of supply shock and the precautionary demand shock thereby determining crude oil prices endogenously. Unalmis et al. (2009), analyse the effects of oil supply shock and precautionary demand shock, considering a New Keynesian DSGE framework that models a small open economy and the rest of the world. The study argues that precautionary oil demand shock occurs when

[12] While a positive precautionary demand shock for crude oil has an immediate impact on the crude oil spot price to rise (Alquist & Kilian 2010, Kilian 2010), a positive speculative demand shock as a result of an increase in inventory holding by the speculators, persuades producers to hold back their inventory holdings in order to sell the same in the future at a higher price (Kilian & Murphy 2014).

[13] See, for example, Unalmis et al. (2009), Unalmis et al. (2012), Tumen et al. (2016), among others.

an expected decline in the world oil supply induces the firms to increase their oil reserves and hence the nature of the shock is the same as the expected future oil supply shortage. Unalmis et al. (2009) find that a precautionary demand shock following an expected future oil supply shortage causes the output to decline and inflation to rise both in the small open economy and the rest of the world. In addition, there is an appreciation of the exchange rate following this shock.

Unalmis et al. (2012) develop a DSGE model incorporating a competitive storage sector of oil of the US economy and estimate the same using quarterly data and the Bayesian technique to examine the effects of an oil supply shock and precautionary oil storage demand shock. The study shows that a negative oil supply shock causes a rise in the real price of oil, a decline in consumption and production demand for oil, a decline in output, and an increase in inflation. The effect of precautionary storage demand shock is similar to that of the negative oil supply shock. Unalmis et al. (2012) further show that the model without the possibility of a storage facility shows amplified effects of oil supply shocks and thus ignoring the oil storage sector while modelling may lead to overestimation of the effects of such supply shocks.

Against this backdrop, the present chapter develops a New Keynesian (NK) Dynamic Stochastic General Equilibrium (DSGE) model for India, recognizing the financial as well as economic properties of crude oil. The DSGE setup has been used extensively in understanding the effects of oil price shocks on the economy as this approach allows for the identification of the various sources of oil price shocks and also helps one to understand the responses of the economy to such shocks (Balke & Brown 2018). In general, there has been an increasing application of the DSGE model in understanding macroeconomic dynamics with significant progress in its specification and estimation. This has become a useful tool to policymakers including central banks in identifying sources of fluctuations and examining the effects of structural changes along with predicting the effects of policy changes (Tovar 2009; Banerjee et al. 2023). In the literature, most of the DSGE models either incorporate the elements of the New Keynesian paradigm or follow the real business cycle approach. In the New Keynesian framework, micro-foundations for the Keynesian concepts such as aggregate fluctuations, nominal price stickiness, and non-neutrality of money are provided (Gali & Gertler 2007).

While a large number of studies have focused on the effects of crude oil prices shocks on domestic output and inflation in oil-exporting countries, much less attention has been given to oil-importing countries. In the present chapter, the scope of inquiry is expanded by using a medium-sized DSGE model of the Indian economy, an oil-importing economy. The model provides a mapping from various structural shocks – such as an unexpected increase/decrease in the supply of crude oil, an increase/decrease in current use and precautionary demand for crude oil – to observables such as crude oil prices, crude oil inventory, and other measures of macroeconomic activity such as real GDP and inflation. The calibration method is used to determine the values of the model's parameters and to assess the stochastic process generating the exogenous shocks that allows one to identify the two kinds of shocks and to estimate their effects on crude oil prices, inflation and Indian real GDP. The core structure/framework of the model is essentially a standard New Keynesian that includes nominal frictions. The novelty of the New Keynesian DSGE framework presented in this chapter is that it allows the inventory holder to participate in the derivatives market and analyses the changes in responsiveness of different variables in the presence and absence of derivatives trading. The rest of this chapter is organized as follows: In Section 5.2, the structure of the model is laid out. In Section 5.3, the results obtained from calibration have been discussed and finally, Section 5.4 concludes the chapter.

5.2 The Model

The basic features of the model presented here resembles recent New Keynesian DSGE models including the benchmark models of Clarida et al. (2001) and Galí (2002). The economy is assumed to comprise of economic agents including households, firms, a monetary authority, and crude oil inventory holders. For the sake of simplicity, the presence of any fiscal policy authority is considered. Households consume the final goods and derive utility. They also supply labour to the producing firms and hold capital stock for renting to firms in a perfectly competitive rental market. The firms are owned by the households and therefore the latter earn profits from these firms. It is assumed that the households do not consume crude oil directly. However, firms are assumed to produce a differentiated core consumption goods using capital, labour, and crude oil as input. Following Olovsson (2019), crude oil is incorporated as an input in production[14] along with assuming a precautionary motive for holding oil inventory in the presence of multiple sectors viz. households, final goods, intermediate goods, and crude oil inventory. Since the intermediate product or value-added input and crude oil are considered to be complementary in the process of production, real marginal cost

[14] While crude oil is assumed to be a factor of production, it is assumed that it is not consumed directly (see, for an example, Chan & Dong 2022).

is affected by the movements in crude oil prices. The current form of the model features a closed economy. The supply of crude oil is assumed to be exogenous to the economy. The model, in brief, is as follows.

5.2.1 Households

All households in this economy are assumed to be identical. Thus, the behaviour of only one of them will eventually be focused on. There is a continuum of infinitely lived households indexed $j \in [0, 1]$. The representative household is assumed to maximize the expected present discounted value of utility given by:

$$\max_{C_t(j), L_t(j)} E_t \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t(j)^{1-\sigma}}{1-\sigma} - \frac{L_t(j)^{1+\varphi}}{1+\varphi} \right] \tag{5.1}$$

where $\sigma > 0$ is the inverse of the constant intertemporal elasticity of substitution of consumption, $\varphi > 0$ is the inverse of the constant intertemporal elasticity of labour supply, and $\beta \in [0, 1]$ is the subjective discount factor. $C_t(j)$ and $L_t(j)$ denote consumption and hours of labour supplied, respectively. It is to be noted that the external habit formation for the households is ignored[15]. The aggregation of the households' consumption, with a constant elasticity of substitution (CES) aggregator, is as follows:

$$C_t = \left(\int_0^1 C_t(j)^{\frac{\epsilon}{\epsilon-1}} \, dj \right)^{\frac{\epsilon}{\epsilon-1}} \tag{5.2}$$

[15]Following Unalmis et al. (2008) external habit formation has not been considered in the utility function, for the sake of simplicity. However, the results do not get affected even if external habit formation by the households is considered.

where ϵ is the constant elasticity of substitution between varieties[16]. The utility function should display some properties. $U_C > 0$ and $U_L < 0$ show the positive marginal utility of consumption and the negative marginal utility of labour supply, respectively. Furthermore, $U_{CC} < 0$ and $U_{LL} < 0$ ensure concavity of the utility function.

Households maximize their utility subject to the sequential budget constraints which states that their income from all sources must equal all uses of income within each period. The representative household enters period t with portfolio $B_t(j)$ which pays out one unit of currency, earns the nominal wage W_t by supplying labour, and earns rental income R_t^K from supplying capital to firms. The households also receive profits (dividends) $\pi_t(j)$ from the monopolistic firms. The households purchase consumption as well as investment goods in each period.

