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Financialisation of Food Commodity Markets, Price Surge and Volatility: New Evidence*

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Financialisation of Food Commodity Markets, Price Surge and Volatility: New Evidence

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ABSTRACT

Recent literature points towards the role of speculators in exaggerating the rally in food prices, over and above that explained by the fundamentals of demand and supply. Some studies argue that futures market speculation can only be blamed for the increasing food prices if it is accompanied by hoarding. With this background, the issues that the present chapter deals with are: (i) assessing the impact of indices such as S&P500, and MSCI on commodity prices; and (ii) tracing the volatility patterns in commodity prices, and linking volatility in commodity markets to these variables.Our results show a negative relationship between the commodity market returns and the Dollex, and a positive relationship between commodity market returns and crude oil price returns. The impact of equity markets, inflation and emerging market performance on commodity markets is weak. We also find some evidence of reverse causality or mutual endogeneity, for instance, causality from GSCI, S&P500 and WTI to MSCI, CPI to WTI, and MSCI, S&P500 to Dollex. We also study the causal relationships between the volatility of returns on macroeconomic variables and commodity markets, using the cross-correlation function, and Granger causality tests. Our results confirm unidirectional relationship from (volatilities of) GSCI to S&P500, from GSCI to MSCI, and from Dollex to GSCI. But there is also evidence of atwo-way causality between Inflation and GSCI (volatilities). Thus, the case for financialisation of commodity/food markets driving commodity/food returns and their volatility rests on weak foundations, leaving the door open for the pivotal role of supply-demand fundamentals.

KEY WORDS

Commodity Markets, Financialisation, Prices, Volatility, Speculation, Demand and Supply Fundamentals

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1. INTRODUCTION[1]

Food prices have been rising shaply the world over since July 2010. Although food prices have been increasing since 2000, they increased at a faster pace between 2006 and 2007-08 when prices of major cereals surged very rapidly.After the peak in prices in 2008, good harvests helped the prices to fall back. However, adverse weather conditions in several food exporting countries affected supplies, and there was another food price crisis in 2010. These spikes have been due to a combination of both short-term (such as droughts and trade restrictions) and long-term factors (such as declining productivity and inadequate investments in infrastructure). Another factor is the deep integration between agricultural commodity markets and other markets in the world. For instance, rising crude oil prices have led to an increase in agriculture prices in two ways: rising inputs costs (such as oil-based fertilizers and transportation), and increased demand for agricultural crops for alternate energy sources such as biofuels.

Many analysts claim that speculation and hoarding further fuelled the price rise. Recent studies (Nissanke, 2012; Hernandez and Torero, 2010; Mayer, 2012) point towards the role of speculators in exaggerating the rally in food prices, over and above that explained by the fundamentals of demand and supply. Commodity derivatives are seen as an important portfolio hedging instrument since the returns in commodity sector are uncorrelated with the returns on other assets. This financialisation of commodity markets may not be a source of food inflation; however, it does play an important role in the short term volatility in food prices.

As a World Bank report (2011) points out, much of the recent increase in commodity financial transactions has occurred in the futures markets, including for maize and wheat. This is largely driven by demand from index funds holding and continuously rolling over

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futures positions in commodity markets, without taking physical delivery. The extent to which these inflows affect spot prices, however, remains debatable.

In the context of food prices, speculation may take two forms – hoarding of commodities during shortages in anticipation of a further price rise, and investments into commodity futures or options. Investments in futures have led to prices being out of line with fundamental values. Moreover, futures prices have also been volatile. Some studies argue that futures market speculation can only be blamed for the increasing food prices if it is accompanied by hoarding. Moreover, it is expected that over the next few years, energy price volatility will translate into food price volatility.

With this background, we address the following issues in this chapter: (i) assessing the impact of macroeconomic variables on commodity prices; and (ii) tracing the volatility patterns in commodity prices, and linking volatility in commodity markets to macroeconomic factors. The scheme is as follows. In the next section, we review recent literature addressing these issues. Our study builds on to the extant literature by examining not just the impact of macroeconomic factors on commodity prices, but also highlights a bicausal relationship between them. The third section gives an overview of the time series data characterising commodity market returns. The statistical tests pertaining to the data and methodological issues are covered in section 4. To address the issue of reverse causality that may exist between macroeconomic factors and commodity prices, we use a vector autoregression framework. Empirical results are analyzedin section 5, and section 6 concludes.

2. LITERATURE REVIEW

Recent literature on commodity price movements yieldsmixed results.

Tang and Xiong (2009) empirically study the futures contracts of 28 commodities and segregate the analysis into indexed and non-indexed commodities. They examine the difference in co-movements of indexed and non-indexed commodities by studying the correlations between a commodity return and return on oil. Comparison of the average one year correlation of indexed and non-indexed commodities for the period from 1973 till 2009 suggests that indexed non-energy commodities faced greater volatility compared to non-indexed commodities. This study also suggests that the average correlation in commodities is found to be higher in US than in China.

Gorton and Rouwenhorst (2006) construct an equally weighted performance index of commodity futures to investigate the impact of macroeconomic variables on return of commodity futures for the period from 1959-2004. They examine the correlation of stocks (total return index of SP500 stocks) with returns on commodity futures at various frequencies – quarterly, annual and at intervals of five years. Even though the correlation between returns on commodity futures and stocks is found to be negative for quarterly, one year and five-year intervals, it remains weak. Using the CPI Index, the authors analyse the relationship between inflation and commodity futures returns. They find a positive correlation which is larger at longer intervals (yearly or 5 yearly) compared to shorter intervals (monthly or quarterly). Greer (2000) uses returns of asset class from 1970 till 2000 and is able to conclude that there exists negative correlation between returns on commodities and stocks and bonds. He also shows that there is positive correlation between returns on asset class and inflation. Erb (2006) points out that inflation can explain variations in returns on some commodity futures.

Silvennoinen and Thorp (2013) use DSTCC-GARCH models to assess the changes in correlation of commodity futures returns, stocks and bonds due to changes in observable financial variables and time. The authors use price of futures contracts for 24 commodities for the period from May 1990 to July 2009. Weekly commodity futures returns are calculated. Returns of stock price indices of US, UK, Germany, France and Japan and changes in Dollex are utilized in the study. The authors conclude that the level of correlations between commodity futures returns and US stock index returns increased over time. Buyuksahinet et. al. (2010) employ SP 500 returns and GSCI returns and find that simple correlation between the two during the period June 1992 to June 2008 is almost zero but rolling correlations fluctuate substantially in the chosen period of study. But for the overall period, on using dynamic correlation technique and recursive cointegration, the relation between stock and commodity indices does not vary.

In several important contributions, Wright (2011) and Bobenrieth (2010), among others, have employed a competitive storage model to shed light on foodgrain price spikes. The main argument is: given the substitutability between wheat, rice, and corn in the global market for calories, when aggregate stocks decline to minimal feasible levels, prices become highly sensitive to small shocks, consistent with the economics of storage behaviour. Higher stocks when prices fall reduce the dispersion of price and prevent steeper price slumps. Disposal of stocks when supplies are scarcer reduces the severity of price spikes. Given sufficiency of speculative capital, storage can eliminate negative price spikes but can moderate positive price spikes only as long as stocks are available. When stocks are used up, aggregate use must match an almost fixed supply in the short run.

Most recent explanations of commodity price surges/spikes have relied on “bubbles”. These imply that price rises at the rate of interest, or at a higher “explosive” rate, for a sustained period, followed by a sharp slump and a period of quiescence (Wright, 2011). Bubbles are noticed only after a sequence of price run-up and crash has been completed, often viewed as incompatible with market fundamentals.

Our preceding literature review focused on cash inflow and commodity price spikes. Wright (2011) is deeply sceptical of this link primarily on the ground that there is no evidence suggesting that this cash increased grain stocks during the price spikes in 2007/08. If the excess cash caused a bubble, it must have reduced consumption and increased food stocks. But in 2007/08, stocks in the global markets were close to minimal levels as prices spiked.

There is in fact evidence of massive storing by exporter governments denying their stocks to the global market by restricting supply to protect their domestic consumers. Following the announcement by India of banning of rice exports to protect its consumers from a wheat shortfall, other exporters followed suit while importers resorted to panic buying. The important point here is that charges against private hoarders and financiers of excessive hoarding are misplaced as huge stocks held off the market are overlooked, especially by China.

In 2007/08 the aggregate stocks of wheat, rice and corn were at minimal levels, lower than the amount than would have been observed without mandated diversions of grain and oilseeds for biofuels. Lack of stocks rendered the markets vulnerable to regional weather problems, the boost to biofuel demand from the oil price hike in 2007/08, and the long Australian drought. Moreover, the demand for biofuel was expected to increase in the future, and using stocks of wheat, rice and corn to dampen prices would have been irresponsible and would have lead to rise in their prices in the future. Supplies were adequate to meet food demands without food price hikes but for panic reactions of food exporters and importers.

The spillovers from the financial markets to the commodity markets during the global financial crisis on developing economies of the world have been investigated by Nissanke (2012). The author analyses the price movement of agricultural commodities, crude oil, minerals over the period January 2010 to July 2011. The rise in price level of commodities during 2002-2008 is attributed to the increase in demand from industrial emerging economies. Inventory management is also found to be a determining factor leading to sharp increases in crops such as rice, wheat and maize in 2007-08. Apart from demand supply factors, Nissanke observes that the rise in price of commodities is a result of participation of financial investors as there was a marked jump in the volume of trading of derivatives in 2005. This aspect has been dealt with in detail by Mayer (2012). Aulerich et. al. (2013) argue that the bubble in agricultural commodity prices is not an outcome of index fund investment. Their study uses bivariate Granger causality to investigate the dynamics between position of index traders and agricultural futures prices for the period from January 2004 to September 2009.

Financial investors are categorized into Index traders and Money Managers. Money Managers operate hedge funds with short term horizons, by taking positions on both side of the commodity market, they earn profits from a rise as well as a fall in the commodity prices, whereas Index Traders take long term positions without physically taking delivery of the commodities. Mayer argues that efficient market hypothesis fails in commodity markets due to factors other than market fundamentals of demand and supply and due to positions taken up by financial investors also called the ‘weight of money effect’. Using the Commodity Futures Trading Commission (CFTC) weekly Commitments of Traders (COT) reports, he studies positions of index traders and non- commercial traders (excluding index traders) focusing on eight commodities namely – soybeans, soybean oil, wheat, maize, gold, copper, crude oil and natural gas. The author finds correlations in positions and prices of commodities during sub periods. Regression analysis is performed to study the determinants of the positions taken by index traders and non- commercial traders, with the explanatory variables comprising spot returns, roll returns, volatility, interest rate, correlation with equity market, expected inflation and dollar index. The results suggest that position of index traders are influenced by roll returns while positions of non- commercial traders are influenced by spot returns of commodities. He attributes speculation to diversification objectives since correlation in equity and commodity market is found to be negative and significant in the period from January 1999 and December 2004. Whereas in the period from January 2005 to June 2008, positions taken up by investors are found to be positively related to movements in equity markets. Granger Causality tests are conducted on the positions taken by index traders and money managers with the prices of the eight commodities. The results of Granger causality tests conducted in the study refute the Efficient Market Hypothesis since a significant impact of index traders positions is found on the price level of commodities and not vice versa.

