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Uncovering the complex asymmetric relationship between trading activity and commodity futures price: Evidenced from QNARDL study

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This study cracks the multidimensional asymmetric relationship between trading activity (volume and open interest) and commodity futures prices to analyze the short-term dynamics and long-term cointegrating relationship across different state of the market considering both positive and negative changes in trading activity using a novel Quantile Non-linear Autoregressive Distributed Lag (QNARDL) approach. First, the asymmetric price effect is found in short- and long-run of volume and open interest. Second, the asymmetric price effect due to positive and negative changes in open interest (volume) is found in the short-run (long-run) for copper (gold and crude) futures. Third, distributional asymmetry is found in the above two price effects on all three commodity futures implying that the price effect changes with changes in market conditions such bearish, bullish, and normal. Our findings will help the portfolio managers for effective investment and diversification decision, traders for better trading strategy, hedgers for better risk management strategy, and regulators and concerned exchange for effective policy making in varied market conditions.

Keywords: Commodity futures, gold, crude, copper, volume and open interest, Quantile ARDL and NARDL

JEL classification: Q42, Q43, C52

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1. Introduction

The hedging and diversifying properties of commodities have attracted heterogeneous agents into the commodities markets leading to its financialization (Ordu et al., 2017). In a study taking seven centuries of data Zaremba et al. (2019) found that industrial, energy and agricultural commodities can hedge inflation in a 4-8 years horizon. On other hand, in line with increasing financialization, majority of commodities except gold are found to be considered as separate asset class (Nguyen et al., 2020). Further, exponential growth in trading activities measured in terms of volume and open interest in commodities futures market (see figure 1) is a manifestation of financialization of the commodities (Domanski and Heath, 2007; Buyuksahin et al., 2008). These measures of trading activity reflect the activities of speculators in a traditional sense (momentum directional traders), financial traders (long only index traders considered as speculators) and commercial traders i.e., hedgers (producers and consumers of commodities). Nevertheless, as a major factor for economic growth commodities are required to be priced efficiently for effective allocation of resources, wherein commodities futures market serves as a platform for price discovery and risk transfer from commercial traders (both producers and consumers of the commodity) to speculators (Williams, 2001). Moreover, trading volume and open interest as measures of liquidity are important for the pricing of assets as they involve the cost of transforming cash into a financial asset and vice-versa (Chordia et al., 2001a, b). Overall trade, real income, and fiscal position of the commodity dependent country like India is seriously affected by any violent movement in the commodity prices (Cashin and McDermott, 2002).

Now question arises, how commodity futures prices are affected by the trading activities of these traders in general and speculators in particular since the financialization led trading activity is usually considered as suspicious because of its speculative nature?

The relationships between commodity futures prices and trading activity could be nonlinear and asymmetric in multiple dimensions due to following reasons. First, the presence of heterogeneous agents in the market with varying objectives and investment horizon creates a dynamic investor structure which changes with market condition, that is why, Brook et al. (2001) and Bohl et al. (2011) introduced time-varying dynamics between trading activity and commodity price. Second, at the time of expiration of contracts, huge trading activities observed in both the expiring and the new contract leading to enormous fluctuations in futures prices and structural break in trading activity. This maturity effect is popularly known

as Samuelson effect which is found in the determination of the volatility effect of volume and open interest (Ripple and Moosa, 2009). Further, the day of the week effect is observed in the price and trading activity (Jena et al., 2018). Thus, the combined effect of both dynamic investor structure and seasonality may lead to asymmetric price effect of trading activity in short and long run. Third, volume, as a proxy for information arrival, depends on the direction of the market (Chordia et al., 2000). This directional dependency of volume as a proxy for arrival of information is endorsed by Hodgson et al. (2006). Thus, information asymmetry i.e., market reacts more to negative than positive news may lead to asymmetric price effect of trading activity. Fourth, flight to liquidity is found in the context of the stock market in the theoretical work of Acharya and Pederson (2005) where illiquidity stocks face liquidity risk during the down market and as a pricing factor, liquidity risk claims an annual risk premium of 1.1%. As far as commodity market is concerned, because of its low or negative correlation with other financial assets more trading activity is observed in down than in the up market as during this phase investors and portfolio managers diversify their portfolio to commodities considered as safe. Thus, arrival of more market participants in the search of safe haven assets would bring more liquidity to commodities market. Thus the price effect of trading activity due to flight to liquidity in different market conditions may be asymmetric.

Even if prior studies have been done using non-linear methodology in both time and frequency domain (see the literature), they fail to capture the aforementioned multi-dimensional asymmetry between commodity futures price and trading activity. Also, in related studies where the volume and open interest are decomposed trader-wise and into expected and unexpected components, the findings are inconclusive about the impact of trading activity on prices. The reason could be, as pointed out by Bailey et al. (2017), the difficulty in ascertaining the true nature of trade without having information on trader's portfolio position. Inaccurate trade classification and its biased consequences on economic research is reported by Odders-White (2000). Moreover, classifying trade as buyer and seller initiated based on Lee and Ready (1991) algorithm results in systematic misclassification of trades. Therefore, policy measures based on these findings would adversely impact the risk transfer and price discovery functionality of futures market¹.

Another aspect is heterogeneous interpretation of trading activity in the financial market. Trading volume and open interest are considered as the proxy for strength and potential of

¹ Pirrong (1994), Brunetti et al. (2016)

price change respectively (Jena and Dash, 2014) and demand for speculation and hedging (Bessembider and Seguin, 1996; Lucia and Pardo, 2010). In addition, open interest is more informative of future economic activity² and asset prices than futures prices because of hedging demand in the presence of limited risk absorption capacity in the futures market (Hong and Yogo, 2012). Indeed, Hong and Yogo (2012) state that the futures prices would underreact to news which would result in momentum rather than mean reversion relationship between the futures price and open interest. Consequently, the relationship would be positive and contemporaneous between open interest and futures returns. Since the trading activity such as volume and open interest connote different meaning to different stakeholders, it would lead to a loss of information if it were used in deformation.

Instead of breaking into components, we have taken the total volume and open interest and gone deep into the aspect of market microstructure in uncovering the price impact of trading activity. For the first time in the related literature, we have applied the Quantile Nonlinear Autoregressive Distributed Lag (QNARDL) model, a novel methodology of Bouri et al. (2018), to study the complex relationship dynamics between trading activity and returns in commodity futures market. The novelty of this unique methodology lies in revealing the three aforementioned forms of asymmetry between trading activity and commodity futures prices. First kind of asymmetry arises due to differential impact of positive and negative changes in trading volume and open interest on commodity futures prices. The second aspect is related to long and short-run asymmetry wherein the impact of both positive and negative changes in trading activity on futures prices are estimated both in long- and short-run. The long run asymmetric effect of positive and negative changes of volume and open interest on futures prices is related to the speed of adjustment hypothesis of Chordia and Swaminathan (2000). It states that in the context of the stocks, some stocks have the tendency to adjust more slowly (under reaction) than other stocks to economy-wide information. This paper is the first to study the speed of adjustment factor in the commodity futures market at different market conditions. Third, the locational asymmetry which captures the impact of trading volume and open interest across the entire distribution of the commodity futures prices corresponding to different state of the market in both long and short run for both positive and negative changes. Thus, these three aspects of asymmetric dynamics could be of interest to the portfolio managers, hedgers (both producers and consumers), speculators and arbitrageurs for effective trading and the regulator and concerned exchanges for effective policy making.

² Its pertinent as for bubble in the commodities market, it is the macroeconomic variable, not speculation as widely believed is responsible (Irwin et al., 2009).

The objective of this study is to uncover the complex asymmetric dynamics between the commodity futures prices and trading volume and open interest. The relationship dynamics are studied in both the long and short run at different market conditions for both positive and negative changes to trading activity . We find three kinds of asymmetric price effect of trading activities. First, the asymmetric price effect in short- and long-run is found of both volume and open interest. Second, the asymmetric price effect due to positive and negative changes in open interest (volume) is found in the short-run (long-run) for copper (gold and crude) futures. Third, distributional asymmetry is found in the above two price effects on all three commodity futures.

This study has several contributions to the existing literature on commodities market in general and the commodities market microstructure in particular. First, we study the trading activity and price dynamics covering three broad segments of the commodity futures market such as bullion, metal, and energy futures. Second, unlike the existing literature, the study examines the multidimensional asymmetric effect of trading activity on commodity futures market. In a first stage, we uncover the asymmetry due to positive and negative changes in trading activity. Then in the second stage, we explore the short and long run asymmetry for both positive and negatives changes in trading activity. Finally, we estimate the distributional asymmetry which corresponds to the different market conditions considering the first two aspects of the asymmetry simultaneously. The study is conducted in the Indian commodities futures market i.e., Multi Commodity Exchange MCX (www.mcxindia.com).^{3,4} The choice of India is motivated by the fact that it is the 6th, 3rd and 2nd largest consumer of copper, crude, and gold, respectively.