It is assumed that the price of the consumption as well as the investment goods are the same, P_t, the general price level. The expected nominal payoff in period $t+1$ of the portfolio held at the end of the period t, including the shares in firms, is $B_{t+1}(j)$. The representative household's budget constraint in period t is given by:

$$P_t(C_t(j) + I_t(j)) + E_t(Q_{t,t+1}B_{t+1}(j)) \leq W_t L_t(j) + R_t^K K_t(j) + B_t(j) + \Pi_t(j) \quad (5.3)$$

[16] All though it is a common practice to consider oil both in the consumption function as well as in the production function. However, in the present model setup, it is assumed that the oil is not directly consumed by the households. This is on account of two reasons. First, unlike other studies in literature, in the present analysis, crude oil is considered instead of oil (any refinery products of crude oil) as in India crude oil is traded in the commodity derivative market and not its refinery products. Households cannot directly consume crude oil and rather consumes final goods which are produced using crude oil as an input of production. Second, the average share of petroleum products in the basket of Indian households is very small as can be seen from the *Report of the 68th Round National Sample Survey of Ministry of Statistics & Programme Implementation, Government of India.*

where $Q_{t,t+1}$ is the stochastic discount factor for the one period ahead nominal payoff. Now, $1/E_t(Q_{t,t+1}) = R_t$ and R_t is the risk-free nominal interest rate.

Let the investment in period t be $I_t(j)$. The capital accumulation equation is given by:

$$K_{t+1}(j) = (1-\delta)K_t(j) + I_t(j) \tag{5.4}$$

where $0 < \delta < 1$ is the depreciation rate of physical capital. Since it is assumed that there is no adjustment cost for investment, the consumption and investment goods are substitutable.

Since it is assumed that there is a complete domestic asset market, households entertain perfect risk-sharing, which implies the same level of consumption across households regardless of the wage and rental income they receive in each period. Therefore, the notation j can be dropped from consumption and investment functions. The households decision problem regarding consumption, saving, and labour supply can be characterized by the following first-order conditions:

$$\beta E_t \left[\left(\frac{C_{t+1}}{C_t} \right)^{-\sigma} . \frac{P_t}{P_{t+1}} \right] = \frac{1}{R_t} \tag{5.5}$$

$$C_t^{\sigma} L_t^{\varphi} = \frac{W_t}{P_t} \tag{5.6}$$

Equation (5.5) is the Euler consumption function which shows that the discounted marginal utility of consumption of a basket of goods in period $t+1$ enhanced by the interest on savings is equal to the current marginal utility of consumption. In other words, Eq. (5.5) equates the marginal rate of substitution between current consumption and future consumption with the relative price of current consumption in terms of future consumption. On the other hand, the labour supply equation, Eq. (5.6), equates the marginal rate of substitution between consumption and leisure with the relative price of leisure consumption or the real wage. This completes the household component of the DSGE model presented in this chapter.

5.2.2 Firms and Production

It is assumed that the good is produced under monopolistic competition and used for the purpose of consumption and investment. There is a continuum of firms producing a differentiated good indexed by $i \in [0, 1]$ following the constant elasticity of substitution (CES) production function given by:

$$Y_t(i) = A_t \left[(1-\omega_y)^{\frac{1}{\rho_y}} V_t(i)^{\frac{\rho_y - 1}{\rho_y}} + \omega_y{}^{\frac{1}{\rho_y}} O_t(i)^{\frac{\rho_y - 1}{\rho_y}} \right]^{\frac{\rho_y}{\rho_y - 1}} \tag{5.7}$$

where $Y_t(i)$ is the amount of goods produced by the i^{th} producer, $V_t(i)$ is the value-added input, and $O_t(i)$ is the amount of crude oil used in the production of the core good. $0 < \omega_y < 1$ is the share of the crude oil in the production and ρ_y is the elasticity of substitution between crude oil and value-added inputs. A_t is the total factor productivity shock that affects all firms equally. Furthermore, the value-added input is being produced by the firms using both capital and labour and following the CES production technology, which is as follows:

$$V_t(i) = \left[(1-\omega_v)^{\frac{1}{\rho_v}} K_t(i)^{\frac{\rho_v - 1}{\rho_v}} + \omega_v{}^{\frac{1}{\rho_v}} L_t(i)^{\frac{\rho_v - 1}{\rho_v}} \right]^{\frac{\rho_v}{\rho_v - 1}} \tag{5.8}$$

where ρ_v is the elasticity of substitution between capital and labour inputs, and $0 < \omega_v < 1$ is the share of labour in the production[17].

It is further assumed that the firms consider the prices of each input as given. The cost minimization of the firm then implies:

$$\frac{P_{s,t}^{O} O_t(i)^{\frac{1}{\rho_y}}}{\omega_y^{\frac{1}{\rho_y}}} = \frac{W_t L_t(i)^{\frac{1}{\rho_v}}}{\omega_v^{\frac{1}{\rho_v}} (1-\omega_y)^{\frac{1}{\rho_y}} V_t^{\frac{1}{\rho_v}-\frac{1}{\rho_y}}} = \frac{R_t^K K_t(i)^{\frac{1}{\rho_v}}}{(1-\omega_v)^{\frac{1}{\rho_v}} (1-\omega_y)^{\frac{1}{\rho_y}} V_t^{\frac{1}{\rho_v}-\frac{1}{\rho_y}}} \tag{5.9}$$

where $P_{s,t}^{O}$ is the spot price of crude oil, W_t is the wage rate, and R_t^K is the return to capital. The above relationship holds for each firm i. The nominal marginal cost of production which is constant and equal for all firms, is given by:

$$MC_t^y = \left[(1-\omega_y) MC_t^{v\,(1-\rho_y)} + \omega_y P_{s,t}^{O\,(1-\rho_y)}\right]^{\frac{1}{(1-\rho_y)}} \tag{5.10}$$

where

$$MC_t^v = \left[(1-\omega_v) R_t^{K\,(1-\rho_v)} + \omega_v W_t^{(1-\rho_v)}\right]^{\frac{1}{(1-\rho_v)}} \tag{5.11}$$

Aggregate output is given by:

$$Y_t = \left(\int_0^1 Y_t(j)^{\frac{\zeta}{\zeta-1}}\, dj\right)^{\frac{\zeta}{\zeta-1}} \tag{5.12}$$

where ζ denotes the elasticity of substitution between different varieties. The Eq. (5.12) represents an index for the aggregate output produced as well as consumed. Output demand is then given by:

[17]The model is made simpler by not considering any stationary labour productivity shock, as in Unalmis et al. (2012) or Tumen et al. (2016).

