Essays on Indian Futures Markets

by

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Aum Aum Aum.

ABSTRACT

This thesis studies the impact of two regulatory reforms undertaken by the Forward Market Regulator (FMC) and Securities Board of India (SEBI) on the market efficiency, price discovery and market quality in the Indian futures markets. The first regulatory reform is associated with FMC's restriction on the agricultural commodity futures markets by suspending trading in wheat contracts in 2007. The first and the second essays of this thesis argue that such regulatory intervention associated with ban on futures trading is likely to have significant effect on market efficiency and price discovery of commodity futures markets in India because it will reduce credibility and long-term prospects of agricultural contracts. The second regulatory reform follows SEBI's announcement of increase in the minimum contract size for derivatives securities in 2015.[1] The third essay of this thesis argues that upward revision in the minimum lot size is likely to have significant impact on the market quality of index futures contracts because higher contract size have negative impact on traded volume and liquidity, due to increase in transaction cost.

The first essay, using data from the Indian wheat futures contract traded at NCDEX, examines whether government interventions like imposition of trading suspension on futures can reduce the overall market efficiency. Using monthly series, the market efficiency analysis is carried out using a cointegration methodology, quasi error correction model, and relative

[1] The minimum contract value and the framework for determination of lot size for derivative contracts is specified by SEBI. However, contract value may exceed (or fall below) SEBI's prescribed minimum value because of the variations in the prices of the underlying stock/indices over a period of time. Exchanges in India, thus, periodically review the lot sizes for derivative contracts on stocks/indices in pursuance of SEBI's guidelines for the minimum contract sizes. The minimum contract value in the equity derivative segment till July, 2015, was set at Rs. 2 lakh. There were three downward revisions in the contract sizes of equity index contracts over the period 2000-2015, which were periodic revisions of the lot sizes and are also part of this empirical study. However, the upward revision of the lot size in August, 2015, was a distinct regulatory reform case because the increase in the lot size was not a periodic review, instead it resulted from the increase in the minimum contract value from Rs. 2 lakhs to 5 lakhs.

efficiency measure; and results of these tests are compared between the pre- and post-ban periods. Findings suggest that spot and lagged futures are generally cointegrated although the 84-days forecast horizon exhibits no-cointegration in the pre-ban period, which is not uncommon in the longest maturities and relatively new futures contract markets. The empirical results confirm that condition of slope coefficient being close to unity is satisfied except for forecast horizon of 28-days in the post-ban sample. Based on these findings it is likely that futures market became inefficient and biased because uncertainty in the futures trade and frequent instances of suspensions in the Indian agricultural commodities over the years have discouraged market participants and made them more risk-averse in the long-term during post-ban period. In addition, the results from the analysis of the short-term relationship also find that after-ban sample yields more statistically significant lags of changes in the dependent variable for all maturities. Similarly, results from an examination of the relative efficiency also reveal that there is appreciable pattern in the degree of inefficiency in the post-ban sample. Thus, the essay concludes that governments should identify alternative regulatory intervention tools for controlling speculative behaviour and should consider adopting a more stable policy environment to address such inefficiencies in the Indian agricultural futures markets.

The second essay examines the price discovery performance of wheat futures markets in the long and short run, again focussing on the effects of trading suspension on the functioning of Indian futures markets. The main finding using the daily data is that the spot and futures series are cointegrated in both phases of trading, however, futures prices were not unbiased estimate for spot prices in the post-ban period. These results also confirm the evidence found in the first essay which uses the cointegration model of spot and lagged futures. Nevertheless, the finding regarding the positive constant risk premium indicates unfavourable impact of multiple instances of blanket bans on agricultural futures contracts trading at NCDEX, as explained previously. The results from error-correction modelling supports weak exogeneity (of futures series) and long-run prediction hypotheses in both periods, suggesting that wheat futures markets in India can be viewed as an effective platform for long-run price discovery compared to the spot market. However, the short-run dynamics confirm that unidirectional causality running from the futures to the spot markets is prevalent in the pre-ban period, but the two markets interacted bilaterally in terms of information flow during the post-ban period. In summary, the empirical analysis shows that although wheat futures contracts are faster in updating prices and disseminate more information than the spot markets in the long-term, the abrupt regulatory intervention has harmed the short-term price discovery process. Finally, findings of this study have important implications for regulators and policy makers in their attempt to develop futures trading in agricultural commodities on a sustainable basis.

The third essay examines the effects of four instances of revisions in the contract sizes on the market quality of Indian index futures markets. The focus is on two types of respecifications in the Nifty 50 futures contract: first, the size of the contract was decreased thrice by a factor of two, and second, the contract size was tripled. The particular changes in the minimum contract specification provide this study a unique opportunity to empirically test the impact of both decrease and increase in the market lot sizes on the trading activity (TV), market liquidity (BAS) and price volatility (PV), before and after the dates of contract modifications. The analysis is performed in a three-equation structural model framework using the generalized method of moments procedure. Findings suggest that the decrease (increase) in the contract size resulted in higher (lower) TV, reduced (higher) BAS while results regarding the PV are ambiguous. In particular, observations regarding the effectiveness of regulatory intervention in terms of increasing the minimum contract size for reducing speculative trading suggests that the Nifty 50 index futures contract have successfully attracted more hedgers to the market because TV has reduced while open interest continued to increase. Furthermore, results also suggest that the two measurements of market quality (TV and BAS) are negatively impacted but the one other measurement (PV) has decreased following the increase in the contract multiplier. The results of this study have significant practical relevance in terms of evaluating whether contract lot size decisions are an appropriate policy tool for reducing excessive speculation.

SUMMARY

Exchange derivatives trading for national level commodity futures and equity index futures in India started in 2003 and 2001 respectively. Despite of the institutional ecosystem being put in place for nearly two decades, the participation of farmers and Farmer Producer Organizations' (FPOs) in agricultural futures trade is extremely low in India; and unlike most global Exchanges, the decision for contract sizes, margins and open position limits on the equity or equity index derivatives still remains a part of the regulator's mandate.

This doctoral thesis by identifying two regulatory reforms from the Indian market concerning outright suspension of wheat futures contracts and increase in the market lot size of the index futures contracts, focuses on three essays relating to relative market efficiency, price discovery performance and market quality measures. The first essay examines the impact of wheat trading suspension on the degree of market efficiency in the pre-ban and post-ban phases. The second essay using data from the analogous wheat contract analyses if the trading ban have consequences on the market leadership and information flow between the spot and futures prices, under different trading periods. Lastly, the third essay examines whether the increase in the minimum lot sizes of index futures contracts can affect the trading activity variables, market liquidity and price volatility.

Analysis from the first essay show that interventions like abrupt trading bans had negative effects on both the long-run market efficiency and short-run efficiency measure. Further results from the second essay reveal that trading suspensions have negative consequences on the short-run price discovery dynamics. Therefore from a viewpoint of attracting more hedgers (farmers' or

FPOs) into the market for increasing liquidity and depth, regulators must provide stable policy environment for future trade to flourish.

Finally, findings from the third essay suggest that increase in the contract size had positive impact only for the open interest, but the trading volume and liquidity variables were negatively affected. Therefore, the Securities market regulator's interventions in the Exchange's commercial decisions may discourage interest in the equity futures products at large in the long-term.

CHAPTER 1

1. Introduction

1.1. BACKGROUND AND MOTIVATION

This thesis comprises of three essays particularly focussing on two regulatory reforms in the case of Indian futures markets. The first regulatory reform is associated with the Government imposed ban on futures trading of an agricultural commodity contract. Multiplicity of laws like - (a) Central Government can set a Minimum Support Price (MSP) for food grains; (b) the Essential Commodities Act (ECA), 1955, empowers Central and State Governments to exercise powers on setting prices and permitting inventory for commodities that are considered as essential; (c) using the Prevention of Blackmarketing and Maintenance of Supplies of Commodities Act (PBMSCA) 1980, the State Government can also choose to detain persons if they are obstructing supplies in essential commodities with unethical trade practices; and (d) each State Government has its own Agricultural Produce Market Committees (APMCs) Act, 2003, which restricts the physical trading of commodities to the designated regulated market yard only - has had adversely affected the free trade in spot commodities (Singh, Kumar, Singh and Jain, 2005; Dummu, 2009; Fernandez, 2013; Maravi, 2015; Kumar and Garg, 2016).

Besides various laws governing the inventories, prices and supply of certain agricultural commodities, Indian agricultural commodities futures markets are also characterized by frequent government interventions like using regulatory tools for banning trade in certain agricultural contracts and abruptly hiking the margins (Gulati, Chatterjee and Hussain, 2017). In the wake of global food price crisis in 2007-2008, Indian agricultural commodities experienced suddenly heightened spot price volatility. As a consequence, banning the futures trading in commodities, which are perceived as more sensitive from food security point of view, became a subject of national discussion particularly stemming from the vested political interests. After debate, political opposition, growing concerns about increasing agricultural prices and to address the perception that futures trading leads to price rises, the FMC suspended futures trading in wheat contracts on February 27, 2007. Following this directive issued by the market regulator, the National Commodity and Derivative Exchange (NCDEX) on February 28, 2007, announced that no new wheat futures contracts will be traded till further notification. The ban was lifted by the FMC on May 15, 2009 and wheat contracts were made available for trading on the NCDEX platform from May 21, 2009. Similar suspensions in trading of futures contracts (e.g., Japan and India) in the 20th century could be linked to the demands of war economy and aftermath events, World Wars, and the Great Depression. However, the most extreme form of regulatory intervention like a trading ban caused by increasing political pressures may have negative consequences on the functioning of the futures market which may further hamper the information flow between the spot and futures prices. Such trading bans, in the twenty-first century context, are an unexplored area and the impact of increased regulatory uncertainty on the market efficiency and price discovery is still unknown.

Test of market efficiency typically correspond to the semi-strong form proposed by Fama (1970): based on the principle that in an efficiently functioning market, futures prices should fully reflect all publicly available information and the expected returns to speculators in markets should be zero. In this context, the market efficiency hypothesis can be reduced to the joint restriction of simple efficiency by Hansen and Hodrick (1980). Therefore, the efficient futures market enables the current futures prices to act as the unbiased estimator of the future spot prices (Zivot, 2000). The price discovery function, on the other hand, is premised on testing whether new information is first reflected in the futures or spot markets, first put forward by Hoffman (1932). With respect to this view of price discovery, Garbade and Silber (1979) developed the concept of dominant-satellite markets according to which, futures markets should dominate the spot markets in terms of information flow. Under this notion, the prediction (i.e., price discovery) hypothesis can be linked to causality testing such as that developed by Engle and Granger (1987). Therefore, in an informationally efficient market the futures prices are a primary source of information and they unidirectionally cause movement in the spot prices (Yang, Bessler and Leatham, 2001).

While the extant literature devoted to testing market efficiency and price discovery in the context of agricultural commodity futures markets in India is voluminous, previous studies do not address the impact of the trading ban. However, it is often argued in the literature (Carlton, 1984; Bergfjord, 2007, amongst others) that government sponsored interventions would reduce the credibility of futures contracts. Thus, motivated by the missing knowledge of around potential negative effects of commodity-specific bans in a market economy like India, this thesis extends the market efficiency and price discovery literature by raising, and then addressing, the following research questions: (1) To what extent did the futures market become inefficient after the relaunch of trading in the post-ban wheat contracts?; and (2) How are the price discovery dynamics between the spot and futures markets influenced by the ban on the futures trading?.

The second regulatory reform is associated with revisions in the minimum market lot size of an equity index contract by the Indian capital market regulator. Taking the view that three instances of downward revisions (in 2005, 2007 and 2014) in the lot sizes of index futures has increased the contract accessibility and retail investor participation in the equity derivatives segment, the market regulator SEBI in 2015 increased the minimum contract size from 25 lots to

75 lots. The observation that the ratio of turnover of equity derivatives to the equity cash market in India is significantly high in comparison to the developed markets and second only to South Korea (see, Chakravarthy and Somanathan, 2014; Rukhaiyar, 2015; and SEBI Discussion Paper, 2017) was also noted by the regulator while making modifications to the contract lot size. Furthermore, keeping in mind that individual investors account for a significant proportion of trading volume (58%)[2] in the Indian index futures market, the latter regulatory change was imposed to prevent retail investors from incurring huge losses, under the assumption they may not adequately understand the high degree of risk of trading in derivatives, and to create more balanced participation of hedgers and speculators in the equity derivatives markets (SEBI Discussion Paper, 2017; IGIDR Finance Research Group, 2017).

Following SEBI's circular CIR/MRD/DP/14/2015 dated July 13, 2015, on increasing the minimum contract size in the equity derivatives segment, the National Stock Exchange (NSE) on August 07, 2015 announced revision in the minimum size of the Nifty 50 index futures contracts, applicable to contracts with November 2015 expiry and beyond. Unlike most global markets (e.g., America, Australia, Greece, Sweden, and U.K.), where the decisions on readjusting of the contract lot sizes are taken by the Exchanges, designing reforms related to margins, position limits and contract sizes in the Indian market are fixed by SEBI's regulation and Exchanges have no operational flexibility to take these decisions. Thus, revision in the minimum contract size by regulators is still a rare event and potential effects on market quality when the minimum tick size is held constant, is relatively unexplored.

[2] It is observed from the data presented in the SEBI 's Discussion Paper on Growth and Development of Equity Derivatives Markets in India dated July 12, 2017 that Individual Investors account for 58% of trading in the Non-Institutional Non-Proprietary category.

The futures contract design, with regard to maturity date, delivery terms, trading months, units for price quotation and trading hours are generally thought to have been standardized given they are exchange-traded instrument. However, there are features of contract design, such as margin requirement, position limits, tick size[3] and contract size, which can be varied to appeal to both hedgers and speculators (Silber, 1981). Each of these features stand alone as an independent research field in the market microstructure literature (Chng, 2004) and there is large empirical literature concerned with the effects of margin, position limits and minimum tick size regulation on the volume of trade and liquidity of contracts. However, the stream of literature with regard to the effects of change in the minimum contract size are limited because such changes to the multiplier are a rare event. Furthermore, most studies on futures contract design[4] have concentrated on developing specifications for introducing successful new contracts to attract significant trading volume and a desired group of traders, i.e., brokers, speculators and hedgers, to the market (see, Silber, 1981; Black, 1986; Duffie and Jackson, 1989; Cuny, 1993; and Tashjian and Weissman, 1995). In contrast, this study intends to capture the effects on market quality after changes in the minimum contract size are made to the existing futures contract. Motivated by the remaining gaps in the empirical literature, since there are very few examples available of contract size modifications to existing contracts, revision of minimum lot sizes should be a useful means to assess the optimal contract size, and in particular, the careful consideration of the trade-off between volume and transaction cost. Thus, building on the findings from equity market events, stock splits and changes in Minimum Trading Unit (MTU),

[3] Recent studies, for example Chou, Wang and Wang (2015.b), Gwilym and Ebrahim (2013) and tick size Verousis, Perotti and Sermpinis (2018) provide a survey of literature on margin changes, restrictive position limits and implication of tick size changes respectively.

[4] See Tashjan (1995) and Greppmair and Theissen (2021) for the review of theoretical literature on the optimal futures contract design.

and the existing literature on the impact of revision in futures contract on the market quality parameters, the third research chapter asks the question: What is the impact of modifications in the minimum lot size on traded volume, liquidity, and volatility?

1.2. THESIS OUTLINE, CONTRIBUTION AND OVERVIEW

The remainder of the thesis is organized as follows. Chapter 2 studies market efficiency under traditional unbiased expectation hypothesis, examines relative market efficiency around the ban periods and investigates what effects trading suspension may have on the short-run market efficiency using data from the NCDEX wheat contracts. Chapter 2 uses a sample of monthly non-overlapping observations, whereas Chapter 3 studies the price discovery role of futures market under the cost-of-carry model and tests for prediction hypothesis for the two periods using daily data from analogous wheat contracts. Chapter 4 studies the effects of an increase (decrease) in the contract size on trading activity, liquidity, and price volatility, using data from Nifty 50 index futures contract. Finally, Chapter 5 briefly summarises the key findings of the thesis, policy implications, potential future research directions and concludes.

The main contributions of this thesis are as follows: The pronounced price spikes in Indian agricultural commodities have led to more bans in the futures markets during the last decade. The noticeable suspensions in highly traded commodities, viz. guar gum and seed in March 2012, castor seed in January 2016 and chickpea in July 2016, has culminated into a discussion around the negative impacts of Government imposed bans on the futures trading in agri-commodities. The first two research chapters contribute to the ongoing debates that abrupt bans in derivatives trading on the agricultural products reduces hedger participation, deprives markets of liquidity and depth, and as a result futures markets will not be able to function efficiently and achieve its objective of price discovery.

The first research chapter of this thesis (Chapter 2) investigates the impact of regulatory constraints in the futures market by comparing the degree of efficiency for three forecast horizons in the pre-ban and post-ban phases. This is the first empirical analysis of the impact of India's wheat futures trading ban on the long-run and short-run efficiency of the futures market. Moreover, this is also the first study to analyse the short-term efficiency using relative efficiency measure in the Indian market literature. The findings of this study confirm that the market efficiency hypothesis does not hold for the shortest maturity in the post-ban period, as hedgers demand a compensation for assuming the regulatory uncertainty. Also, the wheat futures trading ban lowers the short-run efficiency in all forecasting horizons, while it increases the degree of inefficiency in all maturities.

The second research chapter of this thesis (Chapter 3) examines the influence of increased regulatory pressure associated with trading bans by comparing the dominance in terms of weak exogeneity and information flow across two sub-periods. This study provides empirical evidence for the first time of how a market-wide trading ban on agriculture futures impacts long-run predictive signals and short-run causalities. Additionally, this is the first study to explore the short-run prediction hypothesis using vector error-correction model in the Indian markets. Results of this study suggest that even in an unstable policy environment where several bans on the agricultural futures were placed by the Indian government, the wheat futures market continues to play an important role in terms of dominating the long-run price discovery process. However, the regulatory uncertainty due to abrupt trading suspension has negative consequences on the short-run functioning of the futures markets. This study has found that during the post-ban period spot-futures markets interacted bilaterally in terms of information flow, i.e., futures returns do not have predictive power for spot returns in terms of short-term price discovery.

The continuing high turnover ratio of derivative to cash market in India in comparison with that of international markets caused SEBI to release a discussion paper on "Growth and Development of Equity Derivatives Markets in India" for public consultation in July 2017. The increase in the minimum lot size in 2015 created much outcry among various stakeholders that large contract sizes will force out individual investors from the market and could negatively impact on overall traded volume and liquidity. The third research chapter contributes to the policy discussion to evaluate if derivative regulators or exchanges should use the trading lot size of an existing futures contract as a policy tool to achieve an optimal contract size for promoting (or limiting) the trading activity of small speculators (i.e., individual day traders and individual non-day traders) in the market.

The third research chapter of this thesis (Chapter 4) examines whether the revised lot size of index-derivatives affects the trading activity, liquidity and price volatility in the futures market. This study is the first attempt to utilize a three-equation structural model appropriate for the simultaneity nature of market quality variable, which has not been examined previously in the contract size change literature. Also, this is the first study to provide empirical tests for the contrasting implications of traditional Amihud measure and turnover-based version of Amihud measure in equity futures markets. The results imply that increase (decrease) in the minimum contract size can increase (decrease) open interest and may decrease (increase) trading volume. Also, findings confirm that an increase in the contract size may not increase bid-ask spread and may not decrease price volatility in a substantial manner. Thus, the results indicate that increasing the minimum contract size is a beneficial policy tool for reducing speculative trading.

CHAPTER 2

2. Market Efficiency Under Trading Suspensions: The Case of the Indian Wheat Futures Market

2.1. INTRODUCTION

In theory, pricing of commodity futures contracts has been characterized either through a risk-premium model derived from Fama's (1970) weak form tests of efficiency; or by an arbitrage-free model driven by Kaldor's (1939) concept of convenience yield. The empirical literature on examining the relationship between spot and futures prices have largely focussed on the issues of market efficiency and price discovery role of the futures markets. The definition of market efficiency is conceptualised on the assumption that market participants are risk neutral (or there is no-risk premium) and their expectation about future cash price is formed rationally. Therefore, within this framework of efficient market hypothesis (EMH) it is a common practice to test the efficiency of the markets by verifying the conditions for unbiasedness proposition, which requires that futures prices should be an unbiased predictor of the future cash prices. Another strand of literature that has dealt with the issue of price discovery by examining the relative price leadership between the cash and futures commodity markets has often used cost-of-carry hypothesis for exploiting the long-run equilibrium relationship. The essence of price discovery in this framework refers to the use of leading informational content of competitive reference (futures) prices in determining the subsequent cash (spot) market prices.

Numerous papers have assessed the efficiency of futures markets and analysed their price discovery role in terms of these two alternative hypotheses. The economic phenomena of the commodity markets which motivate the study of market efficiency and price discovery investigates the links between spot and futures markets by modelling their relationship through risk premium approach or the no-arbitrage pricing rule[5] respectively. Both theoretical arguments can however be reconciled using Cointegration-based tests and Error Correction techniques. From the methodological standpoint it is important to recognize that the forms of the cointegration models for the two alternative hypotheses are distinct in terms of their set-up of the cointegrating regression equations. The most recent studies e.g. Chow, McAleer and Sequeira (2000); Kellard, (2002); McAleer and Sequeira (2004); Coakley, Dollery and Kellard (2011); and Mehrotra and Carter (2017) have discussed the model for cointegrating regression and two popular conceptualizations of the commodity futures pricing. However, no studies till date, at the best of knowledge, have examined the market efficiency and price discovery performance of agricultural futures in the model of cointegration between s_t (spot price at contract maturity) and $f_{t-\tau}$ (lagged futures price) and in the cointegration model between s_t and f_t (contemporaneous spot and futures prices) together respectively, within the same sample period, which can enable a direct comparison between the expected price model and carrying cost model.

Since the results of Brenner and Kroner (1995) it is well recognized, assuming s_t and f_t have unit root behaviour, that time leads and lags do not affect the cointegration, that is, if s_t and $f_{t-\tau}$ are cointegrated with the vector $(1, -1)$ then it will also be true for s_t and f_t. While cointegration models for $(s_t, f_{t-\tau})'$ and $(s_t, f_t)'$ can both be used to test for the restriction of $(1, -1)$ on the cointegrating vector, different form of the models are employed to draw inferences on the *relative market efficiency* and *informational efficiency*. To preview, the second chapter of this thesis by focusing on monthly data uses specification of the cointegration model for

[5] There are two standard models of commodity futures pricing. For instance, the unbiased expectation hypothesis is developed from the risk premium approach, whereas the cost-of-carry hypothesis is based on no-arbitrage pricing relationship.

$(s_t, f_{t-\tau})'$; and examined the relative market efficiency issue from the single equation quasi error-correction model. The short-run dynamics under this model measure the *forecasting ability* of futures prices to the future spot price. However, the third chapter models cointegration between s_t and f_t for the analysis of price discovery.[6] Both chapters examine the case for Indian wheat futures contracts traded at NCDEX from 2004 through 2015, that has been banned on February 28, 2007 and was subsequently relaunched on May 21, 2009.

The importance of modelling the spot and futures grain markets has become increasingly apparent for an underlying asset such as wheat, as the sector internationally has been subject to many government regulations and policies, e.g. the United States' farm program policy and Export Enhancement Program (EEP); the European Union's Common Agricultural Policy (CAP); Canada's rail freight subsidy and pricing practice of the Canadian Wheat Board (CWB); Australia's wheat export program dominated by the Australian Wheat Board (AWB); Argentina's wheat export under Common External Tariff (CET) to MERCOSUR member countries (Bessler, Yang and Wongcharupan, 2002; Yang, Zhang and Leatham, 2003; Boaitey, 2013); and India's ECA, 1955, and APMC, 2003 Acts (Singh, Kumar, Singh and Jain, 2005; Maravi, 2015; Rajib, 2015; Kar, 2021), which restricted free trade in various food-grains like wheat.

Historically, the Indian commodities futures market has been subjected to many prohibitions/bans under the Defence of India Act, 1935 (Hathaway, 2007; and Bhagwat, Maravi, Omre and Chand, 2015). In addition to the legal interventions (such as, ECA, APMC, Food Standard and Safety Act (FSSA), 2006, National Food Security Act (NFSA), 2013), price

[6] In contrast to the second chapter, the third chapter asserts cointegration model for $(s_t, f_t)'$ in daily data; and the weak exogeneity of the spot and futures price with respect to the cointegrating parameters is tested in the vector error correction model, which take one equation individually for $(\Delta s_t, \Delta f_t)'$. The short-run dynamics in case of this model convey information about *price leadership* and *information flow*.

stabilization measures through the channel of MSP or via procurement operations of food-grains for the purpose of Public Distribution System (PDS); are some significant aspects governing the spot prices commodities which can adversely impact the wheat market (Ali, Sidhu and Vatta, 2012; Shirur and Gowda, 2014; Kozicka, Kalkuhl, Saini and Brockhaus, 2014; Saini and Kozicka, 2014; Gulati and Saini, 2015; Narayanan, 2015).

The study of agricultural futures markets in India merits attention as, although India is a major producer[7] of several agricultural commodities[8] and its organized futures trading on the National Exchanges has been in existence for nearly 20 years, Indian farmers and FPO's have not been able to draw benefits of hedging their price risk and efficient price discovery in real time, which are considered to be primary functions of futures markets. As argued by Gulati et al. (2017) and Chatterjee, Raghunathan and Gulati (2019), this underperformance (i.e., lack of liquidity and depth) of overall agri-futures trade in India is mainly due to frequent stringent government interventions like abrupt suspensions and as well as impositions of extremely high margins on agricultural commodities trading in futures market. Thus, it is the need of the hour to investigate the potential effects of government intervention on both market efficiency and price discovery function in the light of numerous instances of bans imposed on the agricultural futures trading during the period between 2007-to-2009.

In particular, the FMC of India announced a ban on new listing of wheat futures contracts during early 2007, and further banned trading in cereal grains (like pulses and rice) and several other agricultural commodities between mid 2007-to-2009. Therefore, disruptions caused by the

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[7] Source: Food and Agricultural Organization of the United Nations (FAO), 2017-18.

[8] India is the largest producer of milk, jute and pulses, and is the second-largest producer of wheat, rice, sugarcane, cotton and groundnuts, as well as the second-largest fruit and vegetable producer (FAO, 2017-2018).

various regulatory interventions in the futures markets such as the outright ban of commodity futures contracts, increased margin requirements or stricter position limits; are likely to have had profound implications on the degree of (in)efficiency achieved in the markets under different trading periods. Yet none of the studies on Indian commodity futures markets have updated the analysis by using the spot and futures prices from two trading periods, i.e. pre-ban era and post-trade redemption period, to account for the possible effects of government interventions on the futures market efficiency.

Besides, studies which empirically investigate market efficiency (i.e., unit slope restriction)[9] and/or unbiasedness (i.e., joint restriction)[10] in the Indian agricultural commodity futures markets (for example, Naik and Jain, 2001; Singh, 2001; Raizada and Sahi, 2006; Kumar and Pandey, 2013; Omojevwe, 2013; Soni, 2013; 2014; Inoue and Hamori, 2014; Ranganathan and Ananthakumar, 2014; Sahai, 2014; Yadav and Panigrahi, 2014; Laha and Sinha, 2015; Pandey and Vipul, 2017; Singh and Singh, 2017; and Gupta, Choudhary and Agarwal, 2018) by employing the Johansen cointegration methodology, have rarely focused on the wheat futures contracts. Similarly, this concern was pointed out in Kastens and Schroeder (1996). In that study the authors have used the prices of wheat futures traded on the Kansas City Board of Trade (KCBOT) and provided evidence that the studies on futures market efficiency have often given less emphasis to the grain (like wheat) market in comparison with the livestock (like cattle, hog) markets.

[9] If s_t and $f_{t-\tau}$ are $I(1)$, the unit slope condition $\beta_1 = 1$ in Equation (2.11), is then tested as a restriction on the cointegrating vector, given by $(1, -1)$.

[10] If s_t and $f_{t-\tau}$ are $I(1)$, the test of joint restrictions $\beta_0 = 0$ and $\beta_1 = 1$ in Equation (2.11), is carried out on the cointegrating vector , given by $(1, -1, 0)$.

Overall studies from the international commodity markets have extensively used theory of cointegration to investigate the long-run market relationship, market efficiency and/or unbiasedness hypothesis (Chowdhury, 1991; Crowder and Hamed, 1993; Krehbiel and Adkins, 1993; Beck, 1994; Moosa and Al-Loughani, 1994; Aulton, Ennew and Rayner, 1997; Fujihara and Mougoué, 1997; Sabuhoro and Larue, 1997; Chow, 1998; Peroni and McNown, 1998; Kavussanos and Nomikos, 1999; McKenzie, Jiang, Djunaidi, Hoffman and Wailes, 2002; McKenzie and Holt, 2002; He and Holt, 2004; Li, Hanrahan and McErlean, 2004; Wang and Ke, 2005; Switzer and El-Khoury, 2007; Arouri, Jawadi and Mouak, 2011; Otto, 2011; Algieri and Kalkuhl, 2014; Santi, 2016), by arguing that futures price $f_{t-\tau}$ should be the unbiased predictor of s_t. Therefore, the bulk of evidence supports long-run efficiency of commodity futures market but the studies on short-run efficiency is not common. In general, cointegration with a slope coefficient of unity is considered as an evidence of long-run market efficiency. Due to the fact that spot and futures prices share the same underlying asset, it is expected that the prices move closely, at least in the long-run. However, this intuition is not necessarily true in the short-run, as short-inefficiencies may be present even when futures markets may be unbiased forecasters of subsequent spot prices in the long-run. In case if short-term inefficiency exists, then this potential can be exploited by the speculators to obtain excess profits (Laws and Thompson, 2004). More specifically, markets which exhibit short-run inefficiencies may become more appealing particularly for the speculators and chartists, while long-term investors may not use the markets (Jawadi, Fititi and Hdia, 2017; Algieri and Kalkuhl, 2019). Turning to the measure of short-term market efficiency, a group of studies complimentarily further explored the short-term market efficiency by quantifying the degree of efficiency based on the relative efficiency measure

(Kellard, Newbold, Rayner and Ennew, 1999; Laws and Thompson, 2004; Yang, Liu, Zhang and Luo, 2009; Ballester, Climent and Furió, 2016; Khabiri, 2017; Snaith, Kellard and Ahmad, 2018).

For the Indian markets, most of the studies explored market efficiency of the commodity futures markets in terms of price discovery process (i.e. lead-lag relationship). Previous work (see, e.g., Sahoo and Kumar, 2009; Ali and Gupta, 2011; Masood and Chary, 2015; Samal, Swain, Sahoo and Soni, 2013; Raghavendra, Velmurugan and Sravanan, 2016; Lakshmi, 2017; Singh, 2017; Shanmugam and Armah, 2017; Nirmala and Deepthy, 2018; and Samal and Patra, 2020) used conventional Granger causality test, which involves analysing the relationship in bivariate vector autoregression (VAR) framework at levels (s_t, f_t) or in the return $(\Delta s_t, \Delta f_t)$ series. To account for long-run cointegration relationship between s_t and f_t some studies (see, e.g., Dey, Maitra, Roy, 2011; Chauhan, Singh and Arora, 2013; Malhotra and Sharma, 2013; Sendhil, Kar, Mathur and Jha, 2013; Behera, 2015; Inani, 2018; and Sharma and Sharma, 2018; 2019) examined market efficiency in the context of error-correction mechanism and assessed any causal relationship from relative magnitude of error-correction parameters and/or from the block exogeneity tests.

Another peculiarity surrounding the Indian commodity futures markets is that studies have resorted to other statistical tools such as, autocorrelation tests, runs tests and variance ratio tests (Kaur and Rao, 2010; Sajipriya, 2012; Patel and Patel, 2014; Mittal and Thakral, 2018; Mohanty and Mishra, 2020) for the empirical validation of market efficiency. As discussed previously, most authors have used single-restriction hypothesis and/or joint hypothesis tests while investigating the long-run market efficiency of Indian commodity futures markets, but the application of short-term market efficiency measure to quantify and compare the degree of efficiency has not been employed in the Indian market literature.

This study contributes to the existing literature in two ways. First, none of the previous studies, to the best of knowledge, have explored the efficiency in agricultural future market under pre-ban and post-ban eras. In other words, this study compares the market efficiency hypothesis by employing cointegration-based tests on the Indian wheat futures contracts traded at NCDEX between 2004-2007 and 2007-2015 periods. Following the futures market equilibrium approach, long-run efficiency is examined for three different forecast horizons (of 28, 56 and 84 days) by using the well-recognized cointegration model of Lai and Lai (1991). Second, although many Indian studies have used cointegration methodology, this chapter uses two distinct approaches to test short-term efficiency and relative efficiency of the markets before and after the regulatory changes. The first approach uses a Quasi-Error Correction Model (QECM) with the nonoverlapping monthly data (e.g., Kellard et al., 1999; Newbold, Rayner, Ennew and Marrocu, 1999.a; 1999.b; Kellard, Dunis and Sarantis, 2005; and Kremser and Rammerstorfer, 2017). The second approach uses a relative efficiency measure of Kellard et al. (1999) to indicate the level of short-run inefficiency for different maturities in two trading periods (e.g., Laws and Thompson, 2004; Yang et al., 2009; Ballester et al., 2016; Khabiri, 2017; and Snaith et al., 2018). The results of this chapter confirm that s_t and $f_{t-\tau}$ have stronger cointegration[11] once the Government imposed ban was lifted. The market efficiency hypothesis test using unit slope restrictions indicate that for longer maturities (i.e., 56- and 84-days horizon), the Indian farmers and other hedgers can use the markets efficiency in the post-ban period to manage their long-term price risk

[11] The Johansen cointegration test results based on trace and maximum eigenvalue statistics find evidence of cointegration between spot and futures prices regarding all three forecast horizons in the post-ban period, as the null hypothesis of no-cointergration is rejected at the 5% level of significance, across all lag specifications and for both Cases 2 and 3. However, cointegration results in the pre-ban period are sensitive to the lag length and different model specifications. For example, there is evidence of cointegration only under Case 2 regarding 28-day horizon (selected by AIC and SBIC) and 56-day horizon (selected by AIC) in the pre-ban period. Whereas, for 56-day horizon selected by SBIC, there is no evidence of cointegration in the pre-ban sample.

and for diversifying their portfolio risk without paying any risk premium. For 28-day maturity however, the market efficiency hypothesis does not hold. Thus, the existence of bias in the futures price would increase the cost of transferring the price risk and also would imply additional cost for diversification for the shorter maturity. Interestingly, after assessing the short-run efficiency and applying the relative efficiency measure across the pre-ban and post sub-period, the findings support that pre-ban period is generally more efficient than the post-ban period. There are several possible reasons why wheat futures contracts became inefficient in the post-ban period. First, abruptly imposed trading suspensions in agricultural commodity derivative markets may lower participation from informed traders like hedgers, which in turn may lead to market inefficiency. Second, lack of depth and adequate liquidity (trading volume) in Indian commodity futures markets coupled with frequent government interventions will not help farmers and procedures in the agricultural sectors to receive advance information and right price signals for their cropping and resource allocation decisions. This may discourage genuine players to participate in hedging their post-harvest price risk, which may further deprive the markets of liquidity and depth and may also contribute to the inefficiency in the futures markets. Thus, it was anticipated that enforcement of frequent blanket bans in the agricultural futures markets would reduce market depth leading to lower liquidity, decreased investor participation, harm the price discovery process and finally would reduced market efficiency.

The rest of the paper proceeds as follows. The Section 2.2 describes the relationship between the cointegration model and market efficiency hypothesis. The 2.3 Section describes the data set and the sampling approaches. Section 2.4 explains the testing econometric methodology employed. Section 2.5 presents the estimation results and analyses the findings in the context of the recent national ban on the trading of Indian wheat futures. Finally, the Section 2.6 concludes by summarising the major conclusions of this study.

2.2. THEORETICAL FRAMEWORK

2.2.1. Market Efficiency under the Traditional Unbiased Expectation Hypothesis

Past empirical literature on testing the futures market efficiency has concentrated much attention on the issue of unbiasedness. If the joint nature (i.e. the assumptions of rational expectations and risk neutrality) of the EMH is assumed, then the price of the futures contract would be equal to the expected future spot price at the contract termination date. Consequently, in line with Kellard, Newbold and Rayner (2001), Laws and Thompson (2004), and Snaith et al. (2018) this condition can be illustrated formally by equation:

$$f_{t-\tau} = E_{t-\tau}[s_t] \tag{2.1}$$

Here, s_t = ln (S_t) and $f_{t-\tau}$ = ln ($F_{t-\tau}$), where S_t and $F_{t-\tau}$ are the levels of the commodity spot price and the τ-period (i.e., τ days back from the contract maturity) futures price for the same commodity contract expiring in time t; and $E_{t-\tau}[s_t]$ denotes the mathematical expectation of the future spot price formed in period $t-\tau$ (where $t-\tau$ corresponds to a period between opening of the contract and the expiry date).

The first assumption of *rational expectation hypothesis* requires that the economic agents in the market must use all relevant and available information at period $t-\tau$, in forming their expectation about the future spot price for period t (Frenkel, 1979; Sabuhoro and Larue, 1997). The explicit specification of this hypothesis applied by Frenkel (1981) and, more recently Peroni and McNown (1998), McKenzie and Holt (2002), He and Holt (2004), and He and Hong (2011), is embodied in the specification as:

$$s_t = E[s_t | I_{t-\tau}] + \varepsilon_t \tag{2.2}$$

where $I_{t-\tau}$ signifies the information set available to the market participants at time $t-\tau$; and $E[s_t|I_{t-\tau}]$ expresses the expectation of the spot price at time t, conditional upon the information set, $I_{t-\tau}$, available to the agents. In this case the forecast error, ε_t, inherits the properties of conventional rational expectation error and satisfies:

$$E[(\varepsilon_t)] = 0 \text{ and,} \tag{2.3}$$

$$E[\varepsilon_t(s_t|I_{t-\tau})] = 0 \tag{2.4}$$

Therefore the projection error,

$$\varepsilon_t = s_t - E_{t-\tau}[s_t] \tag{2.5}$$

is uncorrelated with the information set. Here $E_{t-\tau}[s_t] = E[s_t|I_{t-\tau}]$.

According to the second assumption of *no-risk premium hypothesis*, equilibrium must be reached in the markets in which neither the net long nor the net short positions consistently win at the expense of the other. In case of future markets, this condition of a zero risk premium means that speculators will not be compensated for taking any risk (Krehbiel and Adkins, 1993; Kawamoto and Hamori, 2011). Many suggest that equality in expectations, as shown in Equation (2.1), will be forced by the market agents under the conditions of zero risk premium and no market friction due to transaction cost; see for example Peroni and McNown (1998), He and Holt (2004), and Rossi and Magistris (2013).

The expected spot price is not directly measurable in practice, therefore the actual realized spot price is substituted by combining the Equations (2.1) and (2.2) to obtain a simple model for testing the Unbiased Expectation Hypothesis (UEH):

$$s_t = f_{t-\tau} + \varepsilon_t \tag{2.6}$$

where $s_t - f_{t-\tau}$ is the expected rate of return on the futures contract. Equation (2.6) captures the notion of the efficiency of futures market in the sense that expected return to the speculators in the commodity futures markets will be zero (Hansen and Hodrick, 1980; Kremser and Rammerstorfer, 2017).

However, the latter restriction of risk neutrality contradicts with the other well-known hypothesis[12], (i.e., Risk Premium Hypothesis - RPH), which recognizes the existence of risk premium if the market participants are risk-averse under rational expectation. Therefore, to account for the uncertainty in the system, the model of risk premium (or RPH) can be presented by revising Equation (2.1) as follows:

$$f_{t-\tau} = E_{t-\tau}[s_t] - \pi_{t-\tau} \tag{2.7}$$

[12] The alternative hypothesis that a risk premium exists arises if economic agents are risk averse (see Hansen and Hodrick, 1980; Hodrick and Srivastava, 1984).

where $\pi_{t-\tau}$, the risk premium of the futures price is explicitly included for reflecting the risk aversion. In this model of market efficiency and rational expectation, risk-averse agents may be compensated for the riskiness of the contract by discounting the futures prices. Therefore, the futures price, $f_{t-\tau}$, equals the expected future spot price, $E_{t-\tau}[s_t]$, minus a risk premium component $\pi_{t-\tau}$, of the futures contract.

The empirical model based on Equations (2.7) and (2.2):

$$s_t = f_{t-\tau} + \pi_{t-\tau} + \varepsilon_t \tag{2.8}$$

which may also be expressed as,

$$s_t - f_{t-\tau} = \pi_{t-\tau} + \varepsilon_t \tag{2.9}$$

Equation (2.8) assumes behaviour of the risk premium to be a (covariance) stationary process, or $I(0)$, ε_t is the forecast error with zero mean and finite variance under rational expectation, and $s_t - f_{t-\tau}$ in Equation (2.9) is the rational expectation risk premium. However, the risk premium has the possibility of having a nonzero mean, $E[\pi_{t-\tau}] \neq 0$, or a time varying component. The empirical specification of the corresponding RPH can be expressed as follows:

$$s_t = \alpha + \beta f_{t-\tau} + \varepsilon_t + \pi_{t-\tau} \tag{2.10}$$

It is now well known that the theory of cointegration processes developed by Engle and Granger (1987) does not require identification of risk premium for testing the necessary conditions for market efficiency. Most researchers to date have investigated the unbiased pricing condition (e.g., Aulton et al., 1997; Wang and Ke, 2005; Laws and Thompson, 2004; Switzer and

El-Khoury, 2007; Algieri and Kalkuhl, 2014; and Khabiri, 2017) in Equation (2.6) and risk premium pricing (e.g., Moosa and Al-Loughani, 1994; Chow, 1998; and Peroni and McNown, 1998) in Equation (2.10) by using a cointegrating regression model or equilibrium relationship between spot and lagged futures price:

$$s_t = \beta_0 + \beta_1 f_{t-\tau} + u_t \tag{2.11}$$

In the specification of UEH, the parameter restrictions, in the absence of risk premium, requires $\beta_0 = 0, \beta_1 = 1$ and cointegrating residual u_t, should be serially uncorrelated in Equation (2.11). However, under alternative preference specification of RPH, the risk-averse hedgers, for example commodity producers, will demand for the short futures contracts to insulate themselves from the spot price risk (Keynes, 1930). Conversely, the risk-assuming speculators are needed to supply price insurance, and therefore are required to be compensated for their risk-bearing by the hedgers (Deaves and Krinsky, 1995). In this context, the possible bias created by the risk premium will appear in the intercept of (2.11), causing $\beta_0 \neq 0$ (Beck, 1994). This would lead to the rejection of market efficiency (or UEH to be more precise) in the simple linear regression model of Equation (2.11).

On the other hand, if the levels of commodity price series have unit roots, i.e., $S_t, F_t \sim I(1)$, (see Elam and Dixon, 1988; Hein, Ma, and MacDonald, 1990; and Shen and Wang, 1990) then the cointegration techniques provide appropriate framework for the efficiency tests while allowing for the presence of risk premium. Therefore, if s_t and $f_{t-\tau}$ are cointegrated with cointegrating vector $(1, -1)$, then the rejection of null hypothesis $\beta_0 = 0$ in the cointegrating regression would imply the existence of constant risk premium in conjunction with the long-run market efficiency.

Furthermore, for market efficiency under RPH the restriction of $\beta_1 = 1$, in the cointegrating regression in Equation (2.11) implies that error term would be $u_t = \pi_{t-\tau} - \beta_0 + \varepsilon_t$, i.e., the sum of the time varying component of the risk premium and the forecast error. It follows that market efficiency, as long as the $\pi_{t-\tau}$ and ε_t (from Equation (2.10)) are indeed stationary, corresponds to a cointegrating relationship between s_t and $f_{t-\tau}$ with a coefficient of one in Equation (2.11). However, rejection of the null hypothesis of $\beta_1 = 1$, would imply that risk premium ($\pi_{t-\tau}$) will be nonstationary, as it will contain a permanent component from the futures price ($f_{t-\tau}$), since rational expectations forecast error (ε_t) is stationary by assumption. Therefore, if this risk premium contains a unit root component then it can contaminate the cointegrating relationship and the estimates of β_1 in Equation (2.11) (Evans and Lewis, 1994: Frank and Garcia, 2005).

To validate Equations (2.1) and (2.7), the long-term efficiency is formally tested using the cointegration model in Equation (2.11). In the context of Equation (2.11), the implied long-run equilibrium relationship is given by $s_t - \beta_1 f_{t-\tau} - \beta_0 = z_t$; where z_t represents the equilibrium error. Following the approaches of Lai and Lai (1991), McKenzie and Holt (2002), Kenourgious (2005), Wang and Ke (2005), Switzer and El-Khoury (2007), Asche, Misund and Oglend (2016), Khabiri (2017), Kremser and Rammerstorfer (2017), and Chen and Scholtens (2018) present research tests for long-run efficient pricing condition under two distinct cases in Equation (2.11):

(1) $\beta_0 = 0$; implying zero intercept in the cointegrating relation i.e., no risk premium; and testing the following restrictions on the cointegrating vector $(1, -1, 0)$ and,

(2) $\beta_0 \neq 0$; allowing for a nonzero constant in the cointegration space i.e., constant risk premium may exist; and testing for the unitary cointegrating vector $(1, -1)$.

2.3. DATA SET AND SAMPLING APPROACHES

Taking the ban in Indian wheat futures market as an example, this chapter investigates the efficiency by comparing pre-ban and post-ban trading data for the futures contracts traded at the NCDEX. Futures contract on wheat was first introduced on the NCDEX platform in July 2004 and all contracts would normally have a monthly expiry. This analysis covers all futures contracts with expiry in the period from October 2004 to May 2015, the commodity crop calendar and all contract details are reported in Tables 2.1 and 2.2. The last trading day or the contract expiry of the contracts is 20th of the month. If the 20th day of the expiry month happens to be a trading holiday, a Saturday or Sunday, then the contract expires on the immediate previous working day of the Exchange, not being Saturday. Trading in wheat contract month opens on the 21st of the month and contracts remains open on the last trading day of contract expiry i.e., 20th calendar day of the month. On expiry of the contract the final settlement may be completed by cash settlement or by physical deliveries.

[Tables 2.1 and 2.2 about here.]

The data for this study matches the termination date spot price (S_t) with the end-of-day settlement prices for futures (F_t), sampled for three forecasting horizons $(F_{t-\tau})$ i.e., for value of $\tau = 28$, 56 and 84 days, prior to expiration. The logs of spot price at contract termination (s_t) and the matching lagged futures price $(f_{t-\tau})$ are used in the empirical analysis.

The cash price on the termination date of the futures contract is taken from the spot prices[13] which are disseminated by the NCDEX after the process of polling. In India there is no effective mechanism or real time spot price information of commodities. The only governmental agency which collects and disseminates spot prices across the country is Agmarknet. It collects the post-trade *mandi* (i.e., marketplace) data, but such information is not disseminated real time. Moreover, such prices do not relate to a predetermined quality specification on a consistent basis. The data disseminated is based on the commodity traded on the day in the market with the range of prices within which trades take place. The Exchange on the other hand requires spot price information of the current day and for the commodity quality specifications as stipulated for the futures contracts being traded on its platform. Polling at NCDEX is the process of eliciting information from a cross-section of market players about the prevailing spot price of the commodity in the market. Primarily the data on spot prices is captured at the identified basis centres which are also termed as the primary centre of a commodity, by inviting price quotes from the empanelled polling participants representing different segments in the value chain. The Exchange utilizes the spot price information at the basis centre of the underlying commodity being traded on its platform for the purpose of determination of the Final Settlement Price (FSP).