The remaining of the paper progresses as follows. Section 2 discusses the literature on the price effect of trading activities such as volume and open interest in the commodity futures market. Section 3 describes the data and methodology used in the study. Section 4 analyses the empirical findings and presents the policy implications to different stakeholders. Section 5 concludes and presents policy implications.

³ Multi Commodity Exchange (MCX) is the leader in commodities derivatives market in India with a market share of 90.37% for 2016-17. It is the 7th largest commodity futures exchange in the world in terms of number of contracts traded as per the Annual Volumes Survey for 2016 of Futures Industry Association (FIA)- (As per annual report 2016-17

⁴https://www.mcxindia.com/docs/default-source/investor-relations/annual-report/mcx_annual_report_fy2017.pdf?sfvrsn=2

2. Literature

A lot of studies have been done examining the relationship between trading activity and asset price in general and commodity in particular using different methodologies on varied forms of the variables with varying sample periods. Considered as one of the most important studies, Karpoff (1987) in his survey bringing together the results of previous studies, mentions presence of some forms of asymmetry in the relationship between trading activity and price, but linear models are used to study this relationship. He refers to two sets of theories of information such as the Mixture Distribution Hypothesis (MDH) of Clark (1973) and Sequential Information Flow Hypothesis (SIF) of Copeland (1976) for a positive relation between trading volume and price. MDH states a positive and contemporaneous relationship because of joint dependence of volume and price on a common variable i.e., rate of arrival of information. Whereas, SIF states a lagged positive relationship because information arrives in the market sequentially, unlike contemporaneously under MDH. [In line with the argument, Kao et. al. \(2019\) found asymmetric contemporaneous and lead-lag relationship between volume and return and volume and volatility in S&P 500 VIX futures using GJR-GARCH threshold model. Apart from this, although the previous two theories propose a positive relationship between trading volume and price change, they differ in terms of dissemination of information in the market. MDH assumes symmetrical dissemination of information which leads to immediate restoration of equilibrium price as traders can view the supply and demand simultaneously. Whereas SIF assumes the asymmetrical distribution of information which leads to gradual restoration of equilibrium price. That is why current trading volume affects subsequent return and volatility.](#)

Another theory of information proposed by Blume (1994) in which he emphasizes the quality and precision aspect of the information content of trading volume which has bearing on the price formation process. That means volume reflects quality and precision of information more than price. It contributes to the restoration of the efficient price. Thus, it defies the symmetric arrival of information and its simultaneous impact on price change and trading volume of MDH.

Diverging from the informational argument, Wang (1994) and Llorente et al. (2002) put forward a trade motivation argument which shapes the price and trading activity relationship dynamics. Based on this argument, Wang (2002) proposes two hypotheses: First, the Liquidity Driven Trade (LDT) hypothesis and, second, Information Driven Trade (IDT)

hypothesis. LDT hypothesis states that if the trade is driven by liquidity, the consecutive return will reverse reflecting a negative relationship between volume and subsequent return. On the other hand, the IDT hypothesis states that if the trade is driven by information, there will be momentum in consecutive return in response to the trade done by informed traders having better private information. The reason being, first, there will be positive (negative) changes in asset price when informed traders buy (sell) because of possession of favourable (unfavourable) private information. Second, partial information assimilation in the price at the beginning leads to a negative (positive) return in the current period followed by another negative (positive) return in the next period. Thus, it results in a positive return and trading volume relationship. Llorente et al. (2002) classify hedging and speculating trades as liquidity driven trade (LDT) and informed driven trade (IDT) respectively. They find that the trades done by hedgers (speculators) generates negative (positive) autocorrelated return.

Thus, the theories of information and trade motivation endorse the existence of an asymmetric relationship between return and trading activity. How do these theoretical arguments hold in short and long-run in different market conditions? Our study is directed validating these theoretical arguments.

As far as empirics are concerned, the literatures related to the relationship dynamics between trading activity and commodity futures price and the resulting gap are discussed below.

Moosa and Silvapulle (2000) report existence of causality relationship between price and volume of crude oil futures market thereby supporting the SIF theory. Apart from this, they have reported the presence of maturity and liquidity effect. The results of Girma and Mougoue (2002) in petroleum futures market also support SIF theory as they find that lagged volume and open interest can explain future spread volatility. Although they use both the linear and nonlinear models, their study fails to capture long-run, short-run and distributional asymmetry.

Moosa et al. (2003) find temporal asymmetry relationship between price change and trading volume in crude oil futures market where the asymmetric impact is due to the positive and negative changes in both variables. These impacts are stronger for negative changes than positive changes. Although the study captures one of the aspects of asymmetry related to positive and negative changes, asymmetries due to long and short run effect and state of the market effect are missing in this study.

Chevallier and Sevi (2012) in their study on crude and natural gas futures market, find positive and contemporaneous relations between trading volume and price volatility. Moreover, they report a symmetric volume-volatility relationship. The reason could be that they have considered only one aspect of the asymmetry relating to positive and negative changes in the independent variable.

Ripple and Moosa (2009) report that trading volume and open interest have significant positive and negative price volatility effects in the crude futures market, respectively. Since different dimensions of asymmetry are not considered, the results may not hold in different state of the market and in different time horizon.

Ordu et al. (2018) find that open interest is significantly connected to spot market whereas the volume is the provider of cross-market information. Though the authors used a time-varying framework, their study ignores the distributional asymmetry. Consequently, these findings cannot be generalised across market conditions.

Magkonis and Tsouknidis (2017) used VAR spillover methodology of Diebold and Yilmaz to measure the dynamic spillover between petroleum spot and futures prices and trading volume and open interest in a time varying framework. Large and persistent spillover of speculative and hedging pressure from trading volume and open interest respectively to petroleum spot and futures markets are observed over the study period. But their methodology does not differentiate between positive and negative changes in trading volume and open interest and the short- and long-term aspect of it.

Using a non-linear quantile model, Fousekis and Tzaferi (2019) investigate the strength and pattern of the impact of trading volume on six agricultural futures markets. They found non-linear association between trading volume and price change wherein price return and volume changes are positively (negatively) associated when price return is positive (negative). However, the intensity of the association rises with the higher level of quantiles. Even though asymmetric related to market conditions and positive and negative changes in prices are considered in the study, it fails to accommodate the short and long association between trading volume and agricultural commodity futures price. Further, it studies the impact of the volume only on the futures prices even though open interest is one of the important measures of trading activity in futures market. Czudaj (2019) has also done his study in seven agricultural futures market using a time varying Bayesian VAR approach to investigate the relationship between return volatility, volume, and open interest. The study found time

varying lag effect of volume and open interest on return volatility of seven agricultural futures market. Although time varying relationship dynamics is captured, the asymmetric effect due to positive and negative changes in trading activity in short and long run is ignored in this study.

Alizadeh and Tamvakis (2016) focus on one of three aspects of the asymmetry i.e., market state in studying the relationship between energy futures volume and return by segregating the market as backwardation and contango based on the slope of the forward curve. Our study is much broader and different in two aspects: First, we study two additional asymmetries namely sign asymmetry and distributional asymmetry. Second, our classification of the state of the market is much broader and different in that it is based on the distribution of the futures return, and each location of quantile on the distribution of the return corresponds to a particular state of the market. That means we have gone much deeper into the two states of the market as described by Alizadeh and Tamvakis (2016). Because in each of their two states of the market, there exists bearish, normal and bull market. So, our findings will provide better asymmetric dynamics between trading volume and return. In addition, we also study the asymmetric dynamics between return and open interest which is another important variable in the futures market.

Altogether, theories of information and trade motivation hypothesis reveal the existence of asymmetry in the trading activity and price relationship dynamics. Even though empirical studies are done to capture these asymmetric dynamics, none of the studies has considered all the three aspect of asymmetries i.e. time horizon asymmetry (short and long -run effect), sign asymmetry (effect of positive and negative changes) and distributional asymmetry (effect of different state of the market). Therefore, this study aims at fulfilling this gap in commodity futures markets using the novel QNARDL methodology of Bouri et al. (2018) which considers all three asymmetric relationships. The study investigates the relationship between futures prices and volume and open interest in three important futures market segments such as metal, bullion, and energy. We have selected the largest trading commodity from each of the above three segments such as copper, gold, and crude futures respectively, trading in Multi Commodity Exchange, India's largest commodity exchange.