$$Y_t(j) = \left(\frac{P_t^*(j)}{P_t}\right)^{-\zeta} Y_t \tag{5.13}$$

Turning to the price-setting behaviour of the firms, prices are assumed to be to be set in a staggered fashion and hence they are sticky à la Calvo (1983). It is assumed that only a randomly selected fraction $(1-\theta)$ of the firms can adjust their prices optimally in each period and the rest of the firms do not adjust their prices. In other words, firms adjust prices with probabilities $(1-\theta)$ independent of the time passed since the previous adjustment. Price re-setting firm i sets a new price at period t to maximize the current value of all future profits given as follows:

$$\max_{P_t^*} E_t \sum_{k=0}^{\infty} \theta^k Q_{t,t+k} \left[P_t^*(j) - MC_{t+k}\right] Y_{t+k}(j) \tag{5.14}$$

subject to the demand constraint

$$Y_{t+k}(j) = \left(\frac{P_t^*(j)}{P_{t+k}}\right)^{-\zeta} Y_{t+k} \tag{5.15}$$

where $Q_{t,t+k}$ is a stochastic discount factor for nominal payoffs[18]. The profit maximization then results in the following price-setting equation.

$$P_t^*(j) = \frac{\zeta}{\zeta-1} \frac{E_t \sum_{k=0}^{\infty} \theta^k Q_{t,t+k} Y_{t+k}(j) MC_{t+k}}{E_t \sum_{k=0}^{\infty} \theta^k Q_{t,t+k} Y_{t+k}(j)} \tag{5.16}$$

Then under flexible prices

$$P_t^*(j) = \frac{\zeta}{\zeta-1} MC_t \tag{5.17}$$

[18] Here, $E_t(Q_{t,t+k}) = \frac{1}{R_t} = \beta E_t \left[\left(\frac{C_{t+1}}{C_t}\right)^{-\sigma} \cdot \frac{P_t}{P_{t+1}}\right]$.

where $\frac{\zeta}{\zeta-1}$ is the standard price markup over marginal cost that is on account of monopolistic competition. The above equation shows that all firms involved in production set the same price when the marginal costs and markups are the same for all the firms. It is to be noted that the only distortion is the price markup, which is on account of monopolistic competition. Therefore, under the sticky price setting, the dynamics of the price index is given by :

$$P_t^{1-\zeta} = \theta P_{t-1}^{1-\zeta} + (1-\theta) P_t^{*1-\zeta} \tag{5.18}$$

5.2.3 Crude Oil Storage and Crude Oil Market Equilibrium

It is assumed that physical storage of crude oil takes the form of holding above-ground crude oil inventories. It is further assumed that there is a continuum of competitive crude oil inventory holders, called the competitive speculators, indexed by $j \in [0,1]$ who store crude oil as well as buy and sell crude oil in the spot market. The competitive, risk-neutral, and profit-maximizing crude oil inventory holders buy and hold above-ground crude oil inventories in one period and sell it in the next period. Following Unalmis et al. (2012) and Tumen et al. (2016), it is also assumed that there are no barriers to entering and exiting from the storage sector and inventory holders are risk neutral. The inventory holders form rational expectations about their returns from their activities.

Storage without the Possibility of Future Trading

A representative inventory holder purchases the crude oil in the spot market at a price $P_{s,t}^{O}(j)$ in period t and earns revenue from selling the same in the

$(t+1)^{th}$ period at an expected price $E_t P^O_{s,t+1}(j)$. The inventory therefore holder holds the crude oil for one period and bears the storage costs. The expected profit for the inventory holder is given as follows:

$$\frac{\alpha E_t(P^O_{s,t+1})Q_t(j)}{r_t} - P^O_{s,t}Q_t(j)\left(1+\Upsilon(Q_t(j))\right) \tag{5.19}$$

where $Q_t(j)$ is the level of inventory holding by the representative competitive speculators and $\Upsilon(Q_t(j)) = \kappa + \frac{\Psi}{2}Q_t(j)$ is the cost of holding one unit of crude oil inventory, $\kappa < 0$ being the convenience yield or relative benefit of holding the physical asset over time. $\psi > 0$ is the increase in cost on account of the increase in inventory holding. It is assumed that $(1-\alpha)$ is the proportion of wastage of crude oil on account of storage, and thus α is the proportion of crude oil inventory available from the previous period for selling in the current period. The profit maximization by the inventory holder results in the following demand function for inventory.

$$Q_t = \frac{1}{\Psi}\left[\frac{\alpha\beta E_t(P^O_{s,t+1})}{P^O_{s,t}} - 1 - \kappa\right] \tag{5.20}$$

In Eq.(5.20), there is no need for the inventory holder-specific index j as each inventory holder shares the same rational expectations with other inventory holders.

Storage with the Possibility of Future Trading

In order to minimize the price risk, the possibility of future trading is introduced in the commodity market. In that case, following Kawai (1983) it is assumed that the inventory-holding dealer can enter into a forward contract at time t. In the same manner as Kawai (1983), the terms “futures” and “forward” are used here interchangeably. For that purpose, following Kawai (1983), it is assumed that i) the commodity contracts are completely standardized; ii) a futures contract is settled when the actual delivery of the commodity takes place; and iii) the derivatives market reopens every period and thus the delivery of the contract takes place in the next period. As it is assumed that the maturity of the futures contract is one period, then its settlement coincides with the inventory holding period. The expected profit for the inventory holder is given as follows:

$$\frac{\alpha\, E_t(P^O_{s,t+1})\, Q_t(j)}{r_t} - P^O_{s,t}\, Q_t(j)\ \left(1 + \Upsilon(Q_t(j))\right) + Z_t(j) \left(E_t(P^O_{s,t+1}) - P^O_{f,t}\right) \tag{5.21}$$

where $Z_t(j)$ is the number of contracts held by the inventory-holding dealer and $P^O_{f,t}$ is the futures price of crude oil. It is assumed that the contracts are so standardized that the size of the contract is equivalent to one unit of inventory. Then, $Z_t(j) = Q_t(j)$ and the revised expected profit function for the inventory holder is as follows:

$$\frac{\alpha\, E_t(P^O_{s,t+1})\, Q_t(j)}{r_t} - P^O_{s,t}\, Q_t(j)\ \left(1 + \Upsilon(Q_t(j))\right) + Q_t(j) \left(E_t(P^O_{s,t+1}) - P^O_{f,t}\right) \tag{5.22}$$

The profit maximization by the inventory holder results in the following demand function for inventory.

$$Q_t = \frac{1}{\Psi}\left[\frac{(\alpha\beta + 1)E_t(P^O_{s,t+1})}{P^O_{s,t}} - \frac{P^O_{f,t}}{P^O_{s,t}} - 1 - \kappa\right] \tag{5.23}$$

5.2.4 Monetary Policy Rule

The monetary policy reaction function is assumed to be a simple Taylor rule with a nominal interest rate as a function of aggregate inflation and the economy-wide output gap. To capture this, a simple generalization of Taylor (1993) has been used as follows:

$$r_t = (r_{t-1})^{\Phi_r} \left(\frac{\pi_t}{\overline{\pi}_t}\right)^{\Phi_\pi} \left(\frac{Y_t}{\overline{\overline{Y}}_t}\right)^{\Phi_y} \tag{5.24}$$

where $\Phi_r \in [0,1]$ is the interest rate smoothing parameter, Φ_π and Φ_y denote the monetary policy responses to consumer price inflation and output, respectively[19]. Therefore, the nominal interest rate depends on its lagged value, output gap, and the deviation of inflation from its target level. The Taylor rule brings closure to the model.