3. COMMODITY PRICE MOVEMENTS

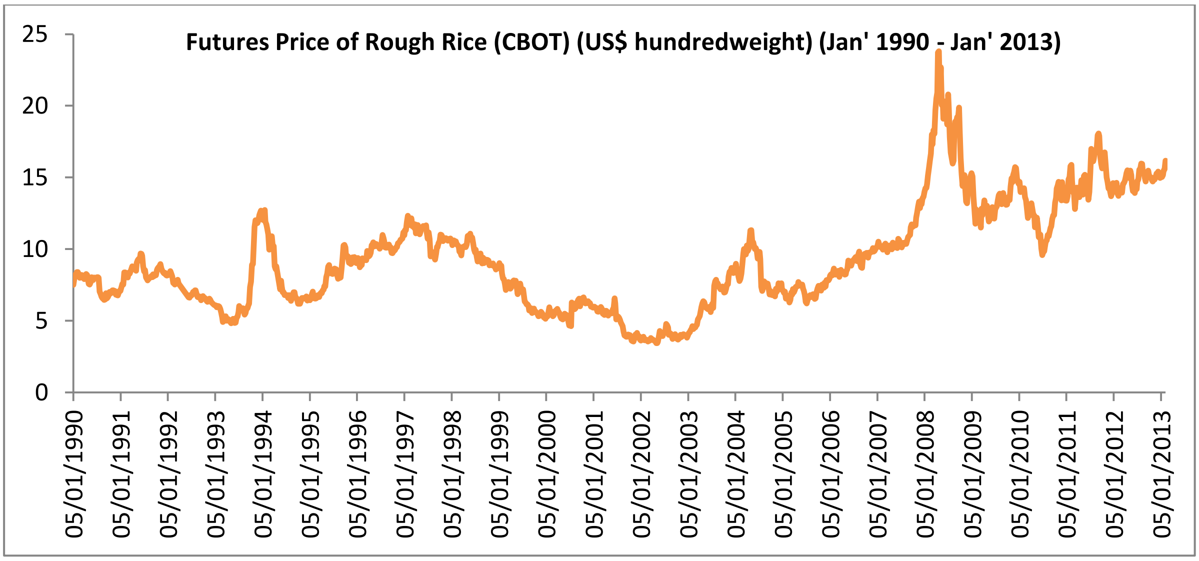
The movement in the futures prices of various commodities have been very volatile in recent times. The futures price of Rough Rice increased slightly from US$7.5 in 1990 to US$8.16 in 1991, and came down in 1992. Following a gradual increase, there was a slight decline in the latter half of the decade. Since 2001, the futures price of Rough Rice has been going up, with a major spike in 2008. If we see Figure 1, for each commodity, there has been a stable movement in prices prior to 2007, and a very pronounced price spike is seen in the year 2008, followed by massive volatility.

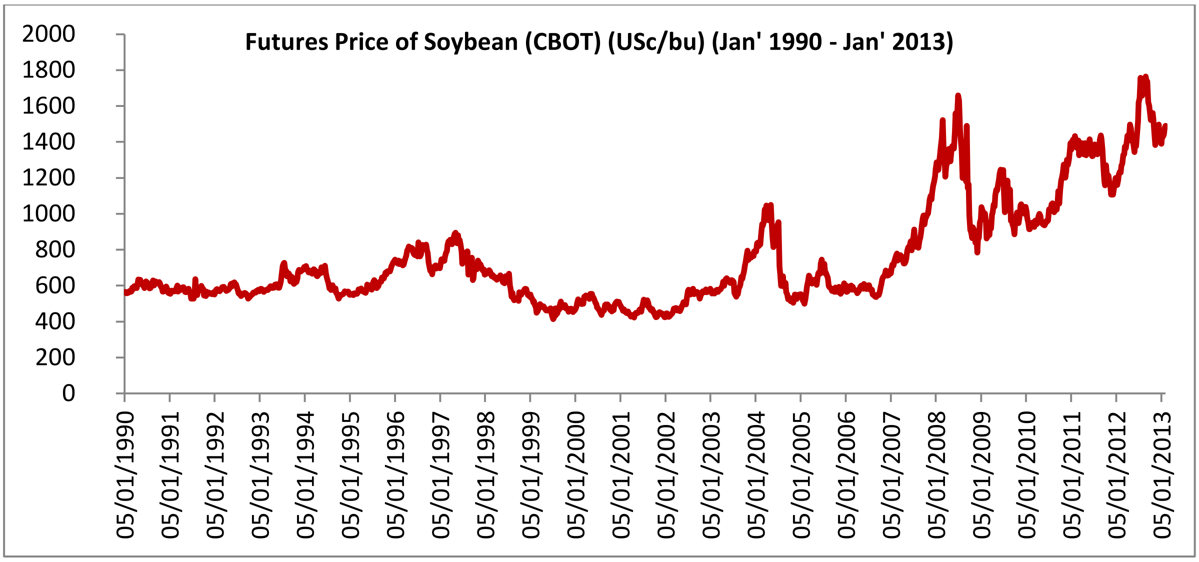
The futures price of soybean was 564 USc/bushel in January 1990 and continued to remain below 894¼ USc/bushel until May 1997. Since then price continued to remain below 800 USc/bushel. A spike in soybean price was experienced in January 2004 when it rose to 835 ¼, resulting from a supply shortage of the commodity. A marked rise in price of soybean took place in 2007 and 2008 and continued to rise until reaching a peak of 1658 USc/bushel in July 2008 which was accompanied by rise in price of crude oil. The price spike havebeen attributed to financialisation of commodities (Masters and Weight, 2008). The commodity in question experienced a sharp fall in the second half of 2008 and prices have continued to remain volatilesince then. Another spike was observed in soybean prices in August 2012 when prices rose to more than 1750 USc/bushel.

Corn also faced similar movements in price. Corn prices remained below 300 USc/bushel in the first half of 1990s. In 1996, corn prices experienced a sharp rise, reaching a peak of 548 USc/bushel in July 1996 due to low stocks, a result of low production of corn in the preceding years. Following the spike, prices continued to fall till 1999 and remained in the range of 200 and 300 USc/bushel till as long as 2008. In 2008, prices shot up, and reached a peak of 754¾ USc/bushel in June 2008, followed by a decline in price in the second half of 2008 reaching to as low as 293 ½ USc/bushel. Prices remained volatile in 2010, succeeded by a peak in corn prices in April 2011 and another spike in July 2012, reaching a level of 824 ½ USc/bushel.

The movement in price of Hard Winter Wheat traded on Kansas City Board of Trade and price of Hard Red Spring Wheat traded on Minneapolis Grain Exchange is similar from 1990 to 2013. Both the varieties of wheat faced a rise in 1996. This was followed by low fluctuation in price level until 2003, when a rise in price level can be observed in both the types of wheat. Prices began to rise in the beginning of 2008 and reached peak levels (1217 USc/ bushel – KCBT wheat and 1944 USc/bushel – MGE Wheat) in February- March 2008. Price of wheat has continued to remain volatile since the beginning of the crisis.

Figure 1: Futures PriceMovements




Futures Price of Soybean (CBOT) (USc/bu) (Jan' 1990 - Jan' 2013)
2000
1800
1600
1400
1200
1000
800
600
400
200
0
05/01/1990
05/01/1991
05/01/1992
05/01/1993
05/01/1994
05/01/1995
05/01/1996
05/01/1997
05/01/1998
05/01/1999
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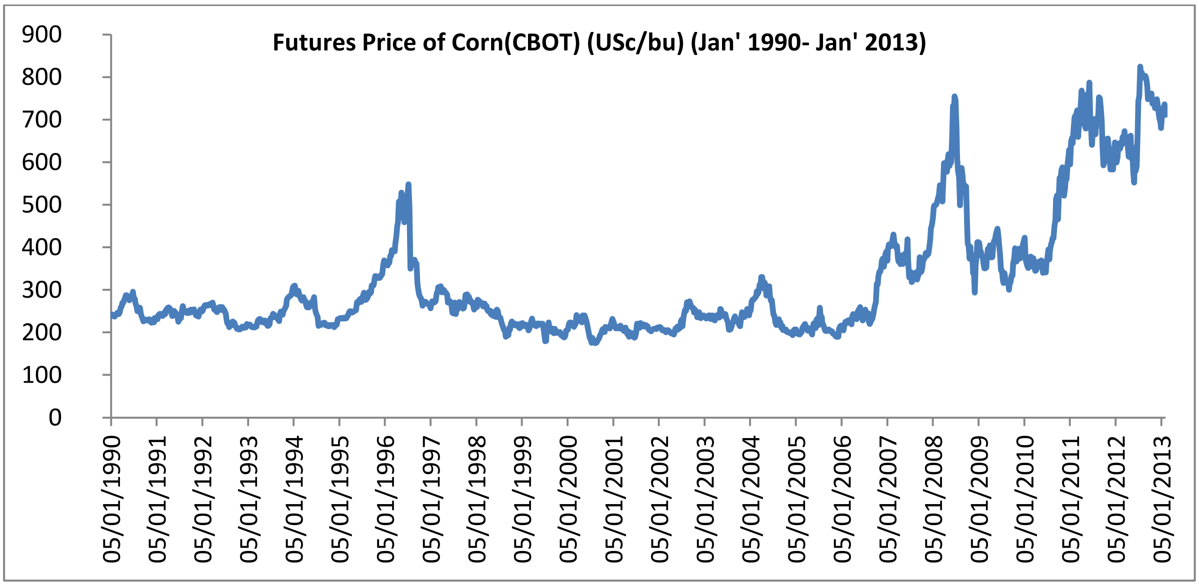
Futures Price of Corn(CBOT) (USc/bu) (Jan' 1990- Jan' 2013)
900
800
700
600
500
400
300
200
100
0
05/01/1990
05/01/1991
05/01/1992
05/01/1993
05/01/1994
05/01/1995
05/01/1996
05/01/1997
05/01/1998
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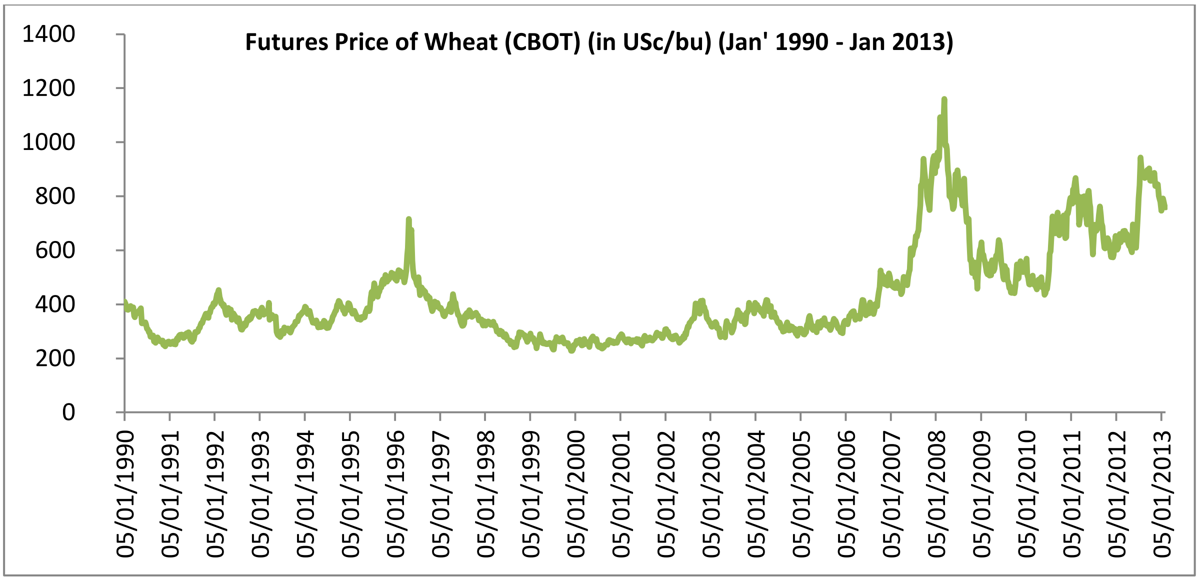
05/01/2013


