# “Modeling tail risk in Indian commodity markets using conditional EVT-VaR and their relation to the stock market”


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| **AUTHORS** | Shalini Agnihotri<br>Kanishk Chauhan |



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**Shalini Agnihotri** (India), **Kanishk Chauhan** (India)

# MODELING TAIL RISK IN INDIAN COMMODITY MARKETS USING CONDITIONAL EVT-VAR AND THEIR RELATION TO THE STOCK MARKET

## Abstract

Investment in commodity markets in India accelerated after 2007; this was accompanied by large price variability, hence, it becomes imperative to measure commodity price risk precisely. It becomes equally important to study the relationship between commodity price variability and the stock market. Hence, this study aims to calculate the tail risk of highly traded Indian commodity futures returns using the conditional EVT-VaR method for risk measurement. Secondly, the linkage between commodity markets and the stock market is also studied using the Delta CoVaR method. Results highlight the following points. There is risk transfer from the extreme increase/decrease in crude oil futures returns to the Nifty Index returns. Both extreme price increase or decrease of crude oil futures driven either by financial or a combination of financial and economic shocks affect the stock market. Zinc and Natural gas futures are not linked to the stock market, which means they can be useful in portfolio diversification. The findings suggest that, in Indian commodity markets, EVT-VaR is a useful tool for measuring risk. Only Crude oil futures shocks affect the stock market, and extreme integration between them becomes more prominent when oil shocks are driven by financial factors. Commodities other than Crude oil are not integrated with stock markets in India.

**Keywords** Delta Co-VaR, portfolio diversification, quantile regression, financialization of the commodity market, value at risk, systemic risk, India

**JEL Classification** G01, G11, Q43

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Shalini Agnihotri, Assistant Professor Management Faculty, Finance Department, Indian Institute of Management, Vishakhapatnam, Andra Pradesh, India. (Corresponding author)

Kanishk Chauhan, Student-IIT Kanpur, Uttar Pradesh, India.

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## INTRODUCTION

In India, investment in commodity markets increased after 2007, which led to a commodity price boom accompanied by price variability. Commodity price volatility is an important issue for an agrarian economy like India. Financialization[1] of the commodity markets has led to a changed correlation dynamics of commodity futures returns with the traditional asset class returns in international markets. An institutional investor invests simultaneously in the stock market and commodity markets (through commodity index investing or derivatives) to diversify their portfolios. Hence, they might link both markets through their financial activity. Literature has documented the important role of institutional investors' behavior in the increased relationship between the stock market and the commodity market and, finally, its impact on commodity prices (see e.g., Buyuksahin & Robe, 2014; Adams & Gluk, 2015). Nazlioglu et al. (2015) have also documented that before the global financial crisis in 2007, risk transferred from oil prices to St. Louis Fed Financial Stress Index. Many com-

1 Growing influence and participation of institutional investors in commodity markets.

modities have experienced large price variability, which attracted the attention of policymakers and researchers on risk measurement and management in the commodities.

A key issue to understand is whether financialization has led to increased commodity price volatility and linkage of the commodity market with the stock market in India. Or else it is majorly driven by fundamental factors of demand and supply. According to Watugala (2015), commodity volatility is predictable by macroeconomic uncertainty and financial uncertainty. For example, the state of the economy affects commodity supply and demand. Growing commodity demands in emerging markets affect commodity volatility. Hence they constitute the fundamental factors affecting commodity price volatility. Singleton (2014) documented that open interest has an important impact on crude oil prices with increased financialization of commodity markets. Kilian and Park (2009) documented that variations in U.S. stock returns can be explained by demand and supply shocks from crude oil. Therefore, it becomes important to study whether economic factors (supply and demand), financial factors, or a combination of both affect commodity prices volatility and their linkage with the stock market (Irwin & Sanders, 2012; Cheng & Xiong, 2014). These factors can help in a thorough analysis of the different channels through which uncertainty influences commodity futures prices and, finally, the linkage of commodity futures to the stock market. Therefore, this study contributes to the literature, firstly, by estimating the tail risk of highly traded commodities in India, and secondly, by estimating the linkage of commodity futures market uncertainty to the stock market.

## 1. LITERATURE REVIEW

Price variability in commodity markets has increased since 2007. The dynamics of a linkage between financial markets and commodity markets are also changing post-2007. Hence, it is important to measure the commodity price volatility, its linkage to the stock market, and underlying factors impacting the linkage. Therefore, a review of the literature will be discussed in two sections, the first section is focused on various methods used in the literature to calculate the downside risk (risk measurement) of asset classes, and the second section highlights the literature relating to the linkage of commodity futures market uncertainty to the stock market.