5.2.5 Goods Market Equilibrium

In a closed economy setup without any fiscal authority, the equilibrium condition in the goods market requires that the production of core goods satisfies the following condition:

$$Y_t = C_t + I_t \tag{5.25}$$

[19]The log-linearized version of the above equation shows that

$$\tilde{r_t} = \Phi_r \tilde{r}_{t-1} + \Phi_\pi \tilde{\pi_t} + \Phi_y \tilde{Y_t}$$

where $\tilde{r_t}$, $\tilde{\pi_t}$, and $\tilde{Y_t}$ are the deviation of interest rate from its steady-state level, inflation's deviation from its target level, and the output gap, respectively.

5.2.6 Crude Oil Market Equilibrium

To arrive at the crude oil market equilibrium condition it is assumed that at each point in time, supply of crude oil in the market is given by an endowment (X_t) of crude oil which is subject to exogenous shocks defined by a stationary autoregressive process of order one which is as follows:

$$lnX_t - ln\overline{X} = \Upsilon_x(lnX_{t-1} - ln\overline{X}) + \xi_{x,t}; \quad \xi_{x,t} \sim i.i.d.(0, \sigma_x) \tag{5.26}$$

The total quantity of crude oil demanded by firms and the total inventory demand are equal to the new supply of crude oil and old inventories of crude oil net of depreciation:

$$O_t + Q_t = \alpha Q_{t-1} + X_t \tag{5.27}$$

5.3 Results and Discussion

In this section, several quantitative experiments have been performed in order to understand the channels through which supply shocks are transmitted within the economy and how the presence of crude-oil storage and the possibility of futures trading affects the impulse responses. Furthermore, the effects of inventory demand shock have also been examined.

5.3.1 Calibration Parameters

The model is calibrated for the Indian economy with reasonable values mostly as they are in the literature. It is often argued that knowing the structural parameters in the case of developing and emerging market economies is difficult (Ghate et al. 2018). The value of structural parameters are given in Table 5.1. Time is measured in quarters. The subjective discount factor, β, is set to be 0.9823 following Levine et al. (2012) and Ghate et al. (2018). Following Anand & Prasad (2010) and Ghate et al. (2018), the value of the inverse of the Frisch elasticity of substitution or the inverse of the elasticity of labour supply, φ, is set to be 3. It is assumed that one-third of the time is spent on working. The inter-temporal elasticity of substitution, σ, following Levine et al. (2012) and Ghate et al. (2018) is assumed to be 1.99. The depreciation rate, δ, is taken as 0.025 in accordance with Banerjee & Basu (2019). This implies that around 10 per cent of capital depreciates every year, and is broadly in line with the existing literature (see, for example, Gabriel et al. 2011; Tumen et al. 2016). Following Levine et al. (2012) and Ghate et al. (2018), the elasticity of substitution between varieties of the same sector goods, ζ, is fixed at 7.02.

The expenditure share of labour in production, ω_v, is taken as 0.66 following Anand & Khera (2016), Khera (2016), Khera (2018). In line with Tumen et al. (2016), the elasticity of substitution between capital and labour is set to be 0.3194. The expenditure share of crude oil in the production of final goods sector is estimated from the 'Supply and Use' table published by the Ministry of Statistics & Programme Implementation, Government of India[20]. The expenditure share of crude oil in production, ω_y, is considered to be 0.032. Following Tumen et al. (2016), the elasticity of substitution between crude oil and the value-added

[20]The 'Supply and Use' table are available from 2011-12 to 2018-19 at base 2011-12. At first, the average expenditure share of crude petroleum has been estimated from the supply table for each year. Then the average value of the expenditure share of crude petroleum for all the years has been used as the parameter in the model.

input is set to be 0.3194. Following Levine et al. (2012), the inflation indexation parameter or the Calvo parameter of measure of stickiness, θ, is set to be 0.75. Similarly, the elasticity of substitution between the varieties of same sector goods, ζ, is assumed to be 7.02, in line with Levine et al. (2012). The original Taylor rule estimates have been used here, and the interest rate sensitivity of the output parameter, μ_y, and the interest rate sensitivity of the inflation parameter, μ_π are at 0.5 and 1.5, respectively. The convenience yield, κ, is assumed to be -0.03 as in Unalmis et al. (2012) and Tumen et al. (2016). Lastly, the proportion of waste on account of storage, $(1-\alpha)$ is assumed to be 0.01 following Unalmis et al. (2012).

Table 5.1: Parameter Values and Definition

Parameter	Value	Definition	Source
β	0.9823	Subjective discount factor	Levine et al. (2012)
δ	0.025	Depreciation rate	Banerjee & Basu (2019)
σ	1.99	Inverse of inter-temporal elasticity of substitution	Levine et al. (2012)
φ	3	Inverse of Frisch elasticity of labor supply	Anand & Prasad (2010)
ρ_y	0.5465	Elasticity of Substitution between crude-oil and value-added	Tumen et al. (2016)
ρ_v	0.3194	Elasticity of Substitution between Capital and Labour	Tumen et al. (2016)
ω_y	0.032	Share of Crude-oil in Production	Estimated
ω_v	0.66	Share of Labour in Production	Anand & Khera (2016)
θ	0.75	Calvo Parameter or Measure of stickiness	Levine et al. (2012)
ζ	7.02	Elasticity of substitution between the varieties of same sector goods	Levine et al. (2012)
μ_y	0.5	Interest rate sensitivity of output	Taylor (1993)
μ_π	1.5	Interest rate sensitivity of inflation	Taylor (1993)
κ	-0.03	Convenience yield in Crude-oil Storage	Tumen et al. (2016)
$(1-\alpha)$	0.01	Waste due to storage	Unalmis et al. (2012)
ξ_x	0.37788	AR(1) coefficient for exogenous crude oil supply	Estimated
ξ_a	0.75	AR(1) coefficient for TFP	Levine et al. (2012)

5.3.2 Impulse Response Analysis

Impulse response functions (IRF) allow to analyse the impact of structural shocks on different macroeconomic variables considered in the model. The main objective here is to investigate the channels which transmit the effects of the shocks related to an increase in crude oil prices. Unalmis et al. (2012) show that crude oil price fluctuations are mostly driven by two shocks, viz. the crude oil supply shock and the storage demand shock. Following Unalmis et al. (2012), in the impulse response analysis, the focus is on a negative crude oil supply shock and a negative speculative demand shock. In Figures 5.1 - 5.4, the impulse responses are shown.

Crude oil Supply Shock

The response of the economy is measured to a one standard deviation shock to the crude oil supply in the absence and presence of future trading, respectively. In this baseline impulse response analysis, the crude oil supply shock is assumed to be completely exogenous. It is observed that a decrease in crude oil supply leads to an immediate increase in the spot price of crude oil (see Figure 5.1). The rise in the spot prices for crude oil in turn leads to the increase in the marginal cost of production of final goods where crude oil is being used as an input to production. As a result, from the demand side, the factor productivity falls followed by a decline in output and crude oil used in production. On account of the decline in factor productivity, the general price level increases leading to inflation. The monetary policy authority may respond to this situation by increasing the nominal interest rates. These results are in line with Unalmis et al. (2012).