To facilitate comparison of efficiency across different duration, three sets of futures prices are used. The first set consisting of closing prices of the futures contract 28 days before maturity, f_{t-28}, was selected by working backward 28 days from the contract termination date. Similarly

[13] Indian wheat market is a case where there is no proper spot (wholesale) market which would support price discovery in the corresponding futures markets. Generally, where spot price data is not available for the same grade of commodity delivered at the same time and location as that specified in the futures contract, authors (Beck, 1994; Snaith et al., 2018) have used an approach of replacing the futures price at the delivery (f_t) in place of the spot prices(s_t). However, considering the nearest futures as a spot price series and the first deferred contract as futures is not considered in this case of the Indian wheat futures. Given that the think tank organizations have referred to the Indian agricultural futures market as a relatively thinly traded futures market than most heavily traded markets characterized by low level participation by the farmers and FPO's, it is more likely that deferred contracts will further lack terms of liquidity and depth than the nearby traded contract.

the second and third set comprises of closing prices of the futures contracts 56 and 84 days before maturity, i.e., f_{t-56} and f_{t-84}. However, adjustments are made in case of non-trading days and the matching futures price is then sampled from the next/forthcoming day i.e., $f_{t-\tau+1}$. This methodology to match spot and lagged futures prices is also been implemented in Kellard et.al. (1999), Kellard (2002), Laws and Thompson (2004), Khabiri (2017), and Snaith et al. (2018). Figure 2.1 to 2.3 show the data for each spot and matched futures time series graphically. This approach in total generated the whole dataset consisting of 105 monthly non-overlapping observations for each forecasting horizon, with spot and futures series expressed as Rupees (Rs) per quintal. Additionally, to assess short-run efficiency by using quasi-ECM model and to apply the relative efficiency measure three corresponding time series of the logarithm of the spot prices (s_{t-28}, s_{t-56}, s_{t-84}) sampled on the same day as $f_{t-\tau}$ are also created.

[Figures 2.1, 2.2 and 2.3 about here.]

According to the trading ban and relaunch on futures trading, the Indian wheat market is divided into two samples in order to study the evolution of market efficiency under two periods. The first sub-sample encompasses 2004-2007, when the Indian commodity market reintroduced agricultural futures trading and began to operate the national commodity exchanges, totalling 35 non-overlapping sample data. The availability of pre-ban period data taken in this study was limited since the wheat futures contract was launched on the NCDEX platform in 2004. To overcome the limitation of short sample size in the pre-event data, an investigation of price discovery using daily data is incorporated in this thesis. This extension of price discovery analysis in the cost-of carry model would be meaningful to observe the feasibility of results obtained from market efficiency hypothesis over a longer-horizon. The second sub-sample is for 2009-2015, when the ban was lifted and markets picked up momentum again, totalling 70 non-overlapping sample data. All data are downloaded from the NCDEX website.

The descriptive statistics for the logarithmic spot (s_t) and each matched futures prices series ($f_{t-\tau}$) are presented in Table 2.3. For completeness, summary measures for whole sample and both sub-samples are shown in the table. It can be observed that futures prices ($f_{t-\tau}$) are less volatile than the spot price (s_t) in the pre-ban period whereas for the post-ban period this trend is reversed. It is also interesting to note that in the pre-ban period the mean of the futures return series tend to increase as the settlement period approaches, whereas for the post-ban sample mean tend to decrease as τ reduces. In addition, for the pre-ban sample the standard deviation tend to reduce as the delivery period τ reduces, but the post-ban sample exhibits inverse relationship between volatility and maturity. As far as comparison across 28-, 56- and 84-day maturities in both the samples are concerned, the futures prices in the pre-ban period was higher on average, and as evidenced by the standard deviation of the three series, displayed greater variation than the post-ban period. These results provide prima facie evidence that abrupt interventions could have negatively affected the futures trading volume and may have made the markets less efficient than the pre-ban period.

[Table 2.3 about here.]

2.4. ECONOMETRIC METHODOLOGY

The econometric techniques for testing the efficiency of the NCDEX wheat futures markets under rational expectation is structured as follows. In view of the non-stationarity in price series, the

ADF test is used for testing the order of integration. A multivariate analysis for the presence of cointegration and testing long-run market efficiency condition was carried out using the Johansen technique. The relationship between s_t and $f_{t-\tau}$ over the shorter time horizon is examined by using a quasi-error correction model and relative efficiency measure proposed in Kellard et al. (1999).

The process of testing for efficiency initially requires tests for the order of integration of the individual series; if these series are found to be nonstationary then it is necessary to test for cointegration as a precondition for market efficiency, and subsequently for unbiasedness. Thus the unit root in prices is investigated through ADF test in which the unit-root as null hypothesis is tested against the alternative of stationarity. If the test statistics are smaller than the corresponding critical values, the null hypothesis of unit root may be rejected. Following suggestions from Crowder and Hamed (1993), Yang et al. (2001), Chopra and Bessler (2005), Carter and Mohapatra (2008) and Snaith et al. (2018), the ADF test is performed for both situations, without trend and with trend.

The Johansen procedure considered in this chapter is based upon a vector autoregressive process (VAR) for X_t as specified in Equation (2.12):

$$X_t = \mu + \Gamma_1 X_{t-1} + \ldots + \Gamma_k X_{t-k} + v_t \tag{2.12}$$

where X_t is a m-dimensional vector of series under investigation, Γ_j are $m \, X \, m$ matrices of autoregressive parameters of lag order k and k is sufficiently large, μ is a $m \, X \, 1$ vector of constant, and v_t is a $m \, X \, 1$ white noise vector.

If X_t is a vector of nonstationary variables, which are integrated of order one, Equation (2.12) can be transformed into its stationary form as vector error correction model (VECM) in Equation (2.13):

$$\Delta X_t = \mu + \delta_1 \Delta X_{t-1} + \ldots + \delta_{k-1} \Delta X_{t-k+1} + \Pi X_{t-k} + v_t \qquad (2.13)$$

Equation (2.13) resembles a VAR model in first differences, except for the presence of an error-correction term, ΠX_{t-k}, which will contain information about the long-run (cointegrating) relationship. This Johansen technique then tests for the rank of long-run multiplier matrix, $\Pi = \Gamma_j - I$. The lag length k was chosen using the Schwarz Information Criterion. Assuming that X_t is a vector of $I(1)$ variables, then ΠX_{t-k} has to be stationary for v_t to be stationary. The absence of cointegration implies that there are no linear combinations of X_t that are stationary $I(0)$ and that the rank (r) of Π is zero.

When spot and futures prices for a commodity are nonstationary, the existence of a cointegrating relationship between the two is a necessary but not a sufficient condition for short-run market efficiency and unbiasedness. Spot and futures prices are determined by the same fundamentals and so efficiency implies they cannot move too far apart. Existence of a cointegrating vector however does not rule out short-run market inefficiencies and pricing biases, whereby past information may improve market forecasts of future spot prices.

Following Kellard et al. (1999), a time-series model of a cointegrated series in Equation (2.11) may be rewritten in quasi-error correction form. Such a transformation renders the series stationary and allows for standard hypothesis testing. A prototypical quasi-ECM useful for testing the short-run relationship, by relating the change in spot price to the percentage basis

$(f_{t-\tau} - s_{t-\tau})$ and lagged changes in spot $(s_t - s_{t-\tau})$ and futures $(f_t - f_{t-\tau})$ prices may be specified in the following model:

$$s_t - s_{t-\tau} = \theta_0 + \theta_1(f_{t-\tau} - s_{t-\tau}) + \sum_{i=1}^{k} \lambda_i\left(s_{t-i} - s_{(t-\tau)-i}\right)$$
$$+ \sum_{i=1}^{k} \gamma_i\left(f_{t-i} - f_{(t-\tau)-i}\right) + \epsilon_t \qquad (2.14)$$

where $(s - s_{t-\tau})$ is the spread in the spot price for the period until selected forecast horizon, $(f_{t-\tau} - s_{t-\tau})$ is the current spread between the futures prices and the spot price, i.e., the *basis* at particular (28/56/84) forecast horizons, θ_1 measure the speed of endogenous variable adjustment towards long-term equilibrium and k is the lag order. The statistical significance of regression coefficients of lagged changes in the endogenous and exogenous variables λ_i and γ_i in Equation (2.14) is generally claimed as an evidence of inefficiency. In other words, operation of futures market would be considered efficient in the short-run if the basis contains all relevant information to optimally forecast changes in the spot prices. Put differently, if the lagged changes in spot and futures prices are nonsignificant they provide no information in addition to the basis. Thus another hypothesis test for all lagged coefficients of changes in spot and futures prices jointly zero is also applied. This test determines if all lagged variables could be easily omitted; and the rejection of null would imply that markets are somewhat inefficient.

Following Kellard et al. (1999), Yang et al. (2009), and Khabiri (2017) another variant of Equation (2.14) can be obtained after removing the short-term fluctuations:

$$s_t - s_{t-\tau} = \theta_0 + \theta_1(f_{t-\tau} - s_{t-\tau}) + \epsilon_t \qquad (2.15)$$

If θ_1 is significantly different from zero then it can be deduced that the basis $(f_{t-\tau} - s_{t-\tau})$ contains information about the changes in spot prices. Moreover, a comparison can be made between θ_1 in the two models in (2.14) and (2.15). If the estimates of the coefficients of the basis θ_1 are very close, then the short-term lag items would have limited impact on the short-run movement in the spot prices. In other words, this would imply that futures market is efficient in the short-run.

The estimates from the QECM eq. may suggest, to a greater or lesser extent, the possibility of some short-run inefficiency in the three forecast horizons. However, such tests cannot indicate degrees of efficiency or give an indication of how well or badly a futures market is functioning across different lengths of forecast periods using both pre-ban and post-ban samples. Therefore, to quantify the degree of short-run inefficiency and to make direct comparison between the pre-ban and post-ban trading periods, the relative efficiency measure of Kellard et al. (1999) is adopted. This efficiency measure, denoted by Φ_c^{τ}, is formed from the ratio of two forecast error variances. The first one (i.e., the numerator of Equation 2.16) is the estimated error variance of ϵ_t, from the short-run OLS regression in Equation (2.14), representing the extent to which the model was unable to forecast the realized change in the spot prices. The second one (i.e., the denominator of Equation 2.16) is the forecast variance of futures prices as the estimator of termination spot price. The market efficiency of the futures market would imply an estimate of $f_{t-\tau} + E[(s_t - f_{t-\tau})]$, allowing for a possibility of systematic discount or risk premium in futures prices and the error variance of this predictor can be calculated through the sample variance of the series $(s_t - f_{t-\tau})$. The resulting efficiency measure is then given by:

$$\phi_c^{\tau} = \frac{(n-2k-2)^{-1}\sum_{t=1}^{n}\hat{\varepsilon}_t^2}{(n-1)^{-1}\sum_{t=1}^{n}[(s_t-f_{t-\tau})-\overline{(s_t-f_{t-\tau})}]^2} \tag{2.19}$$

where n is the number of dependent variable observations prior to taking the lags in estimating Equation (2.15). Thus, the measure Φ_c^{τ} reflects the forecasting ability of the futures prices as predictor of the futures spot price. The range of values that efficiency measure can take is between $0 < \Phi_c^{\tau} \leq 1$. Where $\Phi_c^{\tau} = 0$ would imply a complete short-run inefficiency. In contrast, the ratio $\Phi_c^{\tau} = 1$ would mean the market is fully efficient because the futures price is relatively able to forecast the subsequent spot price. Also, any interim values between 0 and 1 would indicate varying degree of inefficiency. Therefore, $(1 - \Phi_c^{\tau})$ measures the degree of short-run inefficiency.

2.5. EMPIRICAL RESULTS AND DISCUSSION

2.5.1. ADF Unit Root Test

As a precondition, the testing for futures market efficiency requires to test for the order of integration of the series of futures price for each of the considered forecasting horizons and of the series of the spot prices. Thus, empirical analysis is started by examining the stochastic properties of the time series with the ADF unit root test to determine whether the time series are trend-stationary series or integrated processes; and also to determine the order of integration. The ADF approach in both settings (with constant, and with a constant and trend) has been adopted. The values of lags k are decided by minimizing the AIC metric on the values k ranging from 1 lag to 4 lags. Results reported in Table 2.4 suggest that the unit root hypothesis across all series in both sub-periods cannot be rejected uniformly at the 5% significant level. This is true across both models - with and without a trend. After repeating the ADF test for the first difference price series (reported in Panel B, Table 2.4), the result shows that all the time series are $I(1)$ processes and non-stationary at their log-levels. With the same order of integration for relevant spot and futures prices, the next stage entailed testing for the presence of cointegration. Testing for cointegration and testing for the joint restriction $\beta_0 = 0$ and $\beta_1 = 1$ in Equation (2.11) was carried out using the Johansen technique.

[Table 2.4 about here.]

2.5.2. Johansen Cointegration Test

Given that the wheat spot and futures prices are nonstationary with same order of integration, the next step is to investigate cointegration between them at each forecast horizon. The result of the Johansen test can be quite sensitive to the lag length; so the most common procedure to choose a lag length k is to start with the VAR representation of the variables that are to be investigated using the undifferenced data. Then use the same lag-length determination tests as in traditional VAR i.e., from the two broad methods to arrive at the optimal lag length: cross-equation restrictions and information criteria (Enders, 2015; Brooks, 2008).

In order to estimate a model, first the maximum lag length k is considered in an unrestricted VAR representation of each model (three relationships: spot and lagged futures 28/56/84) following Johansen (1995) and Juselius (2006). An appropriate VAR lag length is selected by using the multivariate versions of information criterion. Starting with the pre-specified maximum k lags (longest length set to 10 and 11 in period 1 and 2), the information criteria are used to select the lag length optimally. Table 2.5 presents various information criteria that are used for determining the lag order. In period I, AIC and HQ criteria (except in 28-days horizon) selects VAR with 10 lags, while SBIC chooses a one order as optimal (except in 84-days horizon). In the second period AIC selects a lag length of 2 (except in 84-days horizon), while SBIC and HQ selects a VAR with 1 lag (except in 28-days horizon). Difference in optimal model order could be attributed to the relatively small sample size available with this monthly sample of spot and lagged futures prices compared with the number of observations that are available in contemporaneous spot and futures prices evaluated in Chapter 3, implying that the penalty term in SBIC is more severe on extra parameters in this monthly sampling case. Thus lag length k was chosen by using the Akaike information criterion.

[Table 2.5 about here.]

The Johansen-Juselius approach is sensitive to deterministic components of the X_t system (i.e., constant or deterministic time trend) specified into the model because different specifications of deterministic components may yield different cointegration results. Restrictions on the deterministic components translate into five possible specifications in Johansen's cointegration model. In practice, Johansen (1992) proposed to use the Pantula's (1989) principle to select a proper model for cointegration test. Although Ahking (2002) observed that Case 2 (model with restricted intercept and no deterministic trends in the level data) and Case 3 (model with unrestricted linear intercept and no trends in the cointegration space) are the most plausible models to be used in empirical analysis, the author opts to use the Pantula's principle to select an appropriate model. In contrast, Hjelm and Johansson (2005) found that the standard Pantula's principle is heavily biased towards choosing Model 3 when actually Case 4 (model with the restricted quadratic trend coefficient) is the true model. To avoid this estimation bias arising from the use of the standard Pantula's principle, deterministic trend assumption of the test can be ascertained from the theory. Crowder and Phengpis (2005) argue that rarely the econometrician knows the true deterministic specification a priori. Following the above argument, Johansen's (1992) sequential likelihood ratio (LR) test procedure is used to clarify how μ enters in Equation 2.13, either as constant in the cointegrating vector in the ECM or as a time trend in the original levels' representation (Equation 2.12). Table 2.6 is set up in order, where hypotheses regarding the number of cointegrating relations in the system is first tested with the constant in the cointegrating space (Case 2, where there is no linear trend in the model) followed by the test where constant is outside the cointegrating space (Case 3, where there is a linear trend in the model).

[Table 2.6 about here.]

The aim of the cointegration model is to determine the rank of the matrix Π, because the number of cointegrating vectors that exist among the variables is equal to the rank of matrix Π. In this case specification is $X_t = (s_t, f_{t-\tau})$, so the maximum (full) rank of matrix Π is 2. However, the two variables are cointegrated only if the rank of $\Pi = 1$, because there can be at most one cointegrating relationship for a system containing two variables.

Using the Johansen maximal-eigenvalue and trace statistics, the technique sequentially tests the null hypotheses $r = 0$ and $r = 1$. Test results of cointegration with AIC show that, for both sub-periods, the null of no-cointegrating vector ($r = 0$) is rejected in favour of one coinetgrating vector ($r = 1$) at 5% level of significance (except for 84 day horizon in the Period I). For the 84 day forecast horizon, the null of reduced rank is rejected; implying that s_t and f_{t-84} are stationary, despite the earlier conclusion drawn from the ADF test.

The optimal lags in the cointegration tests are also employed with the minimization of SBIC to double-check the robustness of the empirical findings. For the 56 day horizon the null of no cointegration is not rejected in the first period, however, with lag length of 10 under AIC, rank $r = 0$ is rejected. These results show sensitivity to the chosen lag length and justify the selection of AIC, since SBIC in this case is producing an overly parsimonious approximation. Taken together, cointegration is implied for all forecast horizons in the second sub-period. However, results vary in the first sub-period. These varying results in the first-sub period could be due to the relatively small sample size as compared to the second-sub period.

Further, under sequential testing, the first rejection failure occurs while using the Case 2 model without trend. Therefore, findings support the existence of cointegration (except 84 day horizon in the Period I) between the spot and futures prices without the presence of linear trend in the data, and thus model in Case 2 would be appropriate for the wheat prices.

2.5.3. Examining Long-Run Market Efficiency: Restrictions for unbiasedness, market efficiency and no-risk premium

Augmented Dickey-Fuller tests suggested that the null of a unit autoregressive root, i.e., integration of order 1, $I(1)$, could not be rejected for any series. This result is quite robust to both sub-periods and inclusion of a time trend in the regression. Given the uniform inability to reject the null of ADF test across all forecast horizons, the NCDEX wheat spot and futures prices in levels can be concluded to be non-stationary, while their first differences in all cases are stationary. The cointegration results from the application of the Johansen method to the datasets showed that cointegration is unanimously accepted for all three forecast horizons in the second sub-period. However, the results are sensitive to the lag length and different model specifications are chosen for VECM in the first-sub period.

Maximum likelihood estimates of the parameters of the static cointegrating regression (2.11) and parameter restriction test statistics are reported in Table 2.7. If futures prices are an unbiased forecast of cash prices, then the estimated values for β_0 and β_1 should be equal to zero and unity. As shown in the first panel, the point estimates of the slope coefficients ($\widehat{\beta_1}$) are significant and quite close to unity at all forecast horizons in both pre- and post- ban samples. Whereas the estimated intercepts ($\widehat{\beta_0}$) in most forecast horizons are statistically insignificant at the 5 per cent level (except for period II, 28 days horizon).The formal testing of long-run market efficiency was conducted using joint hypothesis $\beta_0 = 0$ and $\beta_1 = 1$, unit slope hypothesis $\beta_1 = 1$, and absence of a risk premium hypothesis $\beta_0 = 0$; and the test statistics follow a χ^2distribution with respective degrees of freedom equal to two, one and one. The distinguishing fact of testing the joint and individual unity restrictions is that the test statistics reject the joint hypothesis in at least at the 5% level for each of the forecast horizons across both the sub-periods. However, the unit slope restrictions on the cointegrating vector is rejected just for the 28 days forecast horizon in the second sub-period. Considering the first evidence of unbiasedness hypothesis, the results suggest that Indian wheat futures prices appears to be a biased predictor of the future spot prices, which in turn implies the absence of efficiency. However, the restrictions of unbiasedness joint test are too strong to imply market efficiency. As discussed in Beck (1994), McKenzie et al. (2002) and Wang and Ke (2005), the unbiasedness test performed on Equation (2.11) is in fact a joint test of both market efficiency (i.e., rational expectations) and no-risk premium hypotheses. The rejection of joint null hypothesis of $\beta_0 = 0$ and $\beta_1 = 1$ can therefore be interpreted either as market inefficiency or the possible existence of a risk premium or both. In other words, the rejection of joint hypothesis is especially strong when constant term (β_0) is constrained to be zero. McKenzie et al. (2002) point out that futures markets containing a risk premium would be biased, but could still be efficient. Therefore, separate null hypothesis of $\beta_1 = 1$ can be used, since this unitary contraint is the most important indicator of market efficiency. The hypothesis of market efficiency imposes only unit slope restriction while the constant term remains unconstrained to account for a possibility of a constant risk premium. Many studies which have tested the market efficiency in the bivariate cointegration framework under risk premium hypothesis have rejected the joint hypothesis in the long-term, e.g., Chowdhury (1991; nonferrous metals), Lai and Lai (1991; currency markets), Krehbiel and Adkins (1993; silver, platinum and gold), Moosa and Al-Loughani (1994; crude oil), Antonious and Holmes (1996; stock index futures contracts for 3 and 6 month prior to maturity), Peroni and McNown (1998; energy futures), Kellard et al. (1999; crude, gasoil, soybeans, hogs), McKenzie et al. (2002; long grain rice), He and Holt (2004; forest commodity futures), Li et al. (2004; agricultural commodities), Kenourgios (2005; index futures), Wang and Ke (2005; soybean), Arouri et al. (2011; aluminium), Algieri and Kalkuhl (2014; agricultural futures), Santi (2016; non-agricultural and agricultural commodities), Kremser and Rammerstorfer (2017; natural gas), and Chen and Scholtens (2018; salmon forward with maturities between 9 -12 months).

[Table 2.7 about here.]

Therefore, more inferences on the long-term unbiasedness can be drawn from the two individual test restrictions. Interestingly, the hypothesis of market efficiency condition of $\beta_1 = 1$

cannot be rejected statistically at all (28 and 56) forecast horizons in the pre-ban period. However, the hypothesis can be rejected at the 5%, **10%** and **10%** level for the respective 28, 56 and 84 day forecast horizons in the post-ban period. In addition to these results, no-risk premium hypothesis of $\beta_0 = 0$ holds (for 28 and 56 days) in the pre-ban period but the restriction was again rejected for the forecast horizons of 28, 56 and 84 days in the post-ban period at the 5%, 10% and 10% levels respectively. Thus, there is evidence to support that the absence of risk premium, and efficiency hold[14] in the long-run equilibrium during the pre-ban period; that is, the futures and spot prices are cointegrated with a long-run slope coefficient of unity. However, results from the post-ban period are quite different, with forecast horizon of 28 days is the only case where both null of unit slope and zero constant term are rejected at 5 percent significance level. These results imply that although 28-, 56- and 84-day ahead futures prices and termination spot price have stronger cointegration in the mature phase of trading, the Indian wheat future prices are possibly biased in the post-ban period. Furthermore, compared to the p-values associated with the test of no-risk premium hypothesis, the corresponding p-values associated with the market efficiency test are consistently higher in the post-ban period, showing it easier to reject the $\beta_0 = 0$ hypothesis. This suggests that bias of futures prediction may be primarily caused by existence of risk premium in the post-ban period, while one-to-one relationship between the s_t and $f_{t-\tau}$ still largely holds in long-run equilibrium at the general 5% level.

[14] The hypothesis of no-risk premium requires the restriction $\beta_0 = 0$ to hold, and null hypothesis of unit coefficient $\beta_1 = 1$ is required for the long-run equilibrium condition to hold.

2.5.4. Short-Run Market Efficiency: Quasi-error correction mechanism

Last reported results showed that the joint restriction $\beta_0 = 0$ and $\beta_1 = 1$ imposed on the cointegrating vector is rejected for all forecast horizons in both sub-periods. However, the unit slope restriction on the cointegrating vector is rejected just for 28 days forecast horizon in the second sub-period (at 3.0%). Consequently, largely there is evidence to support the hypothesis of efficiency in the long-run. However, long-run efficiency is not sufficient for short-run forecast efficiency. Since augmented Dickey-Fuller tests suggested that the series are characterised by an in-sample nonstationary behaviour, in order to avoid the spurious regression problem (Granger and Newbold, 1974) the evaluation of short-run efficiency testing procedure is carried out within the estimation of QECM framework as recommended in Kellard et al.(1999).

To clarify the approach in the quasi-ECM model in Equation (2.14), the Indian wheat futures market is analysed at different forecast horizons, i.e., the estimated short-run model refers to 28 days, 56 days and 84 days horizons. The short-run regression explains the changes in the spot rate over the forecast horizon and relates this to the basis sampled at the start of the forecast horizon $(f_{t-\tau} - s_{t-\tau})$, and with the lagged changes in spot $\left(s_{t-i} - s_{(t-\tau)-i}\right)$ and future $\left(f_{t-i} - f_{(t-\tau)-i}\right)$ prices over the three forecast horizons. Thus, in this way by analysing the single market with three different forecast horizons it is possible to check whether the results obtained are dependent to a certain extent on the length of the chosen forecast period.

The results of the above short-run OLS regression are reported in Table 2.8 for all the three forecast horizons analysed. The lag lengths were selected through general-to-specific testing starting by setting from $k = 10$ in the 1st period and $k = 12$ in the 2nd period and then eliminating the lags that were insignificant at 10% level but at the same time preserving the symmetry on lag length for the lagged changes in spot prices and futures prices. This procedure removes all evidence of residual serial correlation. The results of QECM model shows that in contrast to the pre-ban period the lagged changes in the spot and futures prices provide significant information in addition to the basis during the post-ban period. More specifically, the larger number of lags are included over all forecast horizons in the post-ban period than the pre-ban period. These results may be interpreted as an evidence of more inefficiency in the short-run during the post-ban period as statistical significance of such lags imply that these terms are useful to predict changes in spot price over the forecast horizon. However, formal testing of short-run forecast efficiency using Equation (2.14) is presented in Table 2.10.

[Table 2.8 about here.]

Two tests of serial correlation-the *Q*-statistic and the Breusch-Godfrey LM test-are used to examine the residuals for evidence of serial correlation.[15] All evidence from the autocorrelation tests are presented in Table 2.9.

[Table 2.9 about here.]

Table 2.10 provides test statistics for the null hypothesis that the coefficients of all lagged variables of changes in spot and futures prices are jointly zero. Initially the results in Table 2.8

[15] The *Q*-statistic is often used as a test of whether the series is white noise. There remains the practical problem of choosing the order of lag to use for the test. If chosen lags are too small, the test may not detect serial correlation at high-order lags. However, if too large lags are chosen, then the test may have low power since the significant correlation at one lag may be diluted by insignificant correlations at other lags (Ljung and Box, 1979; Harvey 1990, 1993). Given the monthly data set, the first 12 lags are appropriate for the tests of serial correlation. The *Q*-statistics are insignificant at all lags, except for 84 days horizon in period 1, indicating no serial correlation in the residuals. However, the Chi-squared version of the serial correlation LM test rejects the hypothesis of no serial correlation for the 84 days and 56 days horizon in the 1st and 2nd period respectively; these conclusions are different from the *F*-version of the test in which the null of no autocorrelation is not rejected.

suggest that both the pre-ban and post-ban trading periods exhibit evidence of inefficiency to some degree. As for pre-ban period there are one, one and seven significant lag coefficients for $\tau = 24$, 56 and 84; whereas in case of post-ban period there are twelve significant lag coefficients for $\tau = 24$, 56 and 84. These results suggest stronger evidence for short-run inefficiency in the post-ban sample. However, Table 2.10 indicates there is not very strong evidence to support the inclusion of the set of lagged variables, except for terms 28 and 56 days horizon in the pre-ban period. The test for the joint inclusion of lagged terms for the change of the spot and futures prices is significant for 28 and 56 days horizon at 3% and 6% level; indicating a stronger evidence to support the inclusion of the set of lagged variables in period 1 in contrast to the 2nd period. These results suggest that the lagged variables in the 1st period provide additional information and hence there is a possibility that the market is inefficient for these forecast horizons during the pre-ban period in the short-run specification.

[Table 2.10 about here.]

For purposes of comparison, Table 2.11 presents results for regressions omitting all lagged changes in spot and futures prices in Equation (2.14). Estimation of Equation (2.15) is analogous to the Fama's (1984) regression approach. Based on the estimates of Equation (2.15) it can be concluded that the basis in both the sample periods contain some information regarding futures change in the spot market. The restriction of $\theta_1 = 1$ at the conventional significance levels cannot be rejected in the post-ban period. These results are not consistent for the pre-ban period as the slope coefficient is significantly different from one. Such results appear to signal that futures markets are not inefficient at all in the post-ban period.

[Table 2.11 about here.]

Finally, results in Table 2.12 presents comparison between θ_1 in Table 2.8 (full QECM model in Equation 2.14) and 2.11 (QECM model without short-term fluctuations in Equation 2.15), which reflects the long-run equilibrium relationship. The difference between the values of θ_1 from model 2.14 and 2.15 in the post-ban period is large, i.e., a difference of 0.1597 (or 20.5%) for f_{t-28}. However, in the pre-ban period, the difference between the value of θ_1 from model 2.14 and 2.15 is small, i.e., a difference of 0.0098 (or 2.2%) for f_{t-28}. It can be inferred that because of the effect of imposing trading ban in the wheat futures markets, the short-term efficiency in the Indian wheat futures market in the post-ban period is lower than the pre-ban period; i.e., the short-term lag items are more sensitive to the value of θ_1 for 28-days forecast horizon in the second period. In case of $\tau = 56$ and 84 the results however show contrasting evidence, that is, more short-run inefficiency in the pre-ban period. It could be argued that evidence of short-run inefficiency in the post-ban period with the 28-days forecast horizon is superior evidence since most of the trading activity is concentrated in the nearest forecast horizon, whereas trading volume fades away as the forecast horizon gets longer. Although as indicated by Table 2.10 there is not a very strong evidence to support the inclusion of the set of lagged variables in the post-ban period.

[Table 2.12 about here.]

2.5.5. Relative Efficiency: Degree of inefficiency for the three forecast horizons

The estimates reported in Table 2.8 (reported above) suggest that all three forecast horizons in the pre-ban and post-ban sample exhibit evidence of short-run inefficiency to some degree. However, such tests cannot indicate degrees of short-run efficiency of futures markets in the pre-ban and post ban periods. Thus, in order to quantify the degree of inefficiency across two periods, pre-ban and post-ban, the results of the test for relative efficiency are presented in Table 2.13.

Values of Φ_c^τ for the three forecast horizons analysed are given in the first row of Table 2.13; whereas row 2 of this table present the degree of inefficiency $(1 - \Phi_c^\tau)$. The inefficiency criterion indicates that the shortest forecast horizon, 28 days, in the two sub-periods are characterized by a relatively higher degree of efficiency. By contrast, the longest forecast horizon, 84 days, is least efficient in both the periods. This finding that short-run efficiency increases as the forecast horizon gets shorter i.e., closer to the settlement date is consistent with Kellard et al. (1999; soybeans), Ballester et al. (2016; electricity futures) and Snaith et al. (2018; crude palm oil, for open outcry sample). However, the Φ_c^τ values shown in Table 2.13 at the 28 (0.61 and 0.50) and 56 (0.60 and 0.40) days maturity in respective sub-periods are quite low when compared to values of other agricultural commodity futures markets. For example, Kellard et al. (1999) recorded figures ranging 0.53 for live cattle (CME) to 1.00 for soybeans (CBOT) at f_{t-28} horizon; and 0.77 for live cattle to 0.99 for live hogs (CME) at f_{t-56} horizon. Also, for crude palm oil (Bursa Malaysia) market Snaith et al. (2018) obtained values ranging from 0.78 to 0.86 for f_{t-28}; and from 0.62 to 0.69 for f_{t-56}. These results can be explained by the fact that the national commodity derivatives exchanges in India are relatively new establishments (since 2003) and have experienced many turbulences due to ban and suspension since 2007-08 and markets may thus lack the maturity of other more consolidated commodity futures markets.

[Table 2.13 about here.]

It is also interesting to note that there is increasing degrees of inefficiency at respective forecast horizons, that is, across all τ in two periods. The findings show that in the post-ban sample wheat futures market is 40% and 35% efficient at forecast horizons of 56 and 84 days respectively. However, in case of the 28-day horizon, wheat futures market is 50% inefficient in the post-ban period. These results may explain the reason for the rejection of market efficiency hypothesis in Table 2.7 in the case of the f_{t-28} but not at the other two forecast horizons. Finally, the results from the inefficiency criterion garnered support that there is an appreciable inefficiency pattern in the post-ban sample of Indian wheat futures market.

2.6. CONCLUSION

The purpose of this study was twofold. When it comes to trading of futures contracts in commodities at the Indian regional exchanges prior to 2003, tracking the price movement in the contract vis à vis the movement in the underlying physical market i.e., the basis, must be difficult and volatile, given that there is no-availability of real-time data of commodity prices transacted over different geographic locations across the country. Accordingly, the setting of centralised national level commodity derivatives exchanges is supposed to aggregate information possessed by the cross section of physical market participants and is expected to cancel out the biases in providing the forecasts of futures spot prices. Hence, in a scenario where the underlying spot market of agricultural commodities sector is decentralized, futures prices are assumed to be both transparent and homogeneous in nature and can also be considered as an efficient predictor. As a first purpose, test for futures market efficiency in the Indian wheat market at both long-run and short-run levels across a selection of maturities was implemented. Also, numerous instances of bans and suspensions in the Indian agricultural futures markets over the last two decades have given rise to the controversy as to whether such interventions could reduce the overall market efficiency. From the viewpoint of attracting more hedgers into the market, increasing farmers' or FPO's participation may enhance liquidity and depth in the futures markets. However, if the futures market for agricultural commodities do not have a stable policy environment and are relatively inefficient, then the farmers/FPOs would avoid using futures platform for commodity price risk management. It has often been conjectured that farmers' planting decision based on previous year's prices could result in agrarian distress whereas efficiently functioning futures market will provide forward looking cropping pattern and farmers stand to benefit from resource allocation. Hence the second purpose was to examine the relative market efficiency corresponding to the pre- and post-ban periods. In the backdrop of few other examples of futures trading ban in grain markets, e.g., *Germany*, Berlin Produce Exchange Act (1896) implemented ban on grain futures; *Austria*, Law of New Exchange Organisation (1903) set ban on futures trading in Viennese grain market; *Japan*, Beikoku Haikyu Tosei Ho (1939, rice distribution control law) prohibited rice trading in futures; this research is the first attempt to examine the consequence of prohibition on grain futures trading under different trading periods.

In respect of testing of efficiency of the Indian commodity futures market based on the regression of spot price, s_t, on the futures price, $f_{t-\tau}$, the literature (e.g., Singh, 2001; Raizada and Sahi, 2006; Chakrabarty and Sarkar, 2010; Soni, 2013; 2014; Haq and Rao, 2014; Ranganathan and Ananthakumar, 2014; Sahai, 2014; Laha and Sinha, 2015; Pandey and Vipul, 2017; and Gupta et al., 2018) so far has concentrated on the cointegration analysis to examine the long-term and short-term efficiency. However, these tests cannot compare the degree of efficiency achieved by a particular forecasting horizon and/or in a specific sample period. This study aims to complement the existing research by applying the relative efficiency measure of Kellard et al. (1999) which allows to quantify the degree of efficiency for different horizons in both pre-ban and post-ban samples.

The efficiency between the two trading periods at the NCDEX wheat futures is investigated for three forecasting horizons, 28, 56 and 84 days for wheat contracts over the period 2004-2015. From the analysis of efficiency test the following conclusions are made:

(a) The results of cointegration tests between spot and lagged futures are shown to be cointegrated for the 28, 56 and 84 day forecast horizons in the post-ban period. However, the results are sensitive to the lag length and different model specifications chosen in the pre-ban period. A possible reason could be that the first period from 2004 to 2007 (before ban) represents the early phase of national commodity exchanges, therefore less developed futures commodity exchanges and low trading volume for longer maturities may account for no-cointegration in the 84 days forecast horizon. Wang and Ke (2005; wheat), Bhar and Hamori (2006; agricultural futures, 1990s sample), Ali and Gupta (2011; wheat and rice) and Kumar and Pandey (2013; more rejection in the sub-period related early stage of the Indian commodity futures) has also shown in their studies that cointegration relationship is violated between the commodity futures and spot markets. However, in case of Indian wheat market the long-run equilibrium relationship between the futures and spot market for all forecasting horizons have become more apparent in the second sub-period as the government intervention was reduced and also because the price mechanism work better with the likely institutional development in the relatively matured future markets.

(b) The joint hypothesis of unbiasedness is rejected for all futures-spot relationship in two sub-samples. These results are consistent with Kumar and Pandey (2013; for most commodities in the second sub-period of trading between 2007-2008), Soni, (2013; guar seed and 2014; agricultural commodities), Sahai (2014; in all four forecasting horizons of refined soy oil), Yadav and Panigrahi (2014; near month aluminium contract and all three maturities of copper), Laha and Sinha (2015; 6 cloth and 3 sacking bags' contracts), Pandey and Vipul, (2017; crude oil), and Gupta et al. (2018; for most agricultural and non-agricultural commodities) who found that $\beta_0 = 0$ and $\beta_1 = 1$ can be rejected for Indian commodity markets. Rejection of long-run unbiasedness assumption however cannot be interpreted as inefficiency in futures pricing, because futures markets counting risk premium would be biased, but such markets could still impound information efficiently. The results indicate the possibility of existence of risk premium, which may be caused by the unfavourable impact of trading bans in the prices of this agricultural commodity. This work found support that in a post-ban period, a nonzero risk premium exists for a 28-day horizon.

The results for the marker efficiency hypothesis of $\beta_1 = 1$ however vary across both sub-samples. The pre-ban period meets the conditions necessary for efficiency imposed on the slope coefficient in the case of 28- and 56-day forecasting horizons. This is not the case for the post-ban sample where the condition is met for the 56- and 84-days but not for the 28-day forecasting horizon. There are similar evidence of rejecting the hypothesis of unity from the studies in the global markets, for example Krehbiel and Adkins (1993; COMEX silver, copper and gold), Peroni and McNown (1998; NYMEX crude oil, heating oil and unleaded gasoline), Wang and Ke (2005; DCE soybeans, in national 1-week and 4-month cases), Khabiri (2017; IME gold coin futures, 15-day horizon) and Kremser and Rammerstorfer (2017; ICE natural gas at NBP, Phase 2 for 2 and 3 month maturities) suggested that efficiency do not hold in the long-run equilibrium in those markets even when the spot and future price series are cointegrated. Similarly, results from studies from Indian commodity futures markets, for example, Singh (2001; turmeric and castor seed-Mumbai), Raizada and Sahi (2006; wheat, for three forecasting horizons), Kumar and Pandey (2013; more rejection in the sub-period related early stage of the Indian commodity futures), Soni, (2013; guar seed and 2014; agricultural commodities), Inoue and Hamori (2014; multi commodity indices, in sub-sample A from 2006-2009), Sahai (2014; in farthest maturity of refined soy oil), Singh and Singh (2017; chickpea), and Gupta et al. (2018; for all the sampled commodities), also find that β_1 is significantly different from 1 in their respective studies.

In the context of this study rejection of unit slope restriction for the 28-day post-ban sample is interesting given: (i) the acceptance of market efficiency for 56- and 84-day prior to maturity. This is consistent with the findings of Antonious and Holmes (1996), and reflects that may be due to the increased trading activity in the contract as it approaches the maturity, biases are created on the 28-day futures prices. Hence, the issue that becomes both surprising and particularly interesting is that, what could possibly create biases in the long-term post-ban sample for 28-day forecasting horizon; while futures prices for 56- and 84-days prior to maturity provides unbiased expectation forecasts of the realized spot prices. As already emphasized, the Indian agricultural commodity futures market is characterised by low level of participation from farmers and FPOs. Therefore, a possible explanation for the finding with respect to the condition of market efficiency could be possibly related to the heavy volume of transactions in the NCDEX wheat futures contracts in the weeks immediately prior to maturity. At the same time it is quite possible that investors who are using the futures contracts for speculation will switch between contracts, which in turn would create biases in the contract when it approaches its maturity i.e., 28-days prior ; (ii) the acceptance of market efficiency in the pre-ban period. This result indicates that greater market intervention by the government in terms of outright bans may affect the long-run efficiency of the contract. Another issue that can be recognized from the rejection of market efficiency hypothesis is that biases are created on futures prices 28 days from maturity due to the emergence of a significant positive risk premium (i.e., $\beta_0 = 0$ was rejected) in the post-ban period. This could be related to the changes in risk aversion for the two periods of trading, i.e., if speculators, as oppose to hedger, have become more risk averse due to the unpredictable changes in the regulatory environment, may demand a premium from hedgers as a compensation for assuming the risk of future spot price volatility (see for example, Kaminsky and Kumar, 1990; and Deaves and Krinsky, 1995). Consequently, there is evidence to suggest that greater market intervention by the government in terms of outright bans, strict regulations, price stabilization through minimum support price or procurement may have negative impact on the long-run market efficiency of the futures markets.

(c) In the view-point that long-run equilibrium condition holds in most cases, the short-run efficiency of the wheat futures market is tested using QECM model. It is found that both sample periods, in all forecasting horizons, exhibits some short-term inefficiency; as confirmed by the statistically significant lags of changes in spot and futures prices. Also, the comparative analysis of sensitivity of θ_1 in QCEM and basis regression model indicates that with effect of trading restrictions in the Indian agricultural futures markets between 2007-2009, the short-term efficiency of 28-day wheat futures markets is lower during post-ban than during the pre-ban period.

(d) In addition, following arguments from Stein (1987), i.e., any forecast error incurs a social cost; Krehbiel and Adkins (1993), i.e., cost of hedging increases with degree of inefficiency; and Murphy and Purcell (1995), i.e., inaccurate future price can cause social loss from misallocation of resources, this thesis chapter also adopts the efficiency measure to compare the degree of inefficiency in pre- and post-ban markets. The short-run market efficiency measure assesses the relative merits of two predictors of short-run spot price changes, namely, the forecast contained in the basis and forecast produced by the best fitting quasi-ECM. The findings suggest that in the pre-ban period, the 28 days forecast horizon is 39% inefficient, the 56 days forecast horizon is 40% inefficient, and the 84 days forecast horizon is 60% inefficient. The analysis was repeated for the three forecast horizons in the after-ban period. The 28 days forecast horizon was then found to be 50% inefficient, the 56 days forecast horizon is 60% inefficient, and the 84 days forecast horizon is 65% inefficient. These findings reveal that there is an increasing degree of inefficiency at the respective forecast horizons in the second period than the first period.

Thus, the examination of the relative efficiency in pre- and post-ban period shows that evidence of long-run inefficiency is solely related to 28-day forecast horizon but the results on the short-run inefficiency is supported in all three forecast horizons. The major inferences drawn from the empirical findings of this study is that, as the Indian agricultural futures market is still emerging, i.e., low hedging demand and lack of liquidity (Chatterjee et al., 2019), government imposed interventions like ban and hikes in margins could further undermine the credibility of the markets. As a result, not only farmers and FPOs but also other informed traders would try to avoid participation or reduce their exposure in the Indian agricultural commodities for their portfolio diversification agenda. Therefore, in a market-based economy, adopting a stable policy with minimal intervention will increase investor participation and will enable futures markets to become more efficient.

This study is the first of its kind in the Indian context to test the potential impact of ban of futures trading on market efficiency and results suggest important lessons: First, by examining the suspension of NCDEX wheat futures contract, this research provides a strong example of the negative implication of imposing an untimely and abrupt ban. Second, results confirm that the future trading ban has harmed the market efficiency both in long- and short-runs. Finally, this chapter shows that Indian agricultural futures markets deserve more attention as they provide the unique opportunity to learn from the frequent events of regulatory interventions in the 21st century. Since 2007 there have been more than 15 recorded suspension events in the Indian agricultural futures markets; the analysis of other agricultural commodities besides wheat contracts seems a promising direction for further research.

Table 2.1: Indian Wheat - Crop Calendar

Plantation & Harvest Period	
Sowing	Oct - Dec
Growth	Jan - Mar
Harvest	Apr -May

Table 2.2: Details of commodity, data period and source

Commodity	Future Exchange	Contracts Period	Place (Spot / Delivery Market)	Number of Observations
Wheat	National Commodity & Derivatives Exchange (NCDEX)	WHTSMQDEL - Monthly (10/04 to 09/05)	Delhi	12
		WHTSMQDELI - Monthly (10/05 to 06/13)	Delhi	70
		WHEAT - Monthly (07/13 to 02/15)	Delhi	23

Table 2.3: Descriptive Statistics for Spot & Futures in Price Change Series : For entire period and two sub-periods

	2004-2015: *n - 104*				**2004-2007: *n - 34***				**2009-2015: *n - 69***			
	Mean	Std. Dev.	Skewness	Kurtosis	Mean	Std. Dev.	Skewness	Kurtosis	Mean	Std. Dev.	Skewness	Kurtosis
Termination spot price												
s_t	0.0068	0.0518	-0.6495	4.6557	0.0088	0.0646	-0.7278	4.0458	0.0042	0.0429	-0.7721	4.3913
Lagged spot : 28 days												
s_{t-28}	0.0066	0.0514	-0.1558	5.0490	0.0098	0.0572	-0.7686	4.0903	0.0044	0.0488	0.3129	5.9505
Lagged futures : 28 days												
f_{t-28}	0.0061	0.0541	0.3539	4.1474	0.0078	0.0594	0.1035	2.5113	0.0037	0.0504	0.5125	5.8153
Lagged spot : 56 days												
s_{t-56}	0.0075	0.0480	0.3107	4.8990	0.0079	0.0534	-0.0685	2.6301	0.0064	0.0454	0.6329	6.9569
Lagged futures : 56 days												
f_{t-56}	0.0053	0.0549	0.5945	4.5518	0.0057	0.0638	0.2843	2.7563	0.0036	0.0493	0.9000	6.7732
Lagged spot : 84 days												
s_{t-84}	0.0077	0.0537	-0.0560	5.9354	0.0059	0.0587	-1.0177	5.4516	0.0062	0.0481	0.3916	6.3147
Lagged futures : 84 days												
f_{t-84}	0.0053	0.0560	0.4786	4.8670	0.0047	0.0670	-0.0791	3.2045	0.0039	0.0487	1.1293	7.0955

Notes: (a) s_t is the logged spot price at termination day of the futures contract.

(b) $s_{t-\tau}$ and $f_{t-\tau}$ represents the logged spot futures prices τ days before the contract termination date, where τ = 28, 56 and 84 days.

(c) Pre-ban sample period: July 28, 2004 - August 20, 2007. Post-ban sample period: May 25, 2009 - May 20, 2015.