This section focuses on various methods used in the literature for calculating downside risk. McNeil and Frey (2000) developed two-stage models to calculate downside risk of stock indices. They combined the GARCH model with the EVT toolkit to cater to the problem of asset returns. The GARCH -EVT framework was able to handle non-normality, as well as heteroscedasticity problems of return series. By using ARMA-GARCH, filters series become i.i.d, better suited for fitting EVT. Many studies have shown the GARCH-EVT framework's superiority compared to other methods in estimating VaR. Bali and Neftci (2003) applied the GARCH-EVT framework to the U.S. short-term interest rate. They used Student-t distribution in modeling the return distribution in the GARCH model. They documented that EVT gave better results than other comparative methods. Karmakar and Shukla (2015), Sinha and Agnihotri (2018), Ergun and Jun (2010), and Watanabe (2012) documented the superiority of using the GARCH-EVT framework for estimating tail risk. Most of these studies focused on estimating left tail risk; in this study both left and right tail risk is studied for the commodity futures market. As in the case of commodities, the right tail is equally important as an extreme increase in the price of a commodity can hurt the market as a whole. All the above studies focus on univariate tail risk estimation. This study extends the above literature by estimating the univariate tail risk in commodity futures and estimating its impact on the stock market. It is important to study how extremely low or high risk in commodities impacts Nifty index.

Following studies in the literature on risk spillover (linkage) between commodity markets and stock market, Reboredo et al. (2016) use the CoVaR method to measure the extreme risk co-movement. CoVaR methodology estimates tail dependence and risk spillover. They have used the Copula VaR method. Chevallier


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et al. (2014) studied volatility spillover in commodity markets. Many studies focus on calculating CoVaR measures to determine systemic risk from oil markets to the rest of the economy, such as Ji et al. (2018)[2]. They used the Copula GARCH model. They documented that there is a contagion risk emanating from oil-specific demand shock to BRICS countries' stock returns. They documented that there is an asymmetric upside, and downside risk spillover is more pronounced with the oil demand shock in India. Kilian and Park (2009) study the effect of oil shocks on countries' equity markets. But research on commodities other than oil is scarce. Gupta and Modise (2013) analyzed different channels of oil price shocks and their impact on South African stock return. Tang and Xiong (2012), Buyuksahin and Robe (2014), Cheng and Xiong (2014), and Bhardwaj et al. (2016) investigated the co-movement between the commodity futures market and the stock market. Kaltalioglu and Soytas (2011) studied how agricultural prices are impacted by oil price shocks and concluded that there is an impact of oil shocks on agricultural prices. Chng (2009) documented that palladium, rubber, and gasoline futures markets are highly interconnected in TOCOM (Tokyo Commodity Exchange). All the above studies majorly focus on the comovement between commodity and stock markets. These studies have not considered the impact of exogenous (underlying factors) factors on the connectedness between asset returns.

Studies in financial sector systemic risk, like the SRISK index of Acharya (Acharya et al., 2012; Brownlees & Engle, 2017), "Shapley Value" (Drehmann & Tarashev, 2013), and the delta-CoVaR method of (Adrian and Brunnermeier, 2011), consider exogenous factors while calculating CoVaR. Hence, in this study, Adrian and Brunnermeier's (2011) methodology is employed to study the contagion risk transfer from the commodity futures returns to the stock market considering exogenous shocks.

Based on the above literature survey, the following gaps appear: very few studies estimate the downside and upside tail risk of highly traded commodity futures in Indian markets with a novel technique of EVT-VaR. Further, most previous studies have considered the co-movement between commodity and stock markets with no exogenous factors. Hence, the purpose of this study is to simultaneously estimate tail risk of highly traded Indian commodity futures return and to study the impact of risk emanating from the commodity market to stock market using exogenous factors acting as determinants of risk for commodity future prices.

## 2. METHODOLOGY

In the following section, the methodology of tail risk, conditional EVT method and CoVaR is discussed.

**EVT and Co-VaR Calculation:** In this study, the McNeil and Frey (2000) methodology is used to study tail risk, where they used the Generalized Pareto Distribution (GPD) to model the tail of the distribution. VaR function using the Pareto distribution is as follows:

$$VaR_q = u + \frac{\beta}{\xi}\left(\left(\frac{n}{N_u}(1-q)\right)^{-\xi} - 1\right), \qquad (1)$$

where, $VAR_q$ represents *VaR* at quantile *q*, *u* is the threshold, $\beta$ = scale parameter, $\xi$ = shape parameter, *n* = total number of observations, and $N_u$ = the number of observations above a threshold. $r_t$ = log return at time *t*, tail probability= $\alpha$. VaR of a long financial position is denoted by left tail of the distribution and is given by ($r_t \leq -VaR_{\alpha,t}\ long$) = $\alpha$, whereas the *VaR* of a short financial position is related to the upper tail of the return's distribution. Thus, in this paper, both downside and upside risk is calculated for commodity futures returns.

### 2.1. Co-VaR calculations

Adrian and Brunnermeier's method (2011) is used to estimate the risk emanating from commodity markets. Quantile regression[3] is used for the same.