Futures Price of Wheat (CBOT) (in USc/bu) (Jan' 1990 - Jan 2013)
1400
1200
1000
800
600
400
200
0
05/01/1990
05/01/1991
05/01/1992
05/01/1993
05/01/1994
05/01/1995
05/01/1996
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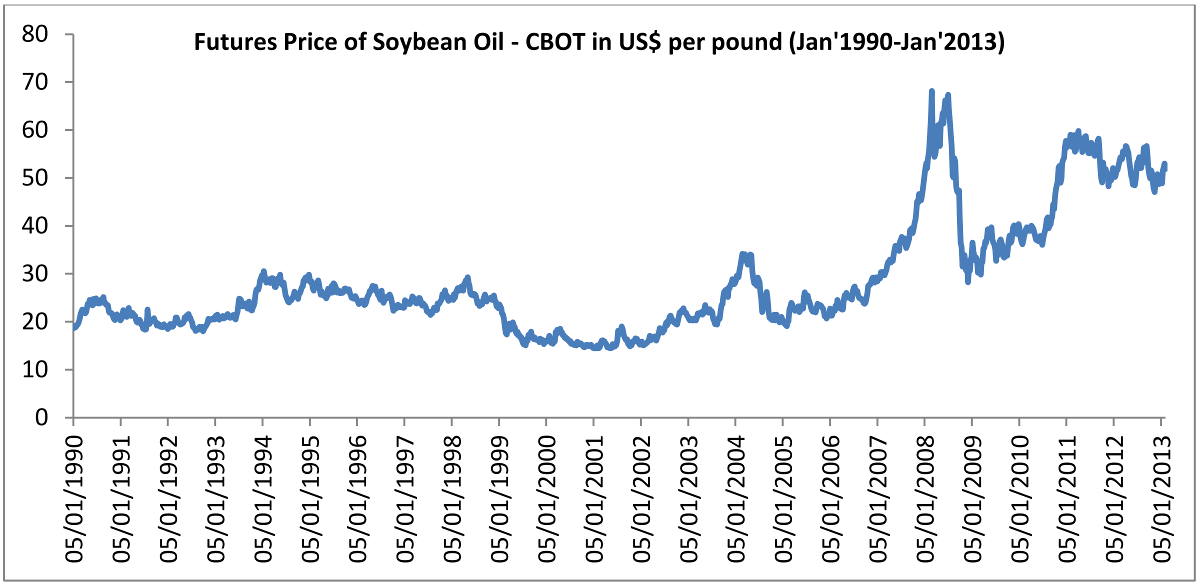


4. Data and Methodology

(A) Data

The data used in this study are the returns on the Goldman Sachs Commodity Index (GSCI), Morgan Stanley Commodities Index (MSCI, which is an indicator of the performance of emerging economies), Standard and Poor Index of 500 companies (S&P 500 which taps the equity market performance), Dollex Index (to capture the exchange rates changes), Inflation Rate as measured by the consumer price index (CPI) and Crude Oil price captured by the price of West Texas Intermediate (WTI). The definitions of the variables used in the econometric analysis are provided in Annexure 1. The notations used for the *monthly returns* on these variables are GSCI, MSCI, SP500, Dollex, CPI, and WTI, respectively[2]. Table 1 gives the summary statistics of the monthly returns on these variables. The statistics include mean returns/growth, standard deviation, skewness, kurtosis, autocorrelation and Portmanteau Q test. Mean returns suggest a more or less stable regime if we look at the complete period; but these may be very volatile. A commonly used measure to estimate volatility is the standard deviation of returns/growth. The returns on CPI (inflation rate) and WTI are more volatile than the returns on commodity markets and other macroeconomic variables. The returns on GSCI, MSCI and S&P 500 are negatively skewed, suggesting that the values lower than the mean are farther from it than those higher than the mean. The coefficient of kurtosis is greater than 3, implying a fat tailed distribution.

[2]Throughout this paper, we use commodity returns for GSCI, and other macroeconomic variables / returns on other markets for MSCI, S&P 500, Dollex, CPI and WTI. For definitions, refer Annexure 1

Table 1: Summary Statistics (Monthly Returns)

	GSCI	MSCI	SP500	CPI	WTI	Dollex
Mean	0.0010	0.0015	0.0013	2.4321	0.0011	0.0000
Standard Deviation	0.0297	0.0305	0.0238	0.8277	0.0508	0.0117
Skewness	-0.8640	-0.8173	-0.7436	1.0071	-0.8811	0.2088
Kurtosis	7.4003	9.1493	9.8295	5.3933	8.6073	3.7552
Autocorrelation						
p1	0.000	0.000	0.000	0.000	0.000	0.000
p2	0.000	0.000	0.000	0.000	0.000	0.000
p3	0.000	0.000	0.000	0.000	0.000	0.000
p4	0.000	0.000	0.000	0.000	0.000	0.000
p5	0.000	0.000	0.000	0.000	0.000	0.000
p6	0.000	0.000	0.000	0.000	0.000	-0.001
p7	-0.038	0.068	-0.079	0.991	-0.098	-0.002
p8	0.000	0.000	0.000	0.000	0.000	0.000
p9	0.000	0.000	0.000	0.000	0.000	0.000
p10	0.000	0.000	0.000	0.000	0.000	0.000
p11	0.000	0.000	0.000	0.000	0.000	0.000
p12	0.000	0.000	0.000	0.000	0.000	0.000
p13	0.000	0.000	0.000	0.000	0.000	0.000
p14	0.030	0.137	0.061	0.981	-0.022	0.036
p15	0.000	0.000	0.000	0.000	0.000	0.000
p16	0.000	0.000	0.000	0.000	0.000	0.000
p17	0.000	0.000	0.000	0.000	0.000	0.000
p18	0.000	0.000	0.000	0.000	0.000	0.000
p19	0.000	0.000	0.000	0.000	0.000	0.000
p20	0.000	0.000	0.000	0.000	0.000	0.001
Portmanteau's Q(20)	2.742	27.503	11.595	2255.8	11.844	1.532

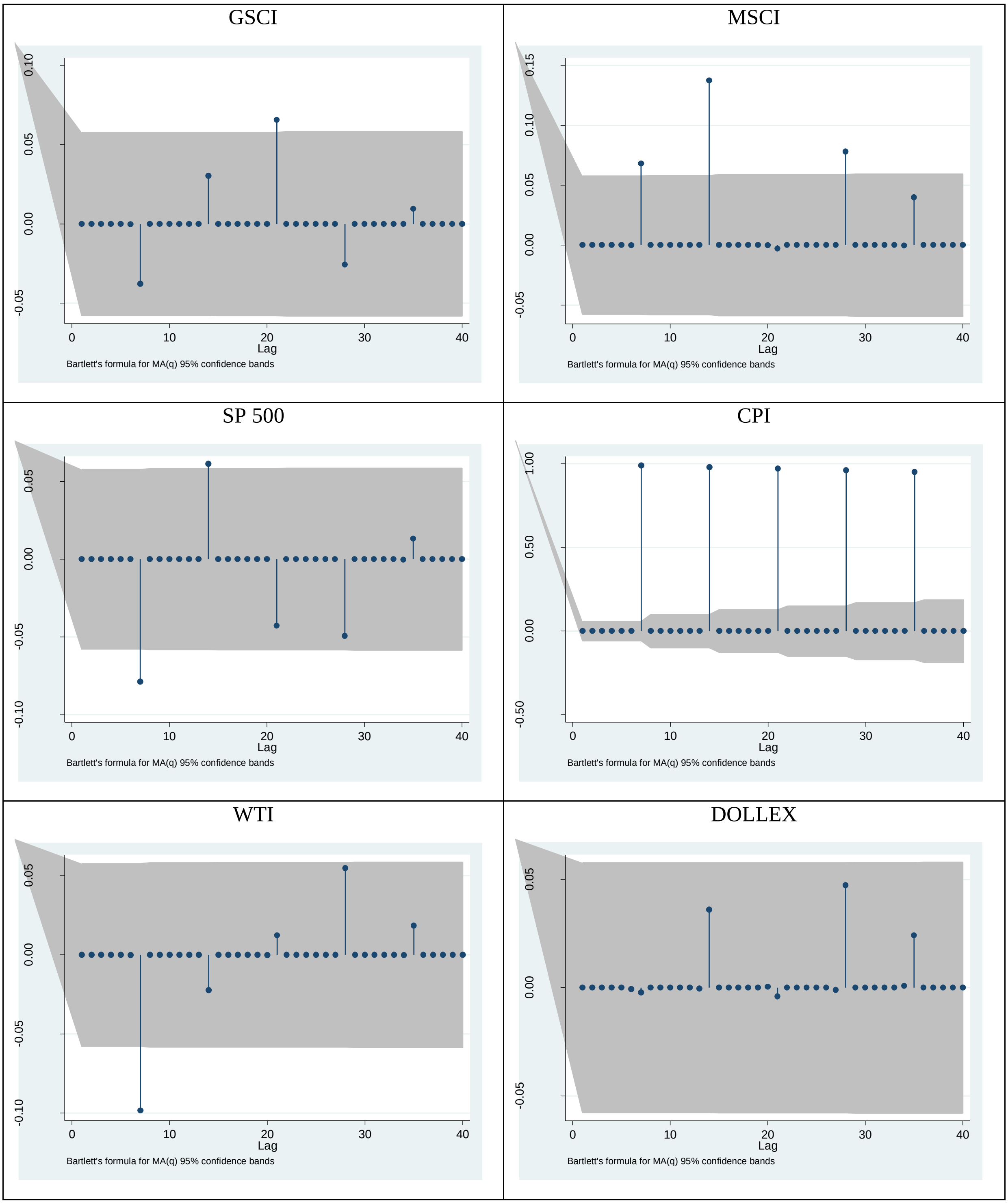
When there is correlation or dependence between observations that are close in time, the disturbance process exhibits autocorrelation or serial correlation. The larger the absolute value of autocorrelation, the more highly autocorrelated are the disturbances. Since we suspect the presence of autocorrelation[3] in the time series, we use estimated residuals to diagnose it using the Q-statistic[4]. Figure 2 shows the serial dependence of various series. The significant value of the Portmanteau's Q statistic provides evidence of strong dependencies in

[3]Autocorrelation is calculated as $r_k = \frac{\sum_{t=k+1}^{T}(y_t-\bar{y})(y_{t-k}-\bar{y})}{\sum_{t=1}^{T}(y_t-\bar{y})^2}$, where k is the number of lags, and y_t is the return at time *t*(Greene, 2008; Campbell, Lo, & MacKinlay, 1997)

[4]The Box Pierce Q-statistic, later refined by Ljung-Box is calculated as $Q = T(T+2)\sum_{k=1}^{p}\frac{r_k^2}{T-k}$., where p is the number of autocorrelations that are squared and summed (Campbell, Lo, & MacKinlay, 1997).

the distribution of returns and justifies the use of autoregressive filters and conditional heteroscedasticity models.