Table 2.4: Augmented Dickey-Fuller Test for Spot & Futures Prices : For two sub-periods

Panel A: Levels

	2004-2007		2009-2015	
	Constant	Constant and Linear Trend	Constant	Constant and Linear Trend
(a) Termination spot price				
s_t	-1.377 (0)	-3.029 (2)	-1.742 (0)	-2.151 (0)
(b) Maturing futures price				
f_t	-0.723 (1)	-3.219 (2)	-1.986 (0)	-2.360 (0)
(c) Lagged spot : 28 days				
s_{t-28}	-1.163 (0)	-2.670 (1)	-2.069 (0)	-2.358 (0)
(d) Lagged futures : 28 days				
f_{t-28}	-1.265 (0)	-3.031 (0)	-1.938 (0)	-2.792 (0)
(e) Lagged spot : 56 days				
s_{t-56}	-1.417 (1)	-2.897 (1)	-1.856 (0)	-2.523 (0)
(f) Lagged futures : 56 days				
f_{t-56}	-1.207 (0)	-2.900 (0)	-1.970 (0)	-3.135 (1)
(g) Lagged spot : 84 days				
s_{t-84}	-1.312 (0)	-2.156 (0)	-1.603 (0)	-2.597 (0)
(h) Lagged futures : 84 days				
f_{t-84}	-1.256 (0)	-2.732 (0)	-1.895 (0)	-2.721 (0)

Table 2.4: continues				
Panel B: Differenced				
	2004-2007		**2009-2015**	
	Constant	Constant and Linear Trend	Constant	Constant and Linear Trend
(a) Termination spot price				
s_t	-6.411**	-6.307**	-7.035**	-6.976**
(b) Maturing futures price				
f_t	-9.939**	-9.800**	-8.674**	-8.613**
(c) Lagged spot : 28 days				
s_{t-28}	-5.134**	-5.043**	-7.554**	-7.536**
(d) Lagged futures : 28 days				
f_{t-28}	-6.880**	-6.779**	-7.122**	-7.092**
(e) Lagged spot : 56 days				
s_{t-56}	-4.339**	-4.267**	-7.723**	-7.679**
(f) Lagged futures : 56 days				
f_{t-56}	-5.083**	-4.786**	-6.263**	-6.240**
(g) Lagged spot : 84 days				
s_{t-84}	-5.569**	-5.487**	-8.191**	-8.143**
(h) Lagged futures : 84 days				
f_{t-84}	-4.458**	-4.426**	-6.486**	-6.454**

Notes: (a) Across all models - H_0: y_t contains unit root, i.e., it is nonstationary.

(b) *k* , the number of lags are determined by minimizing the AIC on the values of *k* ranging from 1 to 4.

(c) The AIC was minimized at the value given in the (), next to the *t* -statistics for the ADF test.

(d) Five percent critical values of the test-statistics are -2.863 (without trend) and -3.413 (with trend).

(e) Asterisk (*) and double asterisk (**) denote variables significant at 5% and 1%, respectively.

Table 2.5: VAR Lag Length Selection - Information criterion for determining the lag order						
		PERIOD I			**PERIOD II**	
Forecasting Horizon	AIC	SBIC	HQ	AIC	SBIC	HQ
s_t & f_{t-28}	10	1	1	2	2	2
s_t & f_{t-56}	10	1	10	2	1	1
s_t & f_{t-84}	10	10	10	1	1	1

Note: (a) Lag order selected by minimising the value of the information criterion.

Table 2.6: Johansen Cointegration Results - Test of Cointegration Rank: $X_t = (s_t, f_{t-\tau})$

Forecast Horizon	Information Criteria	Lag Length	Vector (r)	Cointegration Rank Test using Trace (λ_{trace}) Case 2	Case 3	Cointegration Rank Test using Maximum Eigenvalue (λ_{max}) Case 2	Case 3	Remarks
Period I								
28 days	AIC	10	H_0 : Rank = 0	26.65*	22.80*	20.62*	17.74*	Cointegrated only in Case 2; Rank = 1
			H_1 : Rank = 1	6.03	5.06*	6.03	5.06*	Rejects Noncointegration only in Case 2
28 days	BIC	1	H_0 : Rank = 0	25.63*	24.52*	23.43*	23.38*	Cointegrated; Rank =1
			H_1 : Rank = 1	2.19	1.15	2.19	1.15	Rejects Noncointegration
56 days	AIC	10	H_0 : Rank = 0	47.33*	29.38*	40.93*	23.05*	Cointegrated only in Case 2; Rank = 1
			H_1 : Rank = 1	6.40	6.33*	6.40	6.33*	Rejects Noncointegration only in Case 2
56 days	BIC	1	H_0 : Rank = 0	15.58	14.81	13.92	13.87	Not Cointegrated
			H_1 : Rank = 1	1.67	0.94	1.67	0.94	Does not Rejects Noncointegration
84 days	AIC	10	H_0 : Rank = 0	114.63*	91.43*	96.95*	78.60*	Both in Case 1 & 2, Rank = 2
			H_1 : Rank = 1	17.68*	12.83*	17.68*	12.83*	Null of reduced rank is rejected
84 days	BIC	10						
Period II								
28 days	AIC	2	H_0 : Rank = 0	29.28*	28.95*	25.64*	25.64*	Cointegrated; Rank =1
			H_1 : Rank = 1	3.63	3.30	3.63	3.30	Rejects Noncointegration
28 days	BIC	2						
56 days	AIC	2	H_0 : Rank = 0	39.10*	38.73*	35.65*	35.63*	Cointegrated; Rank =1
			H_1 : Rank = 1	3.45	3.10	3.45	3.10	Rejects Noncointegration
56 days	BIC	1	H_0 : Rank = 0	53.62*	52.88*	49.44*	49.21*	Cointegrated; Rank =1
			H_1 : Rank = 1	4.18	3.67	4.18	3.67	Rejects Noncointegration
84 days	AIC	1	H_0 : Rank = 0	41.13*	40.24*	37.02*	36.67*	Cointegrated; Rank =1
			H_1 : Rank = 1	4.10	3.58	4.10	3.58	Rejects Noncointegration
84 days	BIC	1						

Note: * denotes rejection of the hypothesis at the 0.05 level

Table 2.7: Testing Restrictions in Cointegrating Regression

	Estimates of Eq. (2.11)		Test 1 : $\beta_0 = 0$ and $\beta_1 = 1$ Unbiasedness			Test 2 : $\beta_1 = 1$ Market Efficiency			Test 3 : $\beta_0 = 0$ Absence of Risk Premium		
	β_0	β_1	*χ^2 (2)*	*p-value*	*Comments*	*χ^2 (1)*	*p-value*	*Comments*	*χ^2 (1)*	*p-value*	*Comments*
Period I											
28 days	-0.15	1.03	7.80	0.02	Reject	0.10	0.76	Fail to Reject	0.07	0.79	Fail to Reject
	(0.57)	(0.08)***									
56 days	0.29	0.96	7.52	0.02	Reject	0.14	0.71	Fail to Reject	0.18	0.67	Fail to Reject
	(0.69)	(0.10)***									
84 days											
Period II											
28 days	0.45	0.94	25.19	0.00	Reject	4.82	0.03	Reject	5.19	0.02	Reject
	(0.20)**	(0.03)***									
56 days	0.50	0.93	20.15	0.00	Reject	2.94	0.09	Fail to Reject	3.21	0.07	Fail to Reject
	(0.28)*	(0.04)***									
84 days	0.66	0.91	16.78	0.00	Reject	2.92	0.09	Fail to Reject	3.15	0.08	Fail to Reject
	(0.37)*	(0.05)***									

Notes : (a) Standard errors are reported in parentheses.

(b) Asterisk (*), double asterisk (**), and triple asterisk (***) denote significance at 10%, 5%, and 1% respectively.

(c) For 84 day forecast horizon in Period I, s_t and f_{t-84} are not cointegrated.

Table 2.8: Short-Run Wheat Efficiency, Pre-ban and Post-ban trading period

$$s_t - s_{t-\tau} = \theta_0 + \theta_1(f_{t-\tau} - s_{t-\tau}) + \sum_{i=1}^{k} \lambda_i(s_{t-i} - s_{(t-\tau)-i}) + \sum_{i=1}^{k} \gamma_i(f_{t-i} - f_{(t-\tau)-i}) + \epsilon_t$$

Period I	*28 days*	*56 days*	*84 days*	**Period II**	*28 days*	*56 days*	*84 days*
θ_0	0.02	0.02	0.06		0.01	0.01	0.00
	(2.25)	(2.11)	(2.02)		(2.00)	(0.76)	(0.33)
θ_1	0.44	0.41	0.63		0.62	0.80	0.67
	(2.77)	(2.70)	(1.19)		(3.59)	(3.28)	(2.39)
λ_1	0.14	0.36	0.43		-0.22	-0.29	-0.06
	(0.91)	(2.49)	(1.02)		(-1.27)	(-1.09)	(-0.33)
λ_2	–	–	-0.31		-0.04	0.52	0.27
			(-0.69)		(-0.20)	(2.04)	(1.42)
λ_3	–	–	0.27		-0.13	-0.14	0.12
			(0.53)		(-0.60)	(-0.63)	(0.50)
λ_4	–	–	-0.16		0.26	0.38	0.09
			(-0.36)		(1.24)	(1.92)	(0.49)
λ_5	–	–	0.21		0.08	0.20	0.16
			(0.49)		(0.44)	(1.04)	(0.86)
λ_6	–	–	-0.35		-0.12	-0.06	0.14
			(-0.81)		(-0.64)	(-0.34)	(0.73)
λ_7	–	–	0.20		-0.11	-0.02	-0.09
			(0.52)		(-0.59)	(-0.08)	(-0.48)
λ_8	–	–	–		0.01	0.14	0.02
					(0.05)	(0.77)	(0.08)
λ_9	–	–	–		-0.06	-0.02	0.19
					(-0.36)	(-0.09)	(1.00)
λ_{10}	–	–	–		0.06	0.25	0.15
					(0.40)	(1.11)	(0.87)
λ_{11}	N/A	N/A	N/A		-0.05	-0.18	-0.21
					(-0.38)	(-0.82)	(-1.23)
λ_{12}	N/A	N/A	N/A		0.28	0.37	0.44
					(1.95)	(2.25)	(2.75)
Υ_1	-0.41	-0.13	-0.21		-0.10	0.43	0.37
	(-2.88)	(-0.93)	(-0.49)		(-0.79)	(2.50)	(2.49)
Υ_2	–	–	0.23		0.02	-0.46	-0.14
			(0.54)		(0.16)	(-2.68)	(-0.89)
Υ_3	–	–	-0.36		0.00	0.01	-0.33
			(-0.71)		(0.01)	(0.03)	(-1.94)

Table 2.8: continues

Υ_4	–	–	-0.08	-0.14	-0.22	-0.08
			(-0.21)	(-1.02)	(-1.38)	(-0.52)
Υ_5	–	–	-0.17	-0.22	-0.19	-0.10
			(-0.45)	(-1.69)	(-1.20)	(-0.66)
Υ_6	–	–	0.30	0.02	-0.04	-0.09
			(0.79)	(0.14)	(-0.26)	(-0.59)
Υ_7	–	–	-0.10	0.12	0.31	0.07
			(-0.28)	(0.86)	(1.87)	(0.43)
Υ_8	–	–	–	-0.10	-0.19	0.07
				(-0.74)	(-1.17)	(0.45)
Υ_9	–	–	–	0.00	0.12	-0.10
				(-0.01)	(0.68)	(-0.66)
Υ_{10}	–	–	–	-0.10	-0.14	-0.04
				(-0.70)	(-0.65)	(-0.26)
Υ_{11}	N/A	N/A	N/A	-0.04	0.16	0.16
				(-0.31)	(0.80)	(1.06)
Υ_{12}	N/A	N/A	N/A	-0.09	-0.25	-0.24
				(-0.68)	(-1.69)	(-1.56)

Notes: (a) The table shows the results of QECM, short-run model, in Equation 2.17, with lags selected using AIC.
(b) t statistics in parentheses.

Table 2.9: *Q*-statistics and Serial Correlation LM Test

Forecast Horizon	*Q*-Statistics	*F*-Statistics	χ^2 Version
Period I			
28 days	No serial correlation	No serial correlation	No serial correlation
56 days	No serial correlation	No serial correlation	No serial correlation
84 days	Serially Correlated	No serial correlation*	Serially Correlated*
Period II			
28 days	No serial correlation	No serial correlation	No serial correlation
56 days	No serial correlation	No serial correlation	Serially Correlated
84 days	No serial correlation	No serial correlation	No serial correlation

Notes: (a) H_0 - No serial correlation in the residuals up to the specified order - 12 lags.
(b) * Tested serial correlation up to order 2 because of insufficient degrees of freedom.

Table 2.10: Joint Test of Zero Restrictions on the Coefficient of Lagged Variables in Short-Run Regression

Forecast Horizon	*F* test	*p* -value
Period I		
28 days	F(2, 30) = 4.148	0.026
56 days	F(2, 30) = 3.202	0.055
84 days	F(14, 12) = 0.687	0.751
Period II		
28 days	F(24, 32) = 1.075	0.418
56 days	F(24, 32) = 1.580	0.113
84 days	F(24, 32) = 1.953	0.039

Note: H_0 : No Lagged variables in short-run OLS Regression

Table 2.11: OLS Regression for

$$s_t - s_{t-\tau} = \theta_0 + \theta_1(f_{t-\tau} - s_{t-\tau}) + \varepsilon_t$$

Forecast Horizon	θ_0	θ_1	*p-value*
Period I			
28 days	0.02 (1.86)	0.45* (2.66)	0.00
56 days	0.03* (2.67)	0.51** (3.63)	0.00
84 days	0.04** (3.27)	0.57** (4.25)	0.00
Period II			
28 days	0.01** (3.61)	0.78** (6.89)	0.06
56 days	0.02** (3.90)	0.94** (8.59)	0.59
84 days	0.02** (3.62)	0.99** (8.06)	0.97

Notes: (a) *t* statistics in parentheses.
(b)*, ** denotes significance at a 5% and 1% levels.
(c) *p* value for the test of the hypothesis $\theta_1 = 1$.

Table 2.12: OLS Regression for two models in (2.14) and (2.15)				
	Model in (14)		*Model in (15)*	
Forecast Horizon	θ_0	θ_1	θ_0	θ_1
Period I				
28 days	0.02 (2.25)	0.44 (2.77)	0.02 (1.86)	0.45 (2.66)
56 days	0.02 (2.11)	0.41 (2.70)	0.03 (2.67)	0.51 (3.63)
84 days	0.06 (2.02)	0.63 (1.19)	0.04 (3.27)	0.57 (4.25)
Period II				
28 days	0.01 (2.00)	0.62 (3.59)	0.01 (3.61)	0.78 (6.89)
56 days	0.01 (0.76)	0.80 (3.28)	0.02 (3.90)	0.94 (8.59)
84 days	0.00 (0.33)	0.67 (2.39)	0.02 (3.62)	0.99 (8.06)

Note: (a) *t* statistics in parentheses.

Table 2.13: Relative Efficiency Measure						
		Period I			**Period II**	
Forecast Horizon (days)	28 days	56 days	84 days	28 days	56 days	84 days
ϕ^{τ}_{c}	0.61	0.60	0.40	0.50	0.40	0.35
Degree of inefficiency	0.39	0.40	0.60	0.50	0.60	0.65

Note: (a) $0 \leq \phi^{\tau}_{c} \leq 1$; $\phi^{\tau}_{c} = 0$ imply total inefficiency; and $\phi^{\tau}_{c} = 1$ imply total inefficiency.

Figure 2.1: Matched Spot and Lagged Wheat Futures: 28 Day Forecast Horizon

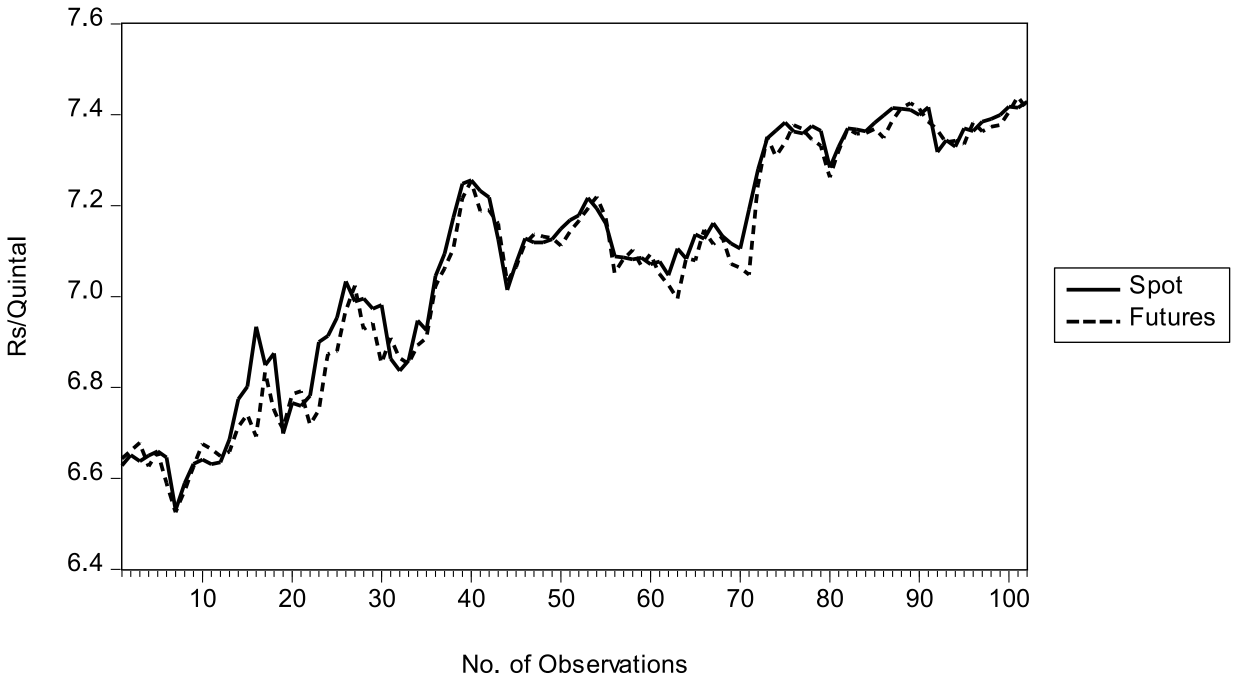


Figure 2.2: Matched Spot and Lagged Wheat Futures: 56 Day Forecast Horizon

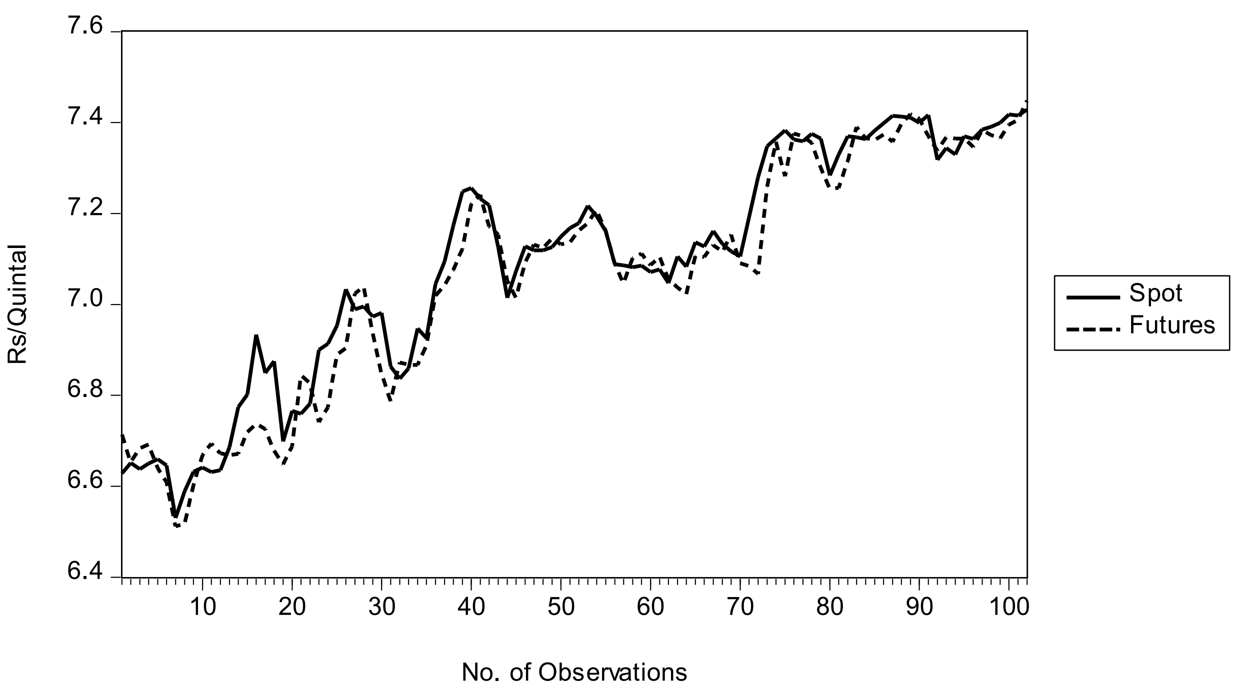
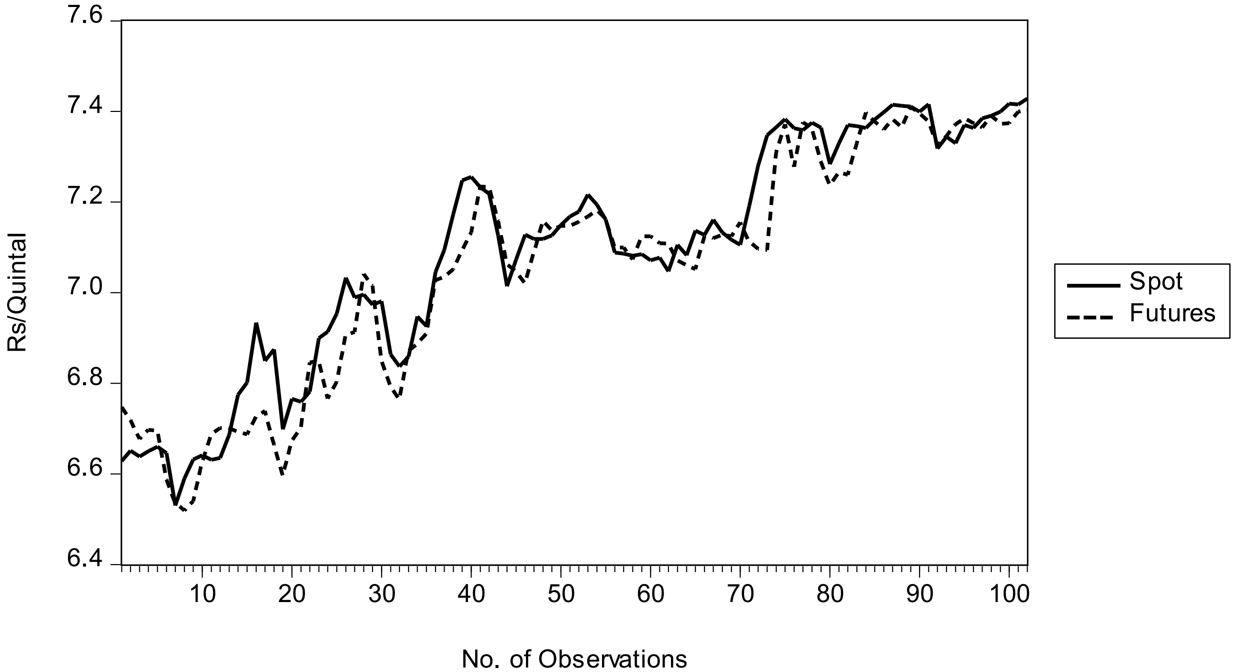


Figure 2.3: Matched Spot and Lagged Wheat Futures: 84 Day Forecast Horizon



CHAPTER 3

3. Effects of Trading Ban on Cointegration and Price Discovery: Evidence from Indian National Commodity and Derivatives Exchange

3.1. INTRODUCTION

Indian commodity futures market has a long history of trading commodity derivatives since the nineteenth century. The organized trading in futures contracts such as cotton, groundnut, castor seeds, jute and wheat were in existence at Bombay Cotton Trade Association Ltd. (established in 1875), Gujarati Vyapari Mandali (established in 1875), Calcutta Hessain Exchange (established in 1927) and the Chamber of Commerce at Hapur (1913). Between the 1920's and 1940's similar markets came up in diverse commodities under following categories: food grains, pulses, edible oils, oilseeds, spices, single vegetables, fibres, and precious metals, at around 300 regional commodity exchanges (Rajib, 2015). The futures markets in India, however, did not have an uninterrupted legal approval. Trading in large number commodities were either disallowed or prohibited altogether during the Second World War (under Defence of India Act, 1943) and after the 1969 ban was imposed by the Central Government (under Securities Contract Regulation Act, 1956). Besides, these bans, free trade in many food commodities were restricted under ECA (1955) and PBMSCA (1980) Acts[16], which are mainly government legislations to control price

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[16] Under ECA (1995), both Central and State governments have authority to issue administrative orders to prevent unfair business practices and to control the prices of commodities. However, a major irony of the Act was that State Governments have been imposing restrictions on the cross-border movement of specific commodities for trade purposes, which hindered the development of inter-state trade. A second piece of legislation, PBMSCA (1980) targets the prevention of unethical trade practices like hoarding and black-marketing etc., in essential commodities. This is administered under the State/Union-Territories Governments and permits the detention of individuals who obstruct the supplies of essential commodities.

These two Acts therefore influence the ability of market participants to hold the inventory. Cash and carry arbitrage involves buying goods on the spot market today and simultaneously selling them on a futures market. This requires legal certainty that holding inventory is not considered hoarding and violative of some laws when offsetting (sales) position is held in futures instabilities. While a number of expert committees (Dantwala Committee, 1966; Khusro Committee, 1980; Kabra Committee, 1994) recommended to revive futures trading in a wide number of commodities, the actual reforms were made following the World Bank - United Nations Conference on Trade and Development (UNCTAD) report in the year 1997, which advocated tremendous scope in revitalizing futures trading. As a consequence, a number of liberalization policy measures were adopted by the Government of India to revamp the futures markets: (1) Securities Laws (Amendment) Bill (1999) lifted prohibitions on forward trading in March 2000; (2) Ministry of Consumer Affairs, Food and Public Distribution notification under Forward Contracts (Regulation) Act, FCRA (1952) completely withdrew the ban on futures trading in April 2003; and (3) Three demutualized multi-commodity electronic exchanges, viz. NCDEX, Multi Commodity Exchange (MCX) and National Multi Commodity Exchange (NMCE), were granted recognition as National Exchanges in 2003.

However, promising growth during initial years (2003-2007) in most new agricultural futures market did not continue because of the frequent regulatory interventions (like abrupt suspensions[17] and bans[18] and increase in margins) and the markets in India therefore lack in liquidity and depth (Gulati et al., 2017; Chatterjee et al., 2019). In the wake of global food price

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market. The existence of such discretionary powers increases the risks to arbitrage activity, which in turn increases the basis risk and reduces the hedging effectiveness of commodities futures.

On 5th June, 2020, the President of India promulgated the ECA (Amendment) Ordinance, 2020, to amend the ECA, 1955 (Act) with the objective to support the development of commodity futures markets. This amendment is expected to trigger efficient discovery, which can provide a better basis for resource allocation i.e., sowing decisions and storage decisions, and thereby avoiding ‘peaks’ and ‘troughs’ in prices.

[17] For example details of Frequency, Year and Duration of suspensions in the Indian agri-futures market with respect to Commodities are as follows: **Raw Jute** (1), 2005, 7 months; **Wheat** (1), 2007, 27 months; **Chickpea** (2), 2008 and 2016, 6 months and 1 year respectively; **Potato** (2), 2008 and 2014, 16 months and 1 month respectively; **Rubber** (1), 2008, 16 months; **Soya oil** (1), 2008, 6 months; **Sugar** (1), 2009, 16 months; **Guar complex** (1), 2012, 14 months; **Pepper** (1), 2013, nearly 5 years; and **Castor seed** (1), 2016, 1 year.

[18] For example ban on **Pulses** (like Tur and Urad) in Jan 2007, and **Rice** in Feb 2007 has not been revoked for more than a decade now.

volatility which erupted in 2007-2008, the spot prices for certain essential agricultural commodities in India also experienced significant upsurge. Before the crisis was hit, around 2006-2007, arguments have been put forward by the Indian policy makers who attributed that excess speculation in the futures trade lead to inflation in agricultural prices. As Government of India confronted this viewpoint along with the intense political pressure, growing especially from the Left parties (then a key ally), the delisting of futures contracts on four commodities (wheat, rice, urad and tur) was ordered in 2007. Following this there were multiple instances of ban on future trading in the agricultural commodity markets. In the light of these regulatory interventions the Indian agricultural futures market is an unique case study to examine whether the interaction pattern (i.e., the way in which prices are discovered) between the spot and futures has changed considerably or not after the ban period. The benefit of commodity futures trading for providing a central platform to register demand and supply side conditions and thus facilitating price discovery is widely acknowledged in the literature from different futures markets, e.g., in the U.S. (Garbade and Silber, 1983; Brorsen, Bailey and Richardson, 1984; Oellermann and Farris, 1985; Oellermann, Brorsen and Farris, 1989; Koontz, Garcia and Hudson, 1990; Schroeder and Goodwin, 1991; Schwarz and Szakmary, 1994; Yang, Bessler and Leatham, 2001; Carter and Mohapatra, 2008; Hernandez and Torero, 2010; Peri, Baldi and Vandone, 2013; Shrestha, 2014; Shrestha, Subramaniam and Thiayagarajan 2020), the U.K. (Ferretti and Gonzalo, 2010), Canada (Brockman and Tse, 1995), Dominican Republic (Zapata, Fortenbery and Armstrong, 2005) or Germany (Adämmer, Bohl and Gross, 2015). Given that the domestic laws and regulations, especially which apply to the spot agricultural markets has a negative impact on the likelihood of success of the futures markets (Carlton, 1984; Bergfjord, 2007), the setting of a ban on futures trading may also have detrimental effects on the price discovery. In this context, the question whether these regulatory changes have implications for the properties of the wheat futures markets including its effects on both long- and short-term price discovery, is relevant. Although there were past instances of bans on the future trading of contracts (for example, Germany, Berlin Produce Exchange Act (1896), ban on grain futures; US, Onion Futures Act (1958), ban on onion futures; and US Dodd-Frank Wall Street Reform and Consumer Protection Act (2010), ban on domestic box office receipt (DBOR) futures), the instances of bans on futures trading in the Indian market are particularly interesting because these abrupt regulatory setbacks are imposed outside the demands of unexpected events like post-World War years, period of Great Depression or food price spikes of 1973-74 (Clapp and Helleiner, 2012). To the best of one's knowledge, this is the first study to examine the consequences of ban on future trading, especially changes in the price discovery relationship between the agricultural spot and futures markets during the pre-ban vs. post-ban period.

This study aims to fill this research gap by investigating the price discovery in NCDEX wheat spot and future markets by examining the following fundamental research questions formalized in the five respective testable hypotheses: (Q1) Do spot and futures prices share a long-term equilibrium relationship, that is, whether they are cointegrated in the pre- and post-ban periods? (Cointegration hypothesis); (Q2) Does the long-run unbiasedness property of the futures prices get influenced by the ban on the futures trading? (Unbiasedness and Joint hypotheses); (Q3) Are futures prices the sole primary informational source for spot price, that is, price discovery in the long-run, for both the period? (Weak Exogeneity hypothesis); (Q4) Does futures price impact spot price, before and after the ban, through the long-run price equilibrium channel? (Long-run Prediction hypothesis); and (Q5) Do lagged futures prices have significant predictive power for spot prices over a finite forecasting horizon? (Short-run Prediction hypothesis).

Many previous studies have examined the price discovery relationship between the commodities and its related futures for the Indian market. Some of the earlier studies of Indian agricultural commodities futures, e.g., Singh (2001), Thomas and Karande (2001), Naik and Jain (2002), Sahadevan (2002), Karande (2006), Lokare (2007) and Roy (2008), are explicitly or largely from the regional exchanges which were set up by the private associations registered under the FCRA (1952) and were operating before the setting of national level multi-commodity Exchanges in 2003. There are some other studies, e.g., Bose (2008), Mahalik, Acharya and Babu (2009), Srinivasan (2012) and Inani (2016), which investigate the price discovery relationship between spot-futures prices in Indian commodity indices of MCX and NCDEX for different sectors, viz., agriculture, energy, metal and aggregate commodities. A number of studies, for instance, Sahoo and Kumar (2009), Deo and Srinivasan (2009), Pavabutr and Chaihetphon (2010), Kumar and Arora (2011), Srinivasan and Ibrahim (2012), Arora and Kumar (2013), Joseph, Sisodia and Tiwari (2014), Lakshmi, Visalakshmi and Padmavathy (2015) and Nirmala and Deepthy (2016), also explore the nexus between spot and futures prices, at the individual commodity level, in precious metal (e.g., gold and silver), non-precious metal (e.g., copper and aluminium) and energy (e.g., crude oil and natural gas) markets.

Similarly, attempts to explain the lead-lag relationship, i.e., the price discovery process by employing Garbade-Silber framework (1983), cointegration tests, Granger-causality analysis and Error Correction Model (ECM) model have been very popular in the empirical research in the context of Indian agricultural commodity markets (Raizada and Sahi, 2006; Nath and Lingareddy, 2007; Easwaran and Ramasundaram 2008; Elumalai, Rangasamy and Sharma, 2009; Iyer and Pillai, 2010; Sen and Paul, 2010; Shihabudheen and Padhi, 2010; Ali and Gupta, 2011; Dey, Maitra and Roy, 2011; Mukherjee, 2011; Chhajed, Mehta and Bhargava, 2012; Gupta and

Ravi, 2012; Sehgal, Rajput and Dua, 2012; Malhotra and Sharma, 2013; Sahai, 2014; Shakeel and Purankar, 2014; Soni, 2014; Joseph, Suresh and Sisodia, 2015; Gupta, Choudhary and Agarwal, 2018; Inani, 2018; Minakshi, 2018; Manogna and Mishra, 2020; Vijaykumar, 2021). A common feature of these twenty-three studies conducted on the price discovery aspect in the Indian agricultural commodity markets is that they either concentrate on the futures contract on which the ban has never been placed or employ the data samples in their respective studies prior to 2007-2008, i.e., when Indian agri-futures markets experienced major turbulence due to suspensions and bans (Raizada and Sahi, 2006; Nath and Lingareddy, 2007; Easwaran and Ramasundaram 2008; Elumalai et al., 2009; Iyer and Pillai, 2010; Sen and Paul, 2010; Shihabudheen and Padhi, 2010; Ali and Gupta, 2011; Dey et al., 2011; Gupta and Ravi, 2012; Sehgal et al., 2012; Malhotra and Sharma, 2013; Soni, 2014; Gupta et al., 2018) or the data set spans from the period from 2008-2009 onwards, i.e., after the majority of bans were lifted (Chhajed et al., 2012; Shakeel and Purankar, 2014; Joseph et al.,2015; Inani, 2018; Minakshi, 2018; Manogna and Mishra, 2020; Vijaykumar, 2021). Although the likely adverse effect of ban on futures trading in commodities has been recognized in the few studies (Srinivasan, 2008; Fernandez, 2013), none of these studies employ samples of banned agricultural commodities in the pre-ban and post-ban phase to examine the price discovery dimension. Srinivasan (2008) using weekly wholesale price index (WPI) and food prices data, from April 2008 to June 2008, for four (chickpea, potato, rubber and soya oil) banned commodities showed that the ban did not help in keeping inflation under control. Fernandez (2013) studied the impact of the ban on the wholesale prices of four banned commodities (wheat, rubber, potato and guar seeds) for the period between 2006 to 2012. This study documents negative relationship between the wholesale prices and future quantity traded; and also showed that placing the ban on the futures trading does not curb food inflation.

The importance of change in regulation in explaining the price discovery over time has also been recognized in global futures markets. For instance, Mattos and Garcia (2004) investigated the price discovery process between agricultural spot and futures markets in Brazil for six commodities following a change in the Brazilian exchange rate policy. Although their results in terms of price discovery were somewhat mixed, in case of coffee market (i.e., most actively traded contract) futures market play a more dominant role in the price discovery process in the second period, reflecting that the pricing relationship is dynamic and is influenced by the reforms in the regulatory framework. Bohl, Salm and Schuppli (2011) investigated the price discovery mechanism between the stock index futures and spot markets in Polish markets, following a change in mutual fund regulation policy. A change in this legislation triggered a considerable increase in the futures trading volume of foreign and domestic institutional investors, causing a decline in the share of individual investors' futures trading volume, who dominated the market before this reform. Their result suggests that in the earlier sample period, price discovery mainly occurs in the spot market during the dominance of unsophisticated individual investors. In contrast, with the change in the investor structure (i.e., rise of institutional ownership), the information flow from futures to spot market has increased considerably in the later sample period. Thus, in line with Mattos and Garcia's (2004) work, they also identified that pricing relationship change over time. A slightly different approach was adopted by Lee, Kuo, Lee and Lee (2016) to study price discovery function in the Australian Real Estate Investment Trust (A-REIT) index futures market. Instead of a domestic regulatory regime shift, their study examines the effects of the Global Financial Crisis (GFC) on the price discovery process. They found that spot market led the A-REIT futures market in price discovery *before* the *GFC*; the two markets interacted bilaterally *during* the *GFC*; and *after* the *GFC*, the futures market followed the spot market again, but less closely. There finding implies that *during* and *after* the GFC, more informed traders are likely to have entered the futures markets and improved its price discovery function. These findings are consistent with the broader notion that price formation process is related to investor structure over time. In the case of Indian agricultural futures markets although Srinivasan (2008) and Fernandez (2013) studied the effects of ban, they more specifically focussed on the impact of futures trading on the WPI. Thus, the aspect of market leadership in the price discovery process and information flow around suspension/ban periods remains neglected thus far in the empirical literature.

Thus, a study dedicated to the Indian wheat futures market is notable for a number of reasons. First, the Indian agri-futures markets offer a unique dataset with which several issues can be examined surrounding frequent suspensions of commodity futures in the 21st century context. In the event of several instances of abrupt bans and suspension in the futures trading, it is plausible that number of market participants (including speculators and genuine hedgers) will decrease as they shift their trading activity to alternative market segments, e.g., overseas futures exchanges, OTC or spot markets. The regulatory measures therefore could have negative influence on the futures trading volume, functioning of transmission of information through the futures markets, and thus may have detrimental effects on the price discovery process. Consequently, examining the implications of regulatory constraints may be of importance to the policy makers, regulators and commodity exchanges when the focus is on the efficient functioning of the agricultural futures markets. Second, contributions by Mattos and Garcia (2004), Bohl et al. (2011) and Lee et al. (2016) has noted the important link between the role of reforms in the regulatory framework and the price formation process. The Indian literature in fact, neglects the potential effects of the trading suspensions, especially stemming from political pressures, on the price discovery process. This chapter aims filling this void. Thus, an investigation of ban on the wheat futures market might offer insight into how regulatory attempts may affect their price discovery function.

In addition, by using daily spot and futures market data this research chapter extends the work of the first chapter and also contributes to the literature in following significant ways. First, to overcome the difficulty of small sample size in the first chapter the monthly time interval between the price observations is reduced to a single day. A data set comprising of daily frequency of spot and future time series for wheat for the period 2004 until 2015 is used. A trading suspension event of wheat futures contract in 2007 allows this research to relate empirical evidence on the price discovery to the pre- and post-ban trading phases. As a consequence, for this empirical investigation the whole sample is split into a subperiod of pre-ban (spanning from August 2004 - July 2007) and a subperiod of post-ban (spanning from June 2009 - January 2015).[19] The resulting datasets in the two chapters thus contain 763 daily (34 monthly) and 1393 daily (69 monthly) observations for the pre-ban and post-ban periods, respectively. As discussed in Schwarz and Szakmary (1994), time interval of analysis is an important factor to make a conclusion about price discovery because future price leadership often run for shorter duration, i.e., minutes ahead of the spot market. Hence, monthly observations used in the previous chapter will be too long to test for price leadership in these markets. Second, unlike the prior studies of Indian agricultural commodity futures markets, this study is the first to examine whether the

[19] Section 3.4.1 on Data Description shows the exact date of suspension of trade in wheat futures, date of relaunch of futures trading after the ban was lifted, and the time period selected for the sampled commodity.

futures market dominates the price discovery process in the similar manner around the regulatory interventions. Consequently, motivated by the trading suspension of wheat futures in 2007, the whole sample is split into a subperiod of initial years of trading, i.e., prior to the ban (2004-2007) as well as a subperiod of relatively mature years of trading, i.e., after the ban (2009-2015). Third, some new evidence is presented for the positive risk premium in the wheat futures market. The unfavourable impact of the trading ban on the risk premium is detected in the post-ban period. The constant risk premium is a simple way to gauge the average level of risk aversion. In line with the intuition, a number of abrupt episodes of regulatory intervention in the agri-future markets are likely to have influenced the level of premium in the wheat futures markets. Fourth, the long-run dynamics between the spot and futures prices modelled by VECM provides strong support for the statistical exogeneity of futures price. This result highlights that future markets are faster and a more reliable platform than the spot markets as it performs the long-run price discovery function despite the uncertainty introduced by the regulatory setbacks. Finally, the evidence of bidirectional short-run information flow in the post-ban period suggests that dominance of the future market in the price discovery process was reduced due to the effect of unexpected regulatory action. Summing-up, estimation results for the two sample periods suggest that while regulatory attempts, such as bans, suspensions or delisting of future contract may be popular interventionist measures of the government, they may compromise the prospects of commodity future trade and harm the functioning of markets in both sensitive and non-sensitive agricultural commodities.

The rest of this study is structured as follows. Section 3.2 outlines the theoretical justification for the connection between the spot and futures prices in the cointegration framework. Section 3.3 explains the empirical methodology and testable hypotheses used to investigate the price discovery process. In Section 3.4 a description of the data for the period covered in the study is provided. Section 3.5 presents the estimation results. Finally, Section 3.6 summarizes key findings and concludes the chapter.

3.2. THEORETICAL FRAMEWORK

3.2.1. Price Discovery and Storable Commodity Futures Market Pricing

Temporal price relationship in commodity markets is concerned about how the structure of prices, current spot, and the corresponding futures contracts are expected to vary over time. Price discovery is an important aspect of temporal price analysis and the issue is often investigated by lead-lag relationships, causality methods and symmetry tests for examining the feedback of information flow between the two markets. In general, the description of price discovery simply refers to the process by which buyers and sellers attempt to reach the market-clearing or equilibrium price of a good in a specific market and at a particular time (Purcell and Hudson, 1985; Schreiber and Schwartz, 1986). Initial efforts to test price discovery in commodity markets were based on the simultaneities of cash and futures prices determination. Some theoretical models that have captured the simultaneous equilibrium in cash and futures markets include those of Johnson (1960), Stein (1961) and Rutledge (1972). Most studies however underscore the belief that futures market in general, will lead the movements in cash market. For example, tests in Garbade and Silber (1983), Brorsen et al. (1984), Ollerman and Farris (1985), Oellermann et al. (1989), Koontz et al. (1990), Schroeder and Goodwin (1991), Schwarz and Szakmary (1994), Brockman and Tse, (1995), Yang et al. (2001), Zapata et al. (2005), Peng, Yong and Suo (2006), Carter and Mohapatra (2008), Ferretti and Gonzalo (2010), Hernandez and Torero (2010), Peri et al. (2013), Shrestha (2014), Adämmer et al. (2015), Xu (2018.a, 2018.b), and Shrestha et al.

(2020), which are interested in the dynamic spot/futures price relationship for various commodities have identified the primacy of futures market in terms of origination of the price discovery process. The notion of price discovery function of futures markets has usually been examined under two aspects: (1) whether the current futures prices are an *unbiased estimate* of the subsequent spot prices. This implies that futures prices should not systematically underestimate or overestimate the swings in cash prices (Leuthold, 1974; Martin and Garcia, 1981); and (2) whether the futures market provides reliable *predictive information* regarding the forthcoming moves in the cash market. This suggests that futures market should adjust to new information and therefore should dominate the cash market in registering the price changes (Garbade and Silber, 1983; Purcell and Hudson, 1985).

The above two questions embodied in the *unbiasedness hypothesis* and *prediction hypothesis* respectively are theoretically examined in the context of both inventory hedging and forward-pricing roles of the futures markets. The role of the futures price in guiding the inventory levels for storable commodities is linked to the Working's (1948) concept of price of storage, however, in case of nonstorables, where no inventories are carried, the pricing link between the cash-futures relationship is summarized by the forward pricing function (Tomek and Gray, 1970; Leuthold, 1974). While inventory guidance and price stability are two major contribution of futures markets, a model of certain price relationship between cash market and futures contract is required to investigate the price discovery functioning of commodities. The next sub-sections briefly discuss the theoretical relation and empirical models that are appropriate to examine commodity futures market pricing.

3.2.1A. Storage Facilitation and Carrying Cost Theory

The theory of storage, formalized by the no-arbitrage pricing relationship or cost-of-carry model, considers that futures price is equal to the commodity's spot price plus the net carrying cost of holding the underlying commodity over the life of the contract for storable assets. The cost-of-carry relationship implies that, to avoid arbitrage opportunities, the following condition must hold:

$$F_{T|t} \quad = \quad S_t e^{(r_t + c_t - d_t)(T-t)} \tag{3.1}$$

In Equation (3.1), $F_{T|t}$ represents the futures price at time t for a contract that matures in period T (for example 3 months ahead) and S_t is the spot price of the commodity observed in period t. The cost of carrying includes relevant cost of capital (interest forgone) during storage, i.e. risk-free rate r_t, plus storage cost associated with the carrying the inventory (e.g., warehousing, transportation and insurance) c_t, less the convenience yield from holding the stocks of some commodities d_t. Here, $T - t$ represents the time remaining until maturity date (T) in the life of futures contract. In practice, researchers have often omitted variables such as c_t and d_t because they have identified that the storage cost is minimal for perfectly storable commodity such as wheat (Covey and Bessler, 1995) and the nature of the convenience yield is unobservable in certain commodity markets (Crowder and Hamed, 1993).

Because the price behaviour of an asset which can be cheaply warehoused is expected to approximate that of a perfectly storable asset (Covey and Bessler, 1995; Yang et al., 2001) and due to the mean reversion tendencies of the convenience yield (Gibson and Schwartz, 1990), it is plausible to assume that both c_t and d_t are negligible in storable commodity markets. Following these assumptions and after taking natural logarithms of Equation (3.1), a cost-of-carry model for storable commodity is obtained as follows:

$$\ln F_{T|t} \;=\; \ln S_t \;+\; r_t\,(T-t) \qquad (3.2)$$

In Equation (3.1) only contemporaneous values of futures and spot prices enter the model, so that no riskless arbitrage profit opportunity could arise in perfectly efficient and frictionless financial markets. In other words, price adjustments in spot and futures markets are instantaneous and there are no deviations in cost-of-carry asset pricing model, i.e., the no-arbitrage equilibrium condition should be satisfied at every time *t* during the life of futures contract T. In the Equation (3.2) the marginal storage cost, $c(T-t)$, and marginal convenience yield, $d(T-t)$, are omitted and only relevant transaction (financing) cost, $r(T-t)$, of the spot commodity is included. If such is the case (3.2), then the spot-equivalent futures price, $F'_{T|t}$, could replace the observed futures price, $F_{T|t}$, in the specified spot/futures relationship. Cho and McDougall (1990) and Schwarz and Szakmary (1994), in their examination of energy futures markets have made similar replacements to discount the observed futures price to its cash-equivalent. The original work of Garbade and Silber (1983) on price discovery also specified the cash-futures relationship as being between S_T and $F'_{T|t}$, so that the price dynamics is net of their financing (interest cost) component. The spot-equivalent futures price result is measured as:

$$\ln F'_{T|t} \;=\; \ln F_{T|t} - r_t\,(T-t) \qquad (3.3)$$

Replacing the observed futures price with the cash-equivalent futures price results in the restatement of (3.2) as:

$$\ln F'_{T|t} \quad = \quad \ln S_t \tag{3.4}$$

Thus, the empirical specification corresponding with the cost-of-carry model in Equation (3.4) for the storable commodities, after ignoring the storage cost and convenience yield, can be specified as follows:

$$\ln F'_{T|t} \quad = \quad \mu + \ln S_t \; + \; e_t \tag{3.5}$$

where e_t is a white noise residual, i.e., with the classical properties of a zero mean and constant variance.