2 Kilian and Park (2009), Abhyankar et al. (2013).

3 Koenker and Bassett (1978).

The following steps are used in estimating Co-VaR:

Step 1: $\tau$ quantile regression is run (where $\tau$ is 0.01). Three equations are run for every commodity future series. Equation (2) corresponds to financial uncertainty variables that drive the individual commodity market return, equation (3) corresponds to the impact of economic uncertainty variables, and equation (4) corresponds to financial and fundamental uncertainty factors. In this way, it is possible to understand that tail dependence is determined by either financial drivers (financial transmission), economic variables (fundamental-based transmission), or both factors. The confidence level $\tau$ is set at 1% for the left tail and 99% for right tail dependence.

$$R_t = \mu_t + \beta_1 x_1 + \beta_2 x_2 + \sigma_t z_t \quad (2)$$

where $R_t$ corresponds to return of commodity futures eturns analogous to market used by Adrian and Brunmmier (2011), $x_1$ corresponds to open interest, and $x_2$ corresponds to return of VIX.

Second equation is modelled by economic variables

$$R_t = \mu_t + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \sigma_t z_t, \quad (3)$$

where $x_3$, $x_4$, and $x_5$ correspond to USD/INR return, MSCI return and t-bill return, respectively.

In the third model, combination of equations (2) and (3) is used to study the mixed model.

$$R_t = \mu_t + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \\ + \beta_4 x_4 + \beta_5 x_5 + \sigma_t z_t. \quad (4)$$

In stage 1, quantile regression is run on equations (2), (3), and (4) using only financial, economic, and all variables. The equation is run for three markets of interest crude oil, natural gas, and zinc.

Step 2: $\tau$ VaR (1% and 99%) is obtained for all the three commodity as predicted values.

Step 3: First two steps are repeated keeping $\tau$ as 50% in order to obtain 50% VaR for commodity *i*.

Step 4: CoVaR of system is calculated, which is the VaR of system condition on oil, natural gas and zinc markets being in distress both on lower and upper tail distribution ($\tau$ fixed at 1% and 99%).

$$CoVaR_t^{system|R^i = VaR_{R^i(\tau_i)}}(\tau) = \\ = \hat{\mu} + \hat{\beta}\widehat{VaR_t^i(\tau_i)} + \hat{c}Z_t, \quad (5)$$

where $R_{system}$ denotes log returns of C&X NSE 500 index returns. $VAR_t$ is VaR calculated in the earlier step, and $z_t$ is term spread.

VaR in a normal condition is also calculated, which is VaR of system condition on the normal situation in oil, gas and zinc markets (represented by 50% quantile regression).

$$CoVaR_t^{system|R^i = VaR_{R^i(50\%)}}(\tau) = \\ = \hat{\mu} + \hat{\beta}\widehat{VaR_t^i(50\%)} + \hat{c}Z_t, \quad (6)$$

where $\hat{\mu}$, $\hat{\beta}$ and $\hat{c}$ are estimated parameters from equations (2), (3), and (4).

Step 6: The $\Delta CoVAR$ measure can be calculated as follows:

$$\Delta CoVaR_t^{system|i}(\tau) = CoVaR_t^{system|R^i = VaR_{R^i(\tau_i)}} \\ (\tau) - CoVaR_t^{system|R^i = VaR_{R^i(50\%)}}(\tau), \quad (7)$$

where $\hat{\mu}$, $\hat{\beta}$ and $\hat{c}$ are estimated parameters from equations (2), (3) and (4); $\Delta CoVAR_t^{system|i}$ compares the CoVaR for "stressed" and normal result for market *i*. When $\tau$ is 99%, the interpretation of $\Delta CoVAR$ means an increase in losses to the rest of the economy when the given market is in distress.

## 3. DATA DESCRIPTION

Daily data of crude oil, natural gas, and zinc futures traded on Multicommodity Exchange (MCX) are taken from July 23, 2009 to April 17, 2020. A total of 2,802 observations. Data is taken from the Thomson Reuters DataStream database. The first generic future contract series (it considers each date price of the contract with the closest maturity) has been used.

C&X Nifty 500 index is taken in the study. It represents 96.1% of the free-float market capitalization of the stock listed on the NSE (National Stock Exchange). It comprises 500 large Indian firms. It is a benchmark indicator of overall stock market conditions. It is a barometer of the Indian economy.


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**Table 1.** Percentage of total contracts of commodity futures traded on MCX

Source: MCX.

| Commodity trading in MCX (% of total contracts traded) | Trading data as of end of 2019 |
|---|---|
| Energy | 70% |
| Base metal | 16% |
| Agriculture | 1% |

Data for commodity futures for the three most traded commodities listed on MCX (multi-commodity exchange) is analyzed. As shown in Table 1, most trading happens in energy commodities, after base metals. Hence, Crude oil futures (oil), natural gas futures (gas), and zinc futures (zinc) daily closing prices are taken in this study (these variables are taken as analogous to the institution taken by Adrian and Brunnermeier (2011)). Commodity futures prices are taken because they are important price signals to guide commodity demand and spot price (e.g., Antoniou & Foster, 1992). It is important to understand how speculations in the commodity futures market affect the Nifty index. As the broader index in the commodity market in India started in 2019, highly traded individual commodities were therefore taken. A set of variables entering quantile regression are taken from the literature (Fama & French, 1989; Ferson & Harvey, 1994) as possible drivers of commodity and stock market returns. Financial variables used in the study are the following:

**India VIX** – Volatility index of India, it captures the implied volatility of Nifty index option prices. It indicates the expected market volatility over the next 30 days. It is an indicator of investor sentiments.