Figure 2: Autocorrelations



We further examine the properties of our data by testing for stationarity. A stationary time series is one whose statistical properties such as mean, variance, and autocorrelation remain constant overtime. If a series has a long term trend, and tends to revert to the trend line (such a series is known as *trend stationary series*), it may be possible to stationarize it by de-trending the series. A *difference stationary series* is one whose statistical properties are not constant overtime even after de-trending, and it has to be transformed into a series of period-to-period changes (also known as first differences). We examine the stationarity of the various time series using unit root test – Augmented Dicky Fuller (ADF) test[5] and the Phillip Perron (PP) test[6](Wooldridge, 2006). The results are shown in Table 2.

Table 2: Tests for Stationarity

	Augmented Dicky Fuller Test for Unit Root			***Phillip Perron Test for Unit Root***		
	Test Statistic Z(t)	5% Critical value	Mackinnon p-value for Z(t)	Test Statistic Z(Rho)	5% Critical value	Mackinnon p-value for Z(t)
GSCI	-23.705	-2.860	0.0000	-1262.765	-14.100	0.0000
MSCI	-20.236	-2.860	0.0000	-1222.470	-14.100	0.0000
S&P500	-23.586	-2.860	0.0000	-1256.093	-14.100	0.0000
CPI	-4.118	-2.860	0.0009	-10.587	-14.100	0.0000
WTI	-25.925	-2.860	0.0000	-1274.636	-14.100	0.0000
Dollex	-23.161	-2.860	0.0000	-1212.072	-14.100	0.0000

The null hypothesis of presence of unit root in the series is rejected for all the series, and thus, the returns exhibit stationarity. These are *difference stationary* series as the first difference of the logarithmic transformation of values is used to calculate returns / growth rates.

(B) METHODOLOGY

The first objective of this chapter is to assess the impact of macroeconomic variables on commodity prices. Towards this objective, we use regression analysis to examine the effects of the various economic variables, following Tang (2012) – the performance of emerging

[5]The Augmented Dicky Fuller test fits the model of the form $\Delta y_t = \alpha + \beta y_{t-1} + \delta t + \varsigma_1 \Delta y_{t-1} + \varsigma_2 \Delta y_{t-2} + \cdots + \varsigma_k \Delta y_{t-k} + \epsilon_t$, testing for the null hypothesis $\beta = 0$. The lag length k is determined using Akaike Information Criterion (AIC) and Schwartz/Bayesian Information Criterion (BIC). The information criterion offers the same conclusion – lag length of 1.

[6] The Phillip-Perron (PP) unit root test fits the following model originally proposed by Dicky and Fuller $y_t = \alpha + \rho y_{t-1} + \delta t + \mu_t$. This specification poses the problem of serial correlation. Hence the ADF test which uses lags of first difference of y_t was an improvisation over this. Phillip-Perron use the original Dicky-Fuller statistics which have been made robust to serial correlation by using Newey-West Heteroscedasticity and autocorrelation consistent covariance matrix estimator. The default lag of 8 given by Newey-West (integer part of $4 * (N/100)^{2/9}$) is used.

market economies as captured by MSCI, equity market performance as measured by the S&P 500, inflation rate, oil price as measured by the WTI and exchange rate captured by the Dollex – on commodity markets in general, captured by the Goldman Sachs commodity index, and then on individual commodity prices. In addition to the explanatory variables, we use time dummies, to examine the impact of the financial and food crises on commodity market returns.

Since the variables in the macroeconomic framework are integrated, we use a VAR framework to capture the relation between each of the macroeconomic variables and commodity market returns in a dynamic setting. The VAR approach models every endogenous variable in the system as a function of lagged values of itself as well as of all the other endogenous variables in the system (Sims, 1980; Stock & Watson, 2001; Watson, 1994).

A reduced form of the VAR (bivariate) model can be represented as follows:

$$\Delta Z_t = \begin{bmatrix} \Delta x_{1t} \\ \Delta x_{2t} \end{bmatrix} = \begin{bmatrix} \omega_1 \\ \omega_2 \end{bmatrix} + \begin{bmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{bmatrix} \begin{bmatrix} \Delta x_{1t-1} \\ \Delta x_{2t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix},$$

where x_i are the endogenous variables, ω_i are the intercept terms, L is the lag operator, such that $A_{11}(L) = \alpha_{11}(0) + \alpha_{11}(1)L + \alpha_{11}(2)L^2 + ... + \alpha_{11}(\mathrm{p})L^p$, where p is the number of lags included in the VAR models, and $L^i x_t = x_{t-i}$, and ε_i are the error terms (Binswanger, 2004).

The VAR model requires variables to be stationary. Since each variable in our study is stationary (at the level of first difference of logarithm), we use a VAR framework to assess the impact of the macroeconomic variables (returns or growth rates) on commodity returns, and the reverse causality.

The second objective of this study is to trace the volatility patterns in commodity prices, and link volatility in commodity markets to macroeconomic factors. Since the volatility of many economic time series is not constant through time,conditional heteroscedasticity models are used to estimate the volatility of commodity returns, and other macroeconomic variables, and the causal relationships between the predicted variances are assessed using cross-correlation functions and vector autoregression models.

Traditional homoscedastic models are not appropriate when using data for commodity prices, because of the presence of conditional heteroscedasticity (Baillie & Bollerslev, 1990; Lamoureux & Lastrapes, 1990a; 1990b; Mandelbrot, 1963). The volatility of many economic time series is not constant through time. For instance, stock market volatility exhibits clustering, i.e. large deviations from the mean tend to be followed by even larger deviations, and small deviations tend to be followed by smaller deviations. The Autoregressive Conditional Heteroscedasticity (ARCH), and its extension, Generalised Autoregressive Conditional Heteroscedasticity (GARCH) address this time dependent volatility as a function of observed time volatility (Bollerslev, 1986; Black, 1976; Bollerslev, Chou, & Kroner, 1992; Bollerslev, Engle, & Nelson, 1994; Engle, 1982; Chiang & Doong, 2001). The ARCH[7] models the variance of a regression model's disturbance as a linear function of lagged values of the squared regression disturbances. The GARCH model, in addition, includes lagged values of the conditional variance. A standard GARCH (*p*,*q*) model may be written as:

$$y_t = x_t\delta + \epsilon_t \qquad \text{(conditional mean)},$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \qquad \text{(conditional variance)},$$

where α_i are the ARCH parameters and β_j are the GARCH parameters. In a GARCH model, an Autoregressive Moving Average (ARMA) process can also be added to the mean equation(Enders, 2004; Hamilton, 1994).

A drawback of the ARCH and GARCH models is the failure to address the problem of asymmetry. Both these models imply a symmetric impact of innovations, i.e. whether the shock is positive or negative makes no difference to the expected variance. However, many economic time series, particularly stock market returns, exhibit an asymmetric effect, i.e. a negative shock to returns generates more volatility than a positive shock. Nelson(1991) addresses the asymmetry problem in GARCH by employing an Exponential Generalised Autoregressive Conditional Heteroscedasticity model (E-GARCH). The conditional volatility equation for an E-GARCH*(p, q)* model is as follows:

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} (\alpha_i |z_{t-i}| + \gamma_i z_{t-i}) + \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-j}^2), \text{ where } z_t = \epsilon_t / \sigma_t$$

[7] Engle (1982) assumed that the error term in the ARCH model follows a normal distribution. However, recent studies have found that the distribution of stock returns has a high skewness, implying that extreme values occur more frequently, thus permitting the use of distributions that can have fatter tails than the normal distribution - Student's t distribution or the generalized error distribution.

The presence of leverage effect can be tested by the hypothesis $\gamma_i = 0$. The impact is asymmetric if $\gamma_i \neq 0$. If $\gamma_i > 0$, the volatility tends to rise when the shock is positive, and if $\gamma_i < 0$, the volatility tends to fall. We use an E-GARCH model to calculate the volatility of various time series, and also experiment with various conditional heteroscedastic models (with and without autoregressive coefficients), and the best fit model is selected on the basis of the log likelihood ratio test.

Having estimated the variance using the conditional heteroscedasticity models for all the variables, we study the causal relationships between these using the cross-correlation function(Cheung & Ng, 1996). The cross-correlation function is implemented as follows. In the first stage, the time varying variance is modelled using conditional heteroscedasticity. In the second stage, the resulting squared residuals are standardized by their conditional variances, and the cross-correlation function of these squared residuals is used to test the null hypothesis of no causality in variance(Constantinou, Georgiades, Kazandjian, & Kouretas, 2005). The cross-correlation function is used by Cheung & Ng (1996) to study the causal relationships between the NIKKEI 225 and the S&P 500 stock price indices.

Since the variables in the macroeconomic framework are integrated, the predicted volatility of any of them should affect others. Thus, we use a VAR framework to capture this relationship. After estimating the VAR model, impulse response functions (IRFs) are derived from the estimates. An impulse response function measures the effect of a shock to an endogenous variable on itself or on another endogenous variable(Hamilton, 1994; Lutkepohl, 1993). We then employ Granger causality tests to find whether there exists any relationship between macroeconomic variables and commodity returns, and the direction of causality.

5. RESULTS

The following subsections analyze the empirical results based on the methodology discussed earlier. The results pertaining to the first objective (relationship between commodity market returns and macroeconomic factors) are given in sections A1 (commodity markets) and A2 (individual commodities). As discussed previously, variables in the macroeconomic framework may be integrated. Hence, we use a VAR framework to capture the relation between each of the macroeconomic variables and commodity market returns, the findings of which are given in section A3. The results for the second objective, linking volatilities in various variables, are given in section B.

A1. Impact of Economic Factors on Commodity Market Returns

To assess the impact of economic factors on the commodity market returns, we regress the return on GSCI on S&P500, MSCI (an emerging markets index), CPI, Exchange Rates (using Dollex) and Crude Oil Price (using WTI). We experiment with two alternate specifications: (a) in the first, we take a single time dummy; (ii) in the second, we take three time dummies.