3. Data and Methodology

3.1. Data

Daily closing price, volume and open interest of near month futures contracts are collected for crude oil, gold and copper futures trading in the Multi Commodity Exchange of India, (MCX) (www.mcxindia.com) the largest commodities market in India. The near month futures contracts are more liquid, as they attract more trading activities from traders and investors for speculation, diversification and investment purpose, than mid and far month contracts (Wang and Chen, 2016; Fousekis and Tzaferi, 2019; Magkonis and Tsouknidis, 2017). The daily data spans from the respective date of their first trading in MCX i.e. from June 4, 2004, November 10, 2003 and February 9, 2005 for copper, gold and crude near month futures contract respectively to December 16, 2020. Daily log returns we denote as GORETURN, CRRETURN and CORETURN are estimated from the futures closing prices of gold, crude, and copper, respectively. For trading activity variables, we consider log series of volume (LVO) and open interest (LOI) for the study. The descriptive statistics are presented through Table 1. The daily mean return is zero for all three commodities. But crude (gold) is most (least) volatile commodity. The value of skewness indicates presence of asymmetry in all the series. The value of kurtosis reflects information at the tail of the distribution requiring quantile analysis. All the series are non-normal. The UDMax statistics of Bai-Perron (2003) tests for 1 to M globally determined breaks confirms the presence of structural break in the series. That is why any linear study on trading activity and prices are miss-specified. Therefore, we have applied Zivot-Andrews (1994) break point unit root test, which confirms the return and log volume, and open interest series are stationary. Further, to justify the application of nonlinear model in the study, we have applied BDS test to find out what kind of bivariate relationship that exists between price and trading activity⁵. The results of BDS test show existence of nonlinear relationship which further strengthens the application of nonlinear model in the study.

< Insert Figure 1 here >

3.2. Methodology

The previous literature suggested two testing procedures to test existence of cointegrating relationships between system variables. In particular, cointegration can be tested using either an F -test (F_{PSS}) (Pesaran et al., 2001) or a t -test (t_{BDM}) of the null of no cointegration. The latter tests are based on the newly developed Autoregressive Distributed Lag (ARDL) model.

⁵ Results are available upon request.

It is worth noting that these tests are adapted to a system of variables having different orders of integration. Indeed, unlike the standard cointegration tests such as the Johansen test and the Engle-Granger test which require the variables to have the same order of integration, I(1), the testing procedure suggested by Pesaran et al. (2001) allows testing cointegration among I(0) and I(1) variables and hence does not have a standard asymptotic distribution. These tests are based on a two-bound decision rule. In particular, the empirically computed F_{PSS} and t_{BDM} should be compared with two critical values called the lower bound and the upper bound, respectively. Indeed, the tests reject the null of no cointegration in case the empirical statistics exceed the upper critical bound; fails to reject the null of no cointegration if the empirical statistics are lower than the lower critical bound; and are inconclusive in case the empirical statistics fall the region between the lower and upper critical bounds.

Although the ARDL model is considered as a turning point in the literature related to cointegration as it relaxed the strong condition regarding the same order of integration – I(1) – of variables and presented a flexible framework to test for cointegration between a mix of I(0) and I(1) variables, it remains insufficient when the relationships between time series are nonlinear and asymmetric. It is now well documented that the dynamics of economic and financial time series as well as their interconnectedness are steered by nonlinearity and asymmetry due to the complexity of existing economic systems and the occurrence of several sudden events (financial crises, wars, natural disasters) and episodes of political tensions.

Consequently, in such a complex setting, the linear ARDL model becomes too restrictive and unable to model all the components driving the dynamics of the relationships among variables. The latter model constraints the long- and short-run adjustment paths of variables to be linear and symmetric. Shin et al. (2014) extended the linear ARDL(p,q) model to a nonlinear setting, leading to the nonlinear ARDL – NARDL(p,q) – model, by decomposing each explanatory variable into its positive and negative partial sums as follows:

$$x_t = x_0 + x^+ + x^- \quad \text{where } x^+ = \sum_{j=1}^t \Delta x_j^+ = \sum_{j=1}^t \max(\Delta x_j, 0) \quad \text{and } x^- = \sum_{j=1}^t \Delta x_j^- = \sum_{j=1}^t \min(\Delta x_j, 0).$$

Introducing the decomposition of explanatory variables into their respective positive and negative partial sums in the linear ARDL model leads to the NARDL model with long- and short-asymmetries.⁶

⁶ See Shin et al (2014) for more details on the functional form of the NARDL model.

Both Long-run and short-run asymmetries are tested using a Wald test of the null of equality of long-run and short-run parameters, respectively. In case the Wald test fails to reject the null of long-run (short-run) symmetry in NARDL model for both regressors, the general NARDL model reduces to the NARDL model with short-run (long-run) asymmetry.

Although the NARDL models (unconstrained/constrained) have the advantage of capturing respective long- and short-run effects of positive and negative shocks of explanatory variables on the dependent variable they all fail to account for the distributional asymmetry often detected in financial and economic time series relationships. We thus extend the NARDL models to a quantile regression setting. More specifically, the quantile version of the unconstrained NARDL, QNARDL, model is written as follows:

$$\begin{aligned}
Q_{\Delta y_t} = & \alpha(\tau) + \rho_y(\tau)y_{t-1} + \rho_{x_1}^+(\tau)x_{1t-1}^+ + \rho_{x_1}^-(\tau)x_{1t-1}^- + \rho_{x_2}^+(\tau)x_{2t-1}^+ + \rho_{x_2}^-(\tau)x_{2t-1}^- + \\
& \sum_{i=1}^{p-1} \theta_i(\tau)\Delta y_{t-i} + \sum_{i=0}^{q-1} (\pi_i^+(\tau)\Delta x_{1t-i}^+ + \pi_i^-(\tau)\Delta x_{1t-i}^-) + \sum_{i=0}^{s-1} (\gamma_i^+(\tau)\Delta x_{2t-i}^+ + \\
& \gamma_i^-(\tau)\Delta x_{2t-i}^-) + \varepsilon_t
\end{aligned} \tag{1}$$

Again, based on the results of the Wald tests for long-run and short-run asymmetry it is straightforward to introduce quantile versions of the constrained NARDL models.

< Insert Table 1 here >

4. Empirical Analysis

At the outset, the general NARDL model for our data is estimated using general-to-specific approach by fixing $p_{\max} = 12$ and $q_{\max} = 12$ and then corresponding Wald test is applied to test the long- and short-run asymmetries. The empirical results of Wald test of long- and short-run asymmetry for gold, copper and crude futures are reported in Table-2. As evidenced from the results for gold and crude futures, Wald tests for long- and short-run asymmetries indicate that volume (open interest) has an asymmetric (symmetric) impact on gold and crude futures price in long-run (short and long run). For copper futures, unlike volume, open interest has an asymmetric effect on the copper futures prices in short-run only. In the long run both volume and open interest have a symmetric effect on copper futures prices.

< Insert Table 2 here >

Firstly, we have estimated the best suited NARDL model for gold, copper and crude respectively to study the long- and short-run asymmetry, i.e. asymmetry due to positive and negative changes in explanatory variables. The results are presented through Table 3.

Secondly, based on the above analysis we have estimated the below QNARDL models (Eq. 2, Eq. 3 & Eq. 4, resp.) for gold, copper and crude to assess the distributional asymmetry in the short- and long-run impact of volume and open interest.

$$Q_{\Delta gold_t} = \alpha(\tau) + \rho_y(\tau)gold_{t-1} + \rho_{vol}^+(\tau)vol_{t-1}^+ + \rho_{vol}^-(\tau)vol_{t-1}^- + \rho_{oi}(\tau)oi_{t-1} + \sum_{i=1}^{p-1} \theta_i(\tau)\Delta gold_{t-i} + \sum_{i=0}^{q-1} \pi_i(\tau)\Delta vol_{t-i} + \sum_{i=0}^{s-1} \gamma_i(\tau)\Delta oi_{t-i} + \varepsilon_t \quad (2)$$

$$Q_{\Delta copper_t} = \alpha(\tau) + \rho_y(\tau)copper_{t-1} + \rho_{vol}(\tau)vol_{t-1} + \rho_{oi}(\tau)oi_{t-1} + \sum_{i=1}^{p-1} \theta_i(\tau)\Delta copper_{t-i} + \sum_{i=0}^{q-1} \pi_i(\tau)\Delta vol_{t-i} + \sum_{i=0}^{s-1} (\gamma_i^+(\tau)\Delta oi_{t-i}^+ + \gamma_i^-(\tau)\Delta oi_{t-i}^-) + \varepsilon_t \quad (3)$$

$$Q_{\Delta crude_t} = \alpha(\tau) + \rho_y(\tau)crude_{t-1} + \rho_{vol}^+(\tau)vol_{t-1}^+ + \rho_{vol}^-(\tau)vol_{t-1}^- + \rho_{oi}(\tau)oi_{t-1} + \sum_{i=1}^{p-1} \theta_i(\tau)\Delta crude_{t-i} + \sum_{i=0}^{q-1} \pi_i(\tau)\Delta vol_{t-i} + \sum_{i=0}^{s-1} \gamma_i(\tau)\Delta oi_{t-i} + \varepsilon_t \quad (4)$$

where $gold_t$, $copper_t$ and $crude_t$ indicate the gold, copper and crude oil futures contract log price observed at time t . vol_t and oi_t refer to volume and open interest in logarithm form observed at time t . Δ is the first difference operator, vol_{t-1}^+ and vol_{t-1}^- are one-period lagged cumulative partial sums for volume and Δoi_t^+ and Δoi_{t-i}^- are positive and negative changes of open interest. ε_t is the error term.