**Future aggregate open interest** – Total outstanding future contracts held at the end of each trading day. It measures the flow of money in the futures market (Hong & Yogo, 2012). Data on India VIX is available from 2008, hence taking data consistency, daily data from 2009 onwards is taken.

The fundamental variable used in the study is as follows:

**MSCI Emerging market Index** – It is a proxy for the strength of economic growth in emerging markets. It determines as a proxy for the commodity demand in emerging markets' (Tang & Xiong, 2012) USD/INR exchange rate daily data. It accounts for the exposure of commodity futures to exchange rate risk (Algieri, 2014a) Government 3-month T-Bills daily return, a short-term interest rate indicator. Variable Z included in equation (12) is term spread. It is calculated as the difference between a 10-year government bond and a 3-month T-bill rate. It is an indicator of output growth and recession (Wheelock & Wohar, 2009).

## 4. RESULTS

In this study, price series are converted into log returns. Table 2 shows that the mean return of natural gas and oil is negative, while zinc has positive mean returns. Standard deviation is maximum for gas returns. Oil is negatively skewed, while gas and zinc are positive. Kurtosis is higher than 3 in all three cases. Jarque-Berra test is rejected for all the three commodity future return series. That means series are non-normal. The ADF unit root test checks the stationarity of the series. It is evident from the results that the return series of all the three commodity derivatives are stationary as null is rejected. To check heteroscedasticity, the ARCH LM test is used. It is evident from the results that heteroscedasticity is present in all three commodity futures prices. Hence, the GARCH family of methods is used to model volatility.

For NIFTY and MSCI, it is also evident that both are negatively skewed and non-normal. The mean return of both is positive. It is evident from the results that returns of both the series are stationary as null is rejected. USD/INR mean returns are positive over the sample period, whereas its kurtosis is higher than 3.

Table 3 reports that Nifty has the highest correlation with oil, then with zinc, and least with gas. If we look at correlations among the commodity futures, oil and zinc have the highest correlation.

The shape parameter is negative for Nifty, and it is positive for the rest of the commodities. This im-

**Table 2.** Descriptive statistics

Source: Authors' calculations.

| Statistic | Mean | Maximum | Minimum | Std. Dev. | Skewness | Kurtosis | Jarque-Bera | Unit Root | ARCH LM (20 lags) |
|---|---|---|---|---|---|---|---|---|---|
| GAS | −0.00012 | 0.216 | −0.239 | 0.028 | 0.337 | 9.146 | 4462.076** | −53.5** | 12.07** |
| INR | 0.00016 | 0.032 | −0.021 | 0.004 | 0.366 | 7.869 | 2829.468** | −51.0** | |
| MSCI | 0.00003 | 0.056 | −0.069 | 0.010 | −0.604 | 7.688 | 2735.28** | −43.8** | |
| NIFTY | 0.00026 | 0.074 | −0.137 | 0.010 | −1.220 | 19.173 | 31222.49** | −18.8** | 48.38** |
| OIL | −0.00029 | 0.234 | −0.258 | 0.022 | −0.740 | 24.907 | 56267.53** | −53.5** | 51.49** |
| SPREAD | −0.00274 | 5.410 | −6.840 | 0.217 | −11.842 | 641.446 | 47637352** | −36.5** | |
| T_BILL | 0.00007 | 0.726 | −0.724 | 0.022 | 0.777 | 790.651 | 72405378** | −36.4** | |
| VIX | 0.00006 | 0.497 | −0.414 | 0.050 | 0.455 | 11.165 | 7877.069** | −50.8** | |
| ZINC | 0.00023 | 0.094 | −0.076 | 0.015 | 0.060 | 5.707 | 856.9157** | −54.9** | 5.04** |

*Note*: ADF stands for the Augmented Dicky-Fuller test, which has a null hypothesis that series has a unit root. Time period considered for the analysis is from July 23rd, 2009 till April 17th, 2020. ARCH test is used to check heteroskedasticity in data, which has the null hypothesis of homoskedasticity. ** and * denote significance at 1% and 5%, respectively. GAS refers to Natural Gas futures, Oil stands for crude oil future series, and zinc stands for zinc metal futures. Spread is the difference between the 10-year government bond rate and 91-day T-bill rate. Nifty stands for the NIFTY 500 index log return, MSCI stands for MSCI emerging market index return.