In Table 3, in Panel A, we take a single time dummy that takes the value 1 for the years 2007-2010 (covering the food and financial crises) and 0 otherwise. This dummy is interacted with each of the explanatory variables, to see the varying impacts over time of the macroeconomic factors. In Panel B, the time dummy takes the value 1 for the period September 2008 to June 2010 (financial crisis) and 0 otherwise.

Table 3: Impact of Macroeconomic Factors on Commodity Markets (Specification 1)

DEPENDENT VARIABLE: GSCI	Panel A			Panel B		
Time Dummy	-0.001	(-0.23)	-	0.002	(0.24)	-
MSCI	0.035	(1.34)	-	0.044	(1.78)	*
*Interaction: Time Dummy*MSCI*	0.253	(3.41)	***	0.376	(3.78)	***
S&P 500	0.037	(1.22)	-	0.022	(0.75)	-
*Interaction: Time Dummy*S&P500*	-0.104	(-1.61)	-	-0.110	(-1.28)	-
Dollex	-0.187	(-4.27)	***	-0.210	(-5.01)	***
*Interaction: Time Dummy*Dollex*	-0.129	(-0.87)	-	0.021	(0.1)	-
CPI	-0.001	(-0.99)	-	-0.001	(-1.48)	-
*Interaction: Time Dummy*CPI*	0.000	(0.2)	-	-0.003	(-0.65)	-
Crude Oil Price (WTI)	0.454	(28.43)	***	0.469	(29.94)	***
*Interaction: Time Dummy*WTI*	0.010	(0.19)	-	-0.071	(-1.25)	-
Constant	0.002	(1.04)	-	0.002	(1.69)	-

Our results show a negative relationship between the commodity market returns and the Dollex, and a positive relationship between commodity market returns and crude oil price returns. The impact of equity markets and inflation on commodity markets is weak except when interacted with time. As suggested by the results in the second panel, emerging markets performance has a positive impact on commodity markets, and this relationship became stronger in the years of the financial crisis. Surprisingly, the overall impact of the two time dummies is insignificant.

In Table 4we experiment with an alternate specification with three time dummies: T1 which takes the value 1 for the period June 2006 to August 2008 (food price crisis) and 0 otherwise, T2 which takes the value 1 for the period September 2008 to June 2010 (financial crisis), T3 which takes the value 1 for the period July 2010 to June 2011 (food price spikes), and each of these dummies in specific cases is interacted with the explanatory variables. The results are similar to those in Table 1 - a negative relationship between the commodity market returns and the Dollex, and a positive relationship between commodity market returns and crude oil price returns. The impact of equity markets, emerging markets and inflation on commodity markets is weak. An additional finding is that the oil price impacts become stronger in the periods of the two food crises. This is consistent with our introductory remarks on the food–energy nexus. Moreover, compared to Table 1, MSCI has a weak coefficient.

Table 4: Impact of Macroeconomic factors on Commodity markets (Specification 2)

DEPENDENT VARIABLE: GSCI	Coefficient		
T1 (June 2006 to August 2008)	0.003	(0.19)	-
T2 (September 2008 to June 2010)	0.002	(0.33)	-
T3 (July 2010 to June 2011)	0.006	(1.18)	-
MSCI	0.036	(1.34)	-
*Interaction: T1*MSCI*	0.029	(0.5)	-
*Interaction: T2*MSCI*	0.384	(3.83)	***
*Interaction: T3*MSCI*	-0.057	(-0.39)	-
S&P 500	0.034	(1.1)	-
*Interaction: T1*S&P500*	-0.112	(-1.31)	-
*Interaction: T2*S&P500*	-0.122	(-1.41)	-
*Interaction: T3*S&P500*	0.209	(1.53)	-
Dollex	-0.181	(-4.05)	***

*Interaction: T1*Dollex*	0.066	(0.41)	-
*Interaction: T2*Dollex*	-0.008	(-0.04)	-
*Interaction: T3*Dollex*	-0.058	(-0.41)	-
CPI	-0.001	(-0.91)	-
*Interaction: T1*CPI*	-0.001	(-0.17)	-
*Interaction: T2*CPI*	-0.003	(-0.69)	-
*Interaction: T3*CPI*	-0.005	(-1.06)	-
Crude Oil Price (WTI)	0.448	(27.58)	***
*Interaction: T1*WTI*	0.178	(3.81)	***
*Interaction: T2*WTI*	-0.050	(-0.88)	-
*Interaction: T3*WTI*	0.110	(1.8)	*
Constant	0.002	(0.99)	-

A2. Impact of Economic Factors on Individual Commodity Returns

In the second set of exercises, we take individual commodity returns, instead of the commodity market index, i.e. the GSCI. We regress returns on various commodies (Corn, Soyabean, Kansas Wheat and Minnesota Wheat) on S&P 500 (equity markets index), MSCI (an emerging markets index), CPI (to capture inflation), Exchange Rates (using Dollex) and Crude Oil Price (using WTI). Our specification uses three time dummies: T1 which takes the value 1 for the period June 2006 to August 2008 (food price crisis) and 0 otherwise, T2 which takes the value 1 for the period September 2008 to June 2010 (financial crisis), T3 which takes the value 1 for the period July 2010 to June 2011 (food price spikes), and each of these dummies in specific cases is interacted with the explanatory variables, to check the varying impacts overtime. The results are given in Table 5. We use different specifications for the four commodities.

For each of the commodities, T3 has a significant positive impact. This implies that the returns were higher in the period of the recent food price spike, i.e. July 2010 to June 2011. There is no significant relationship between equity market performance and returns on the various commodities. In case of Kansas Wheat and Corn, a significant positive relationship is found between the returns, and the indicator of emerging markets performance. The returns on Corn and Minnesota wheat are negatively related to the returns on Dollex, and this relationship weakens during the recent financial crisis, and the food price surge following it.

A positive relationship is observed between returns on both types of Wheat and Inflation rates, with the effect weakening in the wake of the second food price crisis.

Table 5: Impact of Macroeconomic Factors on Individual Commodity Returns

DEPENDENT VARIABLE = Commodity Returns	**Corn**			**Soyabean**		
T1 (June 2006 to August 2008)	-0.025	(-0.7)	-	0.050	(1.55)	-
T2 (September 2008 to June 2010)	0.009	(0.6)	-	-0.011	(-0.77)	-
T3 (July 2010 to June 2011)	0.090	(5.06)	***	0.030	(1.86)	*
S&P 500	0.050	(0.8)	-	-0.043	(-0.75)	-
Interaction: T1*S&P500	-0.244	(-1.14)	-	0.180	(0.92)	-
Interaction: T2*S&P500	0.086	(0.53)	-	0.147	(0.98)	-
Interaction: T3*S&P500	-0.477	(-1.34)	-	-0.311	(-0.94)	-
MSCI	0.084	(1.69)	*	-0.004	(-0.08)	-
Interaction: T1*MSCI	0.164	(1.06)	-	-0.095	(-0.66)	-
Interaction: T2*MSCI	-0.020	(-0.15)	-	0.096	(0.77)	-
Interaction: T3*MSCI	0.286	(0.82)	-	0.377	(1.18)	-
Dollex	-0.208	(-2.15)	**	0.071	(0.8)	-
Interaction: T1*Dollex	-0.533	(-1.39)	-	-0.201	(-0.57)	-
Interaction: T2*Dollex	-1.026	(-3.36)	***	1.034	(3.67)	***
Interaction: T3*Dollex	-1.089	(-2.45)	**	1.007	(2.45)	**
Crude (WTI)	0.024	(1.03)	-	-0.008	(-0.36)	-
Interaction: T1*Crude (WTI)	0.197	(2.2)	**	0.098	(1.19)	-
Interaction: T2*Crude (WTI)	0.022	(0.42)	-	0.083	(1.75)	*
Interaction: T3*Crude (WTI)	0.043	(0.33)	-	0.054	(0.45)	-
CPI	0.001	(0.97)	-	-0.001	(-0.44)	-
Interaction: T1*CPI	0.013	(0.92)	-	-0.016	(-1.22)	-
Interaction: T2*CPI	-0.005	(-0.55)	-	0.007	(0.85)	-
Interaction: T3*CPI	-0.073	(-4.51)	***	-0.022	(-1.49)	-
Constant	-0.004	(-1.15)	-	0.003	(0.83)	-

DEPENDENT VARIABLE = Commodity Returns	**Kansas Wheat**	**Minesota Wheat**

T1 (June 2006 to August 2008)	0.048	(1.18)	-	0.051	(1.36)	-
T2 (September 2008 to June 2010)	0.008	(0.48)	-	0.008	(0.5)	-
T3 (July 2010 to June 2011)	0.073	(3.54)	***	0.065	(3.41)	***
S&P 500	-0.052	(-0.72)	-	-0.063	(-0.94)	-
Interaction: T1*S&P500	0.071	(0.29)	-	0.202	(0.88)	-
Interaction: T2*S&P500	0.061	(0.32)	-	-0.036	(-0.21)	-
Interaction: T3*S&P500	-0.052	(-0.13)	-	0.151	(0.39)	-
MSCI	0.116	(2)	**	0.070	(1.31)	-
Interaction: T1*MSCI	-0.136	(-0.75)	-	-0.120	(-0.72)	-
Interaction: T2*MSCI	-0.059	(-0.37)	-	0.081	(0.55)	-
Interaction: T3*MSCI	0.626	(1.55)	-	0.492	(1.32)	-
Dollex	-0.170	(-1.51)	-	-0.198	(-1.9)	*
Interaction: T1*Dollex	-0.300	(-0.68)	-	-0.044	(-0.11)	-
Interaction: T2*Dollex	-1.559	(-4.39)	***	-1.079	(-3.28)	***
Interaction: T3*Dollex	-1.135	(-2.19)	**	-0.641	(-1.34)	-
Crude (WTI)	0.041	(1.52)	-	0.027	(1.1)	-
Interaction: T1*Crude (WTI)	-0.027	(-0.26)	-	-0.044	(-0.46)	-
Interaction: T2*Crude (WTI)	0.137	(2.29)	**	0.137	(2.48)	**
Interaction: T3*Crude (WTI)	-0.112	(-0.74)	-	-0.091	(-0.65)	-
CPI	0.003	(1.87)	*	0.002	(1.65)	*
Interaction: T1*CPI	-0.018	(-1.1)	-	-0.020	(-1.31)	-
Interaction: T2*CPI	-0.006	(-0.57)	-	-0.007	(-0.7)	-
Interaction: T3*CPI	-0.063	(-3.34)	***	-0.052	(-2.99)	***
Constant	-0.008	(-1.85)	*	-0.006	(-1.51)	-

A3. Bidirectional Relationship between Commodity Market Returns and Macroeconomic Factors

We use a vector autoregression (VAR) framework to capture the relation between macroeconomic variables and commodity market returns in a dynamic setting. The Schwartz Bayesian Information Criterion(SBIC) is used to determine the appropriate lag length for the VAR framework. The variables that we use in our VAR are (i) returns on GSCI, (ii) returns on MSCI, (iii) returns on S&P 500, (iv) inflation rate based on CPI, (v) returns on the WTI (representing oil prices), and (vi) returns on the Dollex index. The lag length obtained for each of the variables, using SBIC is 1. The results of the VAR are given in Table 6.