The distributional asymmetry of the speed of adjustment parameter is tested using Wald test of the null

$$\begin{aligned} \rho_y(0.05) &= \rho_y(0.10) = \rho_y(0.20) = \rho_y(0.30) = \rho_y(0.30) = \rho_y(0.40) = \rho_y(0.50) \\ &= \rho_y(0.60) = \rho_y(0.70) = \rho_y(0.80) = \rho_y(0.90) \end{aligned}$$

Further, similar test is applied to test the long-run asymmetric impacts of the explanatory variables such as volume and open interest.

As evidenced from the results of NARDL model in Table 3, the speed of adjustment parameter ($lgoprice_t$) is significantly negative for all three commodities, thus confirming the stability of the model. That means any deviation from the long-term relationship between commodity futures price and trading activity is corrected. Even though, both volume and open interest have a significant mean long-term relationship with copper futures prices, it is absent in case of both gold and crude. It is to be noted that, even though Wald test

confirmed asymmetric long term relationship between volume and gold and crude futures prices, it is not evident in the average results in Table 3, thus justifying the application QNARDL model to uncover the asymmetry across the distribution. However, volume (open interest) has positive (negative) long term relationship with copper futures price. In short-run, volume is found to have no (contemporaneous and lag negative) impact on gold and crude (copper) futures prices. As far as open interest is concerned, it has contemporaneous (lag) positive (negative) effect on gold (crude) futures price. In case of copper, increase (decrease) in open interest has a positive (negative) effect on its futures price in short run.

Overall, the results endorse an average heterogeneous short-term dynamic and stable long term relationship between commodity futures price and trading activity. Now it must be seen how this average relationship holds in different market conditions such as bull, bear, and normal market. Because market conditions are different in terms information arrival, market participants and sometimes regulation also. In the next section, the quantile NARDL results are presented and discussed exhibiting the short-term dynamics and long-term cointegrating relationship between commodity futures price and trading activity in different market conditions.

< Insert Table 3 here >

The estimated parameters of QNARDL models across the quantiles along with their respective 95% confidence bounds are presented through figure 2, 3, and 4 for gold, copper, and crude futures, respectively. The quantiles below (above) $Q_{0.50}$ are called lower (upper) quantiles corresponds to the bearish (bullish) market. Further, we have gone deeper into these two broader market conditions and identified three sub-markets corresponding to range of estimated quantiles and not at a particular level of quantile by following Kyritsis and Anderson (2019) and Chuang et.al. (2009). First, two sub-markets are, extreme bullish and bearish (moderately bullish and bearish) markets corresponding to $Q_{0.90}$ to $Q_{0.95}$, and $Q_{0.05}$ to $Q_{0.10}$ ($Q_{0.70}$ to $Q_{0.80}$ and $Q_{0.20}$ to $Q_{0.30}$) respectively. Additionally, the quantiles between $Q_{0.30}$ to $Q_{0.60}$ are considered as normal market in the study. Finally, we have investigated the distributional asymmetry of the price impact of volume and open interest using Wald test. The Wald test results for short- and long-run distributional asymmetry across the quantiles are reported through Table-4.

< Insert Figure 2 here >

Figure-2 reports the impact of futures price, volume, and open interest on current gold futures prices at different quantiles in both short and long-run. The Error Correction Parameter (RET (-1)) i.e., the speed of adjustment parameter is negative and significant (positive and significant) in the lower quantiles i.e., $Q_{0.05}$ to $Q_{0.20}$ (in higher quantiles i.e., $Q_{0.80}$ to $Q_{0.95}$). This result indicates that the speed of adjustment is faster in bear market for any shocks to the prices. But price shock has momentum effect in the prices in the bullish market. However, it is not significant during the normal market i.e., $Q_{0.30}$ to $Q_{0.60}$. Further, the Wald test results reported through Table-4 confirm that the speed of adjustment is asymmetric across the quantiles as the null hypothesis is rejected at the conventional levels. The long-term loading parameters for both positive and negative changes in volume (ρ_{vol}^+ and ρ_{vol}^-) are negative and significant at lower quantiles and positive and significant at higher quantiles except for $Q_{0.50}$ quantiles at the conventional significance level of 5%. That means if the long-term price-volume relationship breaks in the bullish market, it is not restored back to its normal level. As a result of which for one unit of shock in trading volume in bull market, it will create a momentum pressure in the same direction (i.e. either price will further go up or go down). Furthermore, the long-term price impact of volume across the quantiles (i.e., across different market conditions) is asymmetric as null hypothesis of Wald test is rejected (see Table -4). The open interest long term loading parameter i.e. (ρ_{oi}) is significantly positive (negative) at lower i.e., $Q_{0.05}$ to $Q_{0.20}$ (higher i.e., $Q_{0.90}$ to $Q_{0.95}$) quantiles. That means any positive or negative changes in open interest at lag one in the bear (bull) market leads momentum (reversal) in gold futures prices. This asymmetric effect across quantiles is endorsed by Wald test presented through Table 4. Thus, in the long-term, unlike volume, open interest helps in stabilising the gold futures price in bullish market (higher quantiles).

In the short run, the price impact of volume (*dlvol*) on gold futures is asymmetric (see Table -4). It is negative and significant (positive and significant) in the lower (upper) quantiles. Volume has no impact on price at $Q_{0.50}$. In bullish market (at upper quartile) it has momentum impact on price. However, in the bear market gold futures price trend is reversed due to either increase or decrease in volume. The short-term effect of open interest (*dloi*) on gold futures price is positive (negative) and significant in lower (higher) quantiles. It shows that in a bear market if open interest falls, the price will fall further and vice versa. In a bull market this reaction is reversed and gold futures price declines to the rise in open interest and vice versa. Wald statistics reported in Table-4 corroborates this short term asymmetric effect of open interest on gold futures prices.

< Insert Figure 3 here >

Figure-3 depicts the impact of past copper futures price, volume, and open interest on current copper futures prices at different quantiles in both short- and long-run. The ECM (speed of adjustment) parameter is positive and significant (negative and significant) in the lower quantiles i.e., from $Q_{0.05}$ to $Q_{0.30}$ except $Q_{0.40}$ (in normal to higher quantiles i.e., $Q_{0.50}$ to $Q_{0.95}$). This asymmetric effect of past futures price on current futures price of copper is endorsed by Wald test result in Table-4 where the null hypothesis of symmetric effect is rejected. The positive relationship of past prices in bearish market implies momentum effect on current prices where if current price falls, it will fall further and vice-versa. But, in a bull market this dynamic is reversed because current futures price shares a negative relationship with past futures price. So, any price shocks in the past are reversed and the current prices will be back to normal. Thus, unlike in a bear market, copper futures price is more stable in a bull market.

The long-term loading coefficient of volume (ρ_{vol}) i.e., VOL (-1) is negative and significant at lower quantiles while positive and significant across the medium to higher quantiles except for $Q_{0.40}$ to $Q_{0.50}$. It shows stronger price momentum effect of volume shocks in bearish than in bull market. This asymmetric volume effect is further endorsed by the significance of Wald test result in Table-4. However, the long-term relationship is missing in the normal market. The long-term loading coefficient of open interest (ρ_{oi}) is quite interesting as it is significantly positive (negative) at lower (medium to higher except at $Q_{0.40}$ to $Q_{0.50}$) quantiles. That means as normally expected in extreme bullish markets when price deviates from the long-term equilibrium level, past open interest helps in restoring normalcy in copper futures. In long run however, it is found that open interest has no impact on copper futures price in a normal to moderate market corresponding to $Q_{0.30}$ to $Q_{0.50}$. This asymmetric effect of open interest is further confirmed by the Wald test results reported in Table-4 where null hypothesis of symmetric effect is rejected at the conventional level.

In the short run, past variations in volume ($dlvol$) i.e., DVOL have a positive and significant impact at lower and higher quantiles at lag 1. This asymmetric impact is again confirmed by Wald test results in Table-4. If volume increases, it will have positive effect on future return in both bull and bear market. Based on the result of Wald test for short- and long-run asymmetry reported in Table-2, the short-term contemporaneous and lag price impact of both positive (DOIP) and negative (DOIN) changes in open interest is reported across the quantiles. The short-term contemporaneous impact of positive change in open interest i.e. DOIP is significantly negative (positive) at lower (higher) quantiles i.e. $Q_{0.05}$ to $Q_{0.20}$ (middle

quantiles i.e., $Q_{0.80}$ to $Q_{0.95}$). So, if open interest increases in a bear market it will have a negative impact on copper futures return contemporaneously. But the short-term lag impact of positive change in open interest i.e., DOIP is significantly positive (negative) in lower quantiles i.e. $Q_{0.05}$ to $Q_{0.20}$ (higher quantiles i.e., $Q_{0.80}$ to $Q_{0.95}$). This is also supplemented by Wald test result reported in Table -4 for distributional asymmetry for contemporaneous and lag effect. The short-term contemporaneous impact of negative change in open interest (*dloin*) i.e., DOIN has a positive (negative) effect at lower quantiles i.e., $Q_{0.05}$ to $Q_{0.30}$ (upper quantiles i.e., $Q_{0.70}$ to $Q_{0.95}$). It is also supplemented by Wald test result reported in Table-4 for distributional asymmetry. So, if open interest decreases in a bear (bull) market it will have a positive (negative) impact on copper futures return contemporaneously. The negative change in open interest has a negative impact on copper futures price in lag 1 (lag 2) at lower quantiles i.e., $Q_{0.05}$ to $Q_{0.50}$ (i.e., $Q_{0.05}$), but it has positive impact at higher quantiles in lag 1 only. At other lags, no significant impact is observed. This asymmetric effect across the distribution is further endorsed by the reported results Wald test for distributional asymmetry in Table-4.