3.2.1B. Forward Pricing and Expected Price Theory

Firstly, market anticipation of the subsequent spot price which is been discovered by the current futures price is regarded as the forward price (Purcell, 1992). For storable commodities with continuous inventories (e.g., grains like corn, soybean and coffee), storage serves an important economic function and the interpretation of forward pricing in this case is tied to the inventory allocation process. Therefore, if all available information including expectations of the economic agents' are fully reflected in the current price formation, then both the set of current cash and current futures prices are viewed within a single constellation; i.e., both prices may be interpreted as an equally valid anticipation of subsequent spot price (Leuthold, 1979). However, markets may exhibit current forward premium (or current price spread), which is represented by the difference between the current period's price of a futures contract for delivery in the next period and the current spot price $F_{T|t} - S_t$. Working (1942; 1948) argued that at least in case of storable commodities, continuous effective arbitrage between the cash and futures markets will prevent this forward premium from exceeding beyond the marginal net cost of carrying the commodity. His work in (1942) and (1949) attributes positive (negative) value of the basis to forward (spot) premium and argues that this not a prediction that the spot price will rise (or fall), but rather a market estimated carrying charge (or inverse carrying charge).

For nonstorables and for commodities with discontinuous inventories, the allocation process is less direct due to absence-of or discontinuous nature of the inventories. However, since no commodities can be classified as purely nonstorable, the precise nature of. In previous studies, Tomek and Gray (1970) and Leuthold and Tomek (1980) explained about the nature of semi-perishables (e.g., butter, eggs, onion, potatoes) based on the seasonality and discontinuous inventory situation. On the other hand Paul, Kahl and Tomek (1981) and Fama and French (1987) argued that animal products (e.g., livestock commodities such as live hogs, pork bellies, live cattle or fresh eggs) are perishable commodities because deterioration of their quality in storage makes storage costs expensive. Particularly, in such cases, the expectations of the agents cannot find full expression in current prices due to limited arbitrage opportunities. The reason for this phenomenon (i.e., where traders' expectations are not fully reflected in the current spot prices) is that the nonstorables and discontinuous-inventory markets have relatively smaller trading volumes; and absence or discontinuity of inventories itself increases the possibility of significant gap in the information flow (Goss, 1981). In these cases, because there are less opportunities for arbitrage between the spot and futures markets, the aspect of traders' expectation about the current spot market activities which cannot be reflected in the spot prices will be contained in the futures prices and hence, in the price spread. That is, if the spot market activities are reduced, then the set of current cash and current futures prices are not viewed as being within a single constellation (Leuthold, 1979). Moreover, for discontinuous and non-inventory markets, where trader' expectations cannot find full expression in the cash prices, it is likely that the elements of their price expectations would be reflected in the futures price and, therefore in the basis (Giles and Goss, 1981). Hence, for nonstorable commodities the only economic function of the future markets is to provide continuously available forward price. Tomek and Gray (1970) pointed that for the no-inventory markets, the futures market fulfils the forward-pricing purposes, which is helpful for producers in rationalising their production decisions and stabilizing their revenue in the absence of storage price links. Similarly, Stein's (1981) work revealed that the expected social loss arising from non-optimal allocation of resources, for commodities with discontinuous inventories, are significantly avoidable. This study implies that the avoidable loss is zero if the futures market at the time when production decisions are undertaken i.e., the forward price, is an unbiased estimate of the spot price at the time of the consumption. However, Peck (1985) demonstrated that for storable commodities, the futures market guides both the storage decision (i.e., allocation of inventories) and forward pricing function (i.e., reliable anticipatory prices for stabilizing annual production and consumption decisions) in appropriate ways.

The notion of forward pricing ability that futures price should be an unbiased estimate of the eventual cash price is developed and tested in the form of expected price theory.[20] Thus the expectation hypothesis[21] is given below:

$$F_{T|t} \;=\; E_t(S_T \,|\, \Omega_t) \tag{3.6}$$

where $F_{T|t}$, in period t is assumed to be equal to the rationally expected future spot price for period T, and $E(.)$ is the mathematical expectations operator conditional on information set Ω_t available to the agents at time t. For ease of notation, the right-hand term in Equation (3.6) can be written as S_T^e, the *expected future spot price*. Assuming that the agents are rational in forming their expectations in period t i.e., they do not make systematic forecasting errors (Hallwood 1988; Moosa and Al-Loughani, 1994), the following equation for the expected spot price must hold:

$$S_T^e \;=\; S_T \;+\; e_T \tag{3.7}$$

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[20] Mehrotra and Carter (2017) used *expected price theory* to explain the difference between contemporaneous spot and futures prices of a commodity (i.e., the basis) as a rational expected change in spot price plus a risk premium. This implies, if the market participants are endowed with rational expectation but is risk averse, then the uncertainty present in the system may require a risk premium. However, under the efficient market assumption tested using the unbiasedness hypothesis, the competitive time arbitrage should compete away the excess profit. Therefore it is assumed in Equation (3.6) that futures price of a contract that matures in period T to be equal to the rationally expected future spot price for period T (see Hallwood 1988; Moosa and Al-Loughani, 1994; Yang et al., 2001; Coakley et al., 2011).

[21] The expectation hypothesis in Equation 3.6 refers to the condition of unbiasedness or Unbiased Expectation Hypothesis (UEH) to be more precise. This formulation of equation in UEH is different from Risk Premium Hypothesis (RPH) proposed by Fama (1984) and Fama and French (1987), which allows for uncertainty in returns by modelling the presence of time-varying expected risk premium in the system.

where S_T is the *realized (or future) spot price* and e_T is white noise. Therefore, Equations (3.6) and (3.7) could be transformed as follows:

$$F_{T|t} \;=\; S_T \,+\, e_T \tag{3.8}$$

Following theoretical work of Brenner and Kroner (1995), some researchers (Yang et al., 2001; Peng et al., 2006; Ferretti and Gonzalo, 2010; Gupta, Kumar and Pandey 2013; Inoue and Hamori, 2014; Choudhary and Agarwal, 2018), have assumed that the first difference in spot prices, ΔS_t, is stationary with a constant mean; and tested the unbiasedness condition with current spot price. Also, this is established in Engle and Granger (1987) that within a cointegration framework if any variables are cointegrated then cointegration must exist at any lead or lag as well. Therefore, following the standard assumption of:

$$\Delta S_t \;=\; S_t - S_{t-1} \tag{3.8.a}$$

is $I(0)$, the empirical specification of Equation (3.8) can be rewritten with S_t instead of S_T. The intuition for bivariate cointegrated system of spot and futures prices is that, time leads or lags do not affect the specification or the statistical outcome of hypothesis tests. Hence, if the forward pricing role is valid description of relationship between spot and futures prices, it can be estimated directly with the empirical form given in Yang et al. (2001):

$$F_{T|t} \;=\; \mu \,+\, S_t + \, e_T \tag{3.9}$$

The above assumption greatly simplifies the expectation hypothesis; by replacing future spot price, S_T, with the *current spot price*, S_t, it enables direct comparison between the cost-of-carry and unbiasedness model in Equation 3.5 and 3.9 respectively.

3.2.2. Price Discovery and Cointegration in Commodity Markets

There exist many statistical tests and methods for exploring the linkages of futures/cash price relationship across commodities i.e., different hypotheses associated with price discovery. The focus of earlier research tends to be either on directional causality (Ollerman and Farris, 1985; Purcell and Hudson, 1985) or the dominant-satellite relationship by using Garbade and Silber's (1983) approach (Oellermann et al., 1989; Koontz et al., 1990). To incorporate the nonstationarity of individual spot and futures commodity prices, i.e., $I(1)$, later studies widely used cointegration framework to perform the price discovery analysis. For example, Baillie and Myers (1991), Bessler and Covey (1991), Schroeder and Goodwin (1991), Fortenbery and Zapata (1993), Karbuz and Jumah (1995), Singh (2001), Naik and Jain (2002), Lokare (2007), Roy (2008), Ali and Gupta (2011), Kumar and Arora (2011), and Sehgal et al. (2012) have used bivariate cointegration analysis. Another popular method to measure price discovery within cointegration framework is the tests of causality using error correction model developed by Engle and Granger (1987), have been employed by Quan (1992), Schwarz and Szakmary (1994), Brockman and Tse, (1995), Mattos and Garcia (2004), Karande (2006), Peng et al. (2006), Carter and Mohapatra (2008), Elumalai et al. (2009), Mahalik et al. (2009), Deo and Srinivasan(2009), Ferretti and Gonzalo (2010), Pavabutr and Chaihetphon (2010), Shihabudheen and Padhi (2010), Dey et al. (2011), Mukherjee (2011), Gupta and Ravi (2012), Srinivasan (2012), Srinivasan and Ibrahim (2012), Arora and Kumar (2013), Malhotra and Sharma (2013), Strydom and

McCullough (2013), Shakeel and Purankar (2014), Soni (2014), Adämmer et al. (2015), Nirmala and Deepthy (2016), Chen and Scholtens (2018), Gupta et al. (2018), Inani (2018), Xu (2018.a, 2018.b), and Manogna and Mishra (2020), to explore the relative price leadership between spot and futures price series.

An alternate type of test which is closely associated with the futures price discovery function is called test for market efficiency which is typically based on the concept cointegration. To test the market efficiency hypothesis, various versions have been estimated by different authors. For example, Serletis and Banack (1990) implied market efficiency in petroleum futures markets just with cointegration between S_t and $F_{t-1,t}$ without explicitly testing for the restrictions on the cointegrating parameters. Chowdhury (1991) tested for efficient pricing condition[22] in four nonferrous metal markets by imposing the assumption of $\alpha = 0$ and $\beta = 1$, thereby assuming no risk premium. The result indicates that three out of four markets do not have steady-state relationship (i.e., cointegration) between futures and subsequent spot prices and implied absence of efficiency across metal markets. Instead of unbiasedness, Beck (1994) tested for market efficiency[23] in US commodity futures markets while allowing for the possible existence of risk

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[22] For testing of market efficiency without a risk premium, cointegration between spot and lagged futures prices is a necessary condition, however, the formal testing implies coefficient restrictions on the constant term and the slope, i.e., if condition $(\alpha, \beta) = (0,1)$ holds in the cointegrating regression. This efficient pricing condition is sometimes referred to as either market efficiency hypothesis (Chowdhury, 1991) or unbiasedness hypothesis (Moosa and Al-Loughani, 1994).

[23] The term unbiasedness hypothesis and market efficiency hypothesis are sometime used interchangeably, however, they are different in the following aspects. The market efficiency condition of unbiasedness is, in fact, a coupling of two hypotheses of risk neutrality and rational expectations. This implies that the futures prices, $F_{t-1,t}$, are an unbiased forecaster of spot price, S_t, on an average, if testable restriction of $\alpha = 0$ and $\beta = 1$ holds and the forecasting error is a white noise process (MacDonald and Taylor, 1989). However, efficient market hypothesis permits risk premium and does not rule out residual serial correlation i.e., systematic forecasting errors may appear due to the variations in the risk premium (Hallwood, 1988). This means that if another test is conducted based on the 'forecast error' and tested for the requirement of forecasting error to be zero (see Liu and Maddala, 1992 for more elaborate discussion), the serial correlation may be found in the forecast error due to the existence of time varying risk premiums and not because of the market agents having an irrational expectation. For example, Moosa and Al-Loughani (1994) tested the hypothesis of efficiency of the forecast error under two model specifications in equations 18 and 19. Therefore, market efficiency hypothesis tests do not require the coefficient restrictions on the constant term and slope, as implied by unbiasedness hypothesis (Beck, 1994).

premium. The test for cointegration between future spot price (S_{t+1}) and current futures price (F_t) show that most series are cointegrated and market efficiency could not be rejected.

Strictly speaking, standard tests of cointegration do not restrict the cointegrating factor to be one nor do they require error term to be a white noise (Engle and Granger, 1987). Therefore cointegration between spot and the futures prices (either for the *basis*, S_t and F_t or the *risk premium*, S_t and $F_{t-1,t}$) require only the residuals of the cointegrating equations to be stationary, which is a weaker condition than white noise. More precisely in process of testing for market efficiency or unbiasedness hypothesis, where both time series are found to be non-stationary, cointegration is just a necessary condition implying long-run (stable) equilibrium relationship between the price series. Once cointegration has been ascertained between the two series then the sufficient condition is a simple restriction on the cointegrating vector, linked to either market efficiency hypothesis or unbiasedness hypothesis (Beck, 1994; Sabhuhoro and Larue, 1997), that can be tested on the coefficients of error correction model.

Crowder and Hamed (1993) also used cointegration techniques to test for simple efficiency hypothesis and arbitrage equilibrium hypothesis which implies cointegration under specifications of $X_t = [S_t, F_{t-1}]'$ and $X_t = [S_t, F_{t-1}, R_t]'$ respectively with the respective cointegrating vector of $[1, -1]'$ and $[1, -1, -1]'$. Their result provides evidence that although the risk-free rate is a non-stationary process, the S_t and F_{t-1} are cointegrated without the inclusion of R_t in the system; i.e., the analysis of the cointegration relation proceeded under specification of $X_t = [1,\ S_t, F_{t-1}]'$ implies that joint restrictions of the simple efficiency hypothesis cannot be rejected. Furthermore, the cointegration results for the arbitrage equilibrium system, i.e., $X_t = [1, S_t, F_{t-1}, R_t\ ]'$, with the inclusion of risk-free rate in the system did not find support either. In general, the cointegration test results between nearby futures prices and cash prices have produced inconclusive and conflicting results across different studies in the commodity markets.

Following the line of reasoning from Bessler and Covey (1991) on the storage function, Covey and Bessler (1995) were the first to argue that marginal support for cointegration or perhaps failure to find cointegration between cash prices and the futures contract for commodities may be due to the storability of an asset. Their result generated support for high cointegration in storable commodity (wheat) than the market for non-storable asset (live cattle). In contrast to the role of asset storability, other researchers (Brenner and Kroner, 1995; Zapata and Fortenbery, 1996) have explained that the inconsistency in the results of cointegration tests for storable commodities have particularly arisen due to model misspecification problem in a bivariate framework. They noted that the cointegration model most often used in the study of agricultural commodity markets has been bivariate formulation between spot and futures prices. They suggest that the bivariate cointegration between the prices will not hold when the costs of maintaining the inventories are high. That is, if either the high interest rates or substantial carrying charges exist between delivery dates, then a bivariate cointegration model would be biased towards rejecting cointegration. Hence they argued that a more appropriate specification would be a trivariate model. Subsequently, some of the later literature on price discovery relationship used either trivariate cointegration formulation (e.g., Zapata and Fortenbery, 1996) to explicitly account for the interest rate behaviour (or for the behaviour of any other nonstationary pricing component such as, transportation cost, storage cost present in the temporal links); or suggested a cost-of-carry model with interest cost (e.g., Fortenbery and Zapata, 1997; Yang et al., 2001; and Mattos and Garcia, 2004), not the interest rate (under such bivariate model specification cash-equivalent relationship is used in the cointegration analysis).

Another strand of literature that explores price discovery in commodity markets (Brockman and Tse, 1995; Ferretti and Gonzalo, 2010; Shrestha, 2014; Adämmer et al., 2015; Shrestha et al., 2020) have employed alternate methods to analyze the price discovery process, such as the permanent-temporary decomposition (Gonzalo and Granger, 1995), the information share (IS) (Hasbrouck, 1995), modified IS (Lien and Shrestha, 2009) and/or generalized IS (Lien and Shrestha, 2014), which are also based on the concept of cointegration. Meanwhile, because this PhD chapter focuses on the usefulness of futures market in providing both an *unbiased estimates* and *predictive signals* to examine the price discovery performance for a storable commodity, the appropriate specification of the cointegrating relationship is obtained from no-arbitrage profit condition as laid out by Brenner and Kroner (1995). As noted previously, the framework for the cointegrating regression discussed in this section is used to test the unbiasedness hypothesis which is only one part of futures price discovery function in this empirical work, another part being the test for the prediction hypothesis. Therefore, the first empirical task is to determine the order of integration for individual cash and futures price series; and if these series are found to be nonstationary, then a possible cointegration relationship for the cash-futures pair will be investigated. In the second part, with determination of cointegration, the prediction hypothesis will be employed to examine the long-run informational causality between the cointegrated cash and futures prices. A prediction hypothesis is used to test the statistical concept of weak exogeneity (Engle, Hendry and Richard, 1983). In the context of price discovery, futures price series will be regarded as weakly exogenous if it causes movements in the cash series in the long run without being influenced by the cash prices. The prediction hypothesis is been tested in several studies, these include Yang et al. (2001), Zhong, Darrat and Otero (2004), Yang, Yang and Zhou (2012), Ngene, Benefield and Lynch (2017), Chen and Scholtens (2018), and Xu

(2018.a). The econometric methodology related to the two hypotheses to be tested will be reviewed in the third section. The next paragraph presents a mathematical representation of no-arbitrage profit condition which links the futures price, spot price and cost-of-carry measure in a cointegrating relationship.

Following the derivation given in Amin and Jarrow (1991), the price of a commodity futures contract, under no-arbitrage argument can be expressed as:

$$F_{t+k|t} = S_t \, . \, \exp(D_{t+k|t}) \, . \, \exp(Q_{t+k|t}) \tag{3.10}$$

where $F_{t+k|t}$ is the price of a futures contract observed in time t period that matures in period $t+k$, $D_{t+k|t}$ represents the expected net cost-of carrying which essentially consists of net storage cost (that is, storage cost less the convenience yield) and the risk-free interest rate from time t to $t+k$, and $Q_{t+k|t}$ is the adjustment term for mark-to-market pricing feature that occurs in the futures market. As described in Brenner and Kroner (1995), the adjustment term decreases to zero as k gets larger (that is, the term vanishes as the contract matures). Taking the natural logarithms of (3.10), the cost-of-carry model for commodity futures price can be written as follows:

$$\ln F_{t+k|t} = \ln S_t + D_{t+k|t} + Q_{t+k|t} \tag{3.11}$$

where $D_{t+k|t}$ is log of net cost-of-carry (assuming that the three variables of net carrying cost are stationary) or stochastic interest rate, $r_{t+k|t}$. Following the convention of setting $k = 1$

and denoting $\ln F_{t+k|t}$, $\ln S_t$ and $D_{t+1|t}$ by f_t, s_t and d_t, respectively; and if $Q_{t+1|t}$ is omitted because the term is not directly observable (McAleer and Sequeira, 2004), then the empirical specification of the cost-of-carry model in Equation 3.10 and 3.11 can be rewritten as follows:

$$f_t = \beta_2 s_t + \mu + d_t + z_t \tag{3.12a}$$

$$f_t = \beta_2 s_t + \beta_3 + z_t \tag{3.12b}$$

where z_t is the (white noise) error; and $\beta_3 = \mu$, the constant term, and items in β_3 can capture stationary variables, e.g., spot and future price differentials or constant risk premium. Therefore, two distinct formulations (i.e., Equations 3.12a and 3.12b) of linear cointegrating relationship may arise depending on whether the time series properties of the cost-of-carry, i.e., d_t is stationary or nonstationary. First, if the researcher assumes d_t to be stationary, then no-arbitrage model implies that f_t and s_t will be cointegrated in a bivariate cointegrating system (as specified in Equation 3.12b) with a vector of $[1, -1]'$, a necessary condition for unbiasedness. However, if the cost-of-carry (d_t) is integrated, then the necessary condition is the existence of a trivariate cointegrating system specified in Equation (3.12a). Some empirical studies (Schwarz and Szakmary, 1994; Fortenbery and Zapata, 1997; Yang et al., 2001; Mattos and Garcia, 2004) which examined price discovery, argued for the existence of cointegration between cash and futures prices to be an indispensable component and made allowance for the stochastic interest rates by replacing the 'original futures price' with the 'spot-equivalent futures price'[24]. Yang et al. (2001) specifically made distinction in their cointegration analysis for storable and nonstorable

[24] Equation 3.1 to 3.5 explains the treatment of interest cost with the spot-equivalent relationship, which can be implemented in the bivaraite cointegration model.

commodities by arguing on the basis of asset storability. They claimed that only storable commodities will entail cost-of-carry and therefore made allowances for stochastic interest rates (by treating the futures price as cash-equivalent futures price) in their cointegration analysis for storable commodities. However, their result intriguingly demonstrates that asset storability does not affect the existence of a long-run relationship between cash and futures prices. Brenner and Kroner (1995), however, do not make any such distinction for storable and nonstorable commodities in their tests for cointegration and unbiasedness hypothesis. Finally, following Ferretti and Gonzalo (2010), interest rates can be considered to be an $I(0)$, a stationary process as a standard no-arbitrage equilibrium condition. Furthermore, the assumption that $r_{t+k|t}$ are flat and stationary (and therefore, d_t, to be stationary) is realistic since the result generated in the bivariate cointegration analysis in Fortenbery and Zapata (1997) and Yang et al. (2001) do not differ after the allowances for the interest rates were introduced into the equilibrium relationship.

3.3. HYPOTHESES AND TESTING METHODOLOGY

3.3.1. Unit Root Tests

Three procedures, the Augmented Dickey-Fuller (1981), the Phillips-Perron (1988), and the Kwiatkowski-Phillips-Schmidt-Shin (1992), abbreviated as ADF, PP and KPSS, are implemented to ascertain the nonstationarity in the data series. All the three tests consider cases with trend and without trend. Of these the null hypotheses for the first two procedures is same i.e., in the ADF and PP test the null hypothesis that the series contains a single unit root is examined against the alternative of stationarity.

The model for ADF unit root test for a particular series y_t by allowing for intercept or intercept and deterministic linear time trend, can be written as the following OLS regression:

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \beta t + \sum_{i=1}^{n} \emptyset_i \, \Delta y_{t-i} + \nu_t \qquad (3.13)$$

where y_t is the series under investigation and $\Delta y_t = y_t - y_{t-1}$, and n is the number of lagged values of the first differences (Δy_t). The value for the lag length n is set to be large enough to account for significant autocorrelation in the error terms ν_t (i.e., for serially uncorrelated errors). The disturbance term is also assumed to be homoskedastic. The test utilized the optimal lag orders by the minimum value of SBIC (Schwarz Bayesian Information Criterion, 1978). The ADF test based on Equation (3.13) examines (H_0: $\alpha_1 = 0$) the null hypothesis of unit root process against (H_0: $\alpha_1 < 0$), zero unit roots (i.e., stationarity). The null hypothesis is rejected if the ADF t-statistics on the coefficient α_1 are more negative and exceeds the critical values. The critical value for the test can be derived either from the tabulated work of Dickey and Fuller (Fuller, 1976; Dickey and Fuller, 1979; 1981) or from recently improved MacKinnon (1991; 1996) critical estimates, which are used in this thesis in reporting the test output.

The second test procedure proposed by Philips-Perron is also used, which has an advantage over the ADF test since it does not require specification for the lag length in the test regression. Another advantage of the PP test is that, although the test is similar to the ADF test in terms of the test regression, the PP test is the non-augmented version of ADF test Equation (3.13), but it differs from the ADF procedure mainly in its method for correcting for any serial correlation and heteroskedasticity in the error ν_t of the test regression. The test regression for the PP procedure is AR(1) process and is based on the following equation:

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \beta t + \nu_t \qquad (3.14)$$

where v_t is $I(0)$. The ADF test, in particular, uses parametric methods to deal with the higher-order serial correlations and make corrections by adding the n lagged difference terms of the dependent variable y_t to RHS of the test regression. The PP test on the other hand proposes nonparametric method and makes correction to the t-statistics for the α_1 coefficient to account for the serial correlation in the errors. This test also has the same hypotheses as ADF test, *Null*: $\alpha_1 = 0$ vs. *Alternative*: $\alpha_1 < 0$. If the PP modified t-ratios fall below the corresponding critical value at a certain degree significance, then the null hypothesis of a unit root may be convincingly rejected. The MacKinnon (1996) critical values for the PP tests of size 1%, 5% and 10% levels are reported underneath in Table 3.2.

Both the above mentioned unit root tests ADF and PP are testing the null hypothesis that the time series $y_t \sim I(1)$. For comparison with the ADF/PP test procedure results, the opposite case of KPSS stationarity test, which require testing the null hypothesis that the time series $y_t \sim I(0)$, is also implemented. The KPSS test starts by decomposing time series y_t into sum of a deterministic trend (d_t), a random walk (r_t) and a stationary random error (ε_t):

$$y_t = d_t + r_t + \varepsilon_t \tag{3.15}$$

where, $d_t = \sum_{i=0}^{p} \beta_i t^i$, for $p = 0, 1$, contains deterministic components of the model (constant or constant plus deterministic time trend); ε_t are i.i.d $\mathrm{N}(0, \sigma_\varepsilon^2)$ and may be heteroskedastic; r_t is pure random walk which satisfies $(r_t = r_{t-1} + u_t)$ with innovation variance σ_u^2 and u_t are i.i.d $\mathrm{N}(0, \sigma_u^2)$. The KPSS test is based on the Lagrange Multiplier (LM) statistics, hypothesizes that r_t has zero variance, that is, $(H_0: \sigma_u^2 = 0)$ against the alternative that $(H_1: \sigma_u^2 > 0)$. If the calculated LM test statistics are greater than the critical values listed in

Kwiatkowski et. al. (1992), the null hypothesis of stationarity in levels can be rejected in favour of the unit root alternative. The stationarity test can be implemented by employing either automatic bandwidth selection methods (Newey-West, 1994; Andrews, 1991) or the test can also run by evaluating the bandwidth from Bartlett lag window of Kwiatkowski et. al. (1992). The user specified bandwidth with $L = 19\ or\ 23$, depending on the two sample periods, corresponds to the $L12 = integer\ [12(T/100)^{1/4}]$ window of Kwiatkowski et. al. (1992).

3.3.2. Cointegration Analysis and Testable Hypotheses

The study aims to investigate price discovery between the NCDEX wheat spot and futures market by addressing both long-term relationship and short-run dynamics. First, the empirical methodology uses Johansen (1991) and Johansen and Juselius (1990) approach to test for cointegration and unbiasedness hypothesis as discussed in Yang et al. (2001), Zhong et al. (2004), Asche, Misund and Oglend (2016), and Chen and Scholtens (2018). Second, to investigate the long-run price discovery performance of futures markets this study closely follows Peng et al. (2006), Carter and Mohapatra (2008), Yang et al. (2012), and Xu (2018.a). Third, the hypotheses test on the VECM model are employed to further investigate the short-run price dynamics between the markets which is similar to the methodology indicated in Mattos and Garcia (2004), Zhong et al. (2004), Liu (2009), Bohl et al. (2011), Ngene et al. (2017), and Chen and Scholtens (2018).

The dynamics of price discovery between Indian wheat spot and futures market is examined by exploring cointegration relationship between s_t and f_t with the maximum likelihood estimation procedure developed by Johansen (1988, 1991) and Johansen and Juselius (1990). In contrast to the Engle and Granger (1987) method, cointegration method of Johansen test is a multivariate approach. The Johansen procedure is based upon VAR process for X_t; where vector X_t inhibits variables which are thought as endogenous. The variables in X_t are assumed to be integrated of order one, i.e., $I(1)$ variables. Since p, the number of endogenous variables, in this study is equal to 2, the element of X_t can be expressed as $\binom{X_{1t}}{X_{2t}}$, where X_{1t} represents the underlying spot price s_t, and X_{2t} represents futures price f_t in natural logarithms. A VAR model with k lags for levels of price series in X_t is given by:

$$X_t = \sum_{i=1}^{k} \Pi_i X_{t-i} + \mu + e_t \quad (t = 1 \; \ldots.. T) \tag{3.16}$$

where X_t is a $p \times 1$ vector of nonstationary price series under investigation measured at time t, Π_i is a $p \times p$ coefficient matrix, μ is a $p \times 1$ vector of constants and e_t is white noise error vector with non-diagonal covariance matrix Ω. The Johansen tests are calculated by transforming the original levels VAR(p) into first difference form, i.e., by subtracting the lagged variables of the endogenous variables from both sides. The VAR model in Equation 3.16 can be written as reduced form ECM as in Equation 3.17:

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \mu + e_t \quad (t = 2 \; \ldots.. T) \tag{3.17}$$

where Δ is the first difference lag operator ($\Delta X_t = X_t - X_{t-1}$), Π is the long-run impact matrix, ΠX_{t-1} is the error correction term which represents the long-run relationship between time series, and Γ_i are the short-run impact matrices. The cointegration relationship is tested by examining the rank of the coefficient of matrix Π. Three possible cases of interest for the rank of Π are:

(i) if $r = p$ [25], then Π has full rank p, (i.e., for this empirical analysis, if $\Pi = 2$), then all variables in X_t are $I(0)$ in levels and the appropriate modelling strategy is to estimate a VAR in levels should be adopted;

(ii) if $r = 0$ so that $\Pi = 0$, then Π is a $p \times p$ null matrix, (i.e., for this empirical analysis, if $\Pi = 2 \times 2$ zero matrix) implying no cointegration vector, hence there is no cointegration relationship between the considered variables. In this case the error-correction term disappears and the appropriate model is the classical VAR in first differences; and

(iii) if $0 < r < p$, i.e., the integer value of r lies between zero and p, then cointegration does exist with r cointegrating vectors (or r stationary linear combinations of X_t) and the long-run level matrix Π can be decomposed into two $p \times r$ matrices α and β such that $\Pi = \alpha\beta'$. The column of β' represents the r linear combinations of X_t that are stationary or cointegrated. The corresponding column of α represent the corresponding error-correction coefficients which measures the speed at which each variable adjusts towards the long-run equilibrium. Therefore in testing the hypotheses of interest on the two matrices α and β, Equation 3.17 can be re-written as:

$$\Delta X_t = \alpha\beta' X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \mu + e_t \quad (t = 2 \ \ldots\ldots T) \tag{3.18}$$

[25] where p is the number of variables in the system and r is the number of cointegrating relationship, i.e., the cointegrating rank.

In this empirical analysis for examining the long- and short-run relationship between the wheat spot and NCDEX futures market, where $p = 2$ and $X_t = \binom{s_t}{f_t}$, the Equation 3.18 can be represented as follows:

$$H_0 : \begin{pmatrix} \Delta s_t \\ \Delta f_t \end{pmatrix} = \mu + \begin{pmatrix} \Pi_{11} & \Pi_{12} \\ \Pi_{21} & \Pi_{22} \end{pmatrix} \begin{pmatrix} s_{t-1} \\ f_{t-1} \end{pmatrix} + \sum_{i=1}^{k-1} \begin{pmatrix} \Pi_{i,11} & \Pi_{i,12} \\ \Pi_{i,21} & \Pi_{i,22} \end{pmatrix} \begin{pmatrix} \Delta s_{t-1} \\ \Delta f_{t-1} \end{pmatrix} + e_t \qquad (3.19)$$

The first necessary condition for the unbiasedness hypothesis is cointegration, that is, whether spot and futures prices share a long-run equilibrium relationship (Fortenbery and Zapata, 1997; Yang et al., 2001; Carter and Mohapatra, 2008; Yang et al., 2012; Chen and Scholtens, 2018). The cointegration hypothesis is formulated by checking for the rank, r, of the long-run matrix:

$$H_1(r): \quad \Pi = \alpha\beta' \qquad (3.20)$$

where $\alpha\beta' = \binom{\alpha_1}{\alpha_2}(\beta_1\ \beta_2)$. For this empirical analysis if $\Pi = 1$, then the two series are cointegrated. To identify the cointegration rank, two Likelihood Ratio (LR) tests, the Trace statistics denoted by LR_{tr} and the Maximum eigenvalue statistics denoted by LR_{max} proposed in Johansen (1988; 1991), are employed. Both the trace test and maximum eigenvalue test are based on the estimated eigenvalues, $\widehat{\lambda_1} > \widehat{\lambda_2} > \widehat{\lambda_3} > \cdots > \widehat{\lambda_p}$, of the matrix Π. The rank of Π is equal the number of non-zero eigenvalues of Π. These eigenvalues equal the squared canonical correlations between ΔX_t and X_{t-1} corrected for lagged differences (ΔX_t) and the constant (μ).

First, a trace test is conducted to test the null hypothesis that there are (at most) r $(0 \leq r \leq p)$ cointegrating vectors against a general alternative hypothesis of more than r cointegrating vectors. The trace test statistics is calculated as follows:

$$LR_{tr} = \lambda_{trace}\left(r \,\middle|\, p\right) = -T \sum_{i=r+1}^{p} Ln\ (1 - \widehat{\lambda_i}) \tag{3.21}$$

where T is the number of observations; and $\widehat{\lambda_{r+1}}, \ldots, \widehat{\lambda_p}$ are the $p - r$ smallest non-zero eigenvalues.

Second, the maximum eigenvalue statistics test the null hypothesis that there are exactly r number of cointegrating vectors against the alternative of $r + 1$. The maximum eigenvalue test statistics can be constructed as:

$$LR_{max} = \lambda_{max}\left(r \,\middle|\, r + 1\right) = -TLn\ (1 - \widehat{\lambda_{r+1}}) \tag{3.22}$$

where $\widehat{\lambda_1^*}, \ldots, \widehat{\lambda_r^*}$ are the r largest non-zero eigenvalues. The distribution for these tests is non-standard. The critical values for the λ_{trace} and λ_{max} statistics are taken from MacKinnon-Haug-Michelis (1999).

Furthermore, testing the rank of Π requires one to clarify how the constant term μ enters into the error-correction term, ΠX_{t-1}, in Equation 3.17. Since the cointegration Equation in (3.12a) has the intercept term for capturing either the components of spot and futures price differentials or a constant risk premium, two models where cointegrating relation $\beta' X_t$, can have non-zero means are of particular interest in this study. These two specifications for the treatment of μ are:

Case 1, $H_1\ (r)$: $\mu\ =\ \mu_0\ =\ \alpha\rho_0$ (restricted constant). This case allows for a non-zero mean ρ_0 in the cointegration space but excludes all deterministic trends in the series in X_t:

$$H_1(r)^{Case1}\colon\ \Delta X_t = \alpha(\beta' X_{t-1} + \rho_0) + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + e_t \tag{3.23}$$

Case 2, $H_1\ (r)$: $\mu\ =\ \mu_0$ (unrestricted constant). This case allows for linear trends in the level dataX_t or non-zero means in the differences, but the cointegrating relations $\beta' X_t$ eliminate these trends:

$$H_1(r)^{Case2}\colon\ \Delta X_t = \mu_0 + \alpha\beta' X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + e_t \tag{3.24}$$

Johansen (1992) has developed a likelihood ratio procedure, described as sequential hypothesis testing, to determine which specification of term μ is appropriate. The approach jointly considers the determination of the number r of cointegraing relationship and the presence of linear trend in the model. According to the sequential hypothesis testing procedure, each of the hypotheses (for instance: $r = 0,\ r = 1, \ldots \ldots r = p$) are tested using both *Case 1*, restricted model (without trend) and *Case 2*, unrestricted model (with trend), starting with the *Case 1*. For example, the test would be in the following order: $H_o\colon (r = 0)^{Case\ 1}, H_o\colon (r = 0)^{Case\ 2}, H_1\colon (r = 1)^{Case\ 1}, H_1\colon (r = 1)^{Case\ 2} 0 \ldots H_1\colon (r = p)^{Case\ 1}, H_1\colon (r = p)^{Case\ 2}$. The sequential procedure is continued in the above order and testing stops at the first time when the null hypothesis fails to be rejected in the sequence. The associated null hypothesis regarding number of cointegrating relationship is accepted along with the linear trend specification suggested by the test. Studies such as Covey and Bessler (1995), Chopra and Bessler (2005), Yang et al. (2001), Yang et al. (2012), and Shi and Xu (2013) have adopted this sequential testing procedure to test for the specification of μ in the cointegration relationship.

The second necessary condition for the unbiasedness hypothesis can be formulated by using a linear restriction on the coefficients of the long-run matrix β. This restriction on the β can be tested in two ways: (i) simple unbiasedness model with restricting the cointegrating vector $\beta = (\beta_1, \beta_2) = (1, -1)$ but without imposing the restrictions on the constant; and (ii) joint hypothesis model by pre-specifying the cointegrating vector close to $(1, -1)$ and pre-specifying the value of the restricted constant (in *Case 1*) as $\mu = 0$ i.e., $(\beta_1, \beta_2, \mu) = (1, -1, 0)$. Mathematically, these hypotheses testing can be expressed as:

$$H_2 \big| H_1: \quad R'\beta = 0 \tag{3.25}$$

where R is the restriction matrix, for the simple unbiasedness hypothesis $R' = (1, 1)$ and for the joint hypothesis $R' = (1, 1, 0)$.

Conditional on the existence of cointegration relationship between the series (s_t, f_t), a bivariate VECM (specified in some studies, e.g., Wahab and Lashgari, 1993; Schwarz and Szakmary, 1994; Pizzi, Economopoulos, O'Neill, 1998; Tse, 1999; Mattos and Garcia, 2004; Zhong et al., 2004; Bohl et al., 2011; Adämmer et al., 2015; and Ngene et al.,2017) for the convenience of expression can be formulated as:

$$\Delta s_t = \mu_1 + \alpha_1 \hat{z}_{t-1} + \sum_{i=1}^{k} \Gamma_i^{11} \Delta s_{t-i} + \sum_{i=1}^{k} \Gamma_i^{12} \Delta f_{t-i} + \varepsilon_{1t}, \text{ and} \tag{3.26}$$

$$\Delta f_t = \mu_2 + \alpha_2 \hat{z}_{t-1} + \sum_{i=1}^{k} \Gamma_i^{21} \Delta s_{t-i} + \sum_{i=1}^{k} \Gamma_i^{22} \Delta f_{t-i} + \varepsilon_{2t} \tag{3.27}$$

where the lagged error-correction term, $ec_{t-1} = \hat{z}_{t-1} = (s_{t-1} - \beta_2 f_{t-1} - \beta_3)$, represent the dynamics of the long-run equilibrium between the two series in period $t-1$. The factor loading α_1 (α_2) attached to the $\hat{z}_{t-1}$, is the speed of adjustment of changes in spot (futures), which shows how the LHS variable (Δs_t / Δf_t) responds to the previous period's deviations and adjust to correct towards the equilibrium in the next period. The statistical significance and relative magnitude of the coefficients (α_1 and α_2), on the equilibrium error $\hat{z}_{t-1}$, have two important implications: (a) for assessing the direction of causal relationship between the spot and futures prices; and (b) for quantifying the speed with which departures from the equilibrium are corrected (Wahab and Lashgari, 1993; Pizzi et al., 1998; Chan, Lin and Hsu, 2004; Lee et al., 2016). Specifically, if the magnitude of α_1 (α_2) is small, spot (futures) has little tendency to adjust to correct a disequilibrium situation. The rationale behind this interpretation is that the markets with higher error-correction coefficients follows and does adjustment to the disequilibria, whereas the markets with lower error-correction coefficients initiates mispricing and does not respond to any disequilibrium in the system. Therefore, small magnitude of α_1 (α_2) implies, most of the adjustment to the long-run equilibrium will be done by future (spot) prices and hence the price discovery occurs primarily in the wheat spot (futures) market. The tests related to the long-run prediction hypotheses ($H_{3a}, H_{3b}, H_{3c}, H_{4a}, H_{4b}$) further investigates which prices are the main contributor to the price discovery process. The remaining portions of the Equation (3.26) and

(3.27) are the lagged first differences of spot (Δs_{t-1}) and futures (Δf_{t-1}) prices, which represents the short-run dynamics of the system. The coefficients on the lagged differenced variables allows for the investigation of short-term price discovery between the spot and futures market by testing hypotheses on Γ_i^{mn}, where the superscript represents the *mn*-th element of the matrix Γ_i.

The specifications in the Equations in (3.26) and (3.27) allows to test for a number of hypotheses related to the priced discovery function of the futures market. Statistical test with respect to the loading matrix α (i.e., the error-correction term coefficients) are normally formulated to test for the long-run prediction hypothesis. However, unlike the standard long-run prediction hypothesis as indicated in Yang et al. (2001), Zhong et al. (2004), and Ngene et al. (2017), this thesis examines the long-run information causality in two parts: (a) to draw the inferences on the informational flow between the spot and futures market. The first test, on the element of the α vector, is based on weak exogeneity (Hansen and Juselius, 1995) of its associated series; and (b) the second test is the joint test of the prediction hypothesis and the unbiasedness hypothesis (Zapata and Rambaldi, 1997).

The weak exogeneity hypothesis tests whether spot (futures) series are weakly exogenous to futures (spot) prices. Stated alternatively, these are tests on whether or not each series responds to the deviations in the cointegrating space. In the context of price discovery (i.e., which market conveys information first), a series is regarded as weakly exogenous if it is causally prior to the other i.e., unidirectionally causes movement in the other series. Therefore, weakly exogenous series serves a leading long-run informational role, and can be used as a predictor for explaining the variations in endogenous series. Following, Yang and Leatham (1999), Haigh and Bessler (2004), Crowder and Phengpis (2005) and Asche et al. (2016), null hypothesis of weak exogeneity of the spot (futures) series examines if the error-correction coefficients in α are equal to zero:

$$H_{3a}:\ \alpha_1 = 0 \tag{3.28a}$$

$$H_{3b}:\ \alpha_2 = 0 \tag{3.28b}$$

This weak exogeneity of spot (futures) test two assumptions: (i) if $\alpha_1 = 0$, then spot price are regarded as weakly exogenous and it leads the futures price, and (ii) if $\alpha_2 = 0$, then futures price are regarded as weakly exogenous and it leads the spot price in the long-run. Rejecting $H_{3a}(H_{3b})$ suggests that the assumption that spot (futures) prices leads the futures (spot) prices in the long-run is rejected. A significantly non-zero $\alpha_1(\alpha_2)$ is consistent with the long-run interpretation of the prediction hypothesis which posits that wheat futures (spot) prices affect the changes in the spot (futures) prices through the long-run price equilibrium channel. Furthermore, Yang et al. (2001), Yang et al. (2012), and Xu (2018.a), suggested that when $\alpha_1 \neq 0$ and $\alpha_2 \neq 0$ (i.e., both $H_{3a}$and H_{3b} are rejected) then there is a bidirectional long-run information flow between spot and futures prices. In which case, another hypothesis is framed to test if futures market are at least as important as spot markets as an informational source in the long-run:

$$H_{3c}:\ \left|\alpha_2\right| = \left|\alpha_1\right| \tag{3.28c}$$

Following the work of Carter and Mohapatra (2008), Liu (2009), Yang et al. (2012), and Xu (2018.a), the prediction hypothesis is also tested jointly with the restrictions readily imposed by the unbiasedness hypothesis. The joint test of unbiasedness and weak exogeneity is formulated as follows:

$$H_{4a}:\ \beta_1 + \beta_2 = 0, \alpha_1 = 0 \tag{3.29a}$$

$$H_{4b}:\ \beta_1 + \beta_2 = 0, \alpha_2 = 0 \tag{3.29b}$$

The rejection of $H_{4a}(H_{4b})$ further convey information about the market leadership of futures (spot) prices in the long-run price discovery process and, therefore, having predictive power for changes in spot (futures) prices.

Having considered the long-run prediction hypothesis, which requires presence of equilibrium relationship for binding the cash-futures prices in the two markets, short-run causality tests can be performed to assess the causal ordering of the two variables. Link between the cointegration and causality stems from the fact that, if spot prices and futures prices are cointegrated, then causality must exist in at least one direction (Granger, 1986), and causality tests thus, should be based on error-correction model instead of the unrestricted VAR model (Engle and Granger, 1987). As stated in Wahab and Lashgari (1993), and Pizzi et al. (1998), presence of cointegration implies each series can be represented by an error-correction model and the aforementioned long-run prediction hypothesis tests thus could be performed in Equations 3.26 and 3.27. However, there is a difference between the long- and short- run prediction hypothesis tests. The long-run prediction hypothesis implies that, given the statistical significance of α_1 (α_2) in 26 (27), changes in futures (spot) prices have the predictive power for the persisting (long-lasting) changes in the spot (futures) prices. Whereas the short-run prediction hypothesis is based on the predictive power of the lagged futures (spot) over the predetermined (finite) forecasting horizon, k. The optimal number of lags (k) in Equations 3.26 and 3.27 are identified by using the Akaike Information Criterion.

As discussed in the literature (e.g., Mattos and Garcia, 2004; Zhong et al., 2004; Carter and Mohapatra, 2008; Liu, 2009; Ngene et al.,2017; and Chen and Scholtens, 2018) the short-run prediction hypothesis can be tested in the VECM system by:

$$H_{5a}\colon\ \Gamma_1^{12} = \Gamma_2^{12} = \ldots = \Gamma_k^{12} = 0 \tag{3.30a}$$

$$H_{5b}\colon\ \Gamma_1^{21} = \Gamma_2^{21} = \ldots = \Gamma_k^{21} = 0 \tag{3.30b}$$

where $\Gamma_i^{12}(\Gamma_i^{21})$ are coefficients for the lagged differenced futures (spot) prices in Equation 3.26 (3.27), for $i = 1, 2, \ldots, k$. In terms of Equation 3.30a (3.30b), the hypothesis corresponds to basic premise of information flow in Granger-causality (Reverse Granger-causality) tests. Intuitively, if $H_{5a}(H_{5b})$ is rejected but $H_{5b}(H_{5a})$ is not rejected, then, changes in futures (spot) have short-run predictive power for changes in spot (futures). Therefore, from the perspective of Granger (Reverse Granger) causality, there is a unidirectional information flow from futures (spot) market to the spot (futures) market. This would convey that in the short-run price discovery takes place in the futures (spot) market, since future (spot) prices lead the movements in spot (futures) prices but there is no reverse feedback from the spot (futures) prices. However, if both hypotheses H_{5a} and H_{5b} are rejected, there is two-way feedback relationship between the spot and futures market. This would imply that there is bidirectional short-run information flow between the spot and futures prices; and hence, the price discovery takes place in both the markets.

3.4. DATA

3.4.1. Data Description

The analysis in the present study consists of closing daily prices for both nearby wheat futures prices (contracts are traded on NCDEX, the leading agri-commodity exchange) and its underlying spot market prices (last polled price). The futures trade in wheat has grown rapidly and is an important commodity on the NCDEX platform since the inception of contracts in 2004. However, the NCDEX for a period of nearly two-and-half-year, along with the two other national commodity exchanges- MCX and NMCE - were banned to trade in some commodities in 2007. The then Finance Minister of the UPA government banned futures trade in four agricultural commodities: Urad (Black Gram), Tur (Pigeon-Peas), Wheat and Rice contracts under pressure from their Left coalition partner, who blamed futures market for high inflation and soaring price rises in essential commodities. Following the directives issued by the FMC (the commodity market regulator until September 28, 2015), the NCDEX delisted Urad and Tur contracts on January 23, 2007[26]; and suspended futures trading in Wheat and Rice contracts with no new positions for the running contracts on February 28, 2007.[27] As wheat prices became stable in the country after record production of wheat in 2007-2008[28] crop year (June-May) and procurement levels in 2008-2009 reached more than the estimated buffer requirement, the ban was made

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[26] Source: NCDEX Circular: Delisting of all Urad and Tur contracts. Circular No.: NCDEX/TRADING-005/2007/018 dated January 23, 2007.

[27] Source: NCDEX Circular: Wheat and Rice contracts. Circular No.: NCDEX/TRADING-013/2007/040 dated February 28, 2007.

[28] According to the data from Directorate of Economics and Statistics, the production of the crop has increased from 75.81 million tonnes in 2006-2007 to 78.57 million tonnes in 2007-2008. The food grain saw a record level harvest in 2007-2008 as the previous highest production of 76.37 million tonnes wheat was recorded during 1999-2000 crop year. Also, during 2008-2009, the production had increased by 2.68 percent (from 78.57 million tonnes to 80.68 million tonnes).

redundant and future contracts were made available for trading from May 21, 2009.[29] The size of single futures contract (i.e., unit of trading and minimum unit of delivery) is specified at 10 Metric Tonnes (MT). The bid/offers and delivery size are accepted in lots of 10 MT or multiples thereof and prices are quoted in Rupees per quintal of wheat. The final settlement of the open positions at the expiration of wheat futures contracts takes place in two ways, by compulsory physical delivery[30] or by cash settlement.[31] Data for closing futures prices were obtained from the official webpage of NCDEX (www.ncdex.com).