With the availability of crude oil storage facility, the dynamics is different for a crude oil supply shock. If there is an inventory holding by the speculative storer, the crude oil supply shortage is alleviated partially/fully by reducing the inventory holding. This leads to a smaller impact on output and inflation. However, the responses of inflation and rate of interest to a one standard deviation negative crude oil supply shock become stronger when the possibility of future trading is made available to the speculative storers. With the negative supply shock, the speculative storers expect the spot prices to escalate in the next pe-

Figure 5.1: Impulse Response to a One Standard Deviation Negative Supply Shock without Future Trading

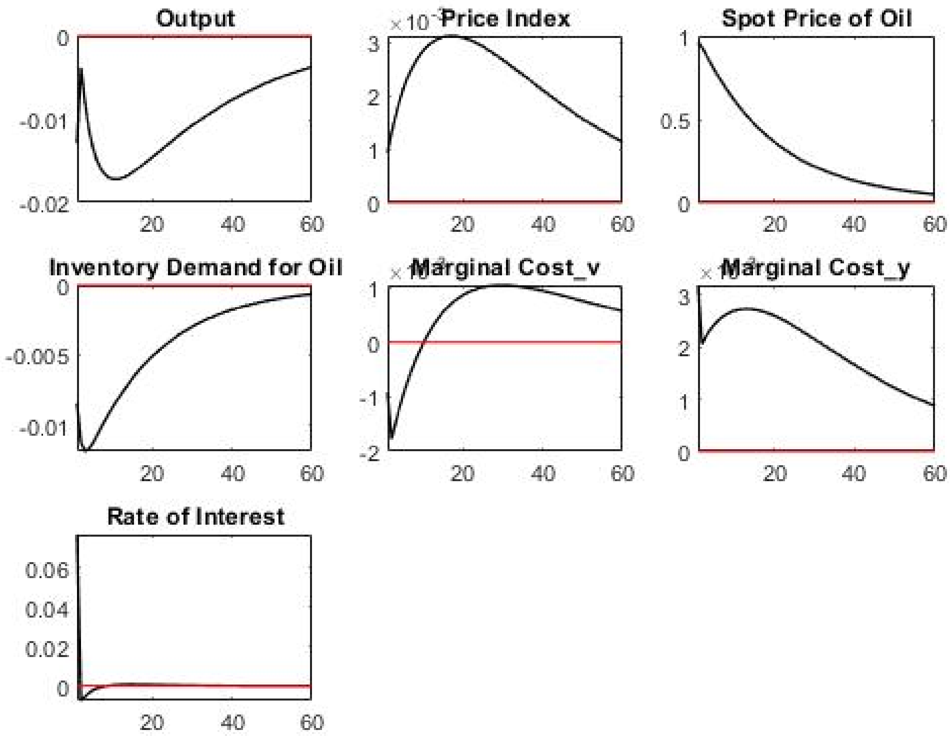
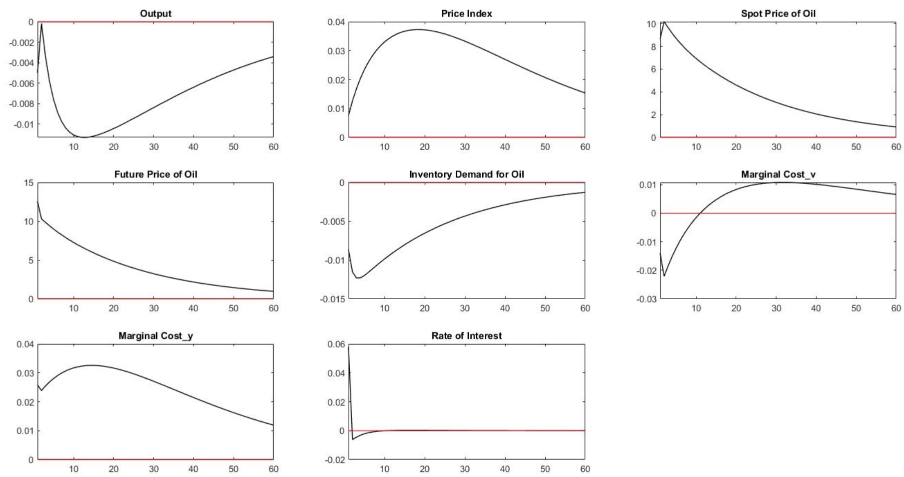


Figure 5.2: Impulse Response to a One Standard Deviation Negative Supply Shock with Future Trading

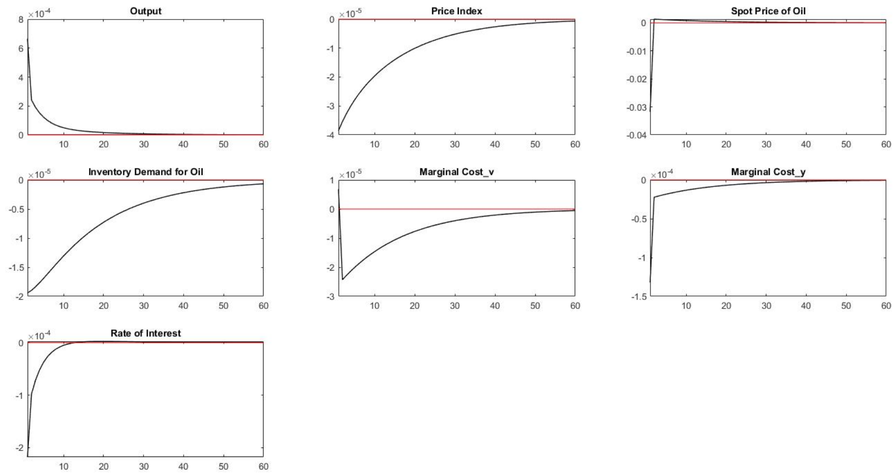


riod, and accordingly, reduce their inventory holding along with taking more long positions in the futures market. As a result, while both the crude oil futures prices and spot prices increase, the rise in spot prices is higher than that when the possibility of future trading is not available. The rise in spot prices is fueled by the rise in futures prices, as an increase in futures prices induces the inventory holders to expect the spot price to further increase in the future (Kilian & Murphy 2014). The rise in spot prices for crude oil increases the marginal costs, leading to inflation. As the effect on the spot prices and marginal cost is higher in this case, the inflation rate increases by a larger extent. However, as the decline in the production demand for crude oil is reduced, the effect on the output is found to be smaller in magnitude than when there is no provision for futures trading. This is shown in Figure 5.2.

Crude Oil Storage Demand Shock

To understand the impulse to a one standard deviation negative inventory demand shock, it is assumed that at time t the inventory-holding dealers learn that there might be an increase in crude oil supply in the next period. As observed from Figure 5.3, the effect of precautionary inventory demand shock is just the opposite of that of negative crude oil supply shock. As soon as the expectation about the possible future increase in crude oil supply appears at period t, a fall in precautionary demand occurs, causing the crude oil price to fall below its steady-state level. The crude oil spot price decreases as the supply of crude oil (inventory available from the period $t-1$ and the exogenous supply) exceeds the total demand for crude oil (sum of production demand and inventory demand).