**Table 3.** Correlations of variables used in the study

Source: Authors' calculation.

| | Nifty | Oil | Gas | Zinc |
|---|---|---|---|---|
| Nifty | 1 | | | |
| Oil | 0.140846 | 1 | | |
| Gas | −0.01038 | 0.131899 | 1 | |
| Zinc | 0.110072 | 0.259442 | 0.01857 | 1 |

**Table 4.** EVT parameter estimates of the Nifty index and commodity futures

Source: Authors' calculation.

| Panel 1: EVT Parameters Estimates | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | GASL | GASU | OilL | OILU | NiftyL | NiftyU | ZINCL | ZINCU |
| Threshold[4] | 1.445 | 1.542 | 1.514 | 1.46 | 1.401 | 1.6015 | 1.55 | 1.552 |
| Nu(%) | 5.9% | 5.4% | 6.4% | 6% | 6.3% | 5.5% | 6.3% | 5.5% |
| Shape Parameter | 0.21** | 0.140* | 0.196* | 0.185** | −0.25* | −0.462* | 0.109* | −0.42 |
| Scale Parameter | 0.39* | 0.67* | 0.731** | 0.430* | 0.74* | 0.728* | 0.491* | 0.921* |
| VaR@99% | −0.062 | 0.075 | −0.057 | 0.049 | −0.024 | 0.021 | −0.036 | 0.036 |
| **Panel 2: Back Testing Result** | | | | | | | | |
| Exceedance expected | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 18 |
| Actual | 14 | 19 | 15 | 23 | 23 | 9 | 13 | 16 |
| LRUC | 0.97 | 0.97 | 0.53 | 1.28 | 1.28 | 0.9 | 1.586 | 0.53 |
| LRIND | 2.77 | 2.77 | 7.84 | 0.58 | 0.59 | 0.92 | 0.29 | 7.84 |
| LRCC | 3.74 | 3.74 | 8.37 | 1.87 | 1.87 | 1.82 | 1.87 | 8.37 |

*Note*: LRUC stands for an Unconditional test. LRIND stands for the Independence test. LRCC stands for the Conditional coverage test. ** and ** denote significance at 1% and 5%, respectively. Nu (%) represents a percentage of values above the threshold. GASL, OilL, NiftyL, and ZincL represent Natural gas futures, Crude oil futures, nifty500 index and zinc futures lower tail parameters, respectively. GASU, OilU, NiftyU and ZincU represent Natural gas futures, Crude oil futures, nifty500 index and zinc futures upper tail parameters, respectively.

plies that all the commodities have heavy tail distributions. It is evident from the VaR values that if investors take a long position in natural gas futures, maximum possible loss in one day at 99% confidence is 6.2%. Whereas, in a short position, maximum possible loss in 1 day at 99% is 7.5%. In the case of oil maximum possible loss at 99% confidence is 5.7%, whereas in the case of a short position, it is 4.9%. In zinc, maximum possible loss at 99% confidence in the long position is 3.6%, while in the short position, it is 3.6%. The riskiest commodity futures is natural gas.

4 For calculating VaR for left tail. Returns are multiplied by −1, and the values of upper threshold are calculated.


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Source: Authors' calculations.

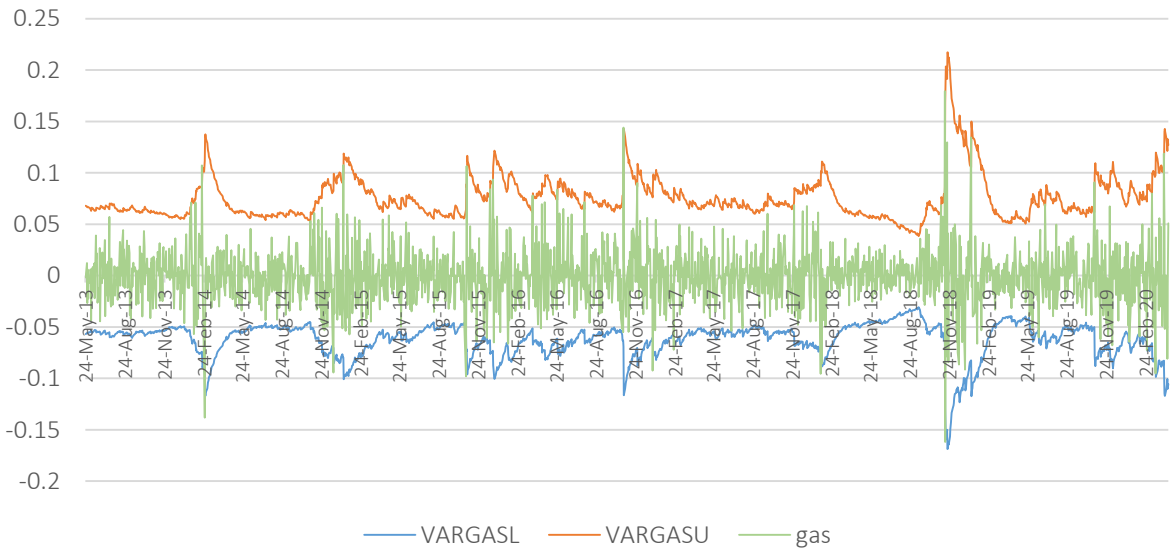


**Figure 1.** Rolling VaR values and returns of natural gas futures

The backtesting result documents that all the commodity passes backtesting using the EVT method. Backtesting has a combination of two tests. One is a test of unconditional coverage, where the null hypothesis says violations = p (level of significance) = 0.01. If the null hypothesis is accepted, the model passes backtesting. The second test is the test of independence; its null says violations are independent of one another. Panel B of Table 4 clearly shows that in all the cases, the model is accepted.