Table 6: VAR Results

DEPENDENT VARIABLE →	GSCI	MSCI	S&P 500	CPI	WTI	Dollex
No. of Obs	1147					
Log Likelihood	15437.34					
Chi2	6.7021	16.3103	10.0650	198745.4	17.9370	9.2505
P>chi2	0.3493	0.0122	0.1219	0.0000	0.0064	0.1600
Lags of						
GSCI (L1)	-0.004 (-0.08)	-0.105 (-1.81)*	-0.051 (-1.12)	-0.007 (-0.06)	0.154 (1.6)	-0.036 (-1.6)
MSCI (L1)	0.020 (0.52)	0.012 (0.3)	-0.017 (-0.54)	0.039 (0.47)	0.004 (0.06)	0.032 (2.06)**
S&P 500 (L1)	-0.030 (-0.63)	0.126 (2.54)**	-0.063 (-1.63)	-0.122 (-1.2)	-0.074 (-0.9)	-0.036 (-1.87)*
CPI (L1)	-0.002 (-1.97)**	0.000 (0.29)	0.000 (0.37)	0.991 (444.37)***	-0.003 (-1.65)*	0.001 (1.41)
WTI (L1)	-0.024 (-0.75)	0.069 (2.14)**	0.032 (1.25)	-0.054 (-0.81)	-0.172 (-3.21)***	0.018 (1.47)
Dollex (L1)	0.050 (0.63)	-0.018 (-0.22)	-0.076 (-1.21)	0.138 (0.83)	-0.019 (-0.14)	0.001 (0.02)
Constant	0.006 (2.25)	0.001 (0.21)	0.001 (0.29)	0.020 (3.44)	0.008 (1.83)	-0.001 (-1.36)

As may be seen from the table above, there is some evidence of reverse causality or mutual endogeneity, for instance, causality from GSCI, S&P500 and WTI to MSCI, CPI to WTI, and from MSCI, S&P500 to Dollex. We also performed a similar analysis taking individual commodity returns instead of the composite GSCI. Some evidence of mutual endogeniety between these variables is found. There is also in some cases reverse causality from commodity return to macroeconomic factors, for example, from Soybean return to the Dollex index[8].

B. Relationship between Volatility in Commodity Markets and Other Markets

Traditional homoscedastic models are not appropriate when using data for commodity prices, because of the presence of conditional heteroscedasticity. Having tested for the presence of ARCH effect[9], the appropriate lag length for the mean equation is calculated using the

[8] Details available on request

[9] This is done using Engle's Lagrange multiplier test for the presence of autoregressive conditional heteroscedasticity(Adkins & Hill, 2011).

Akaike Information (AIC) criterion. The order of E-GARCH (*p.q)* is estimated using diagnostic tests, t-values and the log likelihood ratio of alternate specifications. Based on the post-estimation diagnostic tests, we choose the following models: E-GARCH(1,1) for GSCI, AR(2)EGARCH(1,2) for MSCI, AR(1) EGARCH(1,1) for S&P 500, ARCH(1) for CPI, EGARCH(1,1) for WTI, and E-GARCH(1,1) for Dollex.

Table 7 gives the parameters of the conditional heteroscedasticity models for all the six variables. The significance of the γ coefficients suggests the presence of leverage effects. The positive values for the various variables suggest that positive shocks generate more volatility than negative shocks. This is surprising, especially in the case of commodity markets, but given the fairly long time series studied, there might be variations from one time period to the other. The coefficient α captures the symmetric effect, and the coefficient β measures the persistence in conditional volatility.

Table 7: Parameter Estimates of Conditional Heteroscedastic Models

Model	E-GARCH(1,1)	AR(2) EGARCH(1,2)	AR(1) EGARCH(1,2)	ARCH(1)	EGARCH (1,1)	EGARCH(1,1)
	GSCI	MSCI	S&P 500	CPI	WTI	DOLLEX
No. of Obs	1154	1154	1154	1148	1154	1154
Wald Chi2	-	29.18***	10.04***	-	-	-
π0	0.000 (0.39)	0.001 (1.45)	0.001 (2.74)***	2.285 (591.51)***	0.000 (0.12)	0.000 (0.03)
π1	-	0.120 (3.58)***	-0.098 (-3.17)***	-	-	-
π2	-	0.116 (3.93)***	-	-	-	-
α1	0.025 (2.08)**	-0.169 (-7.35)***	-0.208 (-10.13)***	1.021 (10.39)***	-0.026 (-1.35)	-0.003 (-0.23)
γ1	0.183 (8.22)***	0.269 (7.30)***	0.266 (7.12)***	-	0.214 (7.99)***	0.125 (4.44)***
β1	0.982 (171.3)***	0.431 (4.41)***	0.456 (3.61)***	-	0.941 (50.47)***	0.974 (72.59)***
β2	-	0.495 (5.15)***	0.485 (3.82)***	-	-	
ω	-0.129 (-3.12)***	-0.536 (-5.56)***	-0.461 (-5.23)***	0.002 (8.08)***	-0.353 (-3.07)***	-0.236 (-1.97)**
Max LL	2540.297	2563.018	2878.249	-472.101	1896.374	3521.541

π_i are the autoregressive parameters, α_i are the ARCH / EARCH parameters, γ_i are the symmetric parameters of EARCH, β_i are the GARCH / EGARCH parameters and ω is the constant.
*** significance at 1%, ** significance at 5%, and * significance at 10% levels.

Based on the parameters estimated according to the conditional heteroscedastic models, the volatility of the various macroeconomic variables and stock market returns are calculated. Tables 8 and 9 report the cross-correlations between volatility of stock market returns and macroeconomic variables for 20 leads and 20 lags. Table 8 reports the results for causality in the variance. Table 9 reports the results for causality in mean (negative lags denote lags of the macro variables, and positive lags denote lags of GSCI).

Causality in variance runs from volatility in MSCI to volatility in GSCI (at lag 0, 1), from volatility in S&P 500 to volatility in GSCI (at lags 0, 1, 8), from volatility in CPI to volatility in GSCI (at lags 1, 12), from volatility in WTI to volatility in GSCI (at lags 0, 15) and from Dollex volatility to GSCI volatility (at lags 16). Causality in variance runs from volatility in GSCI to volatility in MSCI (at lags 0), from volatility in GSCI to volatility in S&P 500 (at lags 0, 1, 13), from volatility in GSCI to volatility in CPI (at lag 5, 9, 10), from volatility in GSCI to volatility in WTI (at lags 0, 1, 3, 8, 9), and from volatility in GSCI to volatility in Dollex (at lags 0, 1). Therefore, we see in some cases, reversal of causality in volatility.

Table 8: Causality of Variance

Correlation between GSCI and	MSCI	S&P500	CPI	WTI	Dollex
-20	-0.0255	-0.0247	0.0117	0.0138	-0.0036
-19	-0.0122	-0.0288	0.0323	-0.0363	-0.017
-18	-0.0205	-0.0242	0.0181	-0.0192	-0.0445
-17	-0.0034	0.0009	0.024	0.0064	0.0436
-16	-0.0401	-0.0256	0.007	0.0164	0.057**
-15	0.014	0.0184	-0.0133	-0.0526*	-0.0347
-14	-0.0281	-0.0179	-0.0066	0.0024	-0.0202
-13	0.0072	-0.0308	0.0138	-0.0136	-0.0241
-12	-0.019	0.0204	-0.0478*	-0.002	-0.0145
-11	-0.0352	-0.0167	-0.0005	-0.0134	-0.0082
-10	-0.0233	-0.0101	-0.0264	0.0253	-0.0305
-9	0.0235	0.0213	0.0125	-0.0151	0.0335
-8	0.0273	0.0626**	-0.0313	0.0369	0.0271
-7	0.0184	0.0317	-0.0454	0.0067	0.0033
-6	0.0071	0.0084	0.0207	-0.0098	0.0221

-5	-0.0012	0.0166	-0.0123	-0.0238	0
-4	-0.0011	-0.0131	0.0064	-0.0016	-0.0337
-3	0.019	0.0002	0.0299	-0.0351	-0.033
-2	0.0211	0.0151	0.1319	-0.0124	0.027
-1	0.0574**	0.0483*	-0.0236**	0.0092	0.049*
0	0.1879***	0.2446***	0.0239	0.7397***	0.1617***
1	0.0419	0.0736***	0.0112	0.0638**	0.0645***
2	-0.0058	-0.0116	0.02	0.0072	0.0164
3	0.0235	0.0044	-0.0281	-0.0439*	0.0286
4	0.0285	0.0437	0.038	-0.0103	-0.027
5	0.0393	0.0141	0.0632**	0.0156	0.0332
6	-0.011	-0.0279	0.0059	0.0206	-0.0138
7	0.0442	-0.0075	-0.001	0.0003	-0.0044
8	0.0066	0.0119	0.025	0.0539*	-0.0425
9	-0.0121	-0.0057	0.0644**	0.0524*	0.0376
10	-0.0339	-0.0111	-0.0448*	0.0201	0.0332
11	0.0466	-0.0061	0.012	0.0081	0.008
12	0.0046	0.0234	-0.0202	0.0021	-0.0242
13	0.0255	0.0803***	-0.0145	0.0117	0.0193
14	0.021	-0.0173	0.0022	0.0326	0.0052
15	0.0023	-0.0395	0.0241	-0.0354	0.0161
16	-0.0329	-0.0157	0.0086	0.0042	-0.0219
17	-0.0014	0.0257	0.0091	0.0375	-0.0065
18	-0.0403	-0.0111	-0.0337	-0.0168	0.0306
19	-0.0042	0.031	0.0212	-0.0107	-0.0126
20	0.0123	0.0142	-0.0006	0.0331	0.0274

*** significance at 1%, ** significance at 5%, and * significance at 10% levels. Negative lags indicate lags of the macroeconomic variables, and positive lags indicate lags of the stock return

Table 9 reports the results for causality in mean. Causality in mean runs from MSCI to GSCI (at lag 0, 2, 10, 19), S&P 500 to GSCI (at lag 0, 2, 8, 17), CPI to GSCI (at lags 2, 3, 5-14, 17, 18, 20), WTI to GSCI (at lag 0) and Dollex to GSCI (at lags 0, 6, 9, 13, 15).Causality in mean runs from GSCI to MSCI (at lags 0, 7, 9, 17), GSCI to S&P 500 (at lag 0, 2, 7, 17, 18), GSCI to CPI (at lags 1, 5, 6), GSCI to WTI (at lags 0, 8) and GSCI to Dollex (at lags 0, 1, 3, 11). Thus, there are mixed patterns of causality with a few reversals depending on lags.