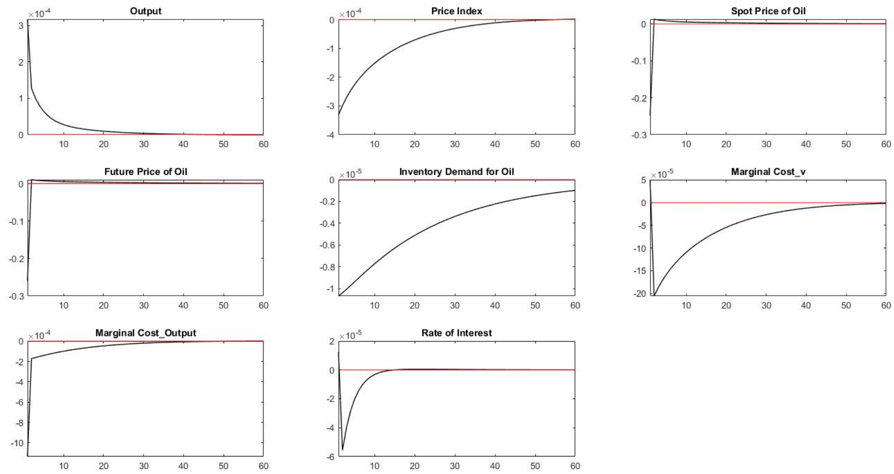
Figure 5.3: Impulse Response to a One Standard Deviation Negative Storage Demand Shock without Futures Trading



This precautionary inventory demand shock has a smaller effect on crude oil prices as compared to the same negative crude oil supply shock. A negative inventory demand shock implies more availability of crude oil for the purpose of production. Thus output increases as a lesser amount of the crude oil supply is stored as inventory for future use. The rise in the availability of crude oil for the real economy leads to the opposite reaction as for the negative crude oil supply shock. The higher output implies higher marginal costs and thereby deflation, to which the monetary authority reacts by lowering the interest rate or monetary easing. These results support the findings of Unalmis et al. (2012).

Turning to the situation when the inventory-holding dealers have provisions for participating in futures trading, as Figure 5.4 shows, the impulse responses to a one standard deviation negative inventory demand shock when the speculative storers or the inventory-holding dealers are allowed to participate in futures trading. In response to the expected future crude oil supply increase, inventory demand for crude oil decreases as the inventory-holding dealers have a

Figure 5.4: Impulse Response to a One Standard Deviation Negative Storage Demand Shock with Futures Trading



profit motive and there is a cost of holding inventory. A rise in the expected crude oil supply for the period $t+1$ decreases the expected spot crude oil price for the period $t+1$. The fall in expected spot crude oil price for the period $t+1$ decreases the expected profit from inventory holding, and hence the inventory demand for crude oil decreases. When there is a provision for getting involved in a future contract, in response to an expected future crude oil supply increase, the speculative storers can take more short positions in the crude oil futures market. As a result, the futures price and hence the spot price of crude oil further decrease.

However, a fall in inventory demand along with a decrease in demand for future contracts results in an amplified effect on spot price and hence marginal cost. The marginal cost, in this case, falls to a larger extent than the case when futures trading is not available. As a result, negative inventory demand shock has a higher deflationary effect when future trading is allowed for. Moreover, since, in this case, the fall in inventory demand is smaller in magnitude; the rise in production demand for crude oil is also smaller. Consequently, the increase in output on account of negative inventory demand shock is smaller in magnitude in the presence of futures trading. A summary of the results is presented in Table 5.2.

Table 5.2: Summary of Impacts of Different Shocks

Model ↓	Variables ⟶ Types of Shock ↓	$\mathbf{Y_t}$	$\mathbf{P_t}$	$\mathbf{P^O_{s,t}}$	$\mathbf{P^O_{f,t}}$	$\mathbf{Q_t}$	$\mathbf{MC_{vt}}$	$\mathbf{MC_{Yt}}$	$\mathbf{r_t}$
Without Future Trading	Negative Supply Shock	↓↓	↑	↑		↓	↑	↑	↑
	Negative Storage Shock	↑↑	↓	↓		↓↓	↓	↓	↓
With Future Trading	Negative Supply Shock	↓	↑↑	↑↑	↑	↓↓	↑↑	↑↑	↑↑
	Negative Storage Shock	↑	↓↓	↓↓	↓	↓	↓↓	↓↓	↓↓

Note: i) An upward arrow implies an increase whereas a downward arrow implies the opposite. A twin arrow implies stronger impact. ii) Y_t is real output, P_t is general price level; $P^O_{s,t}$ is the spot price of crude oil; $P^F_{s,t}$ is the futures price of crude oil; $MC_{v,t}$ is the marginal cost of the intermediate goods producing firms; $MC_{Y,t}$ is the marginal cost of the final goods producing firms; r_t is the nominal rate of interest.

5.4 Summary of Findings

Since the 1980s the fluctuations in crude oil prices have prompted several attempts to examine the cause and effects of crude oil prices on macroeconomic indicators. In the recent past also following the Global financial crisis, the U.S. Shale revolution, the COVID-19 pandemic and the Russia-Ukraine conflict, international crude oil prices experienced sharp movements. It is in this context, this essay has made an attempt to study the macroeconomic consequences of global oil shocks. This analytical essay has used the New Keynesian DSGE framework to decipher the macroeconomic impact of oil shocks. Most of the existing studies, empirical or theoretical, consider crude oil prices to be exogenous, a recent strand of literature vouches for considering crude oil prices as endogenous. While speculative crude oil storage has been incorporated in a DSGE framework, the provision for inventory holders to participate in the futures market has also been considered in the present chapter. This is an improvement over the previous studies that consider speculative crude oil inventories in the DSGE framework to understand the transmission channels of crude oil price shocks to the real economy. Further, an increase in crude oil futures demand increases the futures prices of crude oil, and also signals the spot traders that the spot price of crude oil is going to increase in the future and hence, resulting in further increase in inventory demand for crude oil.

The DSGE set up along with the crude oil inventories and derivatives market allows one to study the dynamic link between crude oil inventories, inventory holders' expectations of prices of crude oil prices, and spot and futures prices of crude oil. Using this setup, the effects of two types of crude oil price shocks have been studied. An increase in crude oil prices can be either on account of a fall in the supply of crude oil or a rise in inventory holding of speculative inventory holders expecting future crude oil supply disruptions. While the effects of the two sources of crude oil price increase are similar on real output or inflation, the transmission channels differ as speculative inventory holders' expectations play a vital role in the case of the latter. Although the results found in this chapter are similar to that in the existing literature, it is also found that when the crude oil futures trading is available, the effects of the shocks get intensified. While the supply of crude oil in this model set-up is considered to be completely exogenous as India is a major importer of crude oil, an obvious extension of this chapter would be to reformulate the model in an open economy set up considering an exporter of crude oil as a trading partner.