Figures 1, 2 and 3 show rolling VaR for oil, gas, and zinc. It is evident that VaR values also fit to return series with very few violations in turbulent times. Hence, the conditional EVT method is the right choice for tail risk calculations.

The next objective is to ascertain the risk transmission from the commodity market to the stock index. VaR values calculated using EVT are taken. The Nifty 500 index return as a dependent variable is taken, while the present study takes the VaR val-

Source: Authors' calculations.

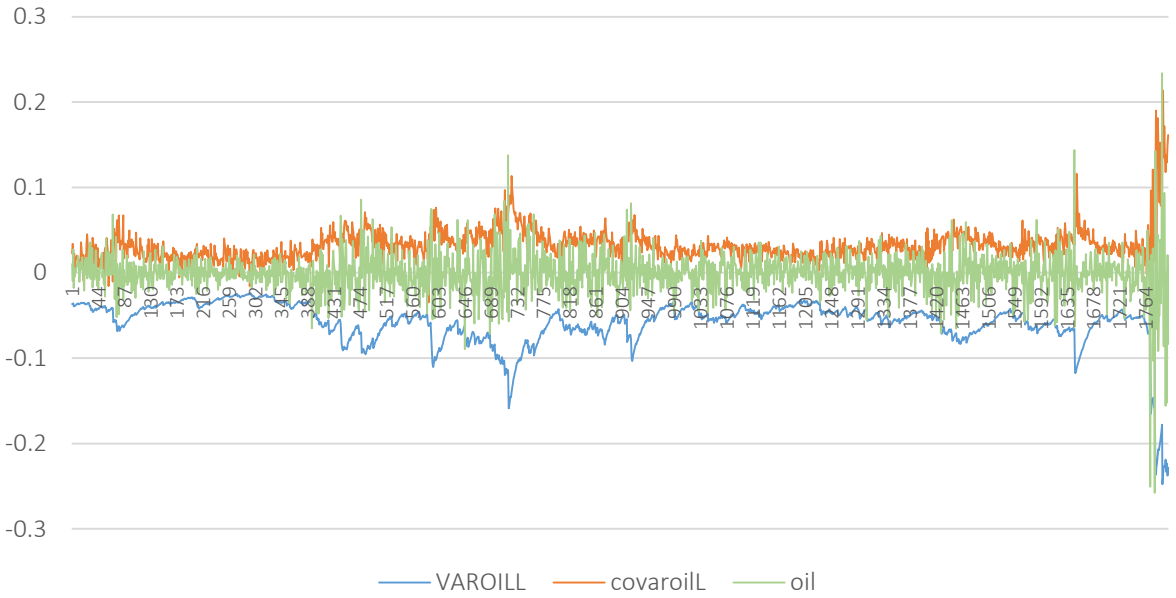


**Figure 2.** Rolling VaR values and returns of crude oil futures

Source: Authors' calculations.

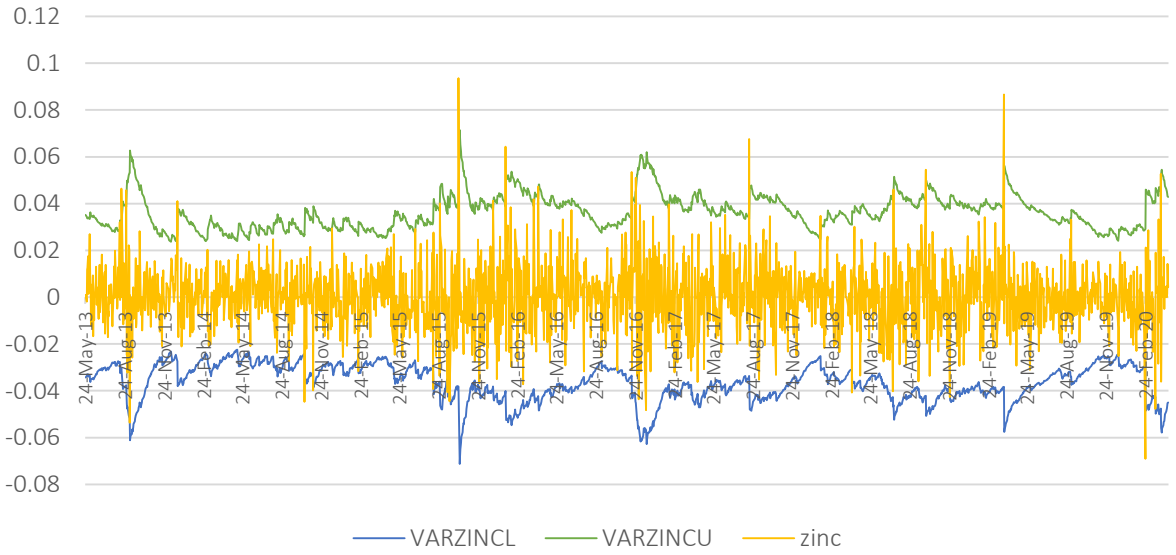


**Figure 3.** Rolling VaR values and returns of zinc futures

ues of oil, zinc and gas as an independent variable. In this study, $\tau = \{0.01\}$ is considered for Nifty. For institutions, that is, the commodity futures market, both right tail and left tail risk are considered ( $\tau = 0.01, 0.99\}$ , where the left tail corresponds to extremely low prices and the right tail corresponds to extremely high prices. The impact of extremely high prices (low prices) on $\tau = \{0.01\}$ quantile of markets was estimated, that is, Nifty 500. The rejection of the null hypothesis, given by a p-value lower than 5%, indicates the commodity market affects the Nifty index.