Table 9: Causality of Mean

Correlation between GSCI and	MSCI	S&P500	CPI	WTI	Dollex
-20	-0.019	0.0112	-0.0458*	0.0107	0.0344
-19	0.0613**	0.0265	-0.0424	-0.0102	-0.0321
-18	0.0282	-0.0285	-0.0566**	-0.0123	-0.0238

-17	0.0414	0.0545*	-0.0553**	-0.015	-0.0005
-16	0.0057	-0.0367	-0.0388	0.0255	0.0167
-15	0.0267	0.0398	-0.0417	-0.0087	0.052*
-14	0.032	0.0391	-0.0465*	0.025	-0.024
-13	0.0428	-0.0335	-0.0454*	0.0191	-0.0616***
-12	0.0077	-0.0231	-0.0566**	-0.013	0.0308
-11	-0.0118	0.0169	-0.0585**	-0.0003	-0.0194
-10	0.0533*	0.0081	-0.0647**	-0.0168	0.0374
-9	0.0103	0.0039	-0.0609**	0.011	0.0494*
-8	0.044	0.0754***	-0.0611**	0.0174	-0.0172
-7	0.0255	-0.0084	-0.0531*	-0.0341	0.0208
-6	-0.0078	0.0345	-0.0631**	-0.0017	-0.06**
-5	-0.0004	-0.0277	-0.0532*	0.0069	0.031
-4	0.0196	-0.0025	-0.045	-0.0173	-0.0095
-3	0.0009	0.0282	-0.0622**	0.0209	0.0037
-2	0.0763***	0.0651**	-0.0731**	0.0132	-0.0126
-1	0.0034	-0.0048	-0.046	-0.0156	0.0018
0	0.2171***	0.167***	-0.042	0.8539***	-0.1995***
1	0.011	-0.001	-0.0537*	0.0077	-0.0487*
2	-0.0366	-0.0774***	-0.0305	0.0344	-0.02
3	-0.0079	-0.0181	-0.02	0.0177	-0.0574**
4	-0.037	-0.0406	-0.0206	-0.0117	-0.0356
5	-0.0144	0.0115	-0.0494*	-0.0195	-0.0314
6	-0.008	-0.0184	-0.048*	0.0217	0.0321
7	0.0582**	0.0573**	-0.029	-0.0406	-0.0436
8	0.035	0.0081	-0.036	0.0539*	-0.0361
9	-0.0561*	0.0126	-0.0275	-0.0077	0.0293
10	-0.037	-0.0071	-0.0197	-0.0148	-0.0265
11	-0.0284	0.0123	-0.0287	-0.0094	0.0679**
12	0.0253	-0.0321	-0.0174	-0.0289	-0.0143
13	-0.022	0.0051	-0.0022	0.0134	-0.0216
14	0.0291	0.0342	-0.0334	0.0164	-0.0149
15	-0.0054	-0.0072	-0.0166	0.0315	-0.0116
16	0.0129	0.0126	-0.024	0.0198	-0.01
17	-0.0603**	-0.0572**	-0.0116	-0.0219	-0.0145
18	0.0026	-0.0757***	-0.0253	0.0022	-0.0301
19	-0.027	-0.012	-0.0148	-0.0043	-0.0156
20	0.0048	0.005	-0.0094	-0.0128	0.0159

*** significance at 1%, ** significance at 5%, and * significance at 10% levels. Negative lags indicate lags of the macroeconomic variables, and positive lags indicate lags of the stock return.

The predicted variance for each of the macroeconomic variables and commodity returns are used in a VAR framework, to assess the causality that exists between them, and the direction of causality. The results of the VAR model are given in Table 10. To estimate the appropriate lag length of the VAR model, we use the SBIC. The lag length obtained using this criterion is2 for the relationship between volatility in MSCI and volatility in GSCI, 2 for the relationship between volatility in S&P500 and volatility inGSCI, 1 for the relationship between volatility in CPI and volatility in GSCI,2 for the relationship between volatility in WTI and volatility in GSCI, and 1 for the relationship between volatility in Dollex and volatility in GSCI.

Examination of statistics in the following tables suggest that volatility in commodity market returns has an impact on the volatility in returns of MSCI, Crude Prices and Dollex. In case of MSCI, there is a reverse causality as well. There is also a significant (unidirectional) relationship between volatilities in equity market returns, and volatilities in commodity market returns.

Table 10: Vector AutoregressionResults

(A) Impact of Commodity MarketReturn on Macroeconomic Variables

	MSCI	S&P 500	CPI	WTI	Dollex
No. of Obs	1152	1152	1153	1152	1153
Log Likelihood	15931.34	16205.7	8243.865	15869	20102.21
Chi2	2871.959	2494.931	24891.87	9921.638	16088.25
P>chi2	0.0000	0.0000	0.0000	0.0000	0.0000
Lags of GSCI					
1	-0.166 (-1.71)*	-0.018 (-0.23)	5.236 (0.34)	0.880 (6.04)***	0.001 (1.75)*
2	0.178 (1.87)*	0.049 (0.65)		-0.697 (-4.74)***	
Constant	0.000 (3.53)***	0.000 (2.82)***	0.012 (0.66)	0.000 (3.53)***	-0.000 (4.08)***

*** significance at 1%, ** significance at 5%, and * significance at 10% levels.

(B) Impact of Macroeconomic Variables on Commodity MarketReturns

	MSCI	S&P 500	CPI	WTI	Dollex
No. of Obs					
Log Likelihood					

Chi2	25078.9	25438.69	24058.01	24496.69	24037.39
P>chi2	0.0000	0.0000	0.0000	0.0000	0.0000
Lags of Macroeconomic variables					
1	0.024 (3.09)***	0.013 (1.23)	-0.000 (-1.01)	-0.001 (-0.07)	0.026 (0.26)
2	0.011 (1.38)	0.044 (4.18)***		-0.009 (-1.02)	
Constant	0.000 (1.52)	0.000 (2.35)**	0.000 (3.03)***	-0.000 (3.83)***	0.000 (1.27)

*** significance at 1%, ** significance at 5%, and * significance at 10% levels.

In our IRFs, we see the impact of a 1 unit positive shock to one variable on the other. The graphs of impulse response function (IRFs) and forecast error variance decomposition (FEVDs) are given in Figure 3.We employ Granger causality tests to find whether there exists any relationship between macroeconomic variables and stock returns, and the direction of causality. In the Granger test of causality, lags of one variable enter into the equation for the other variable. The Granger causality results are given in Table 11. The key findings are summarized below:

- The relationship between volatilities in GSCI and MSCI is unidirectional, the direction being from the former to the latter. A shock to GSCI results in a negative response in MSCI for two periods, followed by a positive response, and after a series of fluctuations, takes the value above its positive equilibrium in the next five periods. The process of returning to the equilibrium value is gradual, and take upto 100 periods.
- The relationship between volatilities in GSCI and S&P 500 is also unidirectional, the direction being from the former to the latter. A shock to GSCI results in a small negative response in S&P500, followed by a positive response for the next 20 periods. There is a gradual adjustment process which brings the value back to equilibrium from its positive high, which takes more than 100 periods.
- No significant relationship is found between GSCI volatility and CPI volatility, hence, we do not report or comment on the IRFs
- The relationship between volatilities in GSCI and WTI is bidirectional. A shock to GSCI generates a positive response in WTI which continues for about 25 periods, and then starts declining towards the equilibrium value, which is a long but gradual process, and

takes more than 100 periods. A shock to WTI generates an initial negative response in GSCI, and then there is a positive movement towards the equilibrium value.

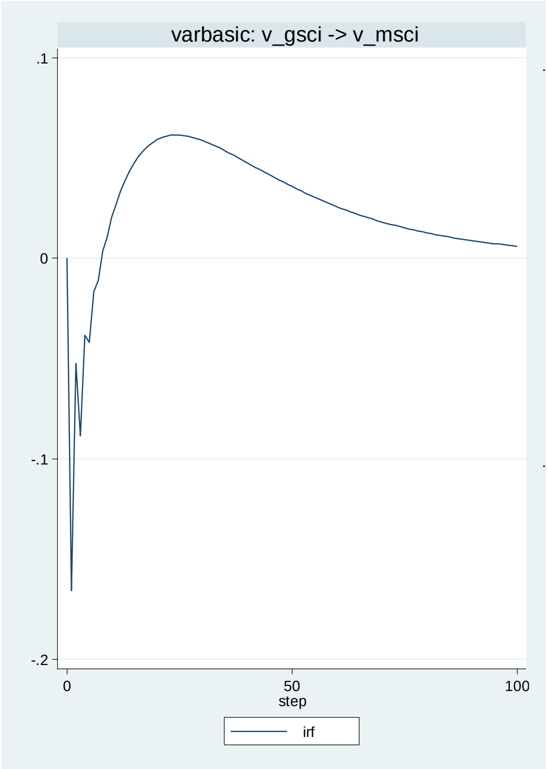
- The relationship between volatilities in GSCI and Dollex is unidirectional, the direction being from the latter to the former. A shock to Dollex generates a positive response in GSCI which persists for about 50 periods, and then starts declining towards the equilibrium value, which is a long but gradual process, and takes more than 200 periods.

Table 11: Granger Causality Results

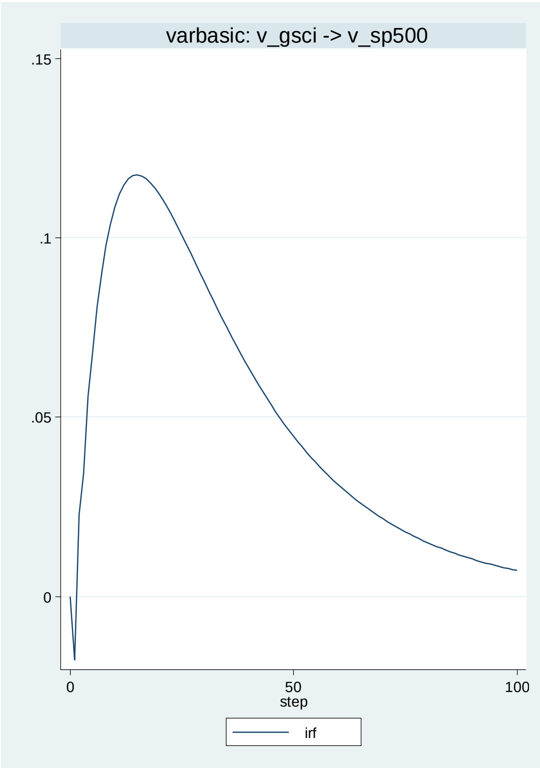
Null Hypothesis	**Chi2**	**Prob.>Chi2**
Volatility in GSCI does not Granger cause volatility in MSCI	32.403	0.000***
Volatility in MSCI does not Granger cause volatility in GSCI	3.6599	0.160
Volatility in GSCI does not Granger cause volatility in S&P 500	48.648	0.000***
Volatility in S&P 500 does not Granger cause volatility in GSCI	2.87	0.238
Volatility in GSCI does not Granger cause volatility in CPI	1.0118	0.314
Volatility in CPI does not Granger cause volatility in GSCI	0.11439	0.735
Volatility in GSCI does not Granger cause volatility in WTI	6.1144	0.047**
Volatility in WTIdoes not Granger cause volatility in GSCI	49.417	0.000***
Volatility in GSCI does not Granger cause volatility in Dollex	0.068	0.794
Volatility in Dollex does not Granger cause volatility in GSCI	3.0588	0.080*