Chapter 6

Conclusions

This thesis is a collection of four essays exploring different aspects of the commodity derivative market in India from a macro-finance viewpoint. In specific, the essays examine the relationship between commodity futures prices with key macroeconomic indicators, and also with other asset prices in India. The four essays have dealt with four important commodity derivative market issues. The first essay has explored the nature and extent of financial contagion in the Indian commodity derivative market vis-à-vis the Indian equity market. The second essay has investigated the nature of pass-through from commodity futures prices to different macroeconomic indicators relevant to monetary policymaking. The third essay has examined the ability of commodity futures prices in forecasting headline inflation in India. The last essay has probed into the dynamics of transmission of shocks from crude oil prices to macroeconomic indicators in a theoretical setup.

Since the adoption of flexible inflation targeting as the monetary policy framework by the Reserve Bank of India in 2016, exploring the potential linkages between different macroeconomic and financial variables has become imperative. Furthermore, estimating the relationships has become more challenging as there were recurrent crises in the two decades since 2000. The eventuation of these crises made the financial markets extremely volatile. As a consequence, the shocks are found to get transmitted from financial markets to the macroeconomy and vice versa. The estimation and prediction of effects of such shocks using pure macroeconomic models without considering asset market variables and disregarding their financial properties are expected to be biased. The existing literature focuses on understanding the behaviour of different financial variables and also on the nature of their impacts on different macroeconomic indicators without neglecting their financial properties.

The commodity is a financial asset and its behaviour is generally understood in terms of movements in commodity prices and its returns. Commodities are used as raw materials in production processes and thus any change in commodity prices has a direct impact on the production decisions of firms and hence the supply of final goods and services. This is the 'cost effect'. Further, market participants including hedgers, speculators, and arbitragers take part in commodity derivatives trading on the basis of their expectations about the future state of the economy, their expectations about future inflation in particular. Their expectations based on all available information determine their long and short trading positions; hence demand for commodity contracts and commodity futures prices. In the literature, the efficient market hypothesis is found to hold and the role of the commodity derivative market in 'price discovery' has been extensively discussed. The linkage between commodity futures prices and macroeconomic indicators through inflation expectations is commonly known as the 'information effect'. While the impact of macroeconomic indicators on commodity futures prices has been extensively studied in the literature, studies on the converse, known as the 'feedback effect', are few and far between. Some of the essays in this thesis have examined the presence and consequences of such a 'feedback effect' in India.

On account of commodity prices' unmediated linkage with inflation, controls and regulations in commodity derivatives trading is very common across countries. In the post-independence India, the commodity market experienced several changes in regulations and policies. In the 1980s, commodity derivatives trading in India was restricted. Following the recommendations of different committees, the union government allowed future trading in selected commodities in the 1990s. The process of liberalization gained momentum in 2002-03 when trading was allowed for a large number of commodities, and a number of regulatory measures were also being adopted in line with international best practices. Following liberalization, different market participants including hedgers, arbitragers, and speculators started trading in the commodity derivative market. This is on account of diversification benefits as there is disassociation of commodity price returns with other traditional asset returns, and also for being an effective hedge against inflation especially during crisis periods. As a result, the volume and value of commodity trading increased manifold across different commodity exchanges in India. On the other hand, increasing participation in the commodity derivative market resulted in an increase in i) financialization, ii) co-movement of commodity prices with other asset prices, and iii) excess volatility in commodity prices and returns.

In the macroeconomics literature, the role of commodity derivatives in India while accounting for their financial properties has not been explored so far. Although the financial properties of commodity futures prices in India have been extensively studied, their linkage with macroeconomic indicators has not been examined. It is often argued that market-determined prices reflect the expectations about future economic performance. Studies show that commodity futures prices contain important information and predict the expected economy-wide price level changes accurately. The connection between inflation expectations and actual inflation and thus its role in monetary policymaking has been well established in the macroeconomics literature. While the role of commodity futures prices as an information variable in monetary policy-making has been extensively studied for developed economies, such attempts are found to be rare for developing and emerging market economies. In specific, no such attempt has been made to examine the role of commodity futures in monetary policymaking in India looking into its ability to predict future trajectory of inflation as well as its linkage with other macroeconomic indicators relevant to monetary policymaking.

The stylized facts presented in Chapter 1 show that investment in the commodity derivative market is linked with the changes in macroeconomic conditions in India. Furthermore, there is a significant cross-correlation between international crude oil prices and Indian macroeconomic indicators including real GDP and inflation. Similarly, there is a strong correlation between the domestic commodity futures price index and Indian macroeconomic indicators such as the index of industrial production and retail inflation. The stylized facts show there are contemporaneous and lead-lag correlations between commodity prices and macroeconomic indicators in India. Therefore, the gaps in the literature and the stylized facts show that there exists a potential for analysing the dynamic relationship between commodity prices and macroeconomic indicators in India.

This thesis has used the commodity futures price index from the database of Multi Commodity Exchange between 2006 and 2019. In the first essay, daily data on commodity futures price index have been used along with the equity price index obtained from the database of the Bombay Stock Exchange. The second and third essays use monthly data of different macroeconomic indicators along with that of the commodity futures price index. The data on the index of industrial production and consumer price index are obtained from the International Financial Statistics database of the International Monetary Fund. The data on nominal rate of interest are collected from the Database of the Indian economy of the Reserve Bank of India. The last essay uses parameter values obtained from the literature to calibrate the theoretical model and simulate the transmission of shocks using the impulse response function.

The first essay (Chapter 2) has examined the nature and extent of co-movement and contagion between the Indian commodity derivative market and the Indian equity market. This chapter is an extension of Roy & Sinha Roy (2017), wherein evidence of significant financial contagion and volatility spillover is found to exist between the Indian commodity derivative market and other Indian asset markets. During the Global Financial Crisis and Eurozone Crisis, both asset and equity markets are found to show high volatility. The returns on commodity derivatives in India also show high volatility during the period of the "Great Plunge in Oil Prices" other than during the aforementioned crisis periods. Volatile returns on commodity contracts during crisis events show the possibility of financial contagion and volatility spillover vis-à-vis other asset markets.

Time series analyses carried out in this chapter show the co-movement between commodity futures price returns and equity price returns increased at the time of these high volatility periods, a phenomenon commonly known as 'financial contagion'. Further, analyses in this chapter show the non-linear nature of financial contagion between returns on commodity futures prices and equity prices.

To examine the dynamic nature of the co-movement of asset returns over time, the time-varying correlation has been estimated using the Dynamic Conditional Correlation Multivariate Generalized Autoregressive Conditional Heteroskedasticity method, while allowing for the possible presence of asymmetries. For the purpose of estimating the nature of financial contagion, the Linear Ordinary Least Square, Quantile regression, and Quantile-on-Quantile regression methods have been applied. While all estimates based on three types of regression analysis show the presence of financial contagion, the Quantile regression and Quantile-on-Quantile regression estimation results show that the contagion is non-linear in nature. The financial contagion in the Indian commodity derivative market is found to exist mainly during periods of high correlation. Moreover, the empirical analysis carried out in this chapter considers commodity future price group indices (such as agricultural, energy, and metals). The non-linear nature of financial contagion is found to exist for commodity futures price indices at the disaggregated level, especially in case of energy commodities and metals.