Table 5 shows that only the oil futures price shock is systematically important for Indian markets – both when oil prices rise or go down. An increase in oil price has more impact. The delta CoVaR of oil is also positive, which means the marginal contribution of oil to financial market risk is high, whereas it is negative for gas and zinc. This also indicates that financialization of commodity markets has not linked commodities other than oil futures to stock market yet. Hence, including zinc and gas in a stock portfolio can help in diversification.

According to Kilian and Park (2009), not all oil price shocks are alike. For example, in the case of oil, the impact of natural calamities on oil price causes supply-side shocks, whereas the impact of the global financial crisis on oil price causes aggregate demand shocks. Hence, the next objective tests whether shocks in commodity prices due to economic, financial, or a combination of both, affect the stock market. To calculate the result of Table 6, VaR is also estimated with quantile regression taking all the external regressors using equation (5).

**Table 5.** Risk transmission from commodity futures to the Nifty 500 index using CoVaR and Delta CoVaR

Source: Authors' calculations.

| CoVaR and Delta CoVaR | | | |
|---|---|---|---|
| **Oil** | | | |
| **CoVaRU** | **CoVaRl** | **DeltacoVaRU** | **DeltaCoVaRL** |
| −0.786** | 0.6016** | 0.00293 | 0.0029 |
| **Gas** | | | |
| −0.3245 | 0.379 | −0.00209 | −0.00215 |
| **Zinc** | | | |
| −0.5001 | 0.704 | −0.002165 | −0.00097 |

*Note*: ** and ** denote significance at 1% and 5%, respectively. CoVaRU: CoVaR for upper tail of oil, gas and zinc on lower tail of Nifty. CoVaRl: CoVaR for lower tail of oil, gas and zinc on lower tail of Nifty. Values of Table 5 are calculated using equations (5) and (7). VaR of commodities is estimated using the EVT method.


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**Table 6.** Diffusion channels of commodity risk to Nifty 500 index

Source: Authors' calculations.

| | Financial | Fundamental | Mixed | Financial | Fundamental | Mixed |
|---|---|---|---|---|---|---|
| | OILL | | | OILU | | |
| CoVaR | 0.092 | −0.0034 | 0.029 | 0.09* | 0.0494 | 0.09* |
| | GASL | | | GASU | | |
| CoVaR | 0.1558 | 0.148 | 0.1521 | 0.1775** | −0.1726* | 0.065 |
| | ZINCl | | | ZINCU | | |
| CoVaR | −0.11 | −0.1 | −0.156 | 0.3427 | −0.1245 | −0.09 |

*Note*: GASL, OilL, NiftyL, and ZincL represent Natural gas futures, Crude oil futures, nifty500 index and zinc futures lower tail parameters, respectively. GASU, OilU, NiftyU, and ZincU represent Natural gas futures, Crude oil futures, nifty500 index and zinc futures upper tail parameters. ** and ** denote significance at 1% and 5%, respectively.

# 5. DISCUSSION

Results in Table 4 confirm that the conditional EVT-VaR method measures tail risk precisely in Indian commodity futures, since this method passes back-testing in all the cases. Bali and Neftci (2003), Karmar and Shukla (2015), and Watanabe (2012) also documented superiority of the EVT-VaR method in measuring risk. It is evident from Table 6, that an increase in oil price transfers risk due to financial uncertainty to the stock market. That means overall volatility in markets represented by VIX and financialization of the commodity market in India represented by open interest related shocks impacts oil prices, which transmits risk faster to stock markets. Similar results were documented by Singleton (2014), Bosch and Smimou (2022), Thuraisamy et al. (2013), and Ding (2021). It is evident from Table 6 that abnormal increases in oil and gas prices generated through financial shocks integrate commodity markets with stock markets. The results are in line with Algieri and Leccadito (2017), Bastianin et al. (2016), and Kang et al. (2017) for oil commodities. The results are consistent with the prior empirical studies.

IN case of oil, when the price increase is due to financial shocks, or a combination of both financial and economic shocks, transmission to the stock market is more pronounced. The results can be explained by the following argument given by Miller and Ratti (2009) that the crude oil price increase affects profitability of firms as crude oil is an important input in production, oil price increase affects corporate profitability and eventually affects stock performance. Secondly, oil is the highest traded commodity in India, increased trading also integrates the commodity market with stock markets as documented by Algieri and Leccadito (2017) and Bastianin et al. (2016). Other commod-

Source: Authors' calculations.