The data employed for the full sample period spans from August 2, 2004 to January 30, 2015. Focusing on the possible impact of trading-ban on the cash-futures price dynamics, the full period is divided into two sub-periods: (1) sub-period 1 (the pre-ban period), covering from August 2, 2004 to July 31, 2007, which corresponds to the contract introduction date and last date of contract trading at the NCDEX before the ban; (2) sub-period 2 (the post-ban period), runs from June 1, 2009 to January 30, 2015, which starts with the official operation of June 2009 futures contract after the trading ban was lifted and terminates on the sample end date. The wheat futures contracts have three maturity horizons with near-, mid- and far-month contracts. With nearby contract expiring on the 20th of every month and the far month contract opening on the 10th day of nearby contract expiry month, three contracts are running concurrently which implies simultaneous trading with at least one maturity per month. To obtain a continuous price series of

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[29] Source: NCDEX Circular: Launch of Wheat futures contracts. Circular No.: NCDEX/TRADING-059/2009/153dated May 20, 2009.

[30] Under this mechanism all sellers with open position shall give physical delivery of the commodity at a particular delivery centre and the buyer with the corresponding open position, matched by the Exchange, are bound to accept the physical delivery. To allocate deliveries in the optimum location for clients, the selling members are needed to give delivery information to the Exchange within the delivery request window.

[31] In the cases where sellers having open position have not provided delivery information or if the intentions of the buyers-sellers remains unmatched in any other delivery information, the process of final settlement of the contract will be in cash and the pay-in and pay-out would be completed on T+1 basis, where 'T' stands for the expiry date of the contract.

future price data the nearby contracts are used except until the beginning of the delivery month, when the time series is rolled over to the next most immediate maturity. Following this procedure, total data points amount to 2,158, 764 and 1394 price quotations for the full sample and during each sub-periods. To match the data on closing futures price, daily series of polled spot prices are also collected from the NCDEX. To ensure that polled spot prices are truly reflective of the physical markets, the Exchange has developed a polling process by accepting spot price quotes of the commodity from different segments of active players viz. traders/brokers, millers/manufacturers, importer/exporter, farmers' producer organization, etc. The data on the spot price quote is captured from various locations including the identified Basis Centre and Additional Delivery Centres spread across the country. The basis delivery centre for wheat contract is Delhi and additional delivery centres include Ahmedabad, Bareilly, Indore, Itarsi, Kanpur, Karnal, Khanna, Kota, Moga, Rajkot and Sirsa. To perform the empirical analysis data points for daily spot and futures price series are transformed to their log return series at time t, as: $\Delta s_t =$ (ln (S_t/S_{t-1})) and $\Delta f_t =$ (ln (F_t/F_{t-1})), where S_t/F_t and $S_{t-1}/F_{t-1}$are the daily closing price and of wheat spot and futures prices at days, t and $t-1$, respectively, leading to 2,157, 763 and 1393 points of price returns for each series.

3.4.2. Statistical Characteristics of the Data

Figure 3.1(a-b) plots the evolution of log-spot (s_t) and log-futures prices (f_t) over the covered time period. The examination of the time plots of full sample in Figure 3.1(a) reveals the onset of ban on the wheat futures in February, 2007 and the re-launch of trading in the contracts in May, 2009. To show that the full sample is non-contiguous, the graph scale is padded with excluded observations. This graph observation supports the division of data into two segments around the period of government intervention (trading ban), to account for the changes in the data. In addition, Figure 3.1(b) presents the graph for continuous sample by dropping the missing period from the graph scale; and as one might expect, the values of spot and futures follow closely at each time. The two series rise and fall together which shows that the prices have strong relationship, and hence a possible linear combination (cointegration) between the cash and futures prices may exist. Figures 3.2(a-b) presents the graph of log return of two time series (Δs_t and Δf_t). The series of log prices in Figure 3.1 do not display mean-reversion whereas the difference series in Figure 3.2 fluctuate about a zero mean; this imply that the prices series exhibit nonstationary behaviour i.e., $I(1)$ processes, whereas return series appears to be stationary processes. This observation supports the use of cointegration framework as a technique for empirical modelling outlined in Section 3.3.

[Figures 3.1(a), 3.1(b), 3.2(a) and 3.2(b) about here.]

Table 3.1 contains descriptive statistics of Δs_t and Δf_t for NCDEX wheat. As is evident, the results of Jarque-Bera test statistics indicate that normality is rejected in both the time series at 1% level, which is consistent with the values of negative skewness and leptokurtosis. Nonetheless, lack of symmetry (left skewed distribution) and kurtosis coefficient of more than three are common features to the returns data in finance literature.

[Table 3.1 about here.]

For the full sample period, the cash market has the higher mean return than the futures markets. The sample means of spot and futures returns are positive, but the comparison of two periods clearly reflect the influence of government intervention since the performance of mean returns in both the contemporaneous spot and futures markets worsened after the ban. In contrast to the spot market, the mean returns for the futures market appear similar across the two sub-periods. The summary statistics on standard deviations reveal that futures prices fluctuate more heavily than spot prices during both sub-periods. Notably, in the post-ban period the two markets (Δs_t, Δf_t) have lower standard deviations when compared with the first sub-period. This pattern in mean returns and volatility across the two sub-periods suggests that the level of hedging and speculation activities are likely to have reduced in the futures market after the ban period.

3.5. EMPIRICAL RESULTS

3.5.1. Unit Root and Stationarity Test

The first step in this empirical analysis is to ensure that both series, current spot and futures prices, are integrated with a uniform order of integration, i.e. $I(1)$. Thus, two standard unit root procedures (ADF, PP) and a stationarity test (KPSS) are implemented in both the log-levels of price data (Panel A) and in their first differences (Panel B), to ascertain the order of integratedness. The results of the three tests for both the cases, with trend and without trend, are presented in Table 3.2. In case of ADF unit root test the optimal lag length (value of k) is determined by minimising the Schwarz Information Criterion (1978). The maximum lag length has been set to 19 or 23 corresponding to each sub-period. As it can be seen from Panel A in Table 3.2, all t-statistics of $\widehat{\alpha_1}$ in the ADF regressions are negative and well below (in absolute value) than their critical values at the 5% level (and even at 10%). Therefore, the null hypothesis of single-unit root in level-specification of each price series cannot be rejected for any of the sample periods. On the other hand, the first differenced series in Panel B reveal that the t-statistics on $\widehat{\alpha_1}$ (from Equation 3.13) are large (in absolute values) and exceeds the tabulated critical values at a very low level of significance; thereby the presence of a second unit root is strongly rejected in each returns series. These results display that, in both the cases and across two-sub periods, the spot and futures prices are first difference stationary processes.

The test of unit root non-stationarity is also performed with the PP nonparametric tests. The statistics for PP test are computed by using Newey-West (1994) bandwidth procedure based on Bartlett kernels. Using the PP test, the null hypothesis of unit root is not rejected at 10% level (critical values for the two cases are -2.568 and -3.129) for both periods in each price series. Also, large (in absolute value) t-statistics in Panel B for both cases provide strong evidence of no unit root in the first differences of spot and futures series. This yield that, PP test also support the existence of unit root in log-prices (s_t and f_t) and confirms that each price series are stationary, $I(0)$, in their first differences ($\Delta s_t, \Delta f_t$).

Lastly, to check the robustness of the results, the KPSS stationarity test has also been performed along the unit root tests (ADF an PP) for the confirmatory data analysis. Because unit root tests have been criticized for their low power to distinguish between a unit root and weakly-stationary alternatives, the stationarity test (KPSS) which reverses the null and alternatives under ADF/PP procedure is also applied. The optimal bandwidth is estimated by Newey and West (1994) automatic bandwidth selection method. In addition, the test is also run by manually specifying the optimal bandwidth with the Bartlett lag window by setting $L = 19$ and $L = 23$ corresponding to the two sample periods, which provided similar conclusion regarding the stationarity of the tested series.[32] The results in Panel A show that null hypothesis of stationarity in price levels is strongly rejected at the 1% level, thus in favour of the alternative that the series have unit root. When the test is conducted on the differenced price series (in Panel B) stationarity is not rejected even at 10% in any of the sub-periods. Thus, the results of the KPSS test reinforces the results of the previously conducted ADF and PP unit root tests.

[Table 3.2 about here.]

It can be concluded from the results of the three tests that because both series (s_t, f_t) have stochastic trend (nonstationarity) in their univaraite time-series presentation while the first difference $(\Delta s_t, \Delta f_t)$ of the price series are stationary, the price pair is integrated to the same order $I(1)$. The result also confirms that use of standard OLS procedure in estimating the model should be avoided and cointegration tests are appropriate to determine the existence of stable long-run relationship between the two markets. The next step is to test for cointegration between the spot and futures prices using the Johansen estimation procedure as represented in Equation 3.17.

3.5.2. Bivariate Johansen Cointegration Rank Test

Once it is evident from Table 3.2 that levels of two series (s_t and f_t) has a single unit root, the rank of cointegration relationship between the spot and futures prices is established by using the Johansen and Juselius (1990) and Johansen (1991) procedure, the multivariate cointegration test. Table 3.3 presents the results of cointegration test, which has been carried out to determine

[32] Test result by using the specified bandwidth parameter with lag length $L = 19$ and $L = 23$ are not reported here but are available from the student.

the existence of a stable long-run relationship between the prices. Before testing for the rank of cointegration two decisions are to be taken: (i) setting the value of lag length so that there is no serial correlation in the residuals; and (ii) assumptions that how the deterministic variables (i.e., intercepts and deterministic trends) appear inside the cointegrating relations (the error-correction term). The optimal number of lags in the Johansen cointegration test as well as in ECM are selected by the minimization of the AIC. Minimization of the SBIC is also employed to select alternative lags and double-check the robustness of the empirical findings. Among the five deterministic trend specifications considered by Johansen (1995), two possibilities that are of particular interest in this study are, *Case 1* with the restricted constant term and *Case 2* with the unrestricted constant term. However, an empirical issue is raised when testing for the cointegration rank of Π. The treatment of the constant μ is particularly important, as under Equation (3.17) the constant term can be decomposed into two parts. That is, (1) if μ contains only the intercept of the cointegrating relation, then X_t has a linear deterministic trend and ; (2) if μ contains a linear time trend then X_t has a quadratic trend in the data generating process. These alternatives lead to sequential hypothesis testing procedure with respect to the rank (r) of Π. This approach jointly considers determination of the rank of cointegrating vector as well as tests whether there is a linear time trend in the model. *Case 1* models the hypotheses if there is no linear time trend in the data, whereas *Case 2* models the hypotheses if there is a linear time trend in the data. As described in Crowder and Hamed (1993), determining the properties of μ is important for two reasons. First, the asymptotic distributions of the cointegration test statistics are dependent upon the presence of trends and/or constant in μ. Second, the unbaisedness hypothesis with the joint restriction requires the constant term to be zero. This represents a testable hypothesis on the parameter μ. Thus, to test for the valid specification that is applicable to the agricultural commodity futures markets, the empirical approach outlined in Section 3.3.2 is followed. Several studies (Covey and Bessler, 1995; Chopra and Bessler, 2005; Yang et al.,2001; Carter and Mohapatra, 2008; Yang et al., 2012; Shi and Xu, 2013) have identified the appropriate deterministic specification by estimating the VECM with both cases, with and without a linear trend, and thereby selecting the model under sequential testing procedure. The results of both cointegration trace and maximum eigenvalue tests are reported in the respective Panels A and B of Table 3.3, which indicates existence of one cointegrating vector between spot and futures prices without the presence of a linear trend in the data.

Trace test results in the both periods reject the null hypothesis of zero cointegrating vector at 5% (except for Period I, *Case 1*, AIC, where the rejection is at 10% significance level), but the null of no more than one cointegrating vector cannot be rejected. Using the maximum eigenvalue rank statistics the evidence for cointegration is further extended and yield similar findings. The maximum eigenvalue test also indicates that null hypothesis of non cointegration ($r = 0$) is rejected at 5% level of significance but not rejected in the case of one cointegrating vector ($r = 1$), across both the cases in two sample periods. Taken together, the Johansen procedure based on two statistics, λ_{trace} and λ_{max}, strongly supports for the existence of at least one cointegrating vector between wheat cash and futures prices. The results are not surprising and are consistent with the theoretical expectations of cost-of carry no-arbitrage argument.

Furthermore, to find the model with appropriate trend specification for the data in this thesis, the sequential testing procedure proposed by Johansen (1992) is followed. Under sequential testing procedure, the process starts by testing in the following orders: (1) For Trace test in Panel A: $H_o: (r = 0)^{Case\ 1}, H_o: (r = 0)^{Case\ 2}, H_1: (r \leq 1)^{Case\ 1}, H_1: (r \leq 1)^{Case\ 2}$; and (2) For Maximum Eigenvalue test in Panel B: $H_o: (r = 0)^{Case\ 1}, H_o: (r = 0)^{Case\ 2}, H_1: (r =$

$1)^{Case\ 1}, H_1: (r = 1)^{Case\ 2}$. Following this process in both the sub-periods and under both the selected information criterions, the first rejection failure occurs with the null hypothesis of $r \leq 1$ (in λ_{trace}) or $r = 1$ (in λ_{max}), while using the model without time trend; thus, a model without trend, which is restricted case, can be considered appropriate for estimating the VECM. It can therefore be concluded from the results that one cointegrating vector without the presence of a linear trend in data exists between the cash and future series for wheat.

[Table 3.3 about here.]

Overall, the cointegration tests for Indian wheat cash and futures markets reveal evidence of significant cointegration relationship. These findings are similar to those of Covey and Bessler (1991; wheat), Crowder and Hamed (1993; oil), Brockman and Tse (1995; canola, wheat, barley and oats), Yang et al. (2001; corn, oat and cotton), Asche and Guttormsen (2002; gas oil), Fortenbery and Zapata (2004; coffee), Switzer and El-Khoury (2007; sweet crude oil), Liu (2009; palm oil), Ferretti and Gonzalo (2010; aluminium, nickel and zinc), Shihabudheen and Padhi (2010; gold, silver, crude oil, castor seed, jeera and sugar), Srinivasan and Ibrahim (2012; gold), Strydom and McCullough (2013; white maize), Shrestha (2014; crude oil, heating oil and natural gas), Soni (2014; maize, chickpea and soybean), Gupta et al. (2018; castor seeds, guar seeds, copper, nickel, gold, silver, crude oil and natural gas), and Xu (2018.a; corn), who also concludes cointegration between s_t and f_t, implying that prices in both spot and futures markets for storable commodities respond efficiently to new market information and share a long-run equilibrium relationship.

3.5.3. Cointegrating Vector and Hypothesis Testing on Beta

To further investigate the price information mechanism among the cointegrated spot and futures prices, estimates of the cointegrating vector are displayed in Table 3.4. In line with the methods used by several other authors (Crowder and Hamed, 1993; Zapata and Fortenbery, 1996; Yang et al., 2001; Peng et al., 2006; Switzer and El-Khoury, 2007; Carter and Mohapatra, 2008; Ferretti and Gonzalo, 2010; Strydom and McCullough, 2013; Ngene et al.,2017; Xu, 2018.a) the normalization is on the spot series. The cointegrating relations, that is $\widehat{z_t}$, for the two respective periods, are given as follows:

$$\hat{z}_t = s_t - 1.141\, f_t + 0.930 \text{ and,}$$

$$\hat{z}_t = s_t - 1.023\, f_t + 0.158$$

[Table 3.4 about here.]

Following two characteristics are evident from the results of estimated cointegrating relationship: (i) among the two estimated long-run coefficients (β_2 and β_3) in the cointegrating vector, the constant terms were not significant (β_3). This confirms the results of Johansen sequential testing procedure, that process is not generated by a linear trend. The coefficient on the futures prices (β_2) are however significantly different from zero in both the periods according to the asymptotic t-test. This implies that same equilibrium prices prevailed between the spot and futures markets in the long-run; and (ii) across both the periods the cointegrating relationships have a slope close to one suggesting that the futures prices are unbiased. This is formally tested in Table 3.5.

As laid out in Brenner and Kroner (1995), Yang et al. (2001), Carter and Mohapatra (2008) and Yang et al. (2012), there are two necessary conditions for the unbiasedness hypothesis. The first necessary condition for the unbiasedness hypothesis is the cointegration between the spot and futures prices, since it ensures that there exists a long-run equilibrium relationship between the two series, specifically when the prices data are characterized by the stochastic trends. Given the results from the Johansen procedure, which confirmed that Indian wheat spot and futures prices are cointegrated, the second necessary condition with respect to the cointegrating vectors is examined by evaluating the coefficients of long-run matrix, β. Thus, the second hypothesis is formulated as a statistical test with respect to the cointegrating vectors[33] is whether $\beta' = (\beta_1,\ \beta_2) = (1 - 1)$. The LR[34] tests, follows a χ^2 distribution, is conducted for the formal testing of the unbiasedness hypothesis and results are shown in Table 3.5. The *LR* test statistics, for the null of $\beta_2 = 1$ which is used to test restriction $(\beta_1, \beta_2) = (1 - 1)$, is 1.184 (0.497) which distributed with $\chi^2\,(1)$ and has p-value of 0.276 (0.481). These results indicate that the unbiasedness hypothesis cannot be rejected for wheat in both periods at the 5% significance level. This suggests that futures prices are more likely to be an unbiased estimate of spot prices to an extent that there is evidence of cointegration, and market participants can rely on the Indian wheat future market, particularly for the long-run forecasts. The inability to reject the unitary elasticity, $(\beta_1 = -\beta_2)$, means that there is only proportional relationship between s_t and f_t.

[33] If the futures prices and the spot market prices are cointegrated, then the cointegration relationship and the parameter restrictions can be tested under two hypotheses: $\beta_2 = 1$ and $\beta_3 = 0$ jointly, and $\beta_2 = 1$ individually. The constraint $\beta_2 = 1$, i.e., in the present context can be expressed as restriction on the cointegrating vector $z = (1, -1, -a)$. This the most important indicator of unbiasedness condition because futures prices can explain the movement in spot price, while β_3 can be non-zero under the existence of a constant risk premium or certain transportation costs. The joint hypothesis of $\beta_2 = 1$ and $\beta_3 = 0$ tested by imposing restriction $z = (1, -1, 0)$. This is the most strong restriction because it tests both market efficiency and the absence of a risk premium jointly. Hence, if $\beta_2 = 1$ is not rejected but the test of the joint hypothesis is rejected, then the futures prices may still explain the movement in the spot prices, though futures prices will be biased forecast of futures spot prices.

[34] The *LR* test is conducted for $\beta^{'} = (SF) = (1 - 1)$.

Therefore, contrary to Yang et. al. (2001), the unbiasedness hypothesis is additionally tested, following Zhong et al. (2004), Asche et al. (2016), and Chen and Scholtens (2018), by imposing restriction on the constant $\beta_3 = 0$. Hence, a second test of unbiasedness hypothesis with the joint restriction, ($\beta_2 = 1$ and $\beta_3 = 0$), of unitary slope and zero interceptis imposed on the coefficients of the estimated cointegration vector to test $(\beta_1, \beta_2, \beta_3) = (1, -1, 0)$. Testing of joint hypothesis yields an asymptotic χ^2 (2) test statistics of 3.281 (6.849) with a p-value of 0.194 (0.033). Although the test of joint hypothesis cannot be rejected for the pre-ban period, it can be rejected at the 5% level of significance for the post-ban period. The rejection of the joint hypothesis results from the non-zero constant term, $(\beta_3) \neq 0$. This suggests that the wheat futures prices are unbiased predictor for spot prices in the long-run for first period, but not a very good predictor for the second period.

[Table 3.5 about here.]

As discussed in Hamilton (1992), Beck (1994) and Yang et. al. (2001), the joint hypothesis may be rejected due to the existence of constant risk premium or certain other components of stationary costs (e.g., transportation costs, physical storage costs, and other transaction costs). However, the combined inference drawn from the results of two separate tests suggest that biases in the futures prediction in the second period can be interpreted to be caused by the positive risk premium. Therefore, one can summarize that in case of Indian wheat futures market the unbiasedness in the long-run cannot be rejected in general. However, the premium arising due to risk aversion in second period does not imply that the markets are biased (or inefficient), rather it has primarily been observed in the markets because investors now require compensation for the regulatory risk that they undertake, especially when abrupt restrictions are been imposed on the futures trading.

3.5.4. Vector Error Correction Models and Adjustment Coefficients

It is apparent from the cointegration test results that a long-run equilibrium relationship exists between spot series and contemporaneous futures series in the NCDEX wheat. Thus, the inferences on the causal relationship between the two prices is made by estimating the bivariate VECMs; results reported in Table 3.6. Since both s_t and f_t are cointegrated with vector $(1, -1)'$, the cointegration (or equilibrium) error is defined with the difference as $z_t = s_t - \beta_2 f_t - \beta_3$. The lagged value of the stationary equilibrium error term (z_{t-1}) is incorporated into the VECM equations through two error-correction terms, α_1, where spot price is a dependent variable and α_2, where futures price is a dependent variable, so that the long-run disequilibrium in any period will be corrected in the next period. Panel A and B displays the parameter estimates for the VECM (from Equation 3.26 and 3.27) over the two sub-samples, Period I and Period II. The optimal lags of $(\Delta s_t, \Delta f_t)$' in the VECM are reported by using Akaike's Information Criteria. For both the periods, when first-order differences of the spot (or futures) is a dependant variable, one autoregressive lag of changes in the spot and futures prices were proved to be adequate in the VECM model. This implies that Δs_t (Δf_t) adjust to the departures from both the long-run equilibrium and short-run fluctuations of up to two days.

For both the periods, the error-correction coefficients (i.e. the adjustment coefficients) for the spot prices, α_1, are highly significant (at a 1% level), which implies that spot market responds to the past equilibrium errors. But, the adjustment coefficients for the futures prices, α_2, are statistically insignificant, implying that the futures price do not adjust to the previous period's deviation from equilibrium. This may be interpreted as evidence that the burden of price adjustment following any disequilibrium (i.e. when the long-run cointegration relationship is perturbed) falls primarily on the spot prices, which tends to make the adjustment in order to restore the long-run equilibrium. In other words, these results provide evidence that the future prices are the main contributors in the price discovery process. Furthermore, the error-correction coefficient in the spot return equation, α_1, bears a negative sign; this is equivalent to saying that when the futures prices are above (below) their equilibrium value at time $t-1$, the spot prices at time *t* are expected to adjust downward (upward), so that the two prices converge in the long-run. The parameter estimates of α_1 in the two periods agree in sign. In contrast, the error-correction terms (α_2) in the futures market equation have statistically insignificant positive (negative) coefficient for the Ist (IInd) Period. These results indicate an unidirectional error-correction, that is, futures prices lead the movement in the spot prices, but not vice-versa.

In addition to the statistical significance, the relative magnitude of the error-correction coefficients can be assessed to examine the causal relationship between the spot and futures prices. The error-correction coefficients for α_1 in equation with Δs_t, in both the periods, are greater in magnitude in terms of absolute values than the α_2 coefficients of the Δf_t equation: -0.026 (-0.039) versus 0.002 (-0.005). Since, the coefficients on α_2 are about less than half in magnitude on the error-correction term in the spot equation, it is clear that spot prices have more tendency to adjust to correct a disequilibrium situation. In other words, the lead from futures-to-spot is detected in both the periods. Consequently, the result in this research work suggests that the wheat futures market are more dominant source of information in the long-term price discovery. The results with respect to the error-correction coefficients are in line with the findings of those of Brockman and Tse (1995; canola and barley), Schwarz and Szakmary (1994; heating oil and unleaded gasoline), Carter and Mohapatra (2008; hog), Ferretti and Gonzalo (2010; aluminium, nickel and zinc) and Adämmer et al. (2015; hog and piglet) from the commodity markets. These error-correction results are expanded upon by applying formal long-run prediction hypotheses tests in Table 3.7. These tests identify whether the spot or futures prices are the determinant factor of price discovery in the wheat market in the long-run.

Again, like the coefficients of error-correction terms in the spot and futures equations, the short-run dynamics of the NCDEX system indicated by the estimated coefficients of lagged first-differenced spot and futures prices, show similar patterns in the short-term interaction of price changes. Panel A and B of Table 3.6 reports that coefficients of changes in the lagged-futures (spot) prices $\Gamma_1^{12}(\Gamma_1^{21})$ are significant (not significant) in the spot (futures) market equation. Hence, the coefficients of lagged returns show that futures market lead the spot markets by 1 lag (1 day), while there is no significant information flow in the reverse direction (i.e., from spot-to-futures). Hence, concerning the Indian wheat market, it can be ascertained that the futures returns have considerable predictive power for the spot returns, but not vice versa. These results are also in line with the general understanding that spot prices move in the direction of the previous movements of the futures prices, implying that short-term price discovery occurs in the wheat futures market and not in the spot markets. This thesis further investigates the short-run causalities with the cointegrated systems with the formal hypotheses tests displayed in Table 3.8.

[Table 3.6 about here.]

3.5.5. Weak Exogeneity and Long-Run Price Discovery

With one cointegrating vector between the spot and futures prices, i.e., results from the *LR* test of restrictions $\beta^{'} = (1 - 1)$, this section tests the three hypotheses to explore the long-run price discovery dynamics among the two markets. As indicated in Yang et. al. (2001), Zhong et al. (2004), Crowder and Phengpis (2005), Carter and Mohapatra (2008), Yang et al. (2012), Ngene et. al. (2017), and Xu (2018.a) long-run prediction hypothesis can be tested by formulating statistical tests based on adjustment coefficients: (i) possibility of weak exogeneity of spot (futures) series relative to long-term equilibrium, and (ii) possibility of bidirectional informational flow in the long-run. The weak exogeneity hypothesis is examined in two parts, such that each element α_j $(j = 1,2)$ of the adjustment coefficient matrix in the VECM (in Equation 3.18) is equal to zero. The unrestricted estimates of the α_j with the corresponding t-statistics are presented above in the Table 3.6. The results of the weak exogeneity of the j^{th} market price are reported below in Table 3.7 (first two rows). With $\alpha_1 = 0$ (and $\alpha_2 = 0$) weak exogeneity of spot (futures) market price, with no restrictions on the β matrix is examined. Testing the weak exogeneity of the spot prices (H_{3a}) yields a χ^2 (1) distributed statistic equal to 14.13 and 47.36 for Period I and II, respectively. Therefore, the null hypothesis that spot prices are weakly exogeneous for the long-run equilibrium is strongly rejected at the 1% level of significance. The analogous test for the weak exogeneity of the futures prices (H_{3b}) yields a test statistics of 0.06 and 0.34 for the two periods. It is clear that this null hypothesis cannot be rejected, indicating that futures prices are not affected by short-run interruptions of equilibrium. These results suggest that the futures prices do not make adjustment to the deviation from the long-run equilibrium prices, or more precisely, the futures prices are weakly exogeneous and only spot prices respond to any disequilibrium in the system; thus providing strong support for the endogeneity of the spot prices. Furthermore, it can be concluded from these results that the weakly exogeneous variable, i.e., futures market, is causally prior (i.e. futures prices leads the spot prices) to the spot market and serves a very important role of price discovery vehicle in the long-run. These results are consistent with findings of Yang et. al. (2001) for the storable commodities (corn, oat, soybeans, cotton and wheat-CBT) and Carter and Mohapatra (2008) for hog markets.

As pointed in Yang et. al. (2001), the equal importance of futures and cash markets as an informational source in the long-run is additionally tested as, $|\alpha_2| = |\alpha_1|$. The third test in Table 3.7 is for bidirectional information flow (H_{3c}) i.e., if the spot and futures prices respond to the disturbances at the same magnitude in the long-run. For both the periods the hypothesis that the futures market is just as important as an informational source as the cash market, is rejected. Overall, this test provides strong evidence that futures prices are primary source of information in both, pre- and post- ban, periods.

Following suggestions from Zapata and Rambaldi (1997), Yang et. al. (2001), Carter and Mohapatra (2008), Yang et. al. (2012), and Xu (2018.a) weak exogeneity and unbiasedness hypothesis are also jointly tested under the long-run prediction hypotheses. The test results of two joint hypothesis (H_{4a} and H_{4b}) are reported in last two rows in Table 3.7. The results from the joint tests are consistent with the individual weak exogeneity hypotheses. With the restrictions imposed on the β matrix identified by the unbiasedness hypothesis, the weak exogeneity of the futures is still not rejected but it is strongly rejected at one percent significance level for the spot prices. Taken together, the results from the individual long-run prediction hypotheses and joint test of hypothesis of no long-run prediction conditional on the cointegration, renders support in favour of weak exogeneity of the wheat futures prices, implying that the futures market leads the spot market in transmitting long-run information. These findings are consistent with an efficient market in which futures prices lead cash prices; for example, Yang et. al. (2001; oat, soybeans, and wheat-CBT), Peng et. al. (2006; copper and aluminium) and Carter and Mohapatra (2008; hog); and manifests that futures markets takes a dominant role in the price discovery process. In addition, the long-run prediction hypotheses results appear to be consistent across the two sub-periods in this analysis, before the ban in July 2007 and after the ban was lifted in June 2009. In summary, the empirical evidence from the long-run price discovery shows that post-ban wheat futures markets were not inferior to the pre-ban period in terms of long-run information flow. This is perhaps not too surprising, given the fact that the market participants were again allowed to trade in futures markets by removing the stringent regulation of ban. It seems that information content of the futures prices increased after the ban was revoked. Therefore, these results suggest that even after a period of high degree of market intervention where genuine players are taken by the sudden surprises of numerous suspensions of trade in the agricultural commodities, wheat futures prices remained a trustworthy element in the post-ban period, in terms of taking a leading role in long-run price discovery performance.

[Table 3.7 about here.]

3.5.6. Short-Run Causality in VECM System

The hypotheses test results related to the causality tests which examines the short-run dynamics between the spot and futures prices are reported in Table 3.8. The formulated '*short-run prediction hypothesis*' and '*short-run causality'* (i.e., from spot-to-futures) corresponds to the concept of 'Ganger causality' (where futures market leads the spot market) and 'Reverse Granger causality' (where spot market leads the futures market). Equations 3.26 and 3.27 summarizes short-run dynamics in the spot-futures relationship. Specifically the null $\Gamma_i^{12} = 0$ in Table 3.8 determine if the coefficients of lagged futures returns have no predictive power for current changes in spot. Whereas the null $\Gamma_i^{21} = 0$ tests if the coefficient of lagged spot returns have no predictive power for current changes in the futures.

After the post-ban period, the result of the short-term causality tests differs from those same tests preceding the ban period. The test with respect to the hypotheses H_{5a} and H_{5b} for testing Granger causality and Reverse Granger causality shows unidirectional informational flow running from the futures to the spot market in I^{st} Period. This finding of unidirectional causal relationship from futures-to-spot in the short-run are in line with the studies from other markets; for example, Karande (2006; castorseed, Ahmedabad) and Carter and Mohapatra (2008; hog). However, the results in the II^{nd} Period imply bidirectional relationship. Recently, Lee et al. (2016; REIT futures, in GFC period) and Ngene et al. (2017; CDS-Bond market, in 13 out of 22 sovereigns credit risk markets) also found the bilateral lead-lag relationship between the two markets in terms of short-term price discovery.

The results in Panel A shows that futures returns have considerable predictive power for spot returns [significant $\chi^2(1)$ = 10.20], while the reverse is untrue [insignificant $\chi^2(1)$ = 0.04]. These findings show that in the short-run causality is very active from futures returns to the spot returns but there is no reverse feedback from the cash price. Therefore the short-run prediction hypothesis that futures return lead spot return is supported in the first period. Similar to the results of first period the results in Panel B shows that null hypothesis of no long-run prediction hypothesis is strongly rejected at the 1% level [significant χ^2 (1) = 26.09]. However, the null of no reverse short-run causality, in the II^{nd} Period, is also rejected at the 10% level [significant

χ^2 (1) = 3.54] of significance. Statistical significance of both, lagged futures price differenced terms in the spot equation and lagged spot price differenced terms in the futures equation, indicate that spot and futures market interacted bilaterally in terms of short-run information flow between the two markets during the post-ban period. In other words, not only do NCDEX futures returns have considerable predictive power for wheat spot returns but wheat spot returns are also useful for predicting NCDEX futures returns.

[Table 3.8 about here.]

Difference in the short-term lead-lag relationship from the causality tests can be explained with the two facts specific to the Indian agri-futures markets. Firstly, prior to the formation of three national commodity exchanges, viz. NCDEX, MCX and NMCE, in 2003, agricultural commodity futures were traded through recognised regional exchanges. The initial sub-period of this study represents the early phase of national commodity exchanges in India when investors may have actively used derivatives for both speculative and hedging purposes. The results imply that even in the initial phase of trading years the future prices were formed before the spot prices and wheat futures market dominated the information transmission process and price discovery. This analysis supports that unidirectional causality running futures to the spot market is prevalent in the causal dynamics during the Ist Period. Secondly, the result of short-term prediction hypothesis from the IInd Period demonstrates that structural changes did occur in the wheat futures market after the ban period, since both the hypotheses, i.e., the causality test and reverse causality test, are rejected in the second period. This evidence can be viewed as presence of bidirectional causality and information flow between the spot and futures markets. Specifically, the finding that spot prices are also used to make decision about the futures prices in the post-ban period reveals that even when the trading ban was lifted, the regulatory uncertainty in the Indian agricultural futures might have hampered the market sentiment which lead to the decline in future market dominance; i.e., in terms of expected price discovery function, futures prices did not unidirectionally Granger caused spot prices in the post-ban period.

Given the results from the unbiasedness test which imply rejection of joint hypothesis because positive risk premium has been experienced in the NCDEX wheat futures in the post-ban period, the market participants now demand additional compensation (i.e., a constant risk premium) to protect the value in their commodity portfolios. Considering several instances of abrupt interventions (with higher margins, suspensions, bans and stocking restrictions) by the Government of India in the agri-futures trade, which is targeted more towards the essential commodities that are perceived to be sensitive from food security point of view, the uncertainty risk and regulatory constraints might have become primary concern for the genuine institutional investors. Hence, the post-relaunch phase of trading in agricultural commodities might have received lower market participation in the NCDEX futures market which has not only harmed the information efficiency and price discovery function after the ban period but also lead to the emergence of risk premium in the wheat market. Therefore, presence of futures bias in the IInd Period is attributable to the constant risk premium and not the expectational error, which might be a consequence of demand for the compensation for the regulatory riskiness of investing in agri-commodity futures. Another notable feature from the second period in addition to the bidirectional flow is that the *LR* test statistics for $\Gamma_i^{12} = 0$ is greater than $\Gamma_i^{21} = 0$. This signifies that even when the ban period has harmed the functioning of agricultural futures trading, the wheat futures market assumes a dominant role over the spot market in the post-ban period as well.

3.6. SUMMARY AND CONCLUSION

The key findings of empirical work are summarized in Table 3.9. This chapter studies the spot-futures relationship in the wheat market for the NCDEX future. By analyzing the suspension of wheat future in 2007, findings of this study contributes to the ongoing debate among the economic policy think tank organizations (Gulati et al., 2017; Chatterjee et al., 2019) and academicians (Srinivasan, 2008; Fernandez, 2013) about the legitimacy of frequent regulatory interventions in agricultural commodity futures markets. It is the first empirical analysis to assess the potential impact of India's futures trading ban on the price discovery process. In particular, this work examines whether the wheat futures prices provide an unbiased estimate of the spot price and effectively serves the price discovery function and also investigates the effects of the trading ban on these two features. This research confirms that the futures trading ban does affect both unbiasedness and prediction hypotheses. The numerous instances of ban on agri-commodity markets has caused uncertainty in futures trade and may have created regulatory risk and negatively affected the price discovery leadership, particularly with respect to wheat futures trading.

The result of the cointegration test are consistent with the theoretical expectation that the spot and futures prices of the investigated agricultural commodity are non-stationary and the two markets are tied together in one cointegration relationship. These findings indicate that even with most extreme form of government interventions, such as banning the commodity altogether, the existence of a long-run relationship is not affected in the subsequent re-launch period. However, the empirical evidence presented in the study reveals that results of the unbiasedness tests do not hold uniformly across the pre- and post-ban periods. The simple unbiasedness model with cointegrating vector $(1, -1)$, without imposing the restrictions on the constant, cannot be rejected across both periods; whereas the test of joint restrictions $(1, -1, 0)$, by imposing $\mu = 0$, is supported in the pre-ban but not in the post-ban period. The analysis of these test of restrictions on β' leads to two interesting implications. (1) First, the finding of unit cointegrating vector emphasizes that futures prices are more likely to be an unbiased estimate for spot prices and also justifies the assumption that items captured in μ are stationary and can adequately capture the spot-futures price differentials or constant risk premium, across both periods. (2) Second, as the restrictions of joint hypothesis cannot be rejected in the first period there is no evidence of risk premium in the pre-ban period. However, the rejection of joint restrictions in the second period cannot be interpreted as a failure of the unbiasedness hypothesis. Because the null hypothesis $\beta' = (1, -1)$ is not rejected in the post-ban period, futures market will still provide a good hedge; but, as joint restrictions do not hold in the second period, the positive risk premium appears in the market during the post-ban period. Risk aversion in the wheat futures market, once the suspension is revoked, is not too surprising given that there were six instances of blanket bans on futures trading in NCDEX between 2007-2009, besides the ban on wheat contracts. For example, Chana (chickpea), Rubber and Soya oil were banned from futures trading in May, 2008 and remained banned for a duration of 6, 16 and 6 months, respectively; whereas trading suspension in pulses (Tur and Urad) and Rice, since 2007, is not been revoked for more than a decade now.

This study investigates the price discovery function and contemporaneous causality among the Indian wheat futures and spot market, in both the long- and the short-run, with vector error-correction modelling. The results are consistent with the weak exogeneity and long-run prediction (joint) hypotheses across the two sub-periods, suggesting that the wheat futures market in India is a useful vehicle in terms of long-term price discovery. This finding is consistent with previous studies from the global commodity markets reviewed in Schwarz and Szakmary (1994; petroleum product markets), Brockman and Tse (1995; agricultural futures), Yang et al. (2001; storable commodities), Asche and Guttormsen (2002; gas oil futures), Mattos and Garcia (2004; more active coffee and live cattle contracts), Zapata et al. (2005; sugar futures), Peng et al. (2006; nonferrous metals), Carter and Mohapatra (2008; a nonstorable commodity), Shrestha (2014; energy related commodities), and Adämmer et al. (2015; thinly traded agricultural futures) which also showed that futures markets play a dominant role in the long-run price discovery process. In the Indian context where a vast body of literature has used the ECM framework, the price discovery role of commodity future markets has not been empirically explored by the prediction hypothesis. These researchers have drawn conclusions about the long-run causality in the system by either assessing the significance and magnitude of the error correction term or by weak exogeneity tests, which has found mixed evidence for both agriculture and non-agriculture commodities in India. One strand of literature, for example, Elumalai et al. (2009; agricultural commodities), Mahalik et al. (2009; commodity indices), Pavabutr and Chaihetphon (2010; gold futures), Mukherjee (2011; wheat, chilli, jeera, castor seed and soya oil), Inani, (2018; ten most liquid agricultural commodities' futures, in case of six markets), and Manogna and Mishra (2020; castor seed, guar seed and chana) has found that there is long-run unidirectional causality futures to spot market, and price discovery occurs in futures market. But another strand of literature, for example, Deo and Srinivasan (2009; mini gold futures), Dey et al. (2011, pepper futures), and Srinivasan and Ibrahim (2012; gold futures), has found the evidence in favour of unidirectional causality running from spot to futures markets in the long-run dynamics. On the other hand, some studies e.g., Karande (2006; Mumbai castor seed), Shihabudheen and Padhi (2010; precious metal and agricultural commodities), Gupta and Ravi (2012; chana futures), Srinivasan (2012; commodity futures indices), Arora and Kumar (2013; non-precious metals), Malhotra and Sharma (2013; guar seed), Shakeel and Purankar (2014; three top traded agricultural commodities), Nirmala and Deepthy (2016; silver futures), and Gupta et al. (2018; agricultural, industrial, precious metal and energy commodities) found that bidirectional flow of information is running between the spot and futures prices, which indicates joint role of both markets for price discovery in the long-run. The mixed results obtained for Indian markets reveal that process of adjustment to disequilibrium in spot-futures commodity markets should be analyzed on the individual commodity markets as the investor participation may vary due to different levels of government regulations across the commodity products.

Since the empirical results show that the NCDEX futures market consistently plays an import role of the primary price discovery point through the long-run equilibrium price channel before the trading suspension 2007 and after the revival of operations in 2009, the findings have two important implications: (1) First, market participants can rely on the price signals from the future markets even if there is a risk premium in the future market. The long-run predictive power of the error-correction for the current changes in the spot and futures markets suggest that the futures market certainly reflects the market-wide information, prior to the spot markets. The dominance of future markets in price discovery is intuitive and often reasoned (Tse, 1999; Brooks, Rew and Ritson, 2001; Floros and Vougas, 2008; Shihabudheen and Padhi, 2010; Xu, 2018.b) as a consequence of reduced transaction costs, greater liquidity, inherent leverage and low initial outlays, absence of short sale restrictions and other associated benefits in contrast to the spot market. The risk premium, especially due to regulatory interventions therefore seems to be more relevant for the new investors (hedgers and/or speculators) than from preventing the long-run impact of the basis in the futures market for efficient price discovery. (2) Second, the result may be of interest to the emerging market policy makers and regulators who face decision regarding the suspensions and interventions, such as hike in special and additional margins in the agri-futures trade. These results provide an evidence that even if the trading in futures market has attracted more liquidity-driven speculators than the hedgers, the long-run price discovery mechanism does not get distorted. The futures market is thus fulfilling its principal objective of reducing uncertainty through the process of price discovery.

The result of this study suggests that NCDEX futures market leads the spot market in the long-term price discovery in the pre- and post-ban periods. The results from the short-term dynamics, the causality tests in the VECM framework involving exclusion restrictions on all Γ_i^{12} in (3.26) and Γ_i^{21} in (3.27), however, reveals a different pattern of lead-lag in the two sub-periods: unidirectional causality running from futures to the spot market is prevalent in the causal dynamics before the ban period; whereas a bidirectional short-run information flow between two markets is evident during the post-ban period. Empirical studies which investigate the short-run causalities, while preserving the cointegration between the two price series, often interpret the unidirectional and bidirectional relationship with different possible explanations. For example, the identification of unidirectional information flow from the spot (futures) market to the futures (spot) market may be due to: inefficiency[35] in the short-run (Carter and Mohapatra, 2008; Liu,

[35] According to Carter and Mohapatra (2008) and Liu (2009) when spot (futures) prices lead movements in the futures (spot) prices but there is no reverse feedback from futures (spot) prices, then the past information will become useful for predicting the movement in the current futures (spot) prices, which will bring inefficiency in the short-run.

2009), or faster (slower) response of the market to incorporate the new information[36] (Zhong et al., 2004; Ngene et al.,2017). Similarly, the evidence of bidirectional short-run causality (or feedback) between the two markets may be due to: relatively low trading volume[37] of the futures contract (Mattos and Garcia, 2004; Adämmer et al., 2015), or changes in the investor structure[38] (Bohl et al., 2011; Lee et al., 2016). Based on the evidence from this thesis, two distinct interpretations can be generated from the short-term interactions between the spot and futures prices. (1) First, the unidirectional information flow from futures to spot markets in the pre-ban sample period signifies the dominance of the futures market over the spot market. Therefore, by intuitively following the argument from Bohl et al. (2011), if the wheat futures market was dominated by unsophisticated traders before 2007, the quality of the price signal emerging from this market would have been presumably noisy and futures prices series in such case would not have unidirectionally Granger-caused the spot prices. These results provide a strong contrasting evidence for the policymakers, who have generally presumed that speculation spree in the agricultural futures market to be the primary cause for driving inflation. (2) Second, there is bidirectional informational flow in the post-ban period, which demonstrates feedback relationship in returns. The findings of bidirectional causality imply that price discovery process is

[36] Zhong et al. (2004) and Ngene et al. (2017) suggests that direction of information flow points to the market in which the price discovery is taking place. If the market trading (price discovery) is in the futures (spot) market, it reflects that the futures (spot) market incorporates new information more quickly compared to the spot (futures) market. Consequently the price change will be transmitted to the slow responding spot (futures) market.

[37] Findings from Mattos and Garcia (2004) and Adämmer et al. (2015) suggest that the level of trading activity is necessary to promote the transmission of price information and for futures prices to play the dominant role. The bivariate short-run causality in both directions, for the thinly traded contracts, is explained in the context of lower trading volume.

[38] Recently Lee et al. (2016) documented bilateral lead-lag relationship pattern in the short-term during and after the global financial crises (GFC) period; the findings show how the shifts in the investor structure can affect the price formation process. In terms of short-term prediction hypothesis, their result provides evidence to suggest that Australian real estate investment trust (A-REIT) spot market leads the futures market in the pre-GFC period, but the information flowed in both directions since the GFC period. They argued that because the prices from two markets interacted bilaterally after the GFC, the price discovery function has improved.

interdependent. However, there is still an evidence of stronger flow from futures to spot market than in the reverse direction. Summing up, the results from 2009 onwards sample period suggest that futures market does not fully perform the expected price discovery function after an untimely and abrupt impact of ban on the futures trading. Furthermore, as the price discovery still primarily occurs in the futures market, it can be viewed as a more effective price discovery platform than the spot market. Therefore, the key policy implications of this study is that the regulators may prevent the instances of abrupt price spike in agriculture commodities through adopting other possible intervention tools, like arbitrage supervision, margin requirements, position limits, and transaction tax before taking the extreme step of banning futures trading altogether.

[Table 3.9 about here.]

In conclusion, NCDEX wheat futures is a more effective vehicle for price discovery although the results in terms of short-run interactions were somewhat mixed but also sheds some light on the effect of futures trading ban and the price discovery process. It is apparent from the results that the price formation process (lead-lag pattern) differs during the pre- and post-ban period. Specifically, the price discovery function has deteriorated since the trading is suspended. However, the source of this weaker transmission of price information in the post-ban period is an unanswered question. It may arise from the reduced trading activity of the NCDEX wheat futures, presence of constant risk premium, shift in the investor structure or other yet unidentified reasons which are caused by the trading ban. Besides these reasons, if the trading activity of the NCDEX wheat spot is relatively lower in the post-ban period, the hedge or speculation need for the NCDEX wheat futures may have decreased to an extent that it has affected the information flow from the futures to the spot markets. These results seem to support that additional research in this area is warranted to verify the reasons for lower price discovery in the post-ban period.

Table 3.1: Descriptive Statistics of the Daily Returns - For the full period and two sub-periods

	The Full Period 2004-2015: *n - 2157*		The Pre-Ban Period 2004-2007: *n - 763*		The Post-Ban Period 2009-2015: *n - 1393*	
	Δs_t	Δf_t	Δs_t	Δf_t	Δs_t	Δf_t
Mean	0.038	0.033	0.044	0.033	0.034	0.034
Maximum	5.573	6.580	4.107	4.707	5.573	6.580
Minimum	-12.014	-11.986	-12.014	-10.119	-4.291	-11.986
Std. Dev.	0.915	1.079	1.190	1.195	0.723	1.010
Skewness	-1.850	-1.641	-2.680	-2.178	0.697	-1.122
Kurtosis	29.524	23.604	25.520	21.313	15.366	24.722
Jarque-Bera	64459.390***	39120.990***	17036.880***	11265.320***	8995.399***	27699.270***
Cross-Correlation	0.316		0.252		0.393	

Notes: (A) The table shows the descriptive statistics for the NCDEX spot and futures returns used in this study. Returns are calculated as first differences of log prices.