Having found the presence of financial contagion in the Indian commodity derivative market vis-à-vis traditional asset markets, and as there is a possibility of transmission of shocks from these asset markets to the larger macroeconomy through the commodity market in presence of such contagion, it is necessary to explore the nature of the association between commodity prices and macroeconomic indicators. The second essay (Chapter 3) has examined the relationship between commodity futures prices and macroeconomic indicators and therefore has reassessed the informational role of commodity futures prices in formulating monetary policy in India. Using the Non-Linear Autoregressive Distributed Lag method and monthly time series data of commodity futures price indices and other macroeconomic indicators, it is found that commodity futures prices provide signals about the future trajectory of inflation and industrial production in India, and thus contain valuable information for monetary policy management. In particular, there is a significant presence of commodity futures prices pass-through to inflation and industrial production, primarily in the long-run.

The observed relationships in Chapter 3 are found to be significantly asymmetric and varying across different types of commodities. The empirical results show that the pass-through effect is the highest in the case of metals which are generally used as raw materials in production. The presence of asymmetries while estimating the relationships between commodity futures prices and macroeconomic indicators permits examining the effects of positive and negative price changes separately. The differential impacts of positive and negative price changes give important insights into the relative strength of the 'cost effect' and 'information effect'. It is to be mentioned that this is the first attempt to model the relationship between commodity futures prices and macroeconomic indicators considering the possible presence of asymmetries. As the results strongly support the presence of asymmetric commodity futures prices pass-through to macroeconomic indicators, the chapter assumes significance for the monetary policy authorities practising flexible inflation targeting.

Extending the analysis of the second essay, the third essay (Chapter 4) has examined the ability of commodity futures prices to forecast headline inflation in India. At the outset, a simple theoretical model has been developed, which shows a positive impact of changes in commodity futures prices on the general price level. The theoretical results form the basis of the empirical analysis carried out in the chapter. Traditionally, inflation is modelled using a Phillips curve approach in which inflation is determined by the demand side factors such as output or employment. Of late, the supply-side Phillips curve approach has been introduced in the literature to model inflation with crude oil prices as a supply side factor. Considering the two approaches, the augmented Phillips curve approach has been brought forth to estimate the Phillips curve considering both the demand as well as supply-side factors. Some recent studies show that the augmented Phillips curve model considering both output and oil prices can predict inflation better than the traditional demand factors-based Phillips curve model or supply-side factors-based Phillips curve model. In this chapter commodity futures price based augmented Phillips curve model has been introduced as against the crude oil price based augmented Phillips curve model. This chapter thus considers four alternatives while estimating Indian inflation: i) output-based Phillips curve, ii) crude oil price-based Phillips curve, iii) output and crude oil price based augmented Phillips curve, and iv) output and commodity futures price based augmented Phillips curve, models.

For the purpose of empirical analysis, the Feasible Quasi Generalized Least Square estimation method has been employed. The methodology helps in circumventing the issues related to persistence, heteroskedasticity and endogeneity that are common when an asset market variable is considered as a predictor in estimation. Following the results obtained in Chapter 3, in this chapter asymmetric commodity futures price changes have been considered along with structural breaks in the predicted variable, scilicet the headline inflation. The empirical results show that the commodity futures price based augmented Phillips curve model can predict Indian inflation better than all the other variants of Phillips curve model.

The last essay (Chapter 5) is set out to understand the possible channels of shock transmissions from the commodity market to the macroeconomy in India. In the last five decades, the world economy experienced a number of crude oil price shocks following the Arab Oil Embargo, the Iranian Oil Revolution, the Gulf War, the Global Financial Crisis, the U.S. Shale oil Revolution, the Great Plunge in Oil Prices, the Covid-19 Pandemic, and the Russia - Ukraine conflict. A large body of empirical as well as theoretical literature came along with these crises analysing the possible effects of crude oil price shocks on different nominal and real macroeconomic indicators. These studies consider the crude oil price shocks as completely exogenous and also assume that crude oil price shocks can only occur on account of exogenous supply disruptions. However, a recent strand of theoretical literature shows that there can be impacts of precautionary motive of crude oil demand as well. The financial properties of commodities such as the possibility of inventory holding can be introduced in a New Keynesian Dynamic Stochastic General Equilibrium setup. The supply shock emerging from the changes in inventory holding by the speculative inventory holders can also have an impact on real macroeconomic indicators. The changes in crude oil prices thus can be on account of exogenous changes in the supply of crude oil or changes in inventory holding by the speculative inventory holders expecting a future disruption in crude oil supplies.

The fourth essay simulates the effects of exogenous crude oil supply shocks and inventory demand shocks in a New Keynesian Dynamic Stochastic General Equilibrium setup by introducing the possibility of futures trading along with inventory holding. In previous studies, the possibility of futures contract trading has been ignored. The present chapter is thus an improvement over the previous studies in analysing the dynamics of crude oil price shocks. The results of the calibration exercise show that the effect of crude oil price shocks on inflation is relatively large and the effect on output is relatively small when the possibility of future trading is introduced along with inventory holding.

Implications for Policy

The results, econometric or otherwise, in the four essays have implications for monetary policymaking. The results of the first essay have important implications, especially for the investors while choosing optimal portfolios as well as for the policymakers. Investors in the Indian commodity derivative market need to be well aware of how other asset markets are correlated with the Indian commodity derivative market and also how similar sentiments of investors can shoot up these correlations. This certainly gives an indication of the possible diversification benefits from the commodities traded in the Indian commodity derivative market. On the other hand, for the market regulators in India, it is important to understand the linkages between the Indian commodity derivative market and other asset markets in order to react promptly at times of stress in the domestic as well as the international economy. Moreover, a high correlation during the turmoil period creates the possibility of shocks transmission from equity markets to commodity markets and hence to the macroeconomy. In particular, the correlations can shoot up during times of stress leading to financial contagion. Understanding the nature of such association is also important for policymakers, especially the central bankers.

The results found in the second and third essays are pertinent for the policymakers especially the central bankers in predicting inflation for the purpose of flexible inflation targeting. The Monetary Policy Committee of the Reserve Bank of India uses international crude oil price movements and movements in international commodity price indices while making predictions about the trajectory of future inflation. Along with validating the argument in favour of using commodity prices in inflation modelling, these results propose that domestic commodity futures price aggregates or domestic commodity futures price indices are better predictors of Indian inflation in comparison to international crude oil prices.

The results found in the fourth essay have important lessons for the monetary authority practising flexible inflation targeting and also for the financial market regulators. The results suggest that when crude oil futures prices are found to increase following an increase in spot prices, the central banks should go for hawkish monetary policy. There is always a tradeoff between inflation and economic growth. Regulations in commodity trading should therefore be in accordance with the policy objectives set off by the central bank. The source of the commodity price shocks and their possible consequences are required to be analysed at the outset, and the policy choices to be accordingly designed for implementation.

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