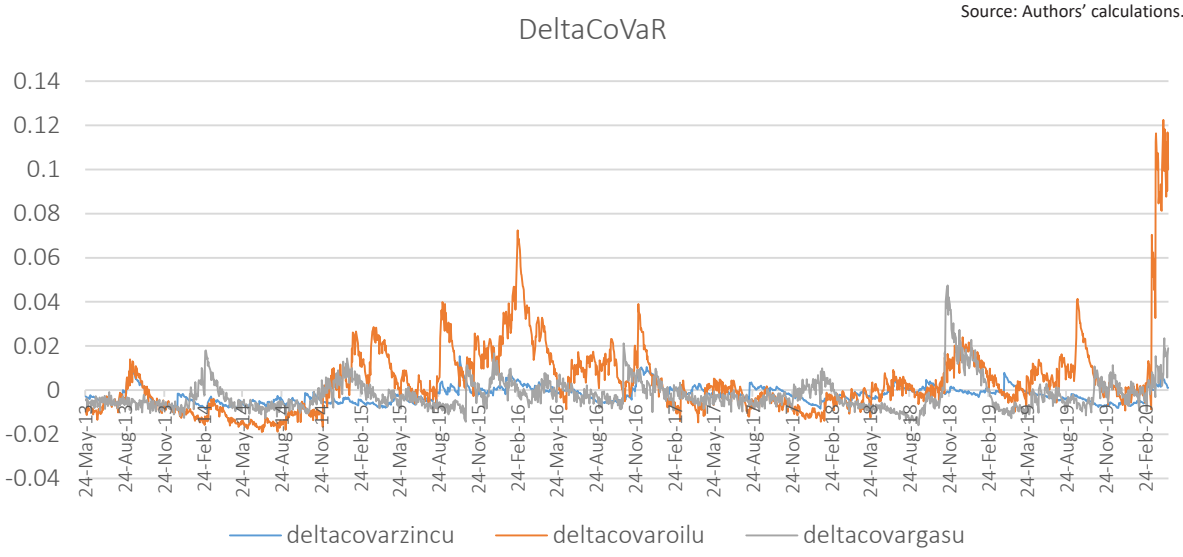


**Figure 4.** Marginal risk contribution of crude oil futures, zinc futures and natural gas futures returns to stock markets

ities than oil are not integrated with stock markets, this is due to less trading as compared to oil futures. Goldstein and Yang (2019) documented that trading activities above a certain level integrate the commodity market with the stock market. It is evident from Table 6 that risk transmission to financial markets in India is only transmitted by crude oil. Natural gas and zinc do not transmit systemic risk to the market, but if natural gas prices increase due to financial uncertainties, then the risk transmisson of natural gas to the stock market is also evident.

The marginal contribution of risk to financial markets is highest for oil, and marginal contribution is high when oil prices are skyrocketing.

## CONCLUSION

Due to the flow of funds from various investor classes in commodity markets in India, there is a substantial effect on the drift and volatilities of commodity future prices, hence, in this study, tail risk of highly traded Indian commodities is explored. Thereafter transmission of extreme price shocks (both upside and downside) from commodity markets to stock markets is also studied as the same class of investors are investing in both stock and commodity futures markets for portfolio diversification.

The results reveal that the conditional EVT-VaR method can be used for precise tail risk measurement in commodity futures. The findings also document that there is risk transmission from an extreme increase/decrease in oil futures returns to the stock market in India. Strong tail dependence between oil and stock market indicates that market traders in Nifty cannot remain insulated from the shocks coming from oil markets. Only for the oil futures, price shocks driven either by financial or combination of financial and economic shocks affect stock markets. Shocks in the oil price has the largest impact on the Nifty index, followed by shocks in Natural gas. From the results, it is inferred that risk transmission from the commodity market to the stock market is more pronounced with increased trading in commodity markets represented by open interest in the financial shocks variable.

Natural gas and zinc futures are not integrated with the stock market, so they can be added to the Nifty index portfolio for better portfolio diversification gains. These results are useful for financial traders to diversify commodity-based assets with the Nifty index for better portfolio diversification, as well as assist traders and portfolio managers in precisely estimating risk of commodity futures for margin calculation. It will be interesting to see in the future with increased index investment the role of institutional investors in the linkage between commodity markets and stock markets. Thus, understanding the commodity-stock market linkage in India and mediating role of increased institutional investors (financialization) in commodity markets is important for portfolio allocation and risk management.

## AUTHOR CONTRIBUTIONS

Conceptualization: Shalini Agnihotri, Kanishk Chauhan.
Data curation: Shalini Agnihotri.
Formal analysis: Shalini Agnihotri, Kanishk Chauhan.
Investigation: Shalini Agnihotri, Kanishk Chauhan.
Methodology: Shalini Agnihotri.
Software: Kanishk Chauhan.
Validation: Kanishk Chauhan.
Writing – original draft: Shalini Agnihotri.
Writing – review & editing: Shalini Agnihotri.


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