(B) *, **, *** denote statistical significance at the 10, 5, and 1 percent level, respectively.

(C) The mean, maximum and minimum returns and std. dev. reported in this table have previously been multiplied by 100.

Table 3.2: Unit Root Tests for the Order of Integration - In two sub-periods

	Without Trend			With Trend		
Series	ADF[1a]	PP[2a]	KPSS[3a]	ADF[1b]	PP[2b]	KPSS[3b]
				Panel A : Test with Price Levels		
2004-2007						
(a) Log-spot price						
$\boldsymbol{s}_t$	-1.319	-1.286	2.681	-2.517	-2.526	0.168
(b) Log-futures price						
$\boldsymbol{f}_t$	-0.918	-1.001	2.667	-2.657	-2.806	0.238
2009-2015						
(c) Log-spot price						
$\boldsymbol{s}_t$	-1.440	-1.469	3.340	-2.160	-2.252	0.341
(d) Log-futures price						
$\boldsymbol{f}_t$	-1.415	-1.556	3.332	-2.312	-2.573	0.423

Table 3.2: continues			
		Without Trend	
Series	ADF[1a]	PP[2a]	KPSS[3a]
		Panel B : Test with First Differences	
2004-2007			
(e) Differenced Series of s_t			
Δs_t	-23.348	-23.367	0.046
(f) Differenced Series of f_t			
Δf_t	-26.309	-26.309	0.087
2009-2015			
(g) Differenced Series of s_t			
Δs_t	-28.851	-29.248	0.055
(h) Differenced Series of f_t			
Δf_t	-36.152	-36.301	0.040

Notes: (A): The values reported in the table are the *t* -statistics (Adjusted *t* -statistics for the PP test and LM *t* -statistics for the KPSS test).
(B): Critical values for the ADF and PP tests are taken from MacKinnon (1996), and for the KPSS test is based on Kwiatkowski et. al. (1992).
(C): For ADF test the lag length is determined by minimizing the Schwarz Information Criterion (SIC). Maximum lag length has been set to 19 or 23 depending on the corresponding sub-periods.
(D): For PP and KPSS tests the lag length is controlled with Newy-West (1994) automatic bandwidth selection procedure.
(1a): For the ADF test with constant and without trend, the critical values are -3.435, -2.863 and -2.568 at the 1%, 5%, and 10% significance level, respectively. (1b): For the ADF test with constant and with trend, the critical values are -3.965, -3.413 and -3.129 at the 1%, 5%, and 10% significance level, respectively.
(2a): For the PP test with constant and without trend, the critical values are -3.434, -2.863 and -2.568 at the 1%, 5%, and 10% significance level, respectively. (2b): For the PP test with constant and with trend, the critical values are -3.965, -3.413 and -3.129 at the 1%, 5%, and 10% significance level, respectively.
(3a): For the KPSS test with constant and without trend the critical values are 0.739, 0.463, and 0.347 at the 1%, 5%, and 10% significance level, respectively. (3b): For the KPSS test with constant and with trend, the critical values are 0.216, 0.146, and 0.119 at the 1%, 5%, and 10% significance level, respectively.

Table 3.3: Johansen's Trace and Maximum Eigenvalue Tests - For Cointegration Rank in Indian Wheat Market

Panel A: Cointegration Rank Test using Trace (λ_{trace})

	Information Criteria	Lag Length	Null: Hypothesized No. of *r* (s)	*Without Linear Trend* Trace Statistic (T)	Critical Value (CV) (5%)	Decision	*With Linear Trend* Trace Statistic (T)	Critical Value (CV) (5%)	Decision
Period I									
	AIC	1	H_0: None ($r = 0$)	18.641*	20.262	F/R	17.702**	15.495	R
			H_0: At most 1 ($r \leq 1$)	1.494	9.165	F#	0.911	3.841	F
	SBIC	0	H_0: None ($r = 0$)	23.325**	20.262	R	22.021**	15.495	R
			H_0: At most 1 ($r \leq 1$)	1.432	9.165	F	0.806	3.841	F
Period II									
	AIC	1	H_0: None ($r = 0$)	58.850**	20.262	R	57.121**	15.495	R
			H_0: At most 1 ($r \leq 1$)	3.367	9.165	F#	2.558	3.841	F
	SBIC	1							

Table 3.3: continues

Panel B: Cointegration Rank Test using Maximum Eigenvalue (λ_{max})									
				Without Linear Trend			*With Linear Trend*		
	Information Criteria	Lag Length	Null: Hypothesized No. of *r* (s)	Max-Eigen Statistic (ME)	Critical Value (CV) (5%)	Decision	Max-Eigen Statistic (ME)	Critical Value (CV) (5%)	Decision
Period I									
	AIC	1	H_0: None ($r = 0$)	17.146**	15.892	R	16.791**	14.265	R
			H_0: At most 1 ($r = 1$)	1.494	9.165	F#	0.911	3.841	F
	SBIC	0	H_0: None ($r = 0$)	21.892**	15.892	R	21.216**	14.265	R
			H_0: At most 1 ($r = 1$)	1.432	9.165	F	0.806	3.841	F
Period II									
	AIC	1	H_0: None ($r = 0$)	55.483**	15.892	R	54.563**	14.265	R
			H_0: At most 1 ($r = 1$)	3.367	9.165	F#	2.558	3.841	F
	SBIC	1							

Notes: (A) **, * asterisk denotes rejection of the null hypothesis at the 5% and 10% levels, respectively.
(B) Critical values are from MacKinnon-Haug-Michelis (1999) *p* -values.
(C) *r* is the number of cointegrating vectors under the null hypothesis.
(D) R indicates that we reject the null hypothesis that the number of cointegrating vectors is less than or equal to *r* (when T or ME is greater than CV at 5%).
(E) F indicates that we fail to reject the null hypothesis that the number of cointegrating vectors is less than or equal to *r* (when T or ME is less than CV at 5%).
(F) F/R indicates that we fail to reject the null hypothesis that the number of cointegrating vectors is less than or equal to *r* at 5% level but can be rejected at the 10% level.
(G) Testing is stopped at the first "F" (failure to reject) when starting at the top of the table and moving sequentially across from left to right and from top to the bottom. The symbol (#) indicates the stopping point.

Table 3.4: Unrestricted Estimates of the Cointegrating Vector (β')

	Period I	Period II
β_1	1.000	1.000
β_2	-1.141*	-1.023*
	(0.126)	(0.033)
	[-9.090]	[-31.482]
β_3	0.930	0.158
	(0.848)	(0.235)
	[1.096]	[0.674]

Notes: (A) β_j are the normalized cointegrating parameter estimates.

(B) The normalization in on the cash prices.

(C) The estimated cointegrating vector is given by $z_t = s_t - \beta_2 f_t - \beta_3$; where β_3 is a constant term inside the cointegrating relationship.

(D) Standard errors in ( ) and *t* -statistics in [ ] are shown in parentheses for the estimated parameters.

(E) An asterisks * (**) denotes statistical significance at the 1% (5%) level.

Table 3.5: Hypothesis Testing on the Cointegrating Vector - LR Test for Restrictions

	Panel A: Test for Unbiasedness Hypothesis: $\beta_2 = 1$ [$\chi^2(1)$]				
	χ^2 (1)	*p-value*	Result	*Decision: Unbiasedness*	*Restricted Estimates*
Period I	1.184	0.276	F	Yes	β' = (1 -1.000 -0.024)
Period II	0.497	0.481	F	Yes	β' = (1 -1.000 -0.011)
	Panel B: Test for Joint Hypothesis: $\beta_3 = 0$ and $\beta_2 = 1$ [$\chi^2(2)$]				
	χ^2 (2)	*p-value*	Result	*Decision: Joint Restrictions*	*Restricted Estimates*
Period I	3.281	0.194	F	Yes	β' = (1 -1.000 0.000)
Period II	6.849	0.033**	R/F	No	β' = (1 -1.000 0.000)

Notes: (A) The notation β' = (β_1, β_2, constant) is used in Table 3.4.

(B) R indicates that we reject the null hypothesis and F indicates that we fail to reject the null hypothesis either at the 1% or 5% significance level. R/F indicates the borderline case where we reject the null hypothesis at 5% significance level but fail to do so at the 1% significance level.

(C) (*) and (**) denotes statistical significant or rejecting of the null hypothesis at 1% and 5% levels, respectively.

(D) Decision on unbiasedness summarizes if futures prices are more likely to be an unbiased estimate of cash prices in the long run.

(E) Decision on joint restrictions further check the sensitivity of unbiasedness hypothesis by also imposing restrictions on the constant term, β_3, in the estimated cointegration relation.

Table 3.6: Estimation of the Vector Error Correction Model

Panel A: VECM Estimates for Period I

	Model for Spot Series					*Model for Futures Series*			
Δs_t	Coef.	Est.	*S.E.*	*t* -statistics	**Δf_t**	Coef.	Est.	*S.E.*	*t* -statistics
z_{t-1}	α_1	-0.026***	0.006	-3.946	z_{t-1}	α_2	0.002	0.007	0.257
Δs_{t-1}	$(\Gamma^{11})_1$	0.132***	0.036	3.642	Δs_{t-1}	$(\Gamma^{21})_1$	0.007	0.038	0.196
Δf_{t-1}	$(\Gamma^{12})_1$	0.115***	0.037	3.142	Δf_{t-1}	$(\Gamma^{22})_1$	0.047	0.038	1.243

Panel B: VECM Estimates for Period II

	Model for Spot Series					*Model for Futures Series*			
Δs_t	Coef.	Est.	*S.E.*	*t* -statistics	**Δf_t**	Coef.	Est.	*S.E.*	*t* -statistics
z_{t-1}	α_1	-0.039***	0.005	-7.157	z_{t-1}	α_2	-0.005	0.008	-0.601
Δs_{t-1}	$(\Gamma^{11})_1$	0.172***	0.027	6.334	Δs_{t-1}	$(\Gamma^{21})_1$	0.076	0.040	1.878
Δf_{t-1}	$(\Gamma^{12})_1$	0.101***	0.020	5.080	Δf_{t-1}	$(\Gamma^{22})_1$	0.007	0.030	0.241

Notes: (A) α_j are the error correction coefficient estimates based on the unrestricted β normalized by s_t.

(B) Coef. stands for coefficient, and Est. is estimate.

(C) Optimal lag length is determined by the Akaike Information Criterion (AIC).

(D) Critical values for *t* -test for 10% level is 1.65, 5% level is 1.96 and for 1% is 2.58.

(E) (*), (**) and (***) denotes the significance at the 10%, 5% level and 1% levels, respectively.

Table 3.7: Price Discovery and Long-Run Prediction Hypotheses

Hypotheses	Restriction Testing		χ^2	*d.f.*	*p-value*	Result
	Panel A: Period I					
H_{3a} : $\alpha_1 = 0$	Weak Exogeneity of Spot	S → F	14.13***	1	0.00	R
H_{3b} : $\alpha_2 = 0$	Weak Exogeneity of Futures	F → S	0.06	1	0.81	F
H_{3c} : $\lvert\alpha_2\rvert = \lvert\alpha_1\rvert$	Equal importance of Futures and Spot	F ⇔ S	10.43***	1	0.00	R
H_{4a} : $\beta = (1,-1)$, $\alpha_1 = 0$	Unbiasedness and Weak Exogeneity of Spot	S → F	15.70***	2	0.00	R
H_{4b} : $\beta = (1,-1)$, $\alpha_2 = 0$	Unbiasedness and Weak Exogeneity of Futures	F → S	1.18	2	0.55	F
	Panel B: Period II					
Hypotheses	Restriction Testing		χ^2	*d.f.*	*p-value*	Result
H_{3a} : $\alpha_1 = 0$	Weak Exogeneity of Spot	S → F	47.36***	1	0.00	R
H_{3b} : $\alpha_2 = 0$	Weak Exogeneity of Futures	F → S	0.34	1	0.56	F
H_{3c} : $\lvert\alpha_2\rvert = \lvert\alpha_1\rvert$	Equal importance of Futures and Spot	F ⇔ S	17.57***	1	0.00	R
H_{4a} : $\beta = (1,-1)$, $\alpha_1 = 0$	Unbiasedness and Weak Exogeneity of Spot	S → F	50.41***	2	0.00	R
H_{4b} : $\beta = (1,-1)$, $\alpha_2 = 0$	Unbiasedness and Weak Exogeneity of Futures	F → S	1.06	2	0.59	F

Notes: (A) S for spot prices, F for futures prices, → denotes unidirectional information flow, and ⇔ denotes bidirectional information flow with equal importance.

(B) The likelihood ratio test statistic for the restrictions has a χ^2 distribution with the degrees of freedom equal to the number of restrictions.

(C) (*), (**), and (***) represents variable significance at 10%, 5% and 1% levels, respectively.

(D) R indicates that we reject the null hypothesis and F indicates that we fail to reject the null hypothesis at the 5% significance level.

Table 3.8: Short-Run Causality Tests

Hypotheses	Restriction Testing		χ^2	*d.f.*	*p-value*	Result
	Panel A: Period I					
H_{5a} : $(\Gamma^{12})_i = 0$	Short-Run Prediction Hypothesis	F → S	10.20***	1	0.00	R
H_{5b} : $(\Gamma^{21})_i = 0$	Short-Run Causality from Spot to Futures	S → F	0.04	1	0.85	F
	Panel B: Period II					
H_{5a} : $(\Gamma^{12})_i = 0$	Short-Run Prediction Hypothesis	F → S	26.09***	1	0.00	R
H_{5b} : $(\Gamma^{21})_i = 0$	Short-Run Causality from Spot to Futures	S → F	3.54*	1	0.06	F/R

Notes: (A) The hypotheses $H_{5a;\,5b}$: $\Gamma^{12}{}_i$ ($\Gamma^{21}{}_i$) tests null that the lagged changes in Futures (Spot) have no predictive power for current changes in Spot (Futures).

(B) S for spot prices, F for futures prices, and → denotes unidirectional causality running from the lagged explanatory (or lagged changes in dependent) variable coefficient to the opposite (similar) price equation.
(C) The likelihood ratio test statistic for the restrictions has a χ^2 distribution with the degrees of freedom equal to the number of restrictions.
(E) (*), (**), and (***) represents variable significance at 10%, 5% and 1% levels, respectively.
(D) R indicates that we reject the null hypothesis and F indicates that we fail to reject the null hypothesis at the 5% significance level. F/R indicates that we fail to reject the null hypothesis of no short-run causality at 5% level but can be rejected at the 10% level.

Table 3.9: Summary Results for Sub-Periods

Hypotheses	Support	*Comments*
Panel A: Period I - Pre Ban Period		
Cointegration	Yes	Cointegration *r* = 1
Unbiasedness	Yes	Cointegrating vector = (1, -1)
Joint test of Unbiasedness	Yes	Cointegrating vector = (1, -1, 0)
Weak Exogeneity	Yes	Leading Market: Futures, $\alpha_2 = 0$
Long-run Prediction	Yes	Leading Market: Futures, $\beta = (1,-1)$, $\alpha_2 = 0$
Short-run Prediction	Yes	Leading Market: Futures, $(\Gamma^{12})_i \neq 0$
Panel B: Period II - Post Ban Period		
Hypotheses	Support	*Comments*
Cointegration	Yes	Cointegration *r* = 1
Unbiasedness	Yes	Cointegrating vector = (1, -1)
Joint test of Unbiasedness	No	Cointegrating vector = (1, -1), $\beta_3 \neq 0$.
Weak Exogeneity	Yes	Leading Market: Futures, $\alpha_2 = 0$
Long-run Prediction	Yes	Leading Market: Futures, $\beta = (1,-1)$, $\alpha_2 = 0$
Short-run Prediction	Yes	Leading Market: Both, $(\Gamma^{12})_i \neq 0$ and $(\Gamma^{21})_i \neq 0$

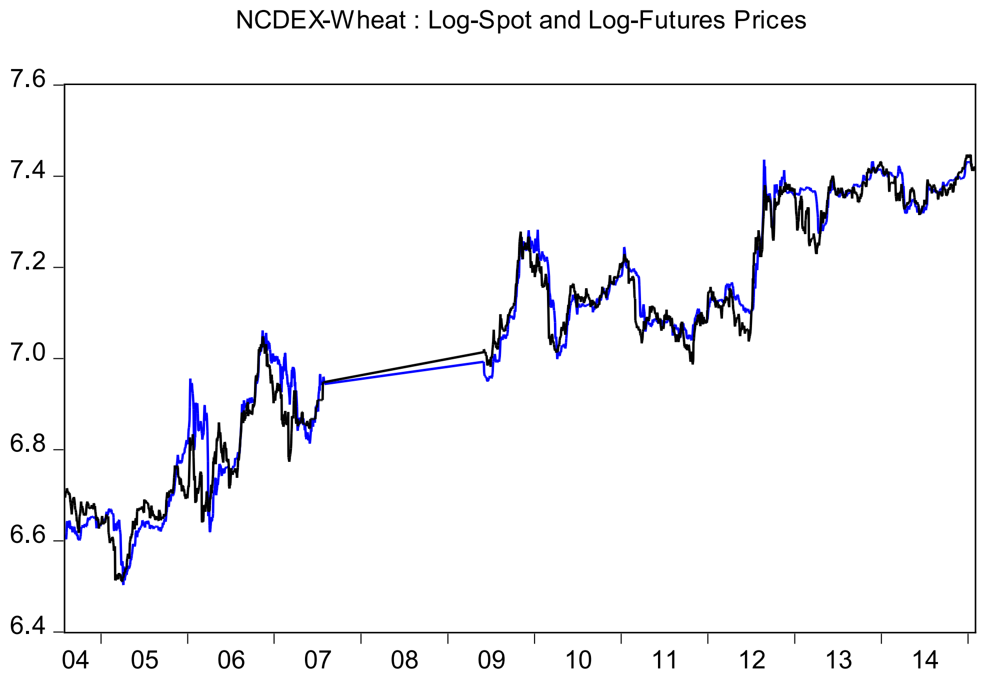

Figure 3.1(a) - Price Series - Full Sample (with Trading Ban Period)

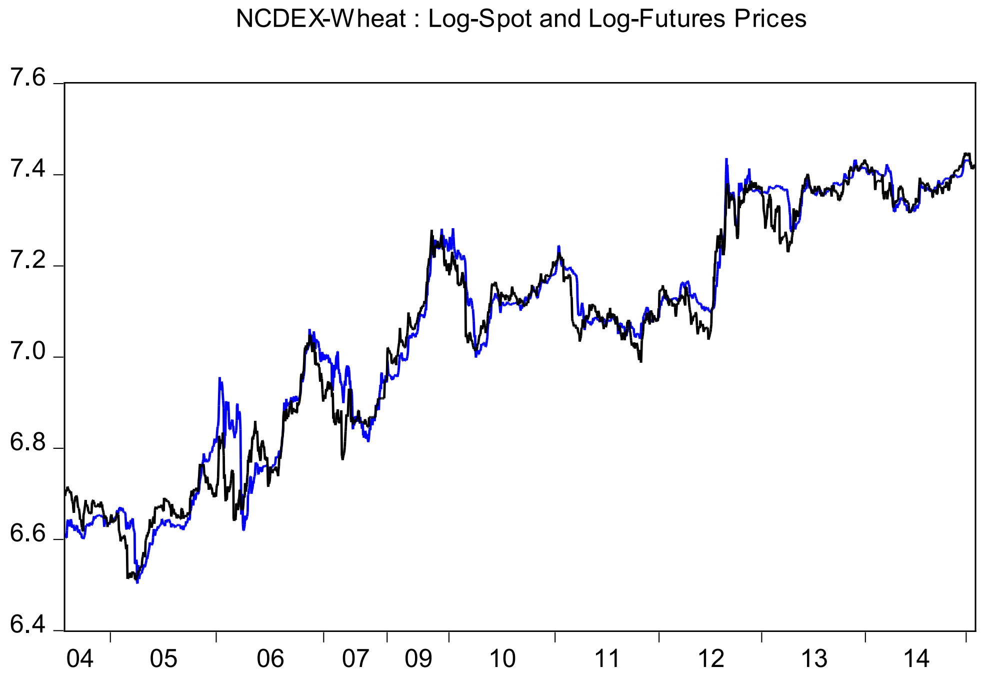

Figure 3.1(b) - Price Series - Full Sample (without Trading Ban Period)

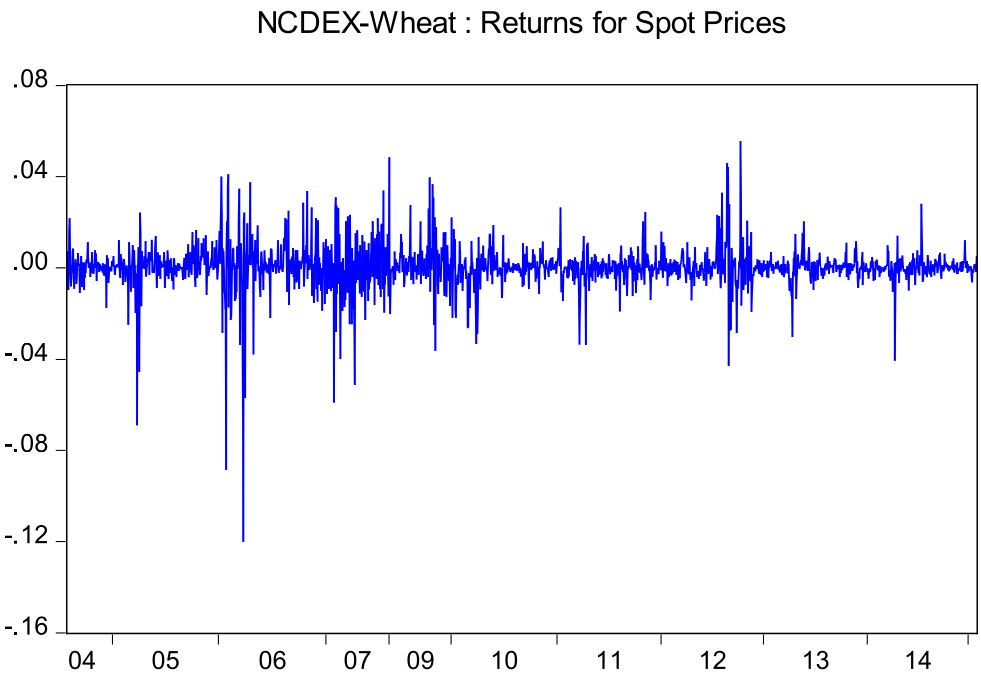

Figure 3.2(a) - Log Differenced Spot

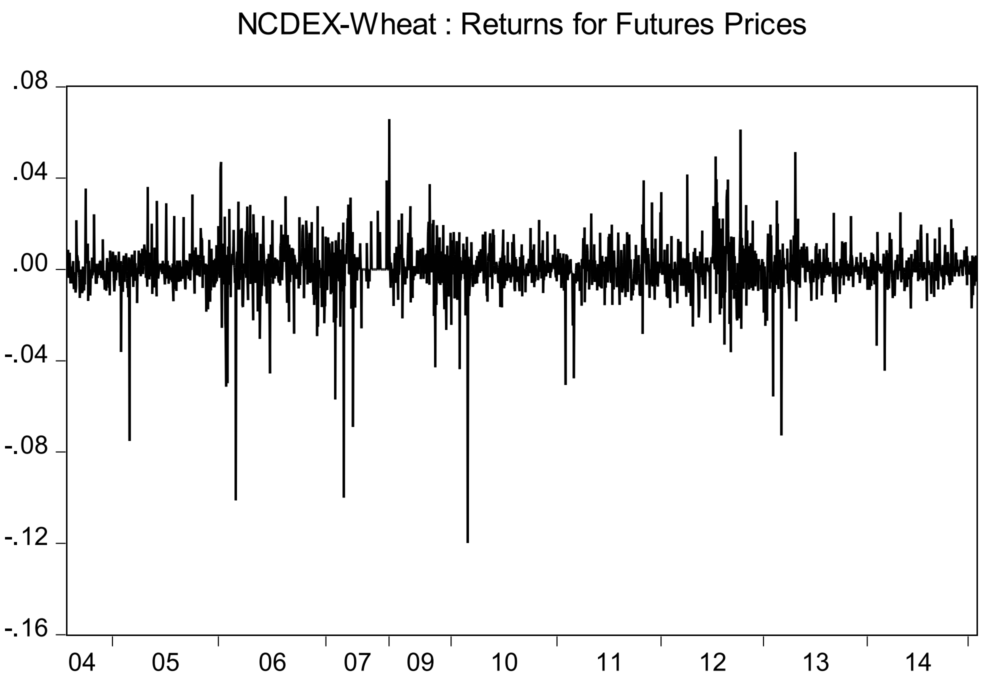

Figure 3.2(b) - Log Diffrenced Futures

CHAPTER 4

4. Revisions in the Minimum Contracts Size of the NIFTY 50 Futures Contract: Effects on Trading Activity, Liquidity and Volatility

4.1. INTRODUCTION

The design parameters of a new or existing equity index futures contract require careful consideration; particularly, regarding contract specifications such as trading cycle, settlement basis[39], contract size[40], and price step (i.e., tick size) in order to maximise market quality. Globally there are no guiding principles to identify the set of contract attributes that will optimise the design parameters. Therefore, identifying the optimal combination of elements for futures contract design is a difficult task in practice. Many historical examples listed in Brown, Laux and Schachter (1991) show that changes in contract design by the relevant futures exchanges were usually an attempt of last resort to revive a failing contract.

Interestingly there are very few examples of contractual redesign of actively traded contracts involving changes either in the contract size alone or in both factors, the contract size and tick size, which occurred at the major futures markets. For example, in 1993, the Sydney Futures Exchange (SFE) respecified the Share Price Index (SPI) and 90-day Bank Accepted Bill (BAB) futures contracts. The size of SPI futures contract was reduced by decreasing the contract multiplier[41] and by increasing the minimum tick size; while BAB contract size was increased by doubling its contract size and minimum tick size was left

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[39] For example, Nifty futures contract have two types of settlements, the daily mark-to-market settlement on a continuous basis at the end of each day, and final cash settlement on T+1 basis.

[40] The word contract size here refers to the lot size for the specific underlying instrument.

[41] The *market lot* also called as "contract multiplier", is the minimum amount of underlying asset under one contract that can be traded (bought or sold) on the Exchange. For example, under the currently permitted contract multiplier for Nifty 50 futures, the lot size is 75. The Nifty futures contract hence can be traded with the minimum quantity, i.e., 75 lot, or with multiples of lot size. Assuming that the current value of Nifty Index level is around 5,000 and since Nifty is traded in the multiples of 75, the appropriate value of the single index future contract would be 75*5000 = Rs.375,000.

unchanged. The Chicago Mercantile Exchange (CME) reduced the size of the S&P 500 contract by decreasing its multiplier while increasing the minimum tick size in 1997. The following year the London International Financial Futures Exchange (LIFFE) modified the specifications for the FTSE-100 index futures contract by lowering the multiplier and held the minimum tick at constant. During the same time in 1998 the Swedish options and futures exchange (OM) reduced the contract size of OMX index futures by splitting the contract to a fourth of its previous value without altering any other aspect of the contract specifications. More recently in 2016, the Athens Stock Exchange lowered the contract multiplier from €5 to €2 for the ATHEX large cap index futures while the minimum tick was held constant at 0.25 index point.

In an Indian context, the recent respecifications of Nifty 50 futures contract at the National Stock Exchange (NSE) is a rare opportunity to evaluate the effect of four instances of lot size changes (in 2005, 2007, 2014 and 2015) within the same futures contract, while all other contract attributes remained intact. As mentioned previously, contract lot sizes are revised periodically and as such first three instances of lot size changes were the expected events of periodic downward reviews to keep the minimum lot value at Rs. 2 lakh, as per SEBI's mandate. However, increase in the lot size in 2015 was not a periodic review event and resulted from SEBI's unexpected announcement of increasing the minimum contract value from Rs. 2 lakhs to 5 lakhs. Revisions in the minimum lot size on the very successful futures contracts are not exclusive to the Indian equity derivatives market, as contract design have been altered from time to time on the different futures exchanges either for the purpose of making the contract more accessible to small investors or to increase commercial participation in particular futures contract. However, the redesigning of the Nifty 50 makes an interesting case for investigating the consequence of increased lot sizes, in terms of its implications for limiting the trading activity of individual traders. In the revision of lot sizes circular, dated July 13, 2015, SEBI did not present any rationale for this policy intervention and also did not provide any evidence to show that increased equity derivatives trading vis-à-vis equity cash had an impact on the overall market quality. This chapter will be primarily concerned with examining the impact of this intervention on some market quality measures.

Relatedly, the issue of high derivatives to cash turnover ratio for the emerging markets (e.g., Korea, India, Hong Kong and Russia) in comparison to the developed markets (e.g., Japan, Australia and the Euro zone) has attracted significant attention from both regulators and the financial press in India (e.g., Fratzcher, 2006; Jobst, 2007; Mihaljek and Packer, 2010; Aysun and Guldi, 2011; Sundaram, 2012; Chakravarthy and Somanathan, 2014; Thomas, 2014; Chakravarty, Ngeshwaran and Ranade, 2015; and Rukhaiyar, 2015). Taking into account that a significant proportion of the turnover in the equity derivatives markets comes from the individual day traders, the Indian regulator increased the contract size threefold (from lot size of 25 units to 75 units) in 2015. This has rekindled the debate on the potential impact of the lot size changes on the market quality measures, and its appropriateness as an effective policy tool to change the composition of market participants (i.e., hedgers and speculators). In general, proponents who support (e.g., The Hindu, 2015; Coutinho, 2015; Rajandran, 2015; Shenoy, 2015; and The Economic Times, 2015) the market regulator's move of increasing the minimum contract size argue that it would discourage retail traders from speculating in the equity derivatives segment and will prevent individual investors from incurring huge losses due to high credit/exposure in the market. The lower lot sizes over the years have created retail obsession for index derivatives and opened gates for individual investors who have limited understanding of the risks associated with derivatives markets, even when they have signed the mandatory Risk Disclosure Document (RDD)[42] at the time of on-boarding.

Those who oppose SEBI's intervention argue that increases in the lot sizes of index and stock futures do not necessarily safeguard small investors from high-risk products, as they might shift to more riskier options in the trading segment. Instead, the intervention may adversely affect trading volume and market liquidity (i.e. increase in bid-ask spreads) and increase the cost of hedging, which in turn would lead to an increase in overall cost of transacting in futures markets. Previous empirical studies (Karagozoglu and Martell, 1999; Brown, 2001; Karagozoglu, Martell and Wang 2003; Bollen, Smith and Whaley, 2003; Chen and Locke, 2004; Bjursell, Frino, Tse and Wang, 2010) regarding the effects of changes in the futures contract specification investigate the issue of change in minimum contract size combined with the changes in minimum tick size, which has lead to conflicting evidence and different conclusions because of the offsetting effects. In particular, if the decrease (increase) in the contract size increases (decreases) trading volume and open interest, the bid-ask spread are expected to decline (increase) after the changes; whereas the increase (decrease) in the level of the minimum tick is expected to increase (decrease) the bid-ask levels and quoted depth, i.e., the number of contracts that the dealers are willing to trade at a given quoted price. For example, Karagozoglu et al. (2003) examine the effect of reduction in S&P 500 futures contract size (500 to 250) and an increase in minimum tick (0.05 to 0.10). They find that the benefits of halving the contract size are likely to be outweighed by its potential transaction cost of increasing the minimum tick by a factor of 2; the adjusted trading volume and adjusted open interest declined while the estimates of effective bid-ask spreads (in levels) increased following the changes in contract specifications.

[42] RDD refers to a document that is mandated under SEBI (Stock Brokers and Sub-Brokers) Regulations 1992, while on-boarding the clients in the derivatives segment. The document makes disclosure of the various risks (such as risk of higher volatility, lower liquidity, wider spreads, news announcements, rumours, system, network congestion etc.) in order to acquaint all the potential investors of the risks that are inherent to trading in the derivatives market, at the time of registration.

Therefore, to make an informed judgement on the effectiveness of contract size policy for reducing excess speculator participation, one should be able to estimate the impact of changes in the two issues (i.e. redesigning involving setting of lot size and tick size) separately on the market quality of futures contracts. In contrast to the documented literature, the *ceteris paribus* change in the Nifty 50 index futures contract enables this chapter to focus on the effects due to the contract lot size changes *per se* on market quality variables (measured by trading volume, bid-ask spreads and price volatility) in a dynamic systems framework, without interference of any other concurrent changes in the contract design elements.

Building on this unique design, this research contributes to the extant literature in several aspects. First, based on a three-equation simultaneous structural model, the relationship among three variables - Trading Volume (TV), Bid-Ask Spread (BAS) and Price Volatility (PV) - before and after the changes in the contract multiplier is evaluated. The empirical modelling confirms that TV, BAS and PV are jointly determined. Unlike previous studies which study the effect of an increase (decrease) in the contract size by applying the two equation model, this is a more appropriate model specification because it accommodates for the endogenous nature of the three market quality measures.

Second, this study uses a new liquidity cost measure in the empirical analysis to examine the aspects of bid-ask spread behaviour. Almost all of the research in the literature has employed estimates of realized bid-ask spreads based on the intraday transactions data, rather than actual quoted spreads. Access to the quote data is limited to only certain securities markets; moreover, unlike other futures exchanges, NSE does not provide market intraday data; therefore, the effect of transaction cost is captured by two illiquidity measures calculated by using the daily trading activity data. Another contribution of this study is the use of the turnover-based version of the Amihud measure ($Amihud^{T}$) developed by Brennan, Huh and

Subramanyam (2013) to capture the liquidity effect without the weakness of any contract size bias.[43] The problem induced by the lot size effects on the traditional Amihud (2002) price-impact measures is mitigated when the turnover (instead of dollar volume of trading) is used to construct the $Amihud^{T}$ measure; an important feature of this study since this practice has not been previously used in the empirical literature.

Third, this analysis has practical relevance in terms of a particular interest to the policy makers and regulators when they are considering using contract lot sizes as a policy tool for limiting the activity of retail consumers. The results of this study provide important insight into the dynamics of trade-off between (a) TV and BAS conditioning on PV, (b) PV and BAS conditioning on TV, and (c) PV and TV conditioning on BAS. In particular, findings indicate that the move of increasing the contract lot size in order to reduce the participation of individual traders without any other changes in the contractual design has resulted in increased hedging activity (i.e., high open interest, OI) and decreased overall trading volume. Although volume and open interest are trading-related variables, based on the assumption that different types of participants i.e., hedgers and speculators have different influence on the trading-related metrics, the literature on the futures market (Rutledge, 1979; Leuthold, 1983; Bessembinder and Seguin, 1993) relates two variables to the participant activity. It is been argued that speculators have more influence on trading volume because they trade frequently as day traders and scalpers, and do not even hold their positions overnight; whereas hedger's impact is primarily reflected on open interest, as by definition it describes the number of outstanding contracts at the end of each trading day and thus excludes the intraday positions

[43] The raw price impact measure, $Amihud^{O}$, leaves a size effect by construction, since it computes the illiquidity per unit of market size i.e., as increase (or decrease) in the contract lot size increases (or decreases) INR trading volume, the illiquidity defined from absolute returns of futures contract divided by INR trading volume apparently decreases (increases). To remove the contract lot size effect over time, $Amihud^{T}$, separates illiquidity from size effects. The turnover-based measure decomposes Amihud (2002) measure into two components: turnover components i.e., absolute futures returns per unit of turnover, and, a futures contract size-related component. Therefore, the proposed turnover version of the Amihud measure does not exhibit an inherent contract lot size-related pattern.

taken by the day traders (see Chang, Chou and Nelling, 2000; Lucia and Pardo, 2010; Carchano, Lucia and Pardo, 2017; Dong and Feng, 2017; Bohl, Siklos and Wellenreuther, 2018; and Wellenreuther and Voelzke, 2018). Therefore, an increase in open interest reflects the rise in the dominance of hedgers in the markets after 2015. However, increased lot sizes did not reduce the market liquidity (i.e., widened BAS) in a similar manner. Furthermore, the effect of increase (decrease) in contract size on PV may not be necessarily decreasing (increasing); as the final result depends on the net effects of the decreased (increased) TV and widened (narrowed) BAS.

The rest of the paper is organized as follows: Section 4.2 provides the background information of NSE regulation and institutional detail related to the trading of the Nifty 50 futures. Section 4.3 presents the related literature on minimum contract size specification and some empirical issues. Section 4.4 explains the estimation methodology and variable measurement. Section 4.5 describes the data and discusses the sample selection. Section 4.6 provides descriptive statistics and results of the preliminary empirical tests along with their methodologies. Section 4.7 presents the empirical results and analysis for the impact of contract size changes on market quality. Section 4.8 reports a brief summary of the findings along with concluding remarks and policy implications.

4.2. INSTITUTIONAL DETAILS - THE INDIAN MARKET

4.2.1. The NSE and Index Futures Contract

A major reform undertaken by SEBI, the securities market regulator, was the introduction of derivatives products in a phased manner, starting with the introduction of Stock Index Futures in Bombay Stock Exchange (BSE) and NSE on June 9, 2000 and June 12, 2000 respectively. In India, derivatives were mainly introduced with the view to curb increasing volatility of the asset prices in financial markets and to introduce sophisticated risk management tools leading to higher returns by reducing risk and transaction costs as compared to individual financial assets (see, Gupta, 2002; Raju and Karande, 2003; Debasish and Das, 2008; and Debasish, 2009). Since the introduction, the market for NSE-derivatives has grown substantially. According to the 2017 Futures Industry Association rankings, NSE is the second largest derivative exchange in the world in terms of number of contracts traded with an annual turnover of 2.5 billion contracts.

The NSE commenced trading in Index Derivatives with the launch of futures contracts based on the popular benchmark Nifty 50 Index. Nifty 50, formerly known as S&P CNX Nifty[44] and CNX Nifty Index[45], launched on April 22, 1996, is owned and managed by NSE Indices Limited (formerly known as India Index Services & Products Limited, IISL), a subsidiary of NSE that was setup in 1998 to provide a variety of indices and index related services and products for the Indian capital markets. With effect from November 9, 2015, NSE rebranded all its indices to include 'Nifty' in their names as against the name 'CNX' used previously, in a bid to capitalise on the brand name of its benchmark index. NSE's flagship 'CNX Nifty Index' was rebranded as 'Nifty 50'.[46]

The Nifty 50 index includes 50 stocks of the approximately 1600 companies listed on the NSE and represents about 65% of the total float-adjusted market capitalization of the NSE. It is a well-diversified index accounting for 12 sectors of the economy and offers

[44] In 1998, NSE and CRISIL launched a joint venture named India Index Services and Products Ltd. (IISL) to focus on index management; where CNX stands for CRISIL NSE Indices. IISL had marketing and licensing agreement with Standard & Poor's Financial Services LLC (S&P), who are world leaders in index services. When S&P came to India to look at market indices, they focussed upon the CNX Nifty as opposed to alternative indices. Their endorsement of the index is evidenced by the old name 'S&P CNX Nifty'.

[45] The licensing arrangement between IISL and S&P has expired with effect from 31st January 2013. Consequently, the trademarks 'S&P' was dropped from the name and accordingly the 'S&P CNX Nifty' Index has been renamed as 'CNX Nifty Index'. Source: IISL Press Release, Expiration of Licensing & Marketing Agreement between IISL and S&P, dated February 11, 2013.

[46] Source: NSE Media Coverage(s): CNX Nifty to be renamed Nifty 50. Financial Chronicle dated September 23, 2015; and CNX Nifty renamed as Nifty 50. Metro India dated November 12, 2015.

investment managers exposure to the Indian market in one efficient portfolio. The Nifty 50 index reflects overall market conditions and is computed using free-float market capitalization method. The Index is well suited for benchmarking fund portfolios, launching of index funds, index-based derivatives, ETFs and structured products. For a stock to qualify for the inclusion in Nifty 50 index, it has to fulfil the liquidity criteria and the company must meet a minimum float-adjusted market capitalization.

4.2.2. Revisions in the Minimum Lot Size of Nifty 50 Futures

The size of the Nifty 50 index futures contract had been revised four times since it started trading in NSE from June 2000, with three downwards and one upward revision. Till 2015, SEBI had specified the *minimum contract size/value*[47] for trading in derivative securities at Rs.2 lakhs (Rs.0.2 million) and the *minimum lot sizes*[48] of derivatives contracts for different securities/index were derived accordingly.[49]

Particular steps taken by SEBI towards revising the minimum lot sizes for trading in futures contracts between 2005-2015 are detailed as follows. On March 17, 2005, the lot size of futures contract was changed for the first time, and was revised downwards from 200 to 100.[50] This reduction was in the view that there has been increase in the prices of the underlying index, and as a result the contract size/value of the Nifty 50 derivative contract far

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[47] The minimum value of the contract as on a particular day is determined by multiplying the market lot by the closing price of the underlying security on that day.

[48] Lot size refers to the number of underlying securities that has to be delivered under one contract. Market lot is also called contract multiplier.

[49] The lot size is determined keeping in mind the minimum contract size requirement at the time of introduction of derivative contracts on a particular underlying. For example, if shares of XYZ Ltd are quoted at Rs.1000 each and the minimum contract size is Rs.2 lakhs, then the lot size for that particular scrips stands to be 200000/1000 = 200 shares i.e. one contract in XYZ Ltd. covers 200 shares.

[50] Source: NSE Circular, Revision of Market Lot of Derivative Contracts. Circular No.: NSE/F&O/96/2005 dated March 17, 2005.

exceeded the stipulated value of Rs.2 lakhs. Further downward revisions in the market lot of the Nifty 50 futures contract in 2007 and 2014, from 100-to-50 and 50-to-25 respectively, were the similar periodic revisions of the contract size/value by the Exchange based on the prescribed minimum contract value of Rs.200,000.[51] Given the backdrop of concerns around individual investors participation in the equity derivatives markets and high derivatives to cash turnover ratio, on 13th July, 2015, SEBI changed the minimum contract size in the equity derivatives segment from Rs.2 lakhs (Rs.0.2 million) to Rs.5 lakhs (Rs.0.5 million).[52] In pursuance of SEBI's guidelines, the lot size of the Nifty 50 futures contract was revised upwards for the first time, from 25-to-75, since its introduction.[53] Meanwhile, the minimum price step (also called the minimum tick size) remained at Rs. 0.05. The changes made to the specifications of the Nifty 50 futures are detailed in Table 4.1.

In addition to annual subscription fees, trading members are required to pay transaction charges on trades undertaken by them. Till September 2009 the transaction charges payable to the exchange by the trading members for the trades executed on the Futures and Options (F&O) segment were fixed at the rate of 0.002% (Rs. 2 per Rs. 1 lakh) of the traded value on each side, subject to a minimum of Rs. 1 lakh per year. In an effort to reduce transaction cost for the trades in the Futures segment, NSE revised the transaction charges downwards, i.e., from its earlier fixed levels to a slab-based structure with effect from October 1, 2009.[54] As

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[51] Source: NSE Circular(s): Revision of Market Lot of Derivative Contracts. Circular No.: NSE/F&O/010/2007 dated February 6, 2007; and Revision of Market Lot of Derivative Contracts on Indices. Circular No.: 069/2014 dated September 30, 2014.

[52] Source: SEBI Circular, Review of minimum contract size in equity derivatives segment. Circular No.: CIR/MRD/DP/14/2015 dated July 13, 2015.

[53] Source: NSE Circular, Revision of Market Lot of Derivative Contracts on Indices. Circular No.: 071/2015 dated August 07, 2015.

[54] Source: NSE Circular, To the Trading Members in the F&O Segment. Circular No.: NSE/F&A/13029 dated September 07, 2009.

per these revisions, the transaction charges now payable by the trading members in the futures segment is at the rate of Rs. 1.90 (each side) per Rs. 1 lakh of gross trade value up to first Rs. 2500 crores of the traded value in a month (0.0019%), subject to a minimum of Rs. 1 lakh per year. The arguments made by the Exchange for revising the transaction charges downwards were to benefit investors by reducing the overall cost of trading, and also to help in wider participation of investors in the capital market. The maximum brokerage chargeable by a trading member in relation to trades effected in the contracts admitted to dealing on the F&O segment of NSE is fixed at 2.5% of the contract value in case of index futures. Although the maximum brokerage charge remained same, commission rates are negotiable between NSE members and their respective clients, and therefore are less likely to be affected by changes in the contract size of the Nifty 50 futures as detailed in Table 4.1.

National Securities Clearing Corporation Limited (NSCCL) undertakes clearing and settlement of all trades executed on the F&O segment of the NSE. It also acts as legal counterparty to all trades on the F&O segment and guarantees their financial settlement. Since futures trading involve payment of initial margins, the most critical component of a risk containment mechanism for the clearing corporations is the online position monitoring and margining system; and all index futures contracts are subject to margins by the NSCCL viz. mark-to-market settlement and initial margins. Initial margin shall be payable on all open positions of Clearing Members (CM), upto client level i.e. NSCCL collects the requisite margins from CM, who will collect it from Trading Members (TM) who in turn will collect from the client; and shall be payable upfront by CM. In the futures segment two types of initial margins are payable on the upfront basis: SPAN margin and Exposure margin. NSCCL uses the SPAN (Standard Portfolio Analysis of Risk) software for the purpose of margining, which uses scenario-based approach to arrive at margins. As value of futures positions depend on, among others, price of the security in the cash market and volatility of the security in cash market; SPAN margin computations are based on worst scenario, loss of a portfolio of an individual client, to cover 99% Value at Risk (VaR) over a two-day horizon across various scenarios of price changes and volatility shifts. The minimum SPAN margin for index futures contracts is 5% which shall be scaled up by the look ahead period as may be specified by the clearing corporation from time to time. Clearing members are subject to Exposure margins in addition to SPAN margins. Exposure margins in respect of index futures contracts is 3% of the notional value of the futures positions, based on the last available trading price.

A Normal (NRML)[55] trade will require the full margin deposit, i.e. total margin percentage on Nifty 50 futures shall be at least 8% of the contract value. Following the upward revision in 2015 the size of the Nifty 50 futures, the initial margin (Span + Exposure) on the contract remained unchanged at minimum 8% of *contract value*[56], however it is expected that small investors might be forced to shift from trading in the index futures because of the increased contract value, and hence the need for higher margins.

[Table 4.1 about here.]

4.3. LITERATURE REVIEW

The section reviews the theoretical literature and empirical studies by identifying three main areas that explain why the changes in the minimum contract size in the futures market can affect TV, BAS and PV. The first area (4.3.1) assesses the relationship between futures

[55] Futures trading is already a margin product and the margin requirement for a particular contract can vary based on the type of product selected while placing the order. While the core functionality of these product types is standard, every broker calls them with different names. Normal Trade (NRML) or Cash and Carry (CNC) is a standard product type for overnight positions in F&O. Once a position is taken as NRML, it can be held till the expiry of contract provided the requisite NRML margin is present in the trading account. Aside from overnight product type, CNC, different intraday products are also available for NSE equity futures trading, for example MIS (Margin Intraday Squareoff), CO (Cover orders) & BO (Bracket orders) etc.

[56] Contract Value (CV) of the Futures on Nifty 50 Index = Nifty 50 Index Level * Market Lot ; and Initial Margin = 8% of CV.

minimum contract size settings and the equity market events, for example stock splits and MTU changes. The second area (4.3.2) assesses the impact of changes in the contract size on the market quality of futures markets with respect to the available empirical literature. The third area (4.3.3) assesses the prior work on the relationship between TV, BAS and PV and the endogeneity of the three variables.