< Insert Figure 4 here >

Figure-4 reports the impact of past crude futures price, volume, and open interest on current crude futures prices at different quantiles in both short- and long-run. The ECM parameter, as reported in the first row second figure i.e., RET (-1), is positive (negative) at lower i.e., $Q_{0.05}$ to $Q_{0.30}$ (higher i.e., $Q_{0.50}$ to $Q_{0.95}$) quantiles. This asymmetry is also confirmed by the Wald test result for distributional asymmetry reported in Table-4. It is not significant in a normal market corresponding to $Q_{0.40}$. So, in bad market past variation in prices creates instability through resulting momentum in current prices. But, in a good market it plays the price stabilising role as any price shock in the past gets corrected in the current price. The long-term volume loading coefficients for positive and negative changes of volume, ρ_{vol}^+ and ρ_{vol}^- are negative and significant across all the quantiles except for quantile $Q_{0.50}$ and $Q_{0.95}$. This is in confirmation with the findings of Moosa et al. (2003). This distributional asymmetry in terms of the size of the price impact of variation in the past volume is not confirmed by the Wald test result as the latter fails to reject the null of distributional asymmetry. So, any positive or negative change in volume negatively impacts crude futures prices, thus acting as long-term trend reversal in crude oil futures market. The long-term open interest loading coefficient ρ_{oi} is insignificant at all quantiles regardless of the state of the market (bearish, normal, and bullish). Wald test also fails to reject the null of parameter constancy across

quantiles rejecting thus distributional asymmetry of the price impact of the past variation in the open interest in the long run. This implies that any variation in the open interest does not impact the crude oil futures price in the long run.

In the short run, the price impact of change in volume (*dv_{ol}* i.e., DVOL) is significantly negative (positive) throughout the lower quantiles i.e., $Q_{0.05}$ to $Q_{0.50}$ (upper quantiles $Q_{0.60}$ to $Q_{0.95}$). Wald test also confirms this distributional asymmetry. That means both in bear and bull market, increase in volume has momentum effect on price where in a falling market it will fall further and in a bull market it will rise further. Similar impact of lag volume (up to lag 4) across quantiles is also observed. The contemporaneous change in open interest has negative effect on crude oil futures price at higher quantile i.e., $Q_{0.90}$ - $Q_{0.95}$. It has no impact at remaining quantiles i.e., $Q_{0.05}$ to $Q_{0.80}$ except $Q_{0.50}$. That means short term contemporaneous increase in open interest leads to decrease in crude futures price bull market. But lag (one to five only) changes in open interest have negative effect through average to higher quantiles $Q_{0.50}$ to $Q_{0.95}$. In other words, no lag effect of open interest is observed in the short-run in lower quantile i.e., in bear market.

< Insert Table 4 here >

Overall, the cointegrating relationship between trading activity and commodity futures prices exists in bull (bear) market only in case of copper and crude (gold). Thus, lack of cointegrating relationship in bear (bull) market in case of copper and crude (gold), trading activity creates momentum effect resulting in instability in the futures price. Interestingly the cointegrating relationship is missing in normal market in all three commodities, thus justifying our study across quantiles. That means cointegrating relationship changes with market conditions. The momentum effect affirms the Information Driven Trade (IDT) hypothesis of Llorente et al. (2002) and Sequential Information Flow (SIF) hypothesis of Copeland (1976), where information arrives in the market sequentially creating positive relationship in consecutive return. Further, Yogo (2012) state that the futures prices would underreact to news which would result in momentum between the futures price and open interest. Whereas cointegrating relationship affirms the Liquidity Driven Trade (LDT) hypotheses of Llorente et al. (2002) where the consecutive return reverses due to liquidity driven trade. As far as nature of trade is concerned, liquidity is driven by the trade by hedgers and information is by speculators Llorente et al. (2002). The regulator and the concerned exchange should put in

place risk management mechanism like price limit and circuit breakers to check momentum trade in the market which crates price instability.

In long run, volume has negative impact on commodity futures price in bear market in all three commodities. However, in bull market, it has positive (negative) effect on gold and copper (crude) futures price. On the other hand, no long-term effect of open interest is found for crude futures. But similar long-term effect of open interest is found in case of gold and copper futures price where it has positive (negative) in bear (bull) market. Thus, it has pricing stabilizing (momentum) effect in bull (bear) market. Overall distributional asymmetry in the long run is observed in the price impact of trading activity across different market conditions for all three commodity futures. This is the manifestation of the presence of heterogeneous agents operating in the commodity futures market with varied level of tolerance of risk (Jouini and Napp, 2008), dissemination and interpretation of information (Kirchler, 2010) and heterogonous belief (Qin, 2013).

In short run, similar impact of volume is overserved in case of gold and crude futures, where, it has negative (positive) effect in bear (bull market). However, even though volume is found to have positive effect in all kinds of market in copper futures, the impact is asymmetric across the distribution, thus justifying our study of locational asymmetry. This supports the SIF hypothesis of Copeland (1976) in bull market only. The short-run impact of open interest is heterogenous across there commodities. Copper futures is found to have asymmetric impact of positive and negative changes in open interest. In case of gold and crude futures, it has contemporaneous and lag asymmetric price effect across market states. That means open interest as proxy of hedging activity (Bessembider and Seguin, 1996), it has mixed price effect in the short run.

It is also observed that the simultaneous impact of increase/decrease in volume and open interest on all three commodities futures price is heterogenous across time and maker conditions.

Thus, in presence of asymmetric effect of trading activity such as volume and open interest on commodity futures prices, trading and hedging activity should be dynamic across market conditions and time. Similarly, the policy measures should be flexible enough to accommodate the trading activity led volatility across time and market states.

5. Conclusion

The commodity futures markets are more complex due to existing stylised facts of seasonality and information asymmetry along with nonlinearity and structural breaks in the relationship between trading activity such as volume and open interest and futures prices. Further, the complexity is multiplied with the arrival of heterogeneous market agents into the commodities futures markets because of financialization of commodities due to low or negative relationship with other asset classes. The empirics along with theories are inconclusive as far as the price effect of trading activity on commodity futures market is concerned. This paper is the first to uncover three kinds of asymmetric price effect of trading activity using a novel QNARDL method in gold, copper, and crude futures trading in Multi-Commodity Exchange (MCX) of India. First, the price effect of trading activity proxied by volume and open interest is found to be asymmetric in short- and long-run. Second, the asymmetric price effect due to positive and negative changes in open interest (volume) is found in the short-run (long-run) for copper (gold and crude) futures. Third, distributional asymmetry is found in the above two price effects on all three commodity futures implying that the price effect changes with changes in market conditions such bearish, bullish, and normal. Our findings will help the portfolio managers for effective investment and diversification decision, traders for better trading strategy, hedgers for better risk management strategy, and regulators and concerned exchange for effective policy making. Thus, in presence of asymmetric effect of trading activity on commodity futures prices the commodity market participants such as traders, hedgers and arbitrageurs should be dynamic in their approach in different market conditions. Similarly, the policy measures should be flexible enough to accommodate the trading activity led momentum effect on commodity futures prices across time and market states.