*** significance at 1%, ** significance at 5%, and * significance at 10% level

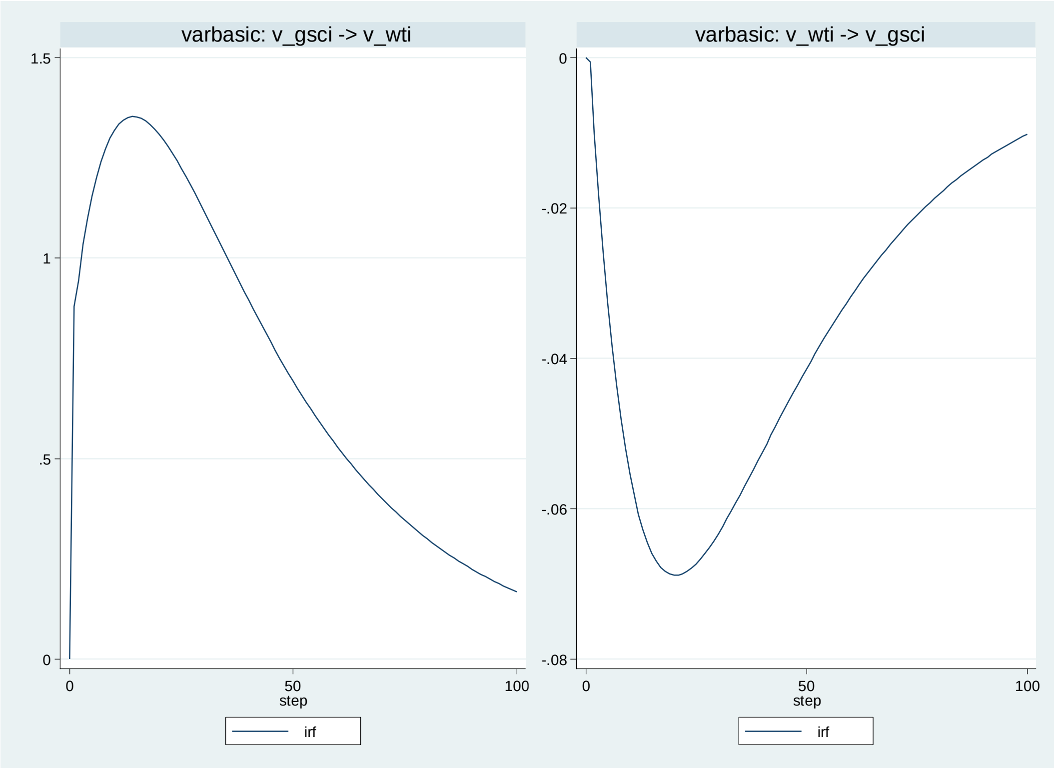
Figure 3: IRFs



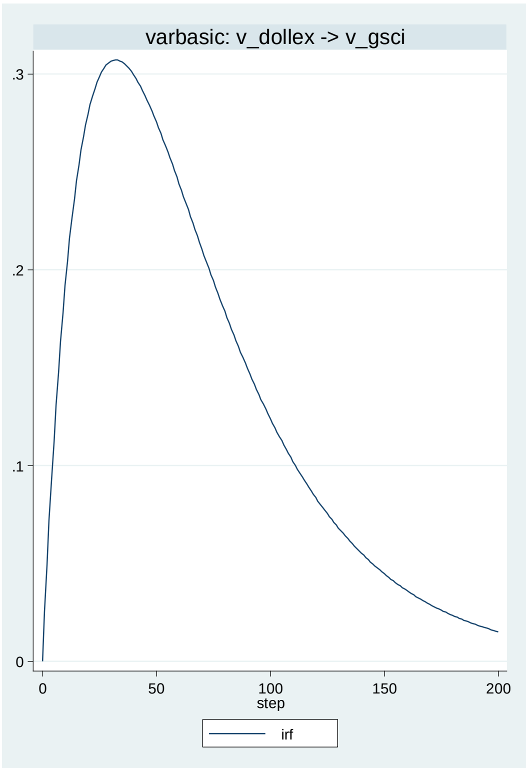
Impulse: GSCI, Response: MSCI



Impulse: GSCI, Response: S&P 500



Impulse: GSCI, Response: WTI ---- Impulse: WTI, Response: GSCI



Impulse: Dollex, Response: GSCI

6. Concluding Observations

The present study builds on the extant literature on financialisation of commodity markets, and assesses the impact of macroeconomic factors on commodity prices, linking both returns and volatility to each other in a dynamic set up.

Our results show a negative relationship between the commodity market returns and the Dollex, and a positive relationship between commodity market returns and crude oil price returns. The impact of equity markets, inflation and emerging market performance on commodity markets is weak.Since the variables in the macroeconomic framework are integrated, we use a VAR framework to capture the relation between each of the macroeconomic variables and commodity market returns in a dynamic setting. We find some evidence of reverse causality or mutual endogeneity, for instance, causality from GSCI, S&P500 and WTI to MSCI, CPI to WTI, and MSCI, S&P500 to Dollex. A similar analysis is also performed using individual commodity returns (for Corn, Soyabean, Chicago Wheat and Kansas Wheat) instead of the composite GSCI.

There are also causal relationships, obtained using the cross-correlation function and Granger causality tests, between the volatility of returns on macroeconomic variables and volatility of return on commodity markets. Our results confirm a unidirectional relationship from (volatilities of) GSCI to S&P500, from GSCI to MSCI, and from Dollex to GSCI. There is also evidence of atwo-way causality between Inflation and GSCI (volatilities).

In conclusion, serious doubts are raised about the findings confirming a strong link between financialisation of commodity/food markets and food pricesand their volatility. Although there is evidence of causality from indices such as S&P500 and MSCI to commodity/food returns and their volatility, there is also evidence of reversal of causality in which commodity/food returns drive S&P 500 and MSCI. Macro factors such as inflation and the dollar exchange rate Granger -cause commodity /food returns while the latter also cause the former. A two-way causality between commodity/food returns volatility and these indices is confirmed, as also between macro factors and commodity/food volatility. Taken together, the case for financialisation of commodity/food markets driving commodity/food returns and their volatility rests on weak foundations, leaving the door open for the pivotal role of supply-demand fundamentals.

ANNEXURE 1: DEFINITIONS OF VARIABLES USED IN THE STUDY

The S&P **GSCI** is designed to be a "tradable" index, providing investors with a reliable and publicly available benchmark for investment performance in the commodity markets. The index comprises the principal physical commodities that are traded in active, liquid futures markets. In addition to numerous related and sub-indices calculated on a single component and multi-currency basis, thematic baskets such as Biofuel and Petroleum are available.

MSCI Emerging Market Index is a free float-adjusted market capitalization index that is designed to measure equity market performance in the global emerging markets.It measures equity market performance in 21 global emerging markets, covering large and mid-cap securities in all industries in the following countries: Brazil, Chile, Columbia, Mexico, Peru, Czech Republic, Egypt, Hungary, Morocco, Poland, Russia, South Africa, Turkey, China, India Indonesia, Korea, Malaysia, Philippines, Taiwan, and Thailand. The Bloomberg ticker symbol for this index is MXEF.

WTI Crude Future (Bloomberg ticker for generic futures series is CL1) traded on NYMEX has a futures contract size of 1000 barrels. The delivery point is Cushing, Oklahoma, US. Light, sweet crudes are preferred by refiners because of their low sulphur content and relatively high yields of high-value products such as gasoline, diesel fuel, heating oil, and jet fuel.

CPI represents changes in prices of all goods and services purchased for consumption by urban households. User fees (such as water and sewer service) and sales and excise taxes paid by the consumer are also included. Income taxes and investment items (stocks, bonds and life insurance) are not included.

DOLLEX currency is a weighted geometric mean of the dollar's value compared only with "baker" of 6 other major currencies which are Euro (57.6% weight), Japanese Yen (13.6%), Pound Sterling (11.9% weight), Canadian Dollar(9.1% weight), Swedish Krona (4.2% weight), Swiss Franc(3.6% weight). It can be traded on Intercontinental Exchange.

For the commodities, weekly closing price of generic futures series (includes near month futures contract) has been downloaded from Bloomberg. We have used weekly prices to calculate weekly returns (log difference of prices) for each of the four commodities.

Soybean(Bloomberg ticker of generic futures:S1)traded on Chicago Board of Trade with a contract size of 5,000 bushels. The deliverable grade for soybeans is #2 Yellow at contract price, #1 Yellow at a 6 cent/bushel premium, #3 Yellow at a 6 cent/bushel discount. The soybean price is quoted in US cents per bushel. The contract months for CBOT Soybean futures are January, March, May, July, August, September and November.

Corn(Bloomberg ticker of generic futures:C1) traded on Chicago Board of Trade with a contract size of 5,000 bushels and calls for the delivery No. 2 yellow corn. The corn price is quoted in US cents per bushel. The contract months for the Chicago Board of Trade corn future are March, May, July, September and December.

Kansas Wheat (Bloomberg ticker of generic futures: KW1) traded on Kansas City Board of Trade with a contract size of 5000 bushels. The price of the futures contract is quoted in US cents per bushel. The deliverable grade of the futures include No. 2 at contract price with a maximum of 10 IDK per 100 grams; No. 1 at a 1 1/2-cent premium.

Minnesota Wheat (Bloomberg Ticker of generic futures: MW1) traded on Minneapolis Grain Exchange with a contract seize of 5000 bushels. The deliverable grade for the contract is No. 2 or better Northern Spring Wheat with a protein content of 13.5% or higher, with 13% protein deliverable at a discount. The contract months are March, May, July, September (New Crop) and December.

Rough Rice (Bloomberg ticker of generic futures:RR1) traded on Chicago Board of Trade with a contract size of 2000 hundredweight(cwt.). The deliverable grade is US No. 2 or better long grain rough rice with a total milling yield of not less than 65%, including head rice of not less than 48%. Rough rice can be used to produce five different types of rice - hulls, bran, brown rice, whole-kernel milled rice, and brokens (broken-kernel milled rice). The contract months for CBOT Rough Rice future are January, March, May, July, September and November.

Wheat (Bloomberg ticker of generic futures: W1) traded on Chicago Board, contract calls for the delivery of #2 Soft Red Winter at contract price, #1 Soft Red Winter at a 3 cent premium and other deliverable grades. The wheat price is quoted in US cents per bushel. The contract months for CBOT Wheat futures are March, May, July, September and December.

Soybean oil (Bloomberg ticker of generic futures: B01) traded on Chicago Board of Trade, has a contract size of 60,000 pounds (lbs). The deliverable grade of soybean oil includes crude soybean oil meeting exchange-approved grades and standards. The price is quoted in US cents per pound. The contract months for the commodity are January, March, May, July, August , September, October and December.

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