4.3.1. Minimum Contract Size Settings and Related Equity Market Events

The redesigning of the futures contract size can be achieved by three diverse approaches - (1) by modifying the contract's multiplier, (2) by changing the level of minimum tick size, and/or (3) by introducing a separate mini-contract which is smaller than the original futures contract - with independent consequences for each method.

4.3.1A. Revision in the Minimum Tick Size

The simplest approach for reducing/increasing the size of the futures contract is by modifying (decreasing or increasing) the minimum lot sizes. However, changes in minimum lot sizes have received little coverage in the extant literature as historically there are very few examples of changes in the multiplier. In contrast, the effects of changes in the minimum tick size on market liquidity have been extensively studied. Nearly all the empirical literature (e.g., Ahn, Cao and Choe, 1996; Bacidore, 1997; Porter and Weaver, 1997; Chakravarty, Harris and Wood, 2001; and Ronen and Weaver, 2001) on the effects of reducing the minimum tick size report a decline in the bid-ask spread. Harris (1997) and Kurov and Zabotina (2005) provide review of theoretical arguments for optimal tick size and the empirical evidence concerning the effect of reduction in the minimum tick size.

4.3.1B. Introduction of Mini-Sized Contracts

There are some studies (Tse and Xiang, 2005; Choy and Zhang, 2010; Pavabutr and Chaihetphon, 2010; Tao and Song, 2010; Wang, Chang and Lee, 2013) which shows the impact of contract design on transaction cost (liquidity) and subsequent price discovery by comparing the standard-sized (intended for institutional customers) and mini-sized (designed to appeal retail customers) index futures contracts. Huang and Stoll (1998) argued that reducing the contract size by introducing a separate mini-contract may result in a fragmented liquidity by drawing it away from the original futures market. "Market fragmentation" literature (e.g., Mendelson, 1987; Khan and Baker, 1993; Bessimbinder and Kaufman, 1997; and Davis and Lightfoot, 1998) shows that individual stock trading in multiple markets may result in lower liquidity and higher price volatility in the established markets. While the opposing "competition effect" literature suggests that multiple listings tend to improve mark quality of the regular product with a narrower BAS (Mayhew, 2002; Boehmer and Boehmer, 2003; Tse and Erenburg, 2003) and enhanced depth (Fleming and Ostdiek, 1999).

The literature on the fragmentation and competition effects mainly focuses on the equity markets (i.e., trading the same equity on two or more exchanges) and has been inconclusive. Whereas, in respect to the market fragmentation issue and competing market effects in the future markets there are only few empirical studies. For example, Ates and Wang (2003) examined the effect of introduction of the electronically traded miniature-sized version futures contracts (E-mini S&P 500 and E-mini NASDAQ 100) on the market quality of the original floor-traded large-sized equity index futures markets (S&P 500 and NASDAQ 100). Their empirical results suggest that BAS and TV have not been negatively impacted but PV has increased following the introduction of E-mini equity index futures. They argued from the investor's (of all sizes) point of view, the benefit of E-mini contracts, i.e., lower margin requirements and smaller contract size making the process of investment/adjustment possible in a small and continuous manner, appears to outweigh the high cost of fragmentation (higher PV). On the other hand, Tse and Xiang (2005) find that after the introduction of smaller E-mini energy futures at NYMEX in 2002, TV and OI decline for regular gas contracts but both statistics rise for the regular crude oil contracts. They also show that the market quality for both regular futures contracts improves from competition effects indicated by lower BAS in the post-introduction period. In contrast, Wang, Chung and Yang (2007.b) find that introduction of E-mini index futures contracts for S&P 500 and NASDAQ indices leads to increase in BAS and deterioration of market depth of the standard futures contracts. Their results provide further evidence that market fragmentation effects on the liquidity of regular contracts appears to come from the lower trading cost and ease of trading in the E-mini futures markets, which has been successful in terms of attracting smaller and retail investors'; whereas the regular large-sized contract are now been identified as a wholesale market with larger BAS as natural consequence. In light of above references it can be ascertained that impact of the introduction of E-mini products on the regular futures markets may have multiple effects, however, the overall impact on market quality will depend on the net of fragmentation and competition effects.

4.3.1C. Stock Split and MTU Reduction in Equity Markets

Previous studies (Ates and Wang, 2003; Bjursell et al., 2010) that have examined the issues of contract size changes in the futures contract design have related the phenomenon to be conceptually similar to stock splits. Extant literature has evaluated the impact of stock splits on the number of trades (see, Lamoureux and Poon, 1987; Maloney and Mulherin, 1992; Mukherji, Kim and Walker, 1997; Dyl and Elliott, 2006; and Lin, Singh and Yu, 2009) and shown that stock splits is a worthy tool to realign the per-share trading price to a desired price range for attracting more investors and broadening the investor base. However, many studies questioned the traditional expectation whether the stock splits encourage liquidity provision? In fact, some studies assert that stock splits can increase certain transaction costs such as higher bid-ask spreads, therefore trading liquidity worsens following the splits (see, Conroy, Harris and Benet, 1990; Schultz, 2000; Easley, O'Hara and Saar, 2001; Gray, Smith and Whaley, 2003; and Daadaa, 2014). The downward/upward revision made to the minimum contract size for derivative securities is not directly comparable to stock splits because fundamentally stock splitting is a firm event where decision making is motivated by the prevalent managerial objective to broaden the investor base and increase the number of individual shareholders (Baker and Gallagher, 1980; Baker and Powell, 1993). Unlike the literature which documents that the "number of shareholders/trades" increases following firm's announcement of splitting its shares, there is little evidence that split leads to improve the volume of trade measured by TV (Copeland 1979; Lakonishok and Lev, 1987; Conroy et al., 1990; Cui, Li, Pang and Xie, 2020). In addition, unlike the firm's stock split decision which is interpreted as a purely accounting cosmetic event driven by the management's view (i.e., a governance tool set by the firms to reduce the per-share trading price into a level which widens the ownership base and increase the number of outstanding shares without changing the market capitalization), the market regulator (in case of Indian derivatives) governs the process of revising the market lots of derivatives contracts. Since corporate managers and market regulators have different objective functions, the identical reaction to the changes in both markets i.e., split (reverse split) experience of equity markets and reduction (increase) in the market lot size of futures markets, should not be expected (Bollen et al., 2003). Therefore, as opposed to the firm driven stock split policy, the respecification of Nifty 50 contracts on the NSE dictated by SEBI will create a purely exogenous effect on the market quality (measured by TV, BAS and PV) of the futures contracts.

Other comparable studies from the equity market are perhaps related to MTU[57] or lot size reduction events that enable small investors with limited financial resources to enter the market for a given stock. Two results from the equity market that are relevant to this work are that the reduction in the MTU: (1) greatly expands the firm's investor base of retail shareholders (e.g., Amihud, Mendelson and Uno, 1999; Hauser and Lauterbach, 2003; Ahn, Cai, Hamao and Melvin, 2005; and Isaka and Yoshikawa, 2013, shows that number of individual shareholders tends to increase significantly following the decrease in MTU) and (2) generates improvement in the liquidity (e.g., Gozluklu, Perotti, Rindi and Fredella, 2015, shows that liquidity increases substantially mainly due to the reduction in adverse selection costs after the MTU reduction).

These results from the equity market studies should however be interpreted with caution. Generally the effects of MTU reductions in the equity market, which enable small investors with limited financial resources to enter the market for a given stock, can be seen as consistent to explain the increase in the contract-accessibility (or commercial-participation) for small (or large) investors following the reduction (or increase) in the size of futures contract. However, unlike the MTU changing rules which are typically determined either by the exchange (for e.g., Tel-Aviv Stock Exchange, Korean Exchange, BorsaItaliana[58]) or by firms (for e.g., Japanese companies[59]), the setting of minimum contract sizes in India is mandated by SEBI's regulation, whereas the NSE has very low operational flexibility for

[57] The MTU or lot size for a firm's stock explicitly state the minimum number of shares or minimum monetary value of an order that investors can trade with a single transaction on an exchange. Lot size is an important factor since investors place a buy/sell order in integer multiple units of the MTU; and the reduction in MTU can lower the minimum amount of money needed for buying the shares.

[58] Hauser and Lauterbach, 2003; Ahn, 2014; Gozluklu et al., 2015 report the effect of MTU reductions on Tel-Aviv Stock Exchange (TASE), Korean Exchange (KRX), BorsaItaliana, (BIt) respectively.

[59] Amihud et al., 1999; Ahn et al., 2005; Isaka and Yoshikawa, 2013; Isaka, 2014 report the impact of MTU changes on different Japanese firms. For example, for large and medium-sized firm listed at major exchanges, Tokyo Stock Exchange (TSE) and the Osaka Stock Exchange (OSE); for young, small and high-growth companies listed on other markets such as, Japan Association of Securities Dealers Automated Quotations (JASDAQ), Mothers and Hercules; and for medium- and small-sized local firms listed at regional exchanges, Nagoya, Fukuoka and Sapporo.

designing the specifications of equity derivatives products. The decision to increase the minimum contract size of trading in Nifty 50 futures contract in 2015 was a regulatory-initiated move to reduce retail consumers participation in the equity derivatives market and to create a more balanced participation of uninformed liquidity traders and informed investors. Because of the different professed intentions of the decision makers for undertaking MTU changes and contract size respecification, the effects should not be expected to be the same in both markets. In addition, the improvement in liquidity after MTU reductions may coincide with the decrease in the futures contract size and its effects for enhancing liquidity; but the favourable liquidity effects in the futures market may not be mainly driven by a reduction in the adverse selection cost.

The market microstructure literature identifies key differences in liquidity provision in equity and derivatives markets. While examining the cost of supplying liquidity in the equity markets, theoretical models (developed in Stoll, 1989; Huang and Stoll, 1997) suggested that three costs must be reflected in the bid-ask spread: order processing costs, inventory holding costs, and adverse information costs. Manaster and Mann (1996) showed that neither of these models can provide accurate description of bid-ask spread behaviour in the futures markets. The adverse selection costs arise at the time of registration, when the liquidity providers operate under asymmetric information. In case of individual stocks, it is easy to imagine that some traders are better informed than others. Many papers have attempted to analyze the information source of the spread in a formal model of securities markets: e.g., Copeland and Galai (1983), Glosten and Milgrom (1985), Kyle (1985), Admati and Pfleiderer (1988) and George, Kaul and Nimalendran (1991). For index futures markets however, the relationship between informational uncertainty and bid-ask spreads, if any, is less clear. Subrahmanyam (1991) demonstrated that adverse selection costs in stock index futures markets is expected to be less severe because the diversification benefit reduces the adverse selection problem in the markets for "baskets"[60] of securities relatives to that in the markets for individual securities. Gorton and Pennacchi (1993) show that composite securities (such as stock index futures) which are created by aggregating the cash flows or values of underlying assets, are a superior trading vehicle which reduces the information advantage of the insider (i.e. investors possessing superior information). Furthermore, studies of liquidity cost (Thompson, Eales and Seibold, 1993; Tse, 1999; Tse and Zabotina, 2004) in the futures markets have often ignored the adverse selection component in their analysis because of lower level of information asymmetry in the futures markets.

Tse (1999) argues that the microstructure (i.e. market marking and order flow mechanism) of futures markets is different from that of the securities markets. More specifically, in the stock markets, there is a dedicated market making facility to infuse liquidity in shares (for example in small- and mid-caps) that are not actively or frequently traded. Market makers function under the regulatory framework (e.g., Guidelines from securities market regulator, Bye-laws rules, Regulations of the stock exchange etc.) and have obligations and responsibilities to provide depth and continuity on the concerned stock exchange. In contrast, there are no designated market makers in the futures markets. Participants (i.e. speculators and hedgers) in the futures markets submit marker orders through floor brokers. Active futures markets rely on the presence of floor traders who may trade for their own account and/or from customers (Kuserk and Locke 1993). Silber (1984) classifies floor traders into following three categories: (1) short-term speculators, (or day traders) who trade from their own account; (2) scalpers, who identify themselves as voluntary market makers trading from their proprietary account and tend to avoid brokering; and (3) floor brokers, who execute transactions for customers. Working (1967) provides empirical evidence

[60] Examples of most popular basket of securities in Subrahmanyam (1991) include: S&P 500 index futures contracts, Major Market Index futures contract, NYSE Composite Index contract, and S&P 100 index options.

that floor traders in futures markets often do both scalping and day trading; and tend to hold relatively small open inventory positions. Manaster and Mann (1996) also find strong anecdotal support for the conjecture that floor traders rarely carry positions home overnight. Silber (1984), Brorsen (1989), and Kuserk and Locke (1993) argue that scalpers are essentially self-styled market makers but are under no affirmative obligation from futures exchanges to provide liquidity to market orders.

Manaster and Mann (1996) provide evidence that scalpers are not merely passive order fillers but are active profit-seekers attempting to earn a profit from filling the market orders. Silber (1984) and Kuserk and Locke (1993) indicate that earnings of a market making scalper primarily stem from his quoted bid-ask spread, from frequent trading in small trade sizes, and from his ability to predict intraday price moves. Silber (1984) was first to confirm the significant positive relationship between scalper's profitability and quoted bid-ask spread; and significant negative relationship between profitability and length of time for which a position is held. Consequently, any exogenous factors, such as decrease/increase in the minimum contract size, which influence scalpers to trade more/less frequently will increase/decrease the scalper's earnings, and depending on the scalper's income elasticity will likely result in narrowing/widening of the quoted spread. The results of earlier empirical studies in both equities (Demsetz, 1968; Epps, 1976; Benston and Hangerman, 1974) and derivatives (Berkaman, 1992; George and Longstaff, 1993; Wang, Yau and Baptiste, 1997, Tse 1999) markets are consistent with the expectation that trading activity variables (such as volume, transaction rates, trade order size) have negative relationship with the bid-ask spreads. Therefore, all else being equal, if the decrease (increase) in the minimum contract size increases (decreases) the trading volume then the bid-ask spread is expected to decrease (increase).

4.3.2. Empirical Studies from Futures Markets

The empirical evidence on the effects of the changes in futures contract size on liquidity and market activity variables are mixed. Karagozoglu and Martell (1999) investigated two cases of contract size respecification involving both decrease (with simultaneous increase in the minimum tick size) and increase (with no changes to the minimum tick size) in the size of futures contracts traded at Sydney Futures Exchange. They find that trading volume was higher (lower) following the reduction (increase) in the size of the SPI (BAB) futures contract. The results regarding the impact of the contract size changes on the bid-ask spread were ambiguous. In the case of decrease in the contract's multiplier, market liquidity is enhanced, while increase in the multiplier resulted in a slight reduction in liquidity. Reduction in the liquidity was contrary to the exchange's anticipation of increasing the commercial participation following the increase in BAB futures contract size. Brown (2001) also examined the reduction in the multiplier and simultaneous increase in the minimum tick of the SPI futures contract. Supporting Karagozoglu and Martell (1999), the empirical analysis of Brown's study indicates that volume of trade increases following a change in contract specification. Three empirical studies examine the effect of halving the multiplier and increasing the minimum tick in the S&P 500 futures contract on liquidity and market dynamics variable and surprisingly their results are in stark contrasts. Work by Karagozoglu et al. (2003) provides evidence that trading volume and open interest did not increase by more than twofold. However, they found more participation of trading by the public customers (i.e., investors with smaller amounts of capital) after the redesigning of the S&P 500 futures. They also report that bid-ask spreads decline temporarily but no significant changes were observed in the volatility following contract modification. For the similar S&P 500 futures contract redesign effects, Bollen et al. (2003) find that trading volume declined significantly, demand from small investors remained unchanged and the bid-ask spread increased. Chen and Locke

(2004) also investigated the consequence of the same respecification of the S&P 500 futures contract. Instead of looking at total volume, they identified two different measures of revenue generation such as internal proprietary volume and outside customer volume. Their results indicate no significant change in the level of customer volume but significant increase in the effective bid-ask spread. In contrast to the results in Bollen et al. (2003) and Chen and Locke (2004), the results in Nordén (2006) for the OMX index futures contract find evidence that bid-ask spread remains unaffected following a reduction in the contract size. However, the results of increased trading volume, after the contract size was reduced by as factor of 4, is consistent with the idea in Karagozoglu and Martell (1999) that decrease in size of futures contract results in enhanced trading activity. Bjursell et al. (2010) examine the relationship between price volatility and trading activity (measured by average trade size and total trading frequency) following change in the size of three futures contracts, SPI futures, BAB futures and FTSE-100 index futures. They report that a decrease (increase) in the contract size increases (decreases) trading frequency and daily price volatility. Finally, Athanasios and Nikolas (2017) examine Greek futures contract (ATHEX) for reduction in contract multiplier and provides evidence of significant decrease in bid-ask spread. However, trading volume remains unaffected after the redesign event.

These contradictory results in the empirical studies are likely arising because, firstly there is a difference in the variable measurement methods, i.e. authors have used different measures to account for trading activity (e.g. trading volume, total dollar trading volume, customer volume, total trading frequency) and transaction costs (e.g. Smith and Whaley, 1994; Bhattacharya, 1983 estimators; aggregate effective bid-ask spread) in their model; secondly, existing literature which captures the effect of changes in the contract multiplier on TV, BAS, and PV, employ different control variables in their regression models. Model specification however, is generally incomplete in these studies because they did not include either the measures of transaction cost, price volatility and/or other explanatory variable(s) in their model. For example, trading volume is assumed to be a function of: intra-day price volatility and futures price level only (in Karagozoglu and Martell,1999); volatility and an indicator variable to capture for the effects pre- and post- contract redesign periods (in Bollen et al., 2003); and volatility and period dummy variables (in Chen and Locke, 2004).

4.3.3. Relation between TV, BAS and PV

Bjursell et al. (2010) while investigating the behaviour of price volatility before and after the change in the contract size, did not take the liquidity effect into the account. Karagozoglu et al. (2003) on the other hand, examined the effect of change in futures contract size by using two-equation simultaneous structural model between TV and BAS. However, their model ignored the economic relationship between volume and volatility (e.g., furnished by Foster, 1995) and bid-ask spreads and price volatility (e.g., provided by Wang, Michalski, Jordan and Moriarty, 1994). Literature from equity markets related to MTU reduction and stock split shows contradictory effects of two events on the price volatility. For example, Hauser and Lauterbach (2003) and Ahn (2014) have documented that volatility or firm-specific price noisiness declines significantly following the MTU reduction. Whereas previous studies on stock splits (Ohlson and Penman, 1985; Dravid, 1987; Dubofsky, 1991) have provided evidence that volatility of stock returns increases significantly after the split.

One of the common features of the futures contract size related studies is the assumption that three market activity variables - TV, BAS and PV- were either considered exogenous to each other, or their model specification did not account for all the three variables. Wang and Yau (2000) however, by using Hausman's (1978) specification error test, confirmed that TV, BAS and PV are jointly determined. In addition, the empirical studies related to futures markets (Karagozoglu and Martell, 1999; Karagozoglu et al., 2003; Bollen et al., 2003; Chen and Locke, 2004; Bjursell et al., 2010) have examined the cases for contract respecification involving both factors: a contract multiplier and a tick size change. The combination of a decrease (increase) in minimum contract size specification and increase (decrease) in minimum allowed price fluctuations may have offsetting effects on the liquidity and market dynamics variables and also may offer conflicting results. To the best of one's knowledge, there is no prior work on the joint examination of TV, BAS and PV in the simultaneous equation system, before and after the changes in the contract size in the futures market literature.

In the case of Nifty 50 index futures, the minimum lot size was revised four times since the time of inception. The contract multiplier was halved three times (200-100-50-25) and was tripled (25-75) in size in its last revision. The minimum tick size remained unchanged throughout all periods of revisions in the market lot sizes.[61] Therefore, this paper has utilized a clean natural experiment afforded by the contract modification which involves changes only to the contract's multiplier for examining the relationship between three market quality measures pre- and post-minimum lot size changes. Furthermore, these events provide unique opportunity to examine the effects of a decrease and subsequent increase in the minimum contract size in the context of its uses in particular futures markets. The methodology used in the empirical tests can be used by researchers, international futures exchanges and global regulators to assess the impact of setting the minimum contract size on three variables, namely, TV, BAS and PV, which are found to be jointly determined.

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[61] There are two important elements of contract design for index futures contracts, one is minimum market lot size and another is minimum tick size. The minimum lot sizes determine the monetary value of the contract (i.e., the minimum amount that can be traded on the Exchange), whereby the minimum tick size sets the lower bound for the bid-ask spread (i.e., minimum allowable bid and ask quotes). The reduction (increment) in the contract lot size reduces (increases) the monetary value of the contract (that is, the index value times the market lot size). The smaller (larger) contract value thus may encourage (deter) small investors from entry to the market. The result of the larger (smaller) minimum tick sizes however has more direct effect of increasing (decreasing) the cost of transacting (i.e., bid-ask spread). The increase (decrease) in the minimum tick sizes thus may drive-away (encourage) customers/market-makers. The value of minimum tick (that is, the minimum tick size times the minimum lot size) on the other hand implies that the single move in the index value would cause a resultant gain or loss equal to the monetary values of minimum tick. Therefore, all else being equal a decrease (increase) in the minimum lot size decreases (increases) the monetary value of minimum tick.

4.4. ESTIMATION METHODOLOGY & VARIABLE MEASUREMENT

4.4.1. Empirical Model Specification

To examine the relationship between TV, BAS and PV before and after the changes in the minimum lot sizes in the Nifty 50 Index futures contract, this paper will resort to the following three-equation structural model framework as suggested in Wang and Yau (2000).

A three-equation simultaneous framework is proposed for two reasons. First, univariate analysis investigates the effect of contract size changes on individual market quality variables. However, trading activity, liquidity and proxy of price risk cannot be modelled independent of one another. Moreover, Wang and Yau (2000) argue that futures TV, BAS and PV are jointly determined and thus should be treated as endogenous variables in an empirical analysis. Accordingly, multivariate analysis is used to test the impact of the contract size respecification using structural model framework. Second, due to potential endogeneity bias, the estimation by ordinary least square (OLS) procedure would yield inconsistent coefficients. The three-equation model estimated by the GMM procedure more carefully addresses the potential endogeneity bias in a simultaneous-equation framework and allows consistent estimates.

$$TV_t = \beta_0 + \beta_1 BAS_t + \beta_2 PV_t + \beta_3 \Delta 3MIBOR_t + \beta_4 OI_{t-1} + \beta_5 TV_{t-1} + e_{1t} \quad (4.1)$$

$$BAS_t = \alpha_0 + \alpha_1 TV_t + \alpha_2 PV_t + \alpha_3 \Delta SP_t + \alpha_4 BAS_{t-1} + e_{2t} \quad (4.2)$$

$$PV_t = \delta_0 + \delta_1 TV_t + \delta_2 BAS_t + \delta_3 TV_{t-1} + \delta_4 PV_{t-1} + e_{3t} \quad (4.3)$$

where TV_t is the trading volume of the contract on the t_{th} day; TV_{t-1} is TV_t lagged 1 day. In the case of decrease (increase) in the contract's multiplier, TV is expected to increase (decrease) if the investor base has broadened (narrowed) following the contract respecification as a result of changes in the level of participations from retail traders and/or institutional investors.

The implicit BAS of the Nifty 50 futures contracts is not directly observable but is estimated by using two alternative liquidity cost measures, illiquidity ratio (Amihud, 2002) and turnover-based Amihud measure (Brennan et al., 2013). Methodology for the estimation of BAS (by using proxies for price impact) will be discussed in section 4.4.3. BAS_t is the BASs of the contract on the t_{th} day; BAS_{t-1} is BAS_t lagged 1 day. If the reduction (increase) in the size of the Nifty 50 index futures contracts attracts increased (decreased) TV, then the liquidity is expected to increase (decrease); and the enhanced (diminished) liquidity would be reflected in lower (higher) BAS.

PV_t is the daily price volatility of the contract on the t_{th} day; PV_{t-1} is PV_t lagged 1 day. PV is measured by daily price range.[62] Since the source of change in PV depends upon two relationships between: (a) PV and the information component (TV), and (b) PV and the liquidity component (BAS); the impact of change in the size of a futures contract on PV will depend on the net of both the information and liquidity effects. Illustratively, if a contract size decrease results in the increased TV, then PV is expected to increase and vice versa. Furthermore, if a contract size decrease (increase) results in decline (rise) in the BAS, a reduction (increase) in PV is also expected. Therefore, the net impact of a change in the minimum contract size on PV could be increasing or decreasing depending on the relative magnitude and interaction of the change in information and liquidity components.

Turning to the control variables in the model, Wang and Yau (2000) employed intraday 3-month T-bill (TB) data as the risk-free rate (RF). The Government of India (GOI) does not

[62] The price risk, PV (or transaction price volatility) is measured by the daily price range, i.e., $FP_H - FP_L$, where FP_H and FP_L represents future's highest and lowest prices of the day.

issue treasury bills regularly as is the case in the United States; GOI issues 91-day T-bills every Wednesday i.e. for weekly frequency. Following Chou and Wang (2006), Nordén (2009) and Chou, Wang and Wang (2015.b)[63] RF_t is proxied by using alternative short-term risk-free benchmark rates from the Indian market, 3-month term MIBOR rates. OI_{t-1} is the open interest of the contract on the t_{th} day lagged 1 day. In terms of examining the effects of changes in the contract size, OI is expected to increase (decrease) if the TV in the futures market is driven by hedging (speculative) needs. SP_t, is the 'Settlement Price'[64] of the futures contract on the t_{th} day. Finally, e_{1t}, e_{2t}, and e_{3t} are the random error terms of Equations (4.1), (4.2) and (4.3), respectively.

4.4.2. Determinants of TV, BAS and PV

This section reviews the determinants of TV, BAS and PV in the futures markets in a three-equation structural model framework. The three empirical models in Equations (4.1) - (4.3) and control for other important factors that are likely to influence trading activity, liquidity, and price volatility are drawn from the existing literature (Wang and Yau, 2000; Chou and Wang, 2006; Wang, Chung and Yang, 2007.a; Nordén, 2009; Bjursell, Wang and Yau, 2012; Martinez, Gupta, Tse and Kittiakarasakun, 2011; Wang, Garcia and Irwin, 2014).

Equation (4.1) includes major determinants of TV in the futures markets as identified by Martell and Wolf (1987) along with a measure of transaction costs as an additional explanatory variable. Martell and Wolf (1987) argues that both speculators and hedgers affect the volume of trade in futures markets. Following this assumption of the trading agents,

[63] Many alternatives for risk-free rates have been used in the empirical studies. Nordén (2009) employed one-month Stockholm Interbank Rate (STIBOR) as a proxy for the risk-free rate of interest while estimating the simultaneous three-equation structural model. Chou and Wang (2005) and Chou et al. (2015.b), on the other hand proxied the risk-free interest rate by the average of the 3-month Certificate of Deposit rates of the three largest banks in Taiwan.

[64] Daily Settlement Price at NSE for Index Futures Contracts is the closing price of the futures contracts on the trading day. Closing price for a futures contract is calculated on the basis of the last half an hour weighted average price of such contract.

surrogates are used in Wang and Yau (2000) to determine the two sources of volume: the "first" one, TV, is for the speculators (the change in the reservation price), and the "second" one, the information set which includes 3MIBOR and OI, is for the hedgers (the change in the expected physical position).

Based on the theoretical model of mixture-of-distributions hypothesis (Clark, 1973), a positive contemporaneous relationship between TV and PV (e.g., Cornell, 1981; and Tauchen and Pitts, 1983) is expected in response to new information arrivals (Harris, 1987). Since speculators readjust their reservation price by observing price volatilities, the PV is expected to be positively related to TV. In Eq. (4.1) two proxies in the information set includes variable that may affect the decisions of hedgers. The intuition behind the two specific components of an information set is that hedgers adjust their expectations based on the long-term futures positions (OI) and the opportunity cost of holding the inventory (3MIBOR). Generally, the higher daily open interest than the volume suggests more flow of hedging activity to the market and provides an indication that more trades will occur in the future. In general, the higher short-term interest rate will cause decline in the hedging requirement due to increased carrying cost in the spot assets. Moreover, higher interest rates can also reduce speculative trading by making alternative investments more attractive. Therefore, consistent with the findings of Wang and Yau (2000), OI is expected to have positive impact on TV, while the 3MIBOR is expected to be inversely related to TV.

Wang et al. (1997) provide anecdotal evidence that transaction costs in futures markets impact the trading volume adversely. Huang and Stoll (1998) suggest that modification in the size futures contract will have implications for the costs of trading. In principle, there are two basic components of transacting in the futures markets: (a) the price of liquidity i.e., bid-ask spreads, and (b) production costs, which includes exchange fees, floor brokerage rates and customer commissions (Tinic, 1972; Huang and Stoll, 1998). In the case of Nifty 50 futures, NSE made revisions to the minimum lot sizes while both the minimum tick size and production costs remained unchanged. Therefore, BAS represents the variable component of the transaction costs since other costs are fixed over the period of this study. A decrease in the contract lot sizes is likely to result in increase of the number of trades. This will raise the total cost of processing the trades because a higher number of small trades will take place. Consequently, customers' total transaction costs would increase even if the customer commissions and floor brokerage fees may choose to respond to the competitive pressures because the exchange transaction charges are assessed on the basis of per contract on each side of the trade. Furthermore, higher execution costs will decrease trading profitability and will cause market participants to search for an alternative trading vehicle with lower transaction costs; all of this will lead to the widening of BAS and decrease in TV. As a result, TV is expected to be negatively related to the magnitude of BAS.

Equation (4.2) includes major determinants i.e., contemporaneous TV and PV, and other controls variables which affects the liquidity measure. SP takes into account that futures contracts with different maturities i.e., the nearby and the first deferred contracts are used. The daily settlement price of the futures contract is employed to control the effect of differing measurement scale for the same contract with different price levels.

Consistent with microstructure models (Ho and Stoll, 1983; Copeland and Galai, 1983), which examines the variations in bid-ask spreads, it is expected that increase in volume will reduce BAS. The line of thought from the inventory models, for example Ho and Stoll (1983), suggest that the spreads are affected by the degree of competition among dealers in market making. Therefore, if the decrease in the contract size increases the trading volume, then the market makers have the opportunity to offset the risk of holding the unwanted inventories. The NSE operates as a competitive dealer market with multiple market makers. It is expected that futures market makers on NSE will face competition and recognize their welfare depending on the actions of other dealers in setting their bid-ask prices and will set/adjust the BAS to attract orders; and hence, BAS will decrease. Second line of thought from the information models, for example Copeland and Galai (1983), assume that economic agents (or dealers), who are making the market for a limited set of securities, are faced by two different types of trader, informed and liquidity traders. These models also predict that lower spreads are associated with higher volume, given the dealer's objective to maximizing his profit by establishing an 'optimal bid-ask spread', which is a trade-off between expected gains from uninformed liquidity traders and expected losses from informed traders. Hence, negative relationship is expected between BAS and TV in Eq. (4.2).

The BAS Equation (4.2) includes transaction price volatility (PV) as a proxy for the price risk perceived by the market makers. Previous work by Benston and Hagerman (1974) and Stoll (1978) suggests a positive relation between per unit cost of immediacy (i.e., BAS) and price risk (i.e., PV), with the manifestations of two risk influences, inventory holding risk and insider information risk. Benston and Hagerman (1974) included both inventory and information effects, since the two are not mutually exclusive in their measure of risk. Stoll (1978) found that the market makers are exposed to two price risk components, systematic and unsystematic risk; however, the empirical findings of this study suggested that unsystematic risk has relatively large and significant positive effect on the spreads. With Wang et al. (1994) and the body of theory concerning determinants of liquidity costs as a basis, the proxy for price risk (PV) is expected to have positive impact on the BAS, because market makers are affected by both the components of unsystematic risk (holding and insider). First, the holding risk is associated with insufficient diversification. The market maker may bear the unsystematic risk component of the holding risk, if they have not adequately diversified their portfolios of assets. Second, the unsystematic risk component, which is associated with the insider risk, is related to the cost of trading with the insiders. A large price change may be a consequence of inside activity, will increase the dealers' costs and hence is likely to affect the per trade spread cost. Therefore, in order to stay in the business, Bagehot (1971) points that, market makers must increase the bid-ask spreads to compensate for their losses of trading with the information-motivated traders and to exceed their earnings from the liquidity-motivated transactors.

In Equation (4.3), the daily price volatility measure (PV) is specified as a function of contemporaneous trading volume, bid-ask spread and lagged trading volume. As indicated above, volume and volatility in future markets should be positively related (e.g., Foster, 1995; Bessembinder and Seguin, 1993; and Daigler and Wiley, 1999), and a wider BAS will allow for larger effects on the future's price variability (e.g., Wang et al., 1994; Wang et al., 1997; Wang and Yau, 2000; and Chou and Wang, 2006).

Futures trading volume is known to get affected by the changes in the contract size.[65] Blume, Easley and O'Hara (1994) suggest that change in the TV (low or high) is an indication of new information content as well as the quality of information (i.e., the precision of signal distribution) which dictates the trading volume. Hence, changes in TV after the revisions (downward or upward) in minimum lot sizes of the futures contract may lead to the possibility of increased price fluctuations, thus creating greater PV. Similarly, studies have documented that greater (reduced) liquidity (i.e., lower/higher bid-ask spreads) is associated with a smaller (larger) contract size (Karagozoglu and Martell, 1999; Karagozoglu et al., 2003). Huang and Stoll (1998) proposed smooth trading hypothesis which predicts that decreasing the size of futures contract will enable smaller investors to enter the market, thereby providing increased liquidity which is then expected to smooth out price fluctuations i.e., decrease price volatility. Therefore, when the BAS narrows (widens) following the changes in the size of a futures contract, it may be attributable to orders from small speculative traders that enter (leave) the

[65] For further discussion, refer to studies such as Karagozoglu and Martell, 1999; Bollen et al., 2003; and Bjursell et al., 2010.

market after the contract respecification, which can affect the market liquidity favourably (unfavourably), eventually leading to smoothening (increasing) of transaction price fluctuations due to the small (large) variations in the BAS.

Based on Foster's (1995) findings that lagged volume is also significant in explaining current price volatility, the trading volume lagged one period is also incorporated in Eq. (4.3), since lagged TV may represent the effects of private information signals coming to the markets (Blume et al., 1994). Consistent with previous research (Wang and Yau, 2000; Ates and Wang, 2003; Wang, Garcia and Irwin, 2014; Chou, Wang and Wang, 2015.a), lagged TV is expected to have negative impact on PV, conditioned on the positive relationship between contemporaneous TV and PV, since traders may overreact to changes in information (i.e., increase in the day trading volume).

In addition, the dynamic three-equation model also includes one-period lagged explanatory variables (i.e., TV_{t-1}, BAS_{t-1}, PV_{t-1}) in Equations (4.1), (4.2), and (4.3) in the context of a partial adjustment to the model. These one-period lagged explanatory variables in each equation accommodate for the distributed lag effects or persistence in the dependent endogenous variables.

4.4.3. Measure of Liquidity: Transaction Costs (BAS)

Wang et al. (1997), and Wang and Yau (2000) both have examined the relationship between trading volume and liquidity (i.e., trading cost). These studies measured liquidity by estimating the "realized" bid-ask spread as a major variable component of the transaction costs. Hung and Stoll (1998) provide evidence for various other components of transaction costs in the futures markets, such as exchange fees, floor brokerage rates and customer commissions, for executing the trades. In the case of Nifty 50 futures, the NSE increased the contract size by increasing only the multiplier while the minimum tick size and other components of transaction costs, for example exchange fees, transaction charges, maximum brokerage charges and Securities Transaction Tax (STT)[66], remained unchanged.[67,68] Given that these other fixed fee components of the trading cost are stable, a liquidity proxy for capturing the variable cost component need to be estimated first before the model estimation.

According to Kyle (1985), the level of market liquidity can be examined across its various dimensions, such as: tightness (e.g. cost measures), depth (e.g. quantity/volume based measures) and resilience (e.g. in terms of time-frame). Not surprisingly, researchers have proposed a variety of trading-based variables to capture these liquidity characteristics either separately or jointly. Ahn, Cai and Yang (2018) have classified some common cost dimension measures into two categories: as "spreads-related"[69] and "price-impact"[70] measures (which includes benchmarks and proxies from two groups). Neither of the measures among these groups can provide a comprehensive insight into the different aspects of trading costs. Liquidity measures in both categories capture either the actual transaction costs or the

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[66] STT was introduced in the Finance Act 2004. It is applicable on all sell transactions for futures contracts and is determined at the end of each trading day. For the purpose of STT calculation, each futures trade is valued at the actual traded price. The prescribed STT rate is payable by the seller. Source: NSE Circular, Securities Transaction Tax. Circular No.: NSE/F&O/0062/2004 dated September 24, 2004.

[67] NSE did not reduce the exchange transaction fees in conjunction with its decision to increase the Nifty 50 futures contract size in August, 2015. Transaction charges in the futures segment till September 2009 were fixed at the rate of 0.002%. From October 1, 2009 onwards, transaction charges were payable according to the slab-based structure, subject to a minimum fixed rate of 0.0019%.

[68] The rate of levy of STT on the sale of futures in securities has remained unchanged since May 24, 2013, at 0.010%. However, there have been three changes in the rates of STT since its adoption by the Exchange. STT rate on the sale of futures has been revised from 0.010% to 0.0133% to 0.017% to finally 0.010% again, in 2005, 2006 and 2013 respectively. Source: NSE Circular(s).: Change of rates of Securities Transaction Tax. Circular No.: NSE/F&A/6165 dated May 20, 2005; Change of rate of Securities Transaction Tax. Circular No: NSE/F&A/7527 dated May 26, 2006; and Changes in relation to Securities Transaction Tax. Circular No.: NSE/FATAX/23500 dated May 24, 2013.

[69] Some examples of the spread-related 'benchmarks' (based on intraday data) and 'proxies' (based on daily data) used in Hasbrouck (2005), Goyenko, Holden and Trzcinka(2009) and Ahn et al. (2018) are: (a) the absolute/quoted, effective and realized spread; and (b) Roll spread, Gibbs estimate and LOT measure.

[70] Some examples of price-impact 'benchmarks' (based on intraday data) and 'proxies' (based on daily data) used in Hasbrouck (2005) and Goyenko et al. (2009) are: (a) Hasbrouck lambda coefficient, Goyenko five-minute price-impact and Huang and Stoll adverse selection costs; and (b) Amihud illiquidity, Amivest liquidity and Pástor and Stambaugh gamma measure.

marginal cost of trading per dollar volume (Fong, Holden and Trzcinka, 2017; Bohmann, Michayluk, Patel and Walsh, 2019). Empirical studies which have analyzed the economic relationship between liquidity costs, trading volumes and price variability in a system of two or three dynamic structural equations, have commonly employed bid-ask spread estimators for measuring the trading costs in the futures markets. Because NSE does not publicly provide the bid-ask spreads quote data for the index futures contracts, quoted spreads cannot be computed even at the daily frequency. Authors in the similar studies of futures markets have used different approaches to estimate the "effective" bid-ask spreads (suggested in Bhattacharya, 1983; Roll, 1984; Thompson and Waller, 1988; Smith and Whaley, 1994; and Wang et al., 1994, 1997) to impute transaction costs from the intraday price data. However, there is no availability of tick-by-tick dataset from NSE[71]; the futures exchange supplements only daily price and volume dataset for the Nifty 50 index futures contracts. It has been well documented in Tse and Zabotina (2004), Anand and Karagozoglu (2006), and Frank and Garcia (2011), that all four moment-based[72] bid-ask spread estimator (Bhattacharya, Thompson and Waller, Smith and Whaley, Wang, Michalski, Jordan and Moriarty/Wang, Yau and Baptiste) rely on high-frequency (intraday) trade data recorded in the futures markets. Unlike others, Roll's estimator is based on the negative autocovariance in consecutive close-to-close price returns (Abdi and Ranaldo, 2017); and the measure can also be applied to low-frequency (daily) data. One of the criticism of Roll's methods however has been that it's restrictive assumption of negative serial correlation in price changes is often violated because

[71] Another limitation of the dataset used in this study is that along with the unavailability of intraday trading records, an account-level data set from the NSE is also not accessible. The advantage of account-level data is that it enables to trace the trading records of each account type (e.g., day traders, proprietary firms, domestic institutions, and foreign institutions) and can clearly identify the trading activity for each trader type. This study however, due to data constraints, could not explore the effects on lot size changes on the trading activity for each type of trader and therefore cannot link them to market liquidity and price volatility.

[72] Moments-based estimators are primarily based on either: the mean absolute price change (Thompson and Waller, 1988), or the first two moments (mean and variance) of absolute price change (Smith and Whaley, 1994), or the mean of price changes that are price reversals (Bhattacharya, 1983), or the mean absolute values of price change that are price reversal computed after excluding the subset of price change that exhibit price continuity (Wang et al., 1994; Wang et al., 1997).

futures price data frequently produces positive values (Smith and Whaley, 1994). Another reason argued in Locke and Venkatesh (1997) for avoiding the application of spread estimators based on price changes in the futures markets is due to the low correlation of these estimators with the actual transaction costs. Furthermore, their study compared the performance of Roll's and Smith and Whaley's estimator and finds that the former estimator tends to underestimate the true transaction cost while the latter overestimates it.

Given that the data is constrained by the absence of recorded bid-ask quotes and high-frequency price data and also due to the applicability issues of Roll's covariance estimator in the context of futures markets, Amihud (2002) illiquidity ratio is used (in lieu of spread proxies) to measure the variable component of transaction costs. Both the "traditional" and "decomposed" versions of Amihud (2002) measure from the daily data are used to measure the transaction cost in the present study. The construction of the two liquidity cost measures is discussed in the next section.

4.4.3A. Traditional Amihud Measure

Amihud's illiquidity ratio is a price-impact measure rather than a spread proxy. The spread-related measures represent the transaction cost faced by the trader in executing a single order of small size, while the price-impact liquidity proxies on the other hand represents the marginal transaction costs associated with the dynamic strategies of a large trade (Fujimoto, 2004; Hasbrouck, 2005; Fong et al., 2017). The Amihud ratio focuses on the absolute daily price change associated with one unit currency of trading volume. The Amihud measure is particularly well suited for this study because the ratio requires only daily trading data; also in comparison to other low-frequency liquidity measures, it has the largest correlation with the liquidity benchmarks constructed from high-frequency data (Goyenko et al., 2009; Marshall, Nguyen and Visaltanachoti, 2012); and it is the best daily "cost-per-dollar-volume" liquidity proxy for global research[73] (Fong et al., 2017). Hence, Amihud's ratio is calculated using the daily price and volume data sourced from NSE. Illiquidity measure for the equity index futures contract i on day t.[74] is defined as:

$$Amihud_{i,t} \quad = \quad \frac{|r_{i,t}|}{V_{i,t}} \tag{4.4}$$

where $r_{i,t}$ is the daily absolute return of the futures contract$i$ on day t; $V_{i,t}$ is the futures trading volume on day t, in units of currency, which in this case is Indian Rupee (INR). To compute the denominator of Eq. (4.4), i.e. INR trading volume, the daily volume of each contract at day t $(vol_{i,t})$ is multiplied by the futures settlement price at day t $(sp_{i,t})$ quoted in INR. The daily Amihud measure is computed for both the nearby and the first deferred contract of index futures.

Initially this thesis chapter has used the Amihud (2002) ratio as a measure of illiquidity (to capture the variable component of transaction costs) in the Nifty 50 index futures market. Even though Amihud's ratio does not exactly measure transaction costs, it is still very useful and convenient as compared to traditional measures of transaction costs, such as the bid-ask spread (Amihud and Mendelson, 1986). Bid-ask spreads obtained at a daily frequency may be uninformative because they are noisy and they usually refer to end-of-day transactions. In particular, Peterson and Fialkowski (1994) show that the quoted spread is a poor proxy for

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[73] Fong et al. (2017) analysed the liquidity proxy performance in both developed and emerging countries. Their sample covers 42 exchanges in 36 countries over 19 years period.

[74] The Amihud measure can be used to compute weekly, monthly, quarterly or yearly illiquidity proxy for the futures contract by averaging the daily illiquidity measure. Similarly this measure by using high-frequency data can also be used to calculate the daily proxy which is average of the intraday measure. Since high-frequency trading data is unavailable from NSE, the daily Amihud ratio is calculated using the formula in Equation (4). Previous studies, see for example the evidence in Wang (2010), Marshall, Nguyen and Visaltanachoti (2012; 2013), Daskalaki, Kostakis and Skiadopoulos (2014), Li (2017), Nguyen and Do (2019) and Benos, Payne and Vasios (2020) among others, have constructed the low-frequency price impact ratio in a similar manner by using the daily close-to-close data.

actual transaction costs. Moreover, closing price bid-ask spreads may be more easily manipulated by market makers, rendering them uninformative.

Despite its insightfulness, Amihud's ratio does not come without its shortcomings. A concern with the seminal Amihud (2002) measure of illiquidity is that it can be distorted by size, i.e., this raw illiquidity measure cannot separate illiquidity from the size effects (Cochrane, 2005; Florackis, Gregoriou, and Kostakis, 2011). In the stock market, the traditional Amihud ratio builds in a size effect because trading volume in monetary terms is positively correlated with firm size (measured by market value of equity); as a result the size of the asset may influence the ratio and it is not possible to compare the liquidity measure across stocks with different market capitalization. With regard to the size effect in the futures returns, the shortcoming of traditional Amihud measure is of particular concern for this study given the high pace of growth in the market size of Nifty 50 index futures over the period 2000-2015 following 3 consecutive downward revisions in the minimum lot sizes (i.e. from 200-100-50-25.

Florackis et al. (2011) and Brennan et al. (2013) propose a solution to this problem. Florackis et al. (2011) use stock turnover rather than dollar volume when calculating illiquidity, while Brennan et al. (2013) decompose the Amihud measure into two components: absolute returns earned per unit of turnover (which is a turnover version of the Amihud measure), and firm size measured by market value of equity, i.e., number of ordinary shares outstanding multiplied by the price per share (which is the size-related element).

Given that the TV and BAS in the simultaneous equation model are incorporated to capture different dimensions of futures market activity, it is more appropriate to consider the decomposition of the Amihud measure (i.e., the turnover version of the ratio) and remove the contract size effect from the traditional illiquidity measure, because it allows to account for illiquidity effects in the absence of potential size biases (Brennan et al., 2013). Therefore, the

TV equation of the empirical model is re-estimated by replacing the original Amihud measure with turnover-based Amihud measure, to remove the effect of lot size factor from the illiquidity measure.

4.4.3B. Turnover-based Amihud Measure

Given the concern that the Amihud measure can be distorted by size, Brennan et al. (2013) recommend the use of a turnover-based version of the Amihud measure, which is denoted as *Amihud^T*. The turnover-based Amihud measure comes from decomposing the original Amihud measure (represented as *Amihud^O*) as follows (Brennan et al., 2013):

$$Amihud^O = \frac{|r|}{DVOL} = \frac{|r|}{turnover} \times \frac{turnover}{DVOL} \tag{4.5}$$

$$= \frac{|r|}{\left(\frac{sharestraded}{sharesoustanding}\right)} \times \frac{\left(\frac{sharestraded}{sharesoustanding}\right)}{(sharestraded\ X\ pricepershare)} \tag{4.6}$$

$$= \frac{|r|}{turnover} \times \frac{1}{(marketsize)} \tag{4.7}$$

$$= Amihud^T \times \frac{1}{(marketsize)} \tag{4.8}$$

Taking natural logarithms on both sides of Equation (4.8), the original Amihud measure, *Amihud^O*, is related to the turnover version, *Amihud^T*, and market capitalization, size, by:

$$ln(Amihud^O) = ln(Amihud^T) - ln(marketsize) \tag{4.9}$$

Brennan et al. (2013) originally proposed this decomposition for stocks; a futures market equivalent for the number of shares outstanding is therefore needed to replicate this decomposition for Nifty 50 index futures market. Recently, Cho, Ganepola and Garrett (2019) suggested that open interest by definition is the total number of outstanding contracts available in the futures market and therefore serves as a measure of the futures market equivalent of the number of shares outstanding. Following Cho et al. (2019) the measures of turnover and size that is used for the Nifty 50 index futures market are defined as:

$$Turnover \ = \ \frac{Numberoftradedfuturescontracts\ (i.e.\ TradingVolume)}{OpenInterest} \qquad (4.10)$$

$$MarketSize = \ Open\ Interest\ \times\ Contract\ Lot\ Size\ \times$$
$$Futures\ Settlement\ Price \qquad (4.11)$$

While comparing the $Amihud^T$ measure to $Amihud^O$, the ratio essentially replaces trading volume with turnover ratio in the denominator. $Amihud^T$ has a similar intuitive interpretation showing how much the futures price responds to one percent of turnover rate. The proposed new price impact ratio not only inherits the conceptual advantages of Amihud's ratio, but it is also free of any size bias because there is no mechanical reason why futures contracts, before or after contract re-specification, should exhibit higher turnover ratios (Florackis et al., 2011). Specifically, it is more appropriate in futures market research for studying the effects of contract size modifications and it enables this study to disentangle the price impact from the market size effects, which are possibly emerging due the decrease (increase) made in the contract's multiplier.