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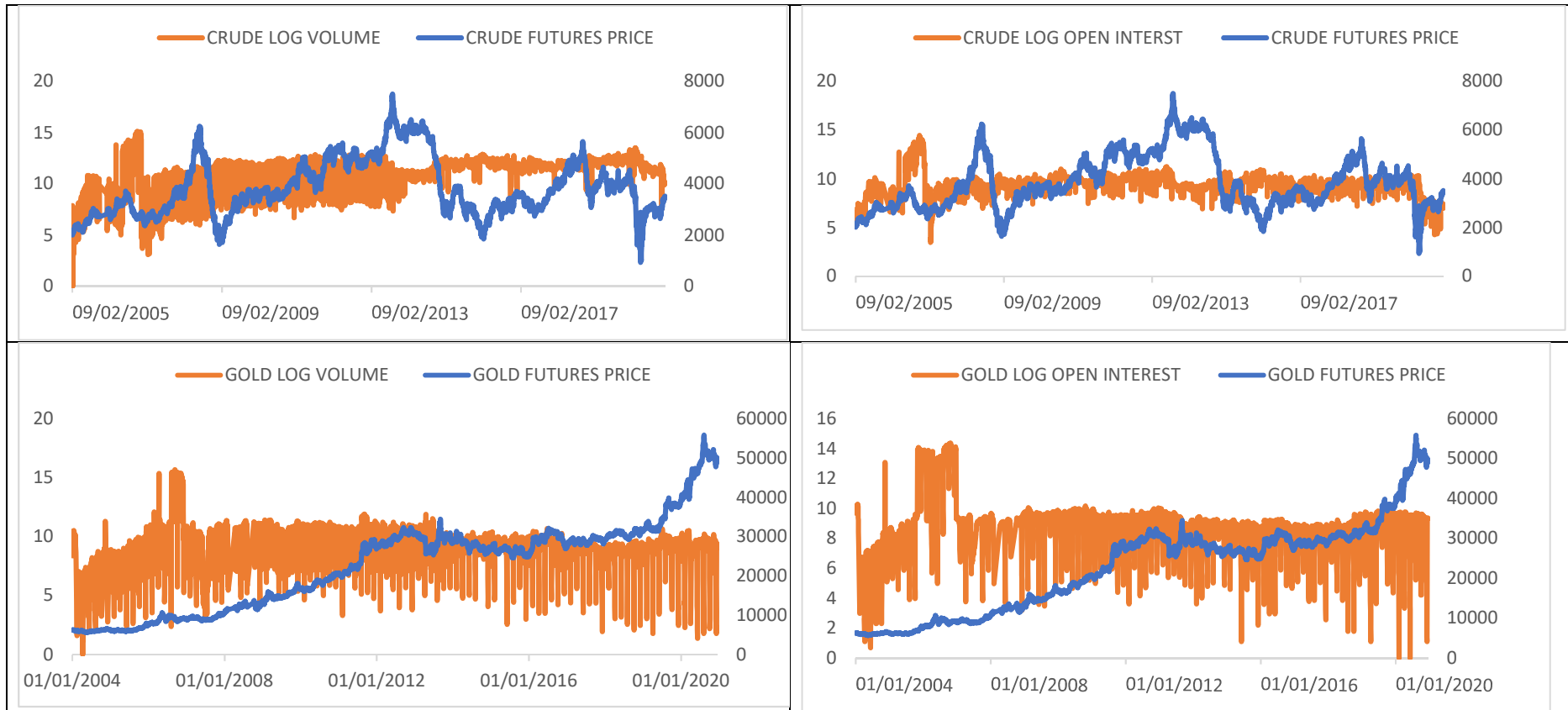
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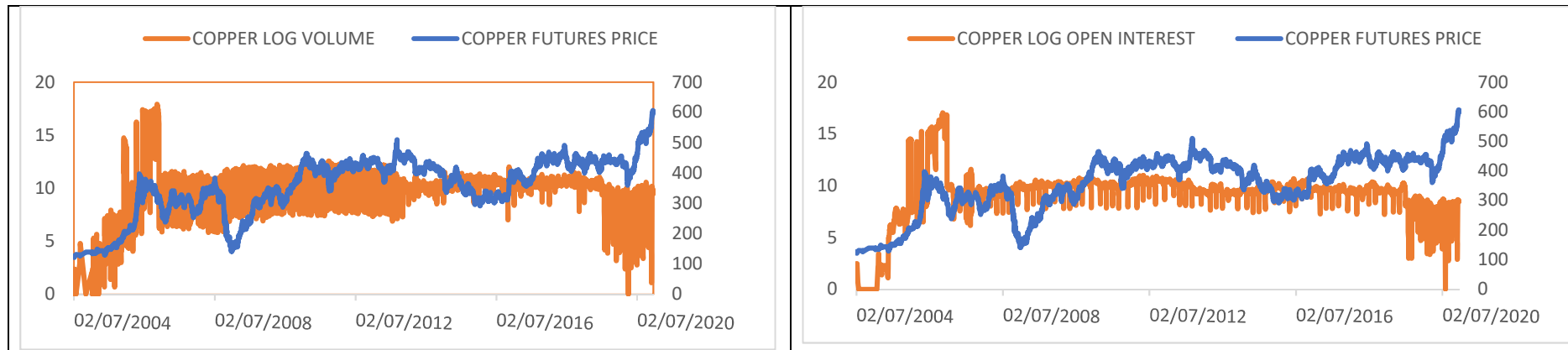
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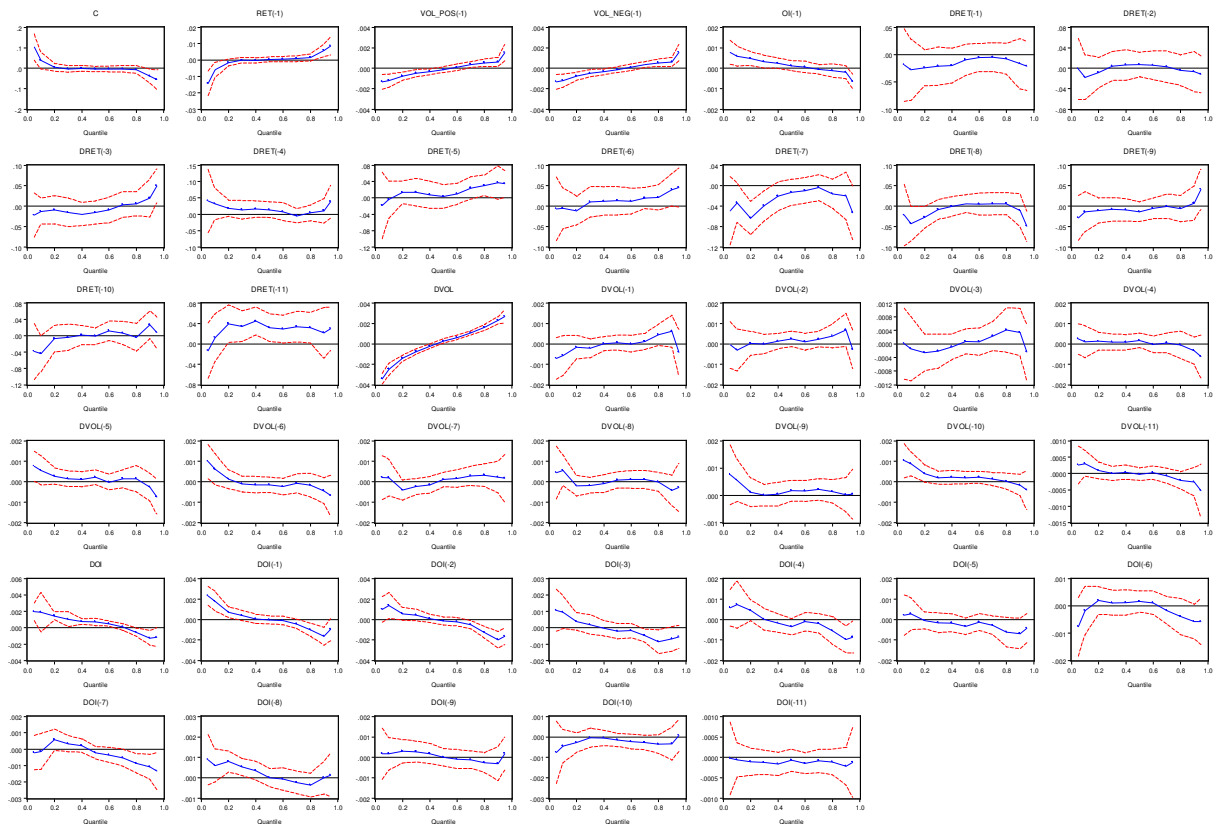
Figure 1: Dynamics of Futures price and trading activity





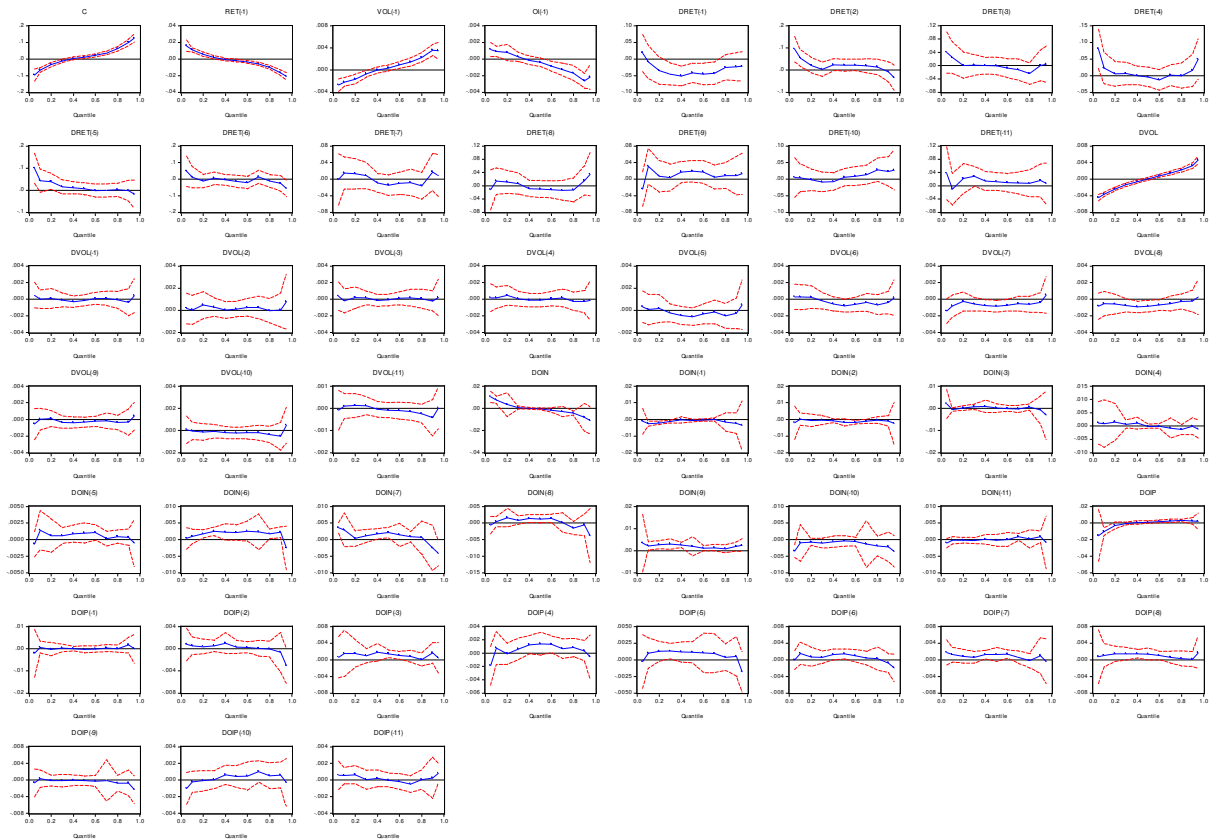
Note : The left side of the graph presents the commodity futures prices vs. trading volume in lacs. Commodity futures price vs. open interest are presented in the right-hand side of the graph. Volume (open interest) represents no of futures contract traded (no of futures contract outstanding) at the close of the trading day of near month contract.

Figure 2: Estimated long- and short-run parameters for gold futures.



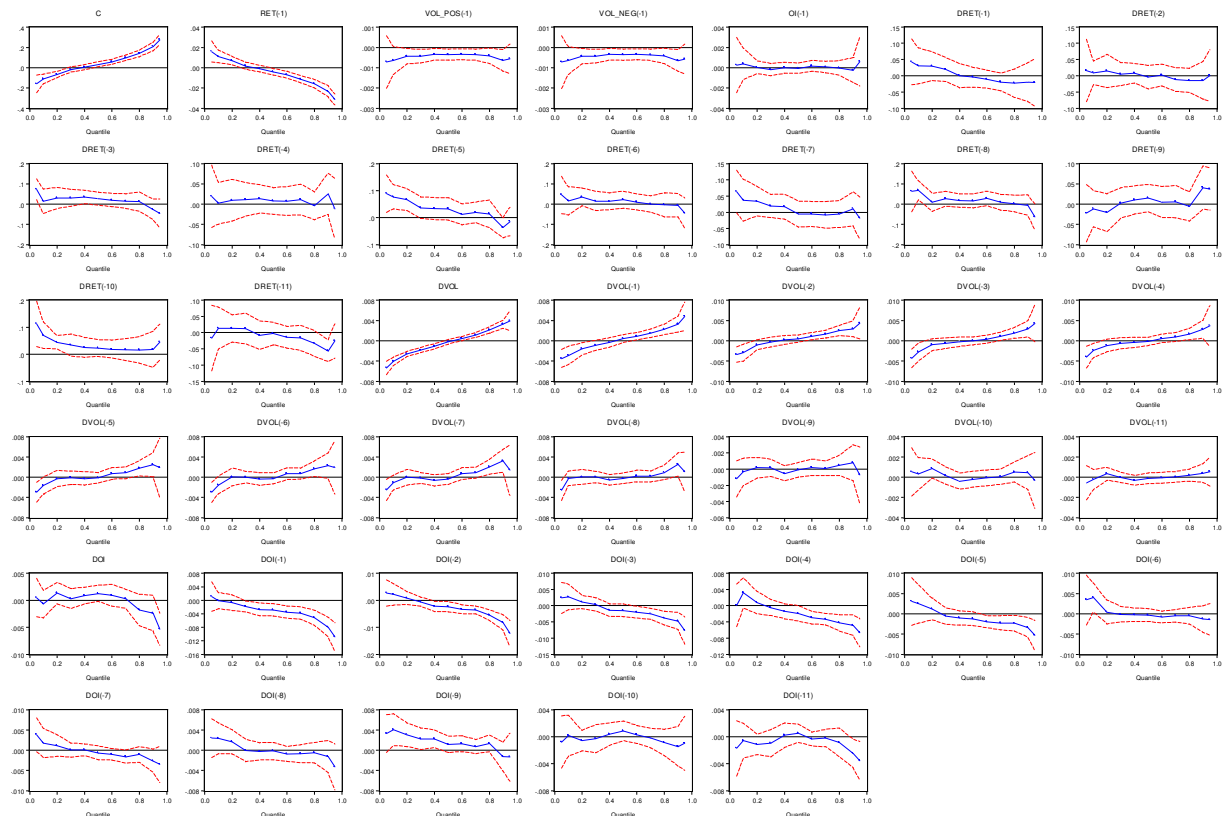
Note : X-axis represents quantiles and Y-axis represents corresponding parameter values for respective variables. Blue and red dotted lines show the value of the parameter and corresponding 95% confidence bounds, respectively. RET(-1) and OI(-1) indicates one-period lagged log gold futures price and one-period lagged log open interest, VOL_POS(-1) and VOL-NEG(-1) denote the one-period lagged log positive and negative cumulative partial sums of volume, respectively. DRET, DVOL and DOI refer to first difference of log-prices of futures contracts, volume, and open interest, respectively.

Figure 3: Estimated long- and short-run parameters for copper futures.



Note : X-axis represents quantiles and Y-axis represents corresponding parameter values for respective variables. Blue and red dotted lines show the value of the parameter and corresponding 95% confidence bounds, respectively. RET(-1), VOL(-1) and OI(-1) indicates one-period lagged copper futures log-price, log-volume and log-open interest, respectively. DRET and DVOL refer to first difference of log-prices of futures contracts and volume, respectively. DOIP and DOIN refer to positive and negative changes of log-open interest.

Figure 4: Estimated long- and short-run parameters for crude futures.



Note : X-axis represents quantiles and Y-axis corresponding parameter values of respective variables. Red and blue dotted lines show the value of the parameter and corresponding 95% confidence bound, respectively. RET (-1) and OI (-1) indicates one-period lag log crude oil futures and one-period lag open interest, VOL_POS (-1) and VOL-NEG(-1) denote the one-period lagged log positive and negative cumulative partial sums of volume, respectively. DRET, DVOL and DOI refer to first difference of log-prices of futures contracts, volume, and open interest, respectively.

Table 1 Descriptive statistics of log returns, log volume and log open interest of gold, crude and copper near month futures contract.

	CR_RET	LCRVOL	LCROI	GO_RET	LGOVOL	LGOOI	CO_RET	LCOVOL	LCOOI
Mean	0.000	11.224	9.566	0.000	9.248	9.014	0.000	10.243	9.554
Median	0.001	11.732	9.626	0.001	9.528	9.143	0.000	10.593	9.702
Maximum	0.697	15.125	14.462	0.098	15.689	14.372	0.104	17.924	17.044
Minimum	-0.779	0.000	3.466	-0.091	0.000	0.000	-0.106	0.000	0.000
Std. Dev.	0.029	1.599	1.105	0.010	1.816	1.653	0.015	2.166	1.845
Skewness	-1.478	-1.620	0.157	-0.330	-0.690	-0.098	-0.114	-0.869	-0.166
Kurtosis	228.427	6.255	8.041	12.711	5.953	7.931	7.876	7.419	11.200
Jarque-Bera	9104201.000	3778.896	4570.353	18368.620	2060.268	4722.026	4333.718	4102.044	12250.840
Probability	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Observations	4299	4300	4300	4653	4654	4654	4365	4366	4366
Zivot-Andrews test statistic	-28.257**	-14.695***	-7.467***	-70.147***	-19.683**	-19.655***	-46.524***	-11.183***	-7.910***
UDMax statistic	1.985	1054.589**	262.247**	3.282	382.925**	158.821**	3.896	182.181**	271.010**
Augmented Dickey-Fuller test statistic	-27.121***			-70.055***			-68.951***		

Note: J-B indicates Jarque-Bera test for normality. Z-A unit root test denotes empirical statistics for stationarity with structural breaks. UDMax statistics denotes Bai-Perron (2003) tests for 1 to M globally determined breaks. ***, ** and * indicate significance at 1% , 5% and 10% level respectively.

Table 2: Wald test results of long- and short-run asymmetry tests

	<i>gold futures</i>		<i>copper futures</i>		<i>crude futures</i>	
	W_{LR}	W_{SR}	W_{LR}	W_{SR}	W_{LR}	W_{SR}
<i>vol</i>	81.470*** [0.000]	2.110 [0.173]	1.071 [0.301]	0.597 [0.440]	9.814*** [0.002]	0.001 [0.978]
<i>oi</i>	0.074 [0.785]	1.033 [0.310]	0.098 [0.754]	5.353** [0.021]	0.133 [0.716]	2.615 [0.106]

Note: The p -values are presented in square brackets. *** indicates significance at the 1% level leading to rejection of null hypothesis. Using general-to-specific approach by fixing $p_{\max} = 12$ and $q_{\max} = 12$, the orders of the respective estimated NARDL models are selected. W_{LR} and W_{SR} denote Wald test statistics for long and short-run respectively.

Table 3: Estimation results of ARDL for gold futures and NARDL model for copper and crude futures.

	Gold futures		Copper futures		Crude futures
Intercept	0.016* (0.009)	Intercept	0.016*** (0.005)	Intercept	0.054*** (0.013)
lgoprice _{t-1}	-0.002** (0.001)	lcoprice _{t-1}	-0.003*** (0.001)	lcrprice _{t-1}	-0.007*** (0.002)
lcrvol ⁺ _{t-1}	-0.0001 (0.0002)	lcovol _{t-1}	0.0006** (0.0003)	lcrvol ⁺ _{t-1}	-0.0002 (0.0004)
lcrvol ⁻ _{t-1}	-0.0001 (0.0002)	lcooi _{t-1}	-0.0007** (0.0003)	lcrvol ⁻ _{t-1}	-0.0002 (0.0004)
lgooi _{t-1}	0.0001 (0.0001)	Δlcoprice _{t-1}	-0.043*** (0.015)	lcroi _{t-1}	-0.0003 (0.0004)
Δlgoprice _{t-4}	0.032** (0.014)	Δlcoprice _{t-2}	0.029* (0.015)	Δlcrprice _{t-7}	0.041*** (0.015)
Δlgoprice _{t-7}	-0.036** (0.014)	Δlcoprice _{t-5}	0.028* (0.015)	Δlcrprice _{t-10}	0.067*** (0.015)
Δlgoprice _{t-11}	0.043*** (0.014)	Δlcoprice _{t-9}	0.028* (0.015)	Δlcrprice _{t-11}	-0.039*** (0.015)
Δlgooi _t	0.001*** (0.0002)	Δlcovol _t	-0.0006** (0.0003)	Δlcroi _{t-1}	-0.005*** (0.001)
-	-	Δlcovol _{t-7}	-0.001** (0.0004)	Δlcroi _{t-2}	-0.004*** (0.001)
-	-	Δlcovol _{t-8}	-0.001** (0.0004)	Δlcroi _{t-4}	-0.002** (0.001)
-	-	Δlcooi ⁺ _{t-5}	0.001* (0.0006)	Δlcroi _{t-9}	0.003*** (0.001)
-	-	Δlcooi ⁺ _{t-8}	0.002*** (0.0007)	-	-
-	-	Δlcooi ⁻ _{t-1}	-0.0015* (0.0008)	-	-
-	-	Δlcooi ⁻ _{t-2}	-0.0017** (0.0008)	-	-
-	-	Δlcooi ⁻ _{t-6}	0.003*** (0.0009)	-	-
-	-	Δlcooi ⁻ _{t-9}	0.0028*** (0.0008)	-	-
-	-	Δlcooi ⁻ _{t-10}	-0.0017** (0.0008)	-	-

Note: ***, ** and* indicate significance at 1%, 5% and 10% level of significance. Standard errors of the coefficients are reported in the brackets. As short run results of volume (Δvol) for gold and crude are insignificant, results are not presented.

Table 4: Results of the Wald test for distributional asymmetry

	<i>gold futures</i>		<i>copper futures</i>		<i>crude futures</i>
ρ	29.534*** [0.000]	ρ	216.737*** [0.000]	ρ	148.557*** [0.000]
ρ_{vol^+}	51.144*** [0.000]	ρ_{vol}	103.001*** [0.000]	ρ_{vol^+}	2.858 [0.985]
ρ_{vol^-}	51.672*** [0.000]	ρ_{oi}	53.177*** [0.000]	ρ_{vol^-}	2.866 [0.984]
ρ_{oi}	27.252*** [0.002]	θ_1	8.373 [0.593]	ρ_{oi}	5.186 [0.878]
θ_1	2.357 [0.993]	θ_2	17.279* [0.068]	θ_1	6.397 [0781]
θ_2	3.124 [0.978]	θ_3	5.718 [0.838]	θ_2	3.981 [0.948]
θ_3	10.000 [0.441]	θ_4	12.981 [0.225]	θ_3	12.789 [0.236]
θ_4	8.040 [0.625]	θ_5	11.359 [0.330]	θ_4	4.351 [0.930]
θ_5	6.111 [0.806]	θ_6	14.220 [0.163]	θ_5	23.163** [0.010]
θ_6	6.276 [0.792]	θ_7	8.091 [0.620]	θ_6	6.514 [0.770]
θ_7	17.559* [0.063]	θ_8	6.746 [0.749]	θ_7	8.096 [0.619]
θ_8	16.864* [0.077]	θ_9	11.465 [0.322]	θ_8	19.594** [0.033]
θ_9	6.630 [0.760]	θ_{10}	5.115 [0.883]	θ_9	8.578 [0.572]
θ_{10}	13.597 [0.192]	θ_{11}	6.925 [0.732]	θ_{10}	6.174 [0.801]
θ_{11}	7.738 [0.654]	π_0	452.707*** [0.000]	θ_{11}	12.418 [0.258]
π_0	451.208*** [0.000]	π_1	3.390 [0.971]	π_0	252.266*** [0.000]
π_1	13.194 [0.213]	π_2	2.414 [0.992]	π_1	49.678*** [0.000]
π_2	9.661 [0.471]	π_3	2.895 [0.984]	π_2	34.494*** [0.000]
π_3	6.951 [0.730]	π_4	2.054 [0.996]	π_3	28.573*** [0.001]
π_4	5.699 [0.839]	π_5	4.051 [0.945]	π_4	21.707** [0.017]
π_5	13.551 [0.195]	π_6	4.562 [0.918]	π_5	20.852** [0.022]
π_6	11.612 [0.312]	π_7	4.107 [0.942]	π_6	21.091** [0.021]
π_7	11.285 [0.336]	π_8	2.926 [0.983]	π_7	26.885*** [0.003]

π_8	10.607 [0.389]	π_9	3.392 [0.971]	π_8	19.154** [0.038]
π_9	4.571 [0.918]	π_{10}	2.911 [0.983]	π_9	10.091 [0.433]
π_{10}	10.503 [0.397]	π_{11}	3.316 [0.973]	π_{10}	11.986 [0.286]
π_{11}	8.809 [0.550]	γ_0^-	65.913*** [0.000]	π_{11}	10.860 [0.368]
γ_0	53.560*** [0.000]	γ_1^-	20.237** [0.027]	γ_0	25.413*** [0.005]
γ_1	45.507*** [0.000]	γ_2^-	7.129 [0.713]	γ_1	25.267*** [0.005]
γ_2	38.461*** [0.000]	γ_3^-	7.426 [0.685]	γ_2	39.683*** [0.000]
γ_3	15286 [0.122]	γ_4^-	6.160 [0.802]	γ_3	22.848** [0.011]
γ_4	22.493** [0.013]	γ_5^-	6.367 [0.783]	γ_4	20.097** [0.028]
γ_5	7.725 [0.558]	γ_6^-	7.646 [0.663]	γ_5	11.599 [0.313]
γ_6	10.269 [0.417]	γ_7^-	20.647** [0.024]	γ_6	8.681 [0.563]
γ_7	25.343*** [0.005]	γ_8^-	15.916 [0.102]	γ_7	11.359 [0.330]
γ_8	15.602 [0.112]	γ_9^-	9.775 [0.460]	γ_8	8.486 [0.581]
γ_9	5.336 [0.868]	γ_{10}^-	11.214 [0.341]	γ_9	14.170 [0.165]
γ_{10}	5.207 [0.877]	γ_{11}^-	11.021 [0.356]	γ_{10}	7.434 [0.684]
γ_{11}	2.515 [0.991]	γ_0^+	52.406*** [0.000]	γ_{11}	16.432* [0.088]
-	-	γ_1^+	3.728 [0.959]	-	-
-	-	γ_2^+	5.841 [0.828]	-	-
-	-	γ_3^+	7.031 [0.722]	-	-
-	-	γ_4^+	8.747 [0.556]	-	-
-	-	γ_5^+	4.756 [0.907]	-	-
-	-	γ_6^+	8.564 [0.574]	-	-
-	-	γ_7^+	7.649 [0.663]	-	-
-	-	γ_8^+	3.292 [0.974]	-	-
-	-	γ_9^+	2.539 [0.990]	-	-
-	-	γ_{10}^+	6.354	-	-

			[0.785]		
-	-	γ_{11}^+	6.677 [0.756]	-	-

Note: The p -values are presented in square brackets. *** indicates significance at 1% level leading to rejection of null hypothesis. W_{LR} and W_{SR} denote the Wald test statistics for long and short-run respectively.