4.5. DATA SOURCE & CONTINUOUS SERIES CONSTRUCTION

4.5.1. Data for Nifty 50 Index Futures Contracts

The data set for this study is directly downloaded from the NSE web page. The sample adopted for this study comprises of all Nifty 50 stock index futures contracts from the inception, traded on the NSE between June 12, 2000 to November 11, 2018. The daily closing data include high and low transaction price, settlement price of futures, trading volume and open interest for the nearby and first distant contract maturities; where trading volume represents the number of contracts traded during a day and open interest is the number of contracts outstanding at the end of each trading day. The Nifty 50 index futures contracts at NSE are settled in cash INR. The nearby and the first deferred contract is used in this analysis essentially because they are the two most actively traded futures contracts (illustrated in Appendix A) on the Nifty 50, in terms of both trading volume and open interest.

4.5.2. Data for Risk-free Rate

Since the periodicity of Government of India (GOI) 91-day T-bills data is of a weekly frequency, the Mumbai Interbank Offer Rate (MIBOR) is used as a proxy for the risk-free rate of interest in the daily sampling of data. MIBOR rates are available for maturity periods of 1-day (overnight), 14-days, 1-month and 3-months, on a daily basis. Following Nordén (2009) and the other empirical studies that employ different measures of 3-month short-term rates as a proxy, 3-month MIBOR is assumed to be a substitute for the risk-free rate of return.

The administration, computation and distribution of MIBOR rates have been revised several times over the concerned sample period. Hence the data set for 3-month MIBOR is collected from a variety of involved organisations. The NSE launched the 3-month MIBOR on December 1, 1998. The same was rechristened as FIMMDA-NSE MIBOR rate in due course.[75]

Since June 2000, the 3-month FIMMDA-NSE MIBOR rates on daily basis are obtained from the debt market segment of the NSE website till September 22, 2015. Following a change in methodology and administration of Term MIBORs in 2015, NSE has stopped publishing FIMMDA-NSE MIBORs from the aforementioned dates.[76] Financial Benchmarks India Pvt. Ltd. (FBIL) commenced operations with the publication of Term (3-month) MIBORs w.e.f. September 23, 2015.[77] The daily data of these short-term rates are collected from the FBIL website from the above specified dates to September 30, 2018. From October 01, 2018, use of the FBIL Term MIBOR data is subject to a payment of usage fee.[78] Although FBIL has been announcing the benchmark rates for Term MIBORs on a daily basis since 2015, in terms of the work process, the Clearing Corporation of India limited (CCIL) is the calculating agent for the rates; and the benchmark rates are also displayed on the websites of CCIL as well as Fixed Income, Money Market and Derivatives Association of India (FIMMDA).[79] Therefore, FBIL 3-month MIBOR from October 01, 2018 onwards are taken from the website of FIMMDA.

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[75] Fixed Income and Money Market Derivatives Association (FIMMDA) became a partner to NSE in co-branding the dissemination of MIBOR rates for the overnight and term segments on March 4, 2002 and the product thereafter was known as FIMMDA-NSE MIBOR. Source: NSE Fact Book 2006. FIMMDA-NSE MIBID/MIBOR, Wholesale Debt market Segment, Section V, 63-4.

[76] Source: RBI Press Release, RBI announces Revised Methodology for Overnight MIBID/MIBOR from July 22, 2015. Press Release No.: 2015-216/26 dated July 02, 2015.

[77] Source: FBIL Press Statement(s): Publication of FBIL overnight MIBOR dated June 22, 2015; and Publication of FBIL Polled Term MIBOR dated September 23, 2015.

[78] Source: FBIL Notification(s): Data Fee Schedule. Notification No. 2/2018 dated June 26, 2018; and Data Fees Schedule. Notification No. 3/2018 dated August 30, 2018.

[79] FIMMDA is a voluntary market body for the bond, money and derivatives markets. FIMMDA has members representing all major institutional segments of the market.

4.5.3. Sample Selection

Nifty 50 futures contracts have a maximum of 3-month trading cycle viz. near month (1 month), next month (2 months) and far month (3 months). New contracts are introduced on the trading day following the expiry of the near month contracts. On the last Thursday of each month, when the exchange is open for trading, one set of contracts expires and a new one with time to expiration equal to 3 months is initiated. If the last Thursday is a trading holiday, then they expire on the previous trading day. This way, at any point in time throughout a calendar year, there will be 3 futures contracts, i.e. one near month, one mid-month and one far month, available for trading in the market with up to 1, 2, and 3 months left to expiration, respectively.

For example, on January 26, 2008 there would be three-month contracts i.e. Contracts expiring on January 31, 2008, February 28, 2008 and March 27, 2008. On expiration date i.e. January 31, 2008, new contracts having maturity of April 24, 2008 are introduced for trading, while the February contracts (with a time left to expiration equal to 1 month) and the March contracts (with a time left to expiration equal to 2 months) will still be available for trading. In this analysis, data for most active futures contract months (nearby and first deferred) are used since they are the most active contracts in terms of trading volume and open interest.[80]

4.5.4. Rolling Over Method

As noted, our data set includes daily futures transaction data and the daily MIBOR data starting from June 12, 2000 to October 11, 2018. A continuous series of variables are constructed using daily frequency of data on the nearby and the first deferred futures contract. The continuous series of futures and corresponding variable are compiled using a common practice of rollover strategy.

[80] See Appendix A for a detailed derivation of the most active (liquid) contract month for the Nifty 50 Index futures market based on volume shifts, open interest behaviour and concentration of TV and OI in three maturities.

There have been previous studies of the roll decisions in the futures markets. Motivated by the abnormal volatility in futures prices close to their maturity, Samuelson's (1965) study focussed on the effect of constructing continuous series with the prices of the nearest futures contract up to its maturity; and showed that abnormal volatility in the last weeks of life of futures contracts could distort statistical inferences. Moreover, Ma, Mercer, and Walker (1992) showed that typical statistical tests of futures series can be very sensitive to the choice of rollover date and linking method, and demonstrate that important biases are generated from its selection. They studied several futures contracts with diverse underlying assets, concluding that the differences between the return series obtained with each criterion are significant. They suggested that the election of the best methodology depends on the underlying asset. However, they indicated that, in general, the choice of rolling over at the delivery date should be avoided as it almost always generates excessive volatility.

Following Ma et al. (1992) argument, a standard continuous series is constructed by taking a futures price series up to a rollover date. The rollover dates are kept in the second week before the contract's maturity, i.e., on each Friday during the second week of the expiring contract's month. The methodology for the rolling over of the futures contracts is same for the daily nearby and first deferred series. The nearby series is formed using nearest delivery date contracts as a starting point until 9 trading days before the expiration of the nearby, at which point the series then rollover to the second nearest contract and hold that contract up to the next rollover day and so on. The continuous series based on first-deferred contracts is constructed following the same method. For the series based on the distant contracts the rollover procedure is reiterated, but in this case the series switches to the next first-distant month contract instead of the next nearby.

By holding the contracts until 9 trading days before the last trading day, the compiled continuous series will closely follow the literature (Karagozoglu and Martell, 1999; Bollen et al., 2003; Kurov and Zabotina, 2005; Chou and Chung, 2006; Wang et al., 2007.a). As the expiry of the Nifty 50 futures is on the last Thursday of each month, Friday of the second week of the contract expiration is considered as the rollover day.

For example, in compiling the daily series of the nearest to maturity contract, if the current month is January 2002, then the expiry of this month's contract will be on 31st January 2002, which is the last Thursday of the expiry month. On Friday, during the second week prior to the January 2002 contract expiration, i.e. January 18, 2002, the January futures contract data is held to Friday's close. This includes matching with the daily MIBOR data on 3-month rates. Then, a new futures position is initiated using the February 2002 contract, on the Monday, January 21, 2002. Thereafter, the February contract, with expiry on February 28, 2002, is used until the next rollover. If the Monday during the second week before the expiration week is not a trading day, then the series is held until preceding Thursday's close and new futures position is initiated on Friday after matching with the corresponding MIBOR rates.

4.6. PRELIMINARY DATA ANALYSIS& TESTS

4.6.1. Overview of Speculative Activity

Since its introduction, Nifty 50 futures contract size has been modified four times by decreasing (thrice) and increasing (once) the multiplier. To capture the change in speculative behaviour in index futures market along the revision periods, this study first focuses on the daily volume and open interest aggregated at monthly frequency. Overall, the preliminary graphical analysis suggests that trading volume and speculative activity increase as contract size declines and decrease as contract size increases.

Figure 4.4 displays the trading volume between June 2000 and September 2018 on a monthly basis by aggregating the three contracts with different maturities, i.e. the near month, next month and far month. From June 2000 - June 2005 to July 2005 - April 2007, the average monthly volume of index futures grew by more than 600 percent. In October 2014, average traded volumes again rose at a very high rate of 61 percent. During October 2015, monthly average was 16 percent larger than the previous period May 2007 - October 2014. It is only after the increase in the contract size in 2015, the average monthly volume in index futures have declined by 71 percent. A possible reason for this increase in volume till 2015 could be that smaller size of the contracts have made the contract accessible to speculators, especially retail consumers, who contribute a significant proportion in the equity derivatives turnover. The comparative patterns in growth and decline till 2015 and thereafter, suggests that trading may have increased due to reduction in the size of the Nifty 50 futures contract and due to active participation by the short-term speculators, who open and close positions in a relatively short period of time.

[Figure 4.4 about here.]

Next, volume and open interest in the near (as well in 1st and 2nd deferred contract) month as a percent of volume and open interest in all months combined, is calculated to measure the speculative activity in the Nifty 50 futures market (Shah, Thomas and Gorham, 2008). The more this activity is concentrated in the near month (i.e., as the ratio approaches 100%), the more likely the contract is being used for mainly speculative purposes. When the share of trading in the front month is small (i.e. as it moves away from 100%), it suggests substantial commercial participation. Figures 4.5 and 4.6 show the concentration of volume and open interest in the index futures market of Nifty 50. The ratios (TV and OI) are quite high in the nearby month, averaging 85% and 81% respectively; whereas only around 14% and 17% of the totals are concentrated in the first deferred contracts. Although equity futures worldwide tend to have most of their trading and open interest concentrated in the nearby month, Nifty 50 futures have substantially lower concentrations of trading activity in the first deferred month, which suggests that there is less commercial activity in these contracts and more active participation from speculators. Figures 4.5 and 4.6 also show that these ratios in individual maturities do not vary much over the course of changes in the contract size.

[Figures 4.5 and 4.6 about here.]

In order to analyze the relative importance of speculation versus hedging activities in the index futures markets, speculative ratio proposed by Chan, Nguyen and Chan (2013; 2015) is employed, which is defined as daily trading volume (TV) divided by end-of-day open interest (OI). The ratio of futures TV/OI was first used by Garcia, Leuthold and Zapata (1986) to measure speculation. A high (low) speculation ratio indicates high (low) speculative activity with respect to hedging activity. Therefore, a rise in the speculation ratio reflects a rise in the dominance of speculators in the market. The underlying assumption behind the ratio is that hedgers tend to hold their futures market position longer than speculators. Following intuition from the seminal papers (by Rutledge, 1979; Leuthold, 1983; and Bessembinder and Seguin, 1993), there is a convention that the volume of trading is primarily treated as a proxy of trading activity by speculators, whereas the open interest variable is considered as proxy of hedgers activity. The line of reasoning is that the volume takes into account all the amount of trading activity while the open interest only registers the number of outstanding contracts and thus the intraday positions taken by day traders are not reflected in the latter.

Figures 4.7 and 4.8 plot the daily speculative ratio for the nearby and first deferred series of the Nifty 50 futures contracts. Furthermore, the figures display the descriptive statistics for the full sample and across the period of changes in the lot sizes (i.e. 200, 100, 50, 25 and 75) with four effective dates of revisions: June 30, 2005; April 26, 2007; October 30, 2014 and October 29, 2015.

Several comparisons of nearby and first deferred series for the speculative ratios can be carried out based on the summary statistics reported in Figures 4.7 and 4.8. To begin with, the mean values of the speculative ratios for the nearby and first deferred series can be compared. The comparison of the mean values of the speculative ratio for the nearby and first deferred series show that the contracts with longest time to maturity (i.e. first deferred) have the lowest mean value for the full sample (0.0065)[81] and over each sub-period (0.0029, 0.0053, 0.0087, 0.0156 and 0.0047).[82] These results suggest that the near maturity contracts of Nifty futures seem to attract more speculative activity than the first deferred contracts.

[Figures 4.7 and 4.8 about here.]

Then, the mean value of the ratios can also be compared over the course of changes in the contract sizes. For the nearby (as well in first deferred) maturity, the ratios are lowest in the first sub-period prior to the 2005 revision, 0.0052 (0.0029). Also, for the nearby (as well as in first deferred) maturity, the mean value of the daily speculative ratio increases - 0.0052, 0.0093, 0.0146 and 0.0235 (0.0029, 0.0053, 0.0087, 0.0156) - with the three subsequent downward revisions in the minimum lot size, whereas the ratio decreased, 0.0064 (0.0047) after the increase in the size of Nifty futures in2015. In addition, the maximum value is higher in the post-contract size decrease period (periods IV and III in the nearby and first deferred, respectively). Thus, according to the speculative ratios, the futures contract on Nifty 50 index

[81] In nearby series the mean values (0.0106) of full sample is almost twice as much as that of full sample in deferred series.

[82] In contrast, the respective mean values (0.0052, 0.0093, 0.0146, 0.0235 and 0.064) of the sub-periods of nearby series are higher than those of the deferred series.

attracted the lowest speculative demand when the lot size of the contract was highest (i.e. 200) among both the nearby and the first deferred futures contracts. Comparing the growth in the speculative ratios till 2015, when ratios for the index futures were increasing on average, suggest that the Nifty 50 futures contracts are used more for speculative activities for the nearby and first deferred futures contracts. The ratio appears to capture several changes in the index futures market activity; and indicates that degree of speculation increases (decreases) with decrease (increase) in the contract size. More importantly, the changes in the contract size seems to be the driving force behind the increase and decrease of speculative activity in the pre- and post-contract size modification periods.

4.6.2. Summary Statistics

Before proceeding with the empirical estimation, statistical properties of all variables in the model are reported in this section. Following Wang and Yau (2000), all variables in Equation (4.1) through (4.3) are transformed into double logarithmic form (i.e. log-log model) for stabilizing the variance of the residuals and to induce approximate normality in the error terms. Another possibility with log-log regression specification is that the coefficient estimates can be readily interpreted as elasticities of dependant variables (TV, BAS and PV) with respect to their particular independent variables.

Table 4.3 provides the descriptive statistics for each of the daily log-transformed variables under five periods of contract respecifications. Panels A and B of the Table report the statistical analysis in the nearby and first deferred series respectively. As expected, average daily volume in nearby contracts is larger than the volume in the deferred series across all trading periods. The BAS in the deferred contracts exceeds BAS in the nearest traded contracts and exhibits more volatility in all five sub-periods.

It is worth noticing that the preliminary results suggest consistency with textbook contract respecifications. Data reveals that a decrease in the contract size increases the mean (median) trading volume between Period I to IV. Results from Period V demonstrate that trading activity decreases with the increase in the contract size. In contrast to trading volume, the mean (median) open interests show a consistent increase, irrespective of the downward and upward revisions in the market lot of the Nifty 50 contracts. These results suggest that in the smaller lot periods, from Period I to Period III, both speculators and hedgers have increased their trading activities; whereas in Period V, when the multiplier of the contract was increased, the hedging usage of the Nifty contracts increased while the speculative trades declined. It is also observed that in Period IV, after the 3rd downward lot revision, the nearby (deferred) mean open interest decreases from 16,4835 (13,5790) to 16,1926 (13,4723), however, the mean trading volume increases from 12,1732 (8,6944) to 12,3494 (9,0987). These results indicate, regulatory uncertainty or the news and information around sudden increase in the contract lot size will have negative impact on the open interest compared to trading volume. This is because the policy uncertainty turns away hedgers from taking a long-term view but does not immediately disincentivize short-term speculators.

Section 2 in Panel A and B of Table 4.3 reports that bid-ask spreads fell after the decrease in contract size on the NSE. Similarly, Period V of Panel A and B documents that the bid-ask spreads for the Nifty 50 futures contracts have risen following the increase in the minimum lot size. These results support the arguments by the opponents who have criticized the market regulator's (SEBI) move that the increase in the minimum lot size of equity derivatives contracts would reduce market liquidity.

With regard to price volatility, the results are mixed during the periods of contract redesign. The mean (median) high-low volatility increased from Period I to II when size of the Nifty futures contract was reduced. However, the daily volatility measure consistently decreased even during the period of smaller contract sizes in Period II-IV. Price range volatility declined further in Period V during the larger contract size as well. Combining these results across periods there is no clear evidence of a decrease in price volatility due to the upward or downward revision in the contract's multiplier. These results are consistent with the previous findings of Karagozoglu et al. (2003) from U.S. index futures markets. The effects of reducing the multiplier on volatility in the univariate context in Karagozoglu et al.'s (2003) work observes that intraday volatility remains unaffected by the split of the S&P500 contract. Similarly, empirical findings of this study from the multivariate analysis also suggest that no significant change in volatility can be attributed to contract respecification. In the context of Indian market, these results seem to be contrary to the arguments suggested by the regulator that one of the main reasons for increasing the lot sizes of the derivatives contracts in the equity derivatives segment is to restrict the influence of retail investors who cause excessive return volatility.

[Table 4.3 about here.]

4.6.3. Testing for a Unit Root in the Time Series

To avoid the problem of spurious regression and to identify the appropriate time series representation for the variables, the Augmented Dickey Fuller (ADF) test (Fuller 1996) and Phillips-Perron (PP) unit root test (1988) are first applied on levels of log-transformed variables. The brief on the technical details of unit root tests are given in Appendix B.

The empirical results of the ADF tests are reported in Table 4.4. For the TV, BAS, PV and OI variables, the test rejects the null hypothesis of unit root in the nearby and deferred contracts, whereas for the 3-month MIBOR rates and futures settlement price variables, the test fails to reject the unit root hypothesis.[83] Results from this section conclude that all series, except the risk-free rate proxies and settlement prices, are stationary. Consequently, all variables of the three-equation model are estimated in their log-levels, except for the 3MIBOR and futures SP, where first differenced forms are used.

[Table 4.4 about here.]

4.6.4. Hausman's Specification Error Test

In order to confirm the specification of the three-equation model that TV, BAS and PV are simultaneously determined, Hausman's (1978) specification test is formally applied to the three-equation system in two ways (Test 1 and 2 in section 4.6.4A and 4.6.4B, respectively).

4.6.4A. Test 1 - In the first test, the null hypothesis investigates that two of the three variables are exogenous in the equation of the remaining variable. Suppose that for TV equation (Eq. 4.1) in the simultaneous equation model, the null hypothesis (H_0) that BAS and PV are exogenous variables, and the alternative hypothesis (H_A) that they are not exogenous variables, is tested. The F test (based on the augmented regression approach) was used to test the hypothesis. The test procedure was as follows:

4.6.4A1. First BAS is regressed on the rest of the predetermined variables, i.e. on the set of explanatory variables except TV and PV in the BAS equation (Eq. 4.2).

4.6.4A2. The residuals, $\widehat{e_2}$ from the OLS regression of BAS is retrieved.

[83] The PP unit root test procedure is also applied to the data. The tests results gave the same results as the ADF tests for the nearby and first deferred samples. The PP test rejects the null hypothesis of unit root in the TV, BAS, PV and OI series at 1% levels and fails to reject the non-stationarity in the SP and 3MIBOR. To save space, the estimation results of PP unit-root tests in the daily series are not reported.

4.6.4A3. Similarly, PV is regressed on the set of explanatory variables, except TV and BAS, in the PV equation (Eq. 4.3).

4.6.4A4. The residuals, $\widehat{e_3}$ from the OLS regression of PV is retrieved.

4.6.4A5. Now the TV equation (Eq. 4.15) is estimated by OLS after including the residuals $\widehat{e_2}$ and $\widehat{e_3}$ as additional regressors.

$$TV_t = \beta_0 + \beta_1 BAS_t + \beta_2 PV_t + \beta_3 3MIBOR_t + \beta_4 OI_{t-1} + \beta_5 TV_{t-1} + \lambda_2 \widehat{e_2} + \lambda_3 \widehat{e_3} + \varepsilon_{1t} \tag{4.15}$$

4.6.4A6. The *F*-test is used to test the joint restrictions H_0 that $\lambda_2 = \lambda_3 = 0$, where λ_2 and λ_3 are coefficients of $\widehat{e_2}$ and $\widehat{e_3}$.

4.6.4A7. If the null hypothesis is rejected, BAS and PV should be treated as endogenous variables in the estimation of coefficients of the TV equation (Eq. 4.1).

4.6.4A8. On the other hand if the null is not rejected, BAS and PV can be treated as exogenous for TV equation, and there is no useful additional information available for TV from modelling BAS and PV as endogenous variables.

The *F*-test results of joint significance of the coefficients on the included residuals are presented as Case 1 in Table 4.5. All *F* statistics in the model are significant, and the H_0 was rejected at the 1% level for both nearby and distant futures contracts. The rejection of H_0 suggests that BAS, PV, or both, were not exogenous; they should be treated as endogenous variables in the estimation of coefficients of the TV equation (Eq. 4.1). Hence, the instrumental variable estimation method, which produces consistent estimates instead of the OLS estimation procedure, should be used in estimating the parameters of the TV equation.

Following the similar procedure, the steps in 4.6.4A (1-8) are repeated to test the H_0 that TV, PV, or both are exogenous in the BAS equation (Eq. 4.2); and to test the H_0 that TV, BAS, or both are exogenous in PV equation (Eq. 4.3). Results of these tests are helpful in determining if there is a three-equation simultaneous equation system or not. Results for the BAS equation (Eq. 4.2) and the PV equation (Eq. 4.3) are presented as Case 1 in Tables 4.6 and 4.7 respectively. Similar to the results for TV equation, the F-test rejects the H_0 in all periods of the BAS equation. For PV equation, the test rejects the null hypothesis mostly for both contracts (except for Period V in deferred series).

However, under the above procedure (i.e. the test of joint restrictions) only the exogeneity of all the variables under question are tested and it cannot be ascertained that which one or whether both of the two explanatory variables are endogenous in the system. The Hausman test for exogeneity by OLS cannot be applied for testing the exogeneity of a subset of endogenous variables.

4.6.4B. **Test 2** - Thus, in the second test, the null hypothesis finds out which one of the two explanatory variables, if any, was exogenous in each equation. Hence, the test assumes that one of the three explanatory variables was exogenous, whereas the other two were endogenous in the system. For instance, for testing the H_0 that BAS was exogenous if PV was endogenous in the TV equation (Eq. 4.1); the H_A was that BAS was endogenous. If the test result failed to reject the H_0, this would suggest that empirically BAS could be treated as an exogenous variable in the TV equation. In other words, a two equation system (i.e., TV and PV in Equations 4.1 and 4.3) would be practically adequate in producing consistent estimates for the TV equation. Alternatively, if the H_0 is rejected, then the BAS should be treated as endogenous in the TV equation. The procedure for the second test is as follows:

4.6.4B1. The parameters of the TV equation were estimated by the two-stage least squares (2SLS) under the assumption that the H_0 was true. Called these predicted values as $\widehat{\beta_0}$, the coefficient estimate of BASs with variance $\widehat{V_0}$.

4.6.4B2. The parameters of the TV equation were estimated by 2SLS under the assumption that the H_A was true. Called these predicted values as $\widehat{\beta_1}$, the coefficient estimate of BASs with variance $\widehat{V_1}$.

4.6.4B3. Obtained the $\widehat{r^2}$, which is the R^2 from the reduced form equation for BASs.

4.6.4B4. Now, the m statistic, which is distributed as chi-square with one degree of freedom, was calculated (as detailed in Maddala, 1992, pp. 510-12):

$$m = \left[\frac{\widehat{q}^2 r^2}{(1-r^2)\widehat{V_0}}\right] \tag{4.16}$$

where $\hat{q} = \widehat{\beta_1} - \widehat{\beta_0}$.

Results are presented as Case 2 in Table 4.5 for the TV equation. The chi-square tests rejected the H_0 for both futures contracts.

Similarly, the test was applied again, assuming that this time PV was exogenous if BAS was endogenous in the TV equation. Results are presented as Case 3 in Table 4.5 for the TV equation. The chi-square tests rejected the H_0 only for the few periods.

When the results of Case 3 are combined with those from Cases 1 and 2, it appears that in estimating the relationship between TV, BAS, and PV for Nifty 50 Index futures contracts for TV equation, the BAS must be treated as endogenous variable, whereas the PV can be treated empirically as an exogenous variable.

The same chi-square tests were applied to the BAS (Eq. 4.2) and PV equations (Eq. 4.3), and the results are reported as Cases 2 and 3 in Tables 4.6 and 4.7. Results for the BAS equation for Case 3 are all statistically significant, whereas the chi-square test for Case 2 in the BAS equation are rarely statistically significant. These test results indicate that TV should be viewed as an endogenous variable and PV should be viewed as an exogenous variable in the BAS equation.

The empirical findings of chi-square test for Case 3 in PV equation rejects the H_0 only for the daily nearby contract but not for all the deferred contracts. For Case 2 in PV equation, all test statistics were not significant, and the H_0 was not rejected even at 10% level for most periods in the nearby and deferred contracts. Thus, where the PV equation is the concern of estimation, TV must be treated as endogenous, whereas BAS could empirically be treated as an exogenous variable.

[Tables 4.5, 4.6 and 4.7 about here.]

On the basis of the results obtained from the specification tests, the simultaneous equations model is adopted in the following analysis. The GMM procedure, an instrumental variable method suggested by Hansen (1982), was used to estimate the parameters of the three-equation model to avoid the potential simultaneous equation bias. The OLS estimation results are also reported for comparison purposes.

4.7. EMPIRICAL RESULTS

The empirical analysis consists of two parts: (4.7.1) estimation results from the simultaneous structural model with regard to Equations (4.1), (4.2) and (4.3); and (4.7.2) an empirical evidence of lot size effects on the futures markets. This section begins by presenting the empirical results for the futures TV, BAS, and PV equations with the traditional Amihud measure ($Amihud^O$). Results from the regression with $Amihud^O$ as a measure of transaction costs are reported in Tables 4.8-4.11. To provide some insight on the illiquidity and contract size effects and the relative usefulness of the turnover version of the Amihud measure ($Amihud^T$), the Spearman rank correlation for the liquidity measures, size variable and trading volume is computed. The results from the correlation analysis suggests that price impact needs to be separated from the size effects, to ensure that the illiquidity measure do not suffer from the size bias. To examine whether TV equation results are driven by the lot size effects, the key regression is re-estimated by replacing $Amihud^O$ with $Amihud^T$. The coefficients in a model for the joint determination are estimated by the GMM approach. The optimal weighted matrix used in the GMM estimation is the estimated consistent covariance matrix under a serially correlated and heteroskedastic error process (proposed by Newey and West, 1987). The merit of HAC weighting matrix is that it provides a set of consistent estimates of parameters as well as corresponding standard errors for each of the parameter estimates under serially correlated and heteroskedastic error terms of the simultaneous equations model.

4.7.1. Regression Results of Three-Equation Structural Model with *Amihud*^{O}

4.7.1A. Trading-Volume Equation (TV Equation)

Tables 4.8 (4.9) and 4.10 (4.11) present the GMM (OLS) estimates for the nearby and deferred series. The results for the TV equation are displayed in Panel A of these tables. The coefficients of BAS are all negatively related to the TV and are statistically significant for most periods at the 1% level, which support the notion that higher transaction costs (such as BAS) discourage trading. These negative coefficients can be interpreted as the short-run estimates of the elasticity of trading volume with respect to the BASs for both the futures contracts studied across different periods. For example, the elasticity of -514 for the Nifty 50 index futures (for Period V in Table 4.8) indicates that the TV for the daily nearby futures will decrease 514% for each 1% increase in BAS. Although the elasticity of TV with respect to BAS had been very high (i.e., coefficients of BAS are very large in terms of the magnitude) during most periods of 2000-2018, it is possibly because of *Amihud*^{O} illiquidity measure being affected by the changes in the contract lot sizes. However, the important implication of TV with respect to BASs in this data suggest that an increase in the BAS due to, say, an increase in the futures contract's multiplier, could substantially reduce trading volume and decrease liquidity for the Nifty index futures contracts.

The coefficients of PV are all positive and statistically significant at the 1% level in most periods. This result is expected, as the theory suggests that an increase in price volatility will change the reservation price of speculators and increase the demand for risk-transfer by hedgers. Both effects should lead to a higher trading volume (Martell and Wolf, 1987). This empirical result is also consistent with those of the previous studies, such as Cornell (1981), Tauchen and Pitts (1983), Bessembinder and Seguin (1993), Wang et al. (1997), Wang and Yau (2000), and others.

In general, higher short-term interest rates increase the cost of carry in the cash or spot assets/commodities, and thus reduces hedging needs in the futures market. In addition, higher interest rates reduce speculative trading by making alternative investments more attractive. Thus, a reduction in speculative and hedging activities in the futures markets would lower trading volume. Hence, it is expected that there is a negative relationship between TV and 3MIBOR. The coefficients for the risk-free rates in the trading volume equations are negative for 15 out of 20 cases, observed in two contracts for GMM and OLS models across five sub-periods, but most of them are statistically insignificant.

The coefficients of OI lagged one period are all positive and statistically significant in most periods at the 1% level. It is generally agreed that higher open interest indicates that more trades are likely in the future. The elasticity of trading volume with respect to open interest varies with the nature of the futures contract. For example, in period IV (in Table 4.10) of first deferred contract model (after the decrease in contract size, from 50 to 25) the elasticities of trading volume with respect to lagged open interest are greater (0.038) and significant at 1% level, whereas the coefficients for nearby model are also positive (0.025) but not statistically significant. During period V (in Tables 4.8 and 4.10) after the upward revision in the contract lot size (from 25 to 75), the lagged open interest has larger positive influence on TV, suggesting that more hedging-driven trades are likely to occur in the future, but the effect is limited to the deferred model (0.168) where trading is less active. In the nearby model (0.039) where trading is active, increase in the subsequent hedging-driven trading volume is less likely to occur; because the coefficient for open interest despite of having the expected sign in period V, is statistically insignificant. Since OI represents the changes in the expected position of hedgers and is found not to be a significant determinant of TV in the latter periods of nearby model, the results suggest that trading activity in the Nifty 50 index futures is not completely hedging-driven after the increase in the contract size.

The coefficients of TV_{t-1} are positively significant at the 1% level. Significance in the coefficients of lagged volume for all periods in the nearby and deferred models lends strong support to the partial adjustment model specification, affirming persistence in trading volume.

4.7.1B. Bid-Ask Spread Equation (BAS Equation)

Panel B in Tables 4.8-4.11 presents the coefficient estimates of the explanatory variables in the BAS equation. Except for two periods in the nearby model, the coefficients of TV are negative and statistically significant at least at the 5% level. The associated coefficients are no smaller than -0.007 (in Table 4.10). This means that a 10% increase in the daily deferred Nifty 50 Index futures trading volume will result in no more than a 0.07% drop in the BAS. These results affirm that a decrease in TV would increase the BAS and reduce market liquidity. These results are consistent with those of Benston and Hagerman (1974), Wang (1994), Wang et al. (1997), Wang and Yau (2000), Chou and Wang (2006), and Sahoo and Kumar (2011). This negative relationship between BAS and TV is due to the fact that with an increase in total trading volume, there will be greater opportunities for traders to offset their undesirable positions, thereby reducing their price risk. This in turn, will lead to a reduction in BAS.

These results of the effect of TV on the BAS equation have important implications for the successive revisions in the minimum contract sizes made by the Securities market regulator. The purpose of increasing the multiplier of the contract was to discourage retail investors' participation. While a larger contract would partly restrict non-institutional investors but will also partly inhibit smoother trading, i.e. less trades will take place at larger values. This will drive up the BAS and reduce market liquidity for both the institutional and non-institutional traders, hurting the retail customers more, other things being equal. As the professional traders (for example: new and small investors, institutional investors with smaller exposure, and the existing investors who wish to make small and continuous adjustments) cannot trade if the contract value is too large, an increase in the minimum lot size would take away the volume needed for a liquid market, and result in the widening of BAS in the futures market. Thus, the upward revisions in the contract sizes, despite its many potential advantages of better managing risk and nature of participants in the futures markets, will inevitably impose negative externalities to futures market trading.

Globally, the decision on setting margins, position limits and contract sizes are seen as commercial decisions taken by exchanges, unlike in India, where these decisions are laid down by SEBI and exchanges have little or no operational flexibility in this regard. From the public policy perspective this deserves careful consideration of the costs and benefits of these interventions. Results from this study provide estimates of the cost of externalities in terms of loss of market liquidity as measured by the widening BAS.

The coefficients of PV were not significant in most periods for nearby and deferred models and the signs of the coefficients are mixed. This result was not expected, as previous studies indicate a significantly positive relationship between futures volatility and bid-ask spread, essentially because an increase in price volatility implies that market makers are faced with increased inventory risk as well as the risk of trading with informed traders, so they tend to increase spreads.

Changes in the daily settlement price (ΔSP) are used to control the measurement scale effect of differing price levels of futures contracts with different maturities. Most of the coefficients for the change in SP are positive and not statistically significant.

The coefficients of lagged BASs (BAS_{t-1}) are mostly positive and statistically significant for nearby contracts. Most of the coefficients in the deferred model are also positive but not significant. Again, this result supports the specification of partial adjustment in the BAS equation.

Consistent with the expectation, the empirical findings in most cases supports the notion that BAS responds negatively to changes in TV and positively to changes in PV; however, these effects are small in terms of magnitude. In sum, these empirical findings reveal that the Nifty 50 index futures market is more liquid following three downward revision in the minimum lot sizes of contracts since 2005; as a result, the costs of execution (BASs) are largely unaffected by the normal changes in trading volume and price volatility. Negligible volume effect is consistent with the Copeland and Galai (1983) framework. For a market in which volume of trading is substantial, the expected time interval between bid-ask quotes is already small. Similarly, negligible volatility effects are consistent with Ho and Stoll (1983), who demonstrate that the effect of variance of return (i.e. price risk) on BAS is moderated when the number of dealers (i.e., liquidity suppliers in the market making) and relative dealer competition increases. These findings highlight the benefit of smaller contracts sizes of the Nifty 50 index futures, which had opened access to additional proprietary traders and non-custodian, non-proprietary traders[84,85] with the smaller lot sizes between 2000-2015.

4.7.1C. Price-Volatility Equation (PV Equation)

Panel C in Tables 4.8-4.11 presents the empirical results on the PV equation. The coefficients of TV and BAS are significantly positive at the 1% level for most periods in the nearby and deferred models. From the estimated PV equation, the sources of change in the observed price volatility can be decomposed into two components: (a) the information component approximated by TV and (b) the liquidity component represented by BAS.

[84] The NSE, decompose the trading data for different trader groups by three different categories of participants in the market, namely: Proprietary (P), Custodians (CP) and Non-proprietary Non-custodians (NCNP) traders.

[85] CP includes institutional participants such as Banks, Mutual Funds (MFs) and insurance firms as well as Foreign Portfolio Investors (FPIs). P includes proprietary trades. NCNP includes trades by individuals (including HNIs), corporates, partnership firms and Non Resident Indians (NRIs).

Results indicate that higher volatility is associated with large trading volume, consistent with the positive volatility-volume relationship found in the prior studies (Karpoff, 1987). The change in the observed price volatility that comes from the increase in trading volume originates from the arrival of new information.

Likewise, the finding of a positive relationship between BAS and PV is also consistent with the theory that bounces in the bid-ask spread have a positive impact on price volatility (e.g., Wang, 1994; Wang et al., 1997; Wang and Yau, 2000; Chou and Wang, 2006; and Sahoo and Kumar, 2011). This finding shows that, a given decrease in contract size, which results in an increase in liquidity (i.e., narrowing/declining BAS), will lead to a decrease in price volatility in the Nifty 50 index futures market; these findings are similar to as postulated by Huang and Stoll (1998).

Since the relations between PV and TV, and between PV and BAS (proxy for a liquidity cost) are both positive, these findings suggest that the impact of increase in the lot size for futures contract on PV will depend on the net effect of the decreasing TV and widening BAS on price volatility. However, it is observed that the coefficients of BAS are relatively larger than the coefficients of TV for all the periods, except for Period I in the nearby model. For example in Table 4.8, the coefficient of TV is 0.009, whereas the coefficient of BAS is 7.159 in Period V for the nearby contracts. Thus, the positive impact of an increase in the BAS on price volatility will offset the negative impact on price volatility from a declining TV. That is, a decrease in TV due to an increase in contract size may not reduce PV; it depends on the net effects of an increase in BAS and a decline in TV.

The coefficients for TV_{t-1} are negative and significant at the 1% level in most cases. These results are consistent with Foster (1995), who found that lagged volume was significant in explaining price volatility in crude oil futures. It implies that knowledge of lagged volume could be used to explain current futures price variability. This is in stark contrast to contemporaneous volume, whose coefficients are positive for all periods in nearby and deferred samples. A negative coefficient implies that an increase in lagged TV (as a measure of liquidity) reduces the current price volatility, conditioned on the current TV and the BAS. These results are also consistent with Bessembinder and Seguin (1993), who found that lagged OI variable (interpreted as a measure of liquidity) has a negative and significant impact on price volatility.

Finally, most of the coefficient of PV_{t-1} are significantly positive, and these results suggest that price volatility also has persistence effect; and that recent volatility has an influence on current volatility.

For comparison purposes, the estimates using OLS procedure are also reported in Appendix C.[86]

[Tables 4.8, and 4.10 about here.]

4.7.2. The Contract Size Effects

The coefficients on BAS in the TV equation reported in the previous section show that there is significant difference between regression coefficients in terms of magnitude in the periods before and after the contract size changes. The pattern of the coefficients in Panel A of Tables 4.8 and 4.10 also indicate a possible association between the proxy of illiquidity cost ($Amihud^{O}$) and lot size effects due to which coefficients of BAS are showing much larger influence in the TV equation after the contract size modifications in period II onwards. To see whether this is indeed the case of contract size bias, turnover-version of the Amihud measure is employed after removing the effects of contract size next. The discussion in this first

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[86] The results from OLS estimations with $Amihud^{O}$ are reported in Tables 4.9 and 4.11. Overall results are similar to those estimated from GMM method, although the statistical significance of many coefficients improve in this case.

section (4.7.2A) shows how illiquidity, as measured by *Amihud*^{O}, and trading volume, coincides with changes in the contract lot sizes of Nifty 50 index futures. The second section (4.7.2B) presents the correlation structure of three factors to demonstrate the relative usefulness of turnover version of Amihud measure (*Amihud*^{T}).

4.7.2A. Evolution of Traditional Amihud Measure, Market Size and Trading Volume

Figure 4.9a (4.10a) plots the natural log of the traditional Amihud measure, ln(Amihud), over time for nearby (deferred) contracts. The graph shows that liquidity increased post 2005 after the contract size was reduced from 200 to 100; and the market liquidity was quite stable between 2005-2018.

Figure 4.9b (4.10b) plots the natural logarithm of market size, ln(market size), over time. Figure 4.9b (4.10b) shows that market size for the Nifty 50 index futures contracts has increased significantly between 2000 and 2007, after the two downward revisions in the minimum lot size. The market size was quite stable between 2007 and 2014; however, the market size decreased towards the end of 2014, perhaps due to a fall in the demand for equity index derivatives, as a result of the news and information around SEBI's expected move to increase the minimum contract size. Although market size appeared to have decreased just before the multiplier of the contract was increased from 25 to 75, the expansion of the Nifty 50 index futures market between 2015 and 2018 suggests that open interest (i.e. hedging-driven trades) has increased in the futures contract following the increase in the contract size.

Figure 4.9c (4.10c) presents the trading volume for the Nifty 50 index futures contracts. The trading volume clearly shows an increasing trend following each downward revision in the contract size; and decreasing trend after the increase in the minimum lot size in 2015. This observation suggests that decrease (increase) in the lot size puts upward (downward) pressure on the trading volume.

[Figures 4.9 and 4.10 about here.]

4.7.2B. Spearman Rank Correlation for Market Illiquidity Measures, Market Size and Trading Volume

To provide some initial insights on the usefulness of the *Aminud*^{T} (i.e. return-to-turnover) ratio and its superior ability to disentangle the size and liquidity effects in comparison to the *Amihud*^{O} (i.e. return-to-volume) ratio, the Spearman rank correlations for the main variables which supports the argument for use of a turnover-based version of the Amihud measure, are computed and reported in Table 4.12 (nearby contracts) and 4.13 (deferred contracts).

According to the findings, the *Amihud*^{O} in Period I is nearly perfectly negatively correlated with market size (MKSZ) at -0.97 in the nearby series and is also highly negatively correlated with MKSZ at -0.79 in the deferred series. However, the correlation becomes -0.68 and -0.52 in Period IV. This suggests that the traditional Amihud illiquidity measure is affected, possibly by the market size: the decrease in *Amihud*^{O} ratio after Period I could be due to the expansion of highly liquid Nifty 50 index futures market in terms of its market size that resulted from the three instances of reduction in the contract lot sizes.

To check how *Amihud*^{T} relates to traditional measures of trading activity and market size, the Spearman rank correlation coefficient between *Amihud*^{T}, MKSZ and TV is also calculated. The results lead to several interesting conclusions. First, the correlation coefficient between the *Amihud*^{T} appears to be least correlated to the market size measure, while the *Amihud*^{O} seems to be highly correlated to MKSZ across all periods in absolute terms. These findings clearly indicate that the proposed turnover-based version of price impact ratio does not exhibit the inherent size bias of the *Amihud*^{O} ratio.

In addition, the results indicate that *Amihud*^{O} is highly negatively correlated with both MKSZ and TV across all periods. Interestingly this is not the case for *Amihud*^{T}, which is also negatively correlated with TV but with relatively low rank correlation coefficients. Also, unlike the traditional illiquidity measure, the *Amihud*^{T} does not show strong negative correlation with MKSZ. This finding supports the previous argument that *Amihud*^{T} measure in the trading volume equation is likely to capture the liquidity dimension of trading costs after removing the discrepancy of size from the conventional price impact ratio. These results are also consistent with Liu (2006), Florackis et al. (2011) and Cho et al. (2019), who also find strong negative correlation between the *Amihud*^{O} and MKSZ, which may lead to severe size biases. Therefore, the modified turnover version of Brennan et al. (2013) recommended in Cho et al. (2019) is used to capture illiquidity in the trading volume equation.

[Tables 4.12 and 4.13 about here.]

4.7.3. Results with Turnover-based Illiquidity Measure (*Amihud*^{T})

Regression (4.1) was re-estimated by replacing BAS_t^O (estimated with *Amihud*^{O}) with BAS_t^T (estimated with *Amihud*^{T}). Results from these GMM[87] estimates are reported in Tables 4.14 and 4.16 for the nearby and deferred series. The results for the TV equation are displayed in Panel A of these tables.

A comparison of the regression coefficients on BAS_t^O in Tables (4.8 and 4.10) and BAS_t^T in Tables (4.14 and 4.16) show that the coefficient of BAS becomes smaller (in absolute terms) when the size factor is removed from the illiquidity measure. This suggests that the elasticities of *TV* with respect to *BASs* was influenced by the size when the equation was estimated with the traditional Amihud measure. The new measure *Amihud*^{T} does not

[87] For comparison purposes the estimates using OLS procedure are also reported in Appendix C under Tables 4.15 and 4.17.

suffer from this contract size bias because it is able to separate illiquidity from size effects in the trading volume equation.

Thus far two interesting empirical results are noteworthy. First, the elasticities of TV with respect to BAS (proxied by $Amihud^T$) for the last period have become very high. For example, from Table 4.14, the result shows that the trading of Nifty 50 index futures decreases 10.76% for each 1% increase in the bid-ask spread before the contract size respecification; it decreases 8.22%, 7.30% and 18.11% for each 1% increase in the bid-ask spread after the respective decrease in the contract sizes from 200-100, 100-50 and 50-25; and it decreases 43.83% for each 1% increase in the bid-ask spread after the increase in contract size from 25-75. The elasticities of the TV using $Amihud^T$ also makes sense as it is consistent with the empirical findings from the literature (e.g., Wang et al., 1997; Wang and Yau, 2000; Nordén, 2006; Nordén, 2009; Martinez et al., 2011; Bjursell, Wang and Yau, 2012; Wang et al. 2014).[88] Furthermore, these findings suggest that market participants change their trading behaviour before and after contract lot size modifications. These results are consistent with the Lucas critique (Lucas, 1976).[89] Thus, any regulation that leads to an increase in the futures trading cost would significantly reduce trading volume and weaken the relative competitiveness of the Nifty 50 index futures market.

[Tables 4.14 and 4.16 about here.]

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[88] Some examples of empirical estimates of elasticities of trading volume with respect to transaction costs are: -2.72 for Deutche Mark futures (Wang et al., 1997); -1.31 for Gold COMEX futures (Wang and Yau, 2000); 54.80 for OMX-index futures (Nordén, 2006); 274.10 (Nordén, 2009); -2.55 for Corn CBOT futures (Martinez et al., 2011); -2.60 for E-mini S&P index futures (Bjursell et al., 2012); and -186.508 for Corn CME futures (Wang et al., 2014).

[89] The Lucas critique (Lucas, 1976) drew attention to the idea that, if the exogenous variables in the simultaneous equation model are changed (as a consequence of any change in government policy) and economic agents (with forward-looking expectation) identify these future actions in policy-shifts/structural-changes, then they would adjust their behaviour according to their new expectations. Therefore, it is expected that some coefficients in the simultaneous equation model may also change when some exogenous policy variables change.

Second, while comparing the elasticities of TV with respect to BAS for all five periods in Table 4.18 suggest that the magnitude of elasticity has been overestimated while using the *Amihud*^{O} measure. For example, in nearby contracts GMM procedure, the point elasticities with *Amihud*^{O} ranges from -1.54 (in Period I) to -934.82 (in Period IV), whereas elasticity with new BAS estimates (*Amihud*^{T}) ranges from -7.30 (in Period III) to -43.83 (in Period IV). As stated above, the results with *Amihud*^{T} of highly significant positive relationship between trading volume and concurrent bid-ask spread are in line with the previous research. Hence, these empirical results show that futures bid-ask spread, whether approximated by *Amihud*^{O} or *Amihud*^{T}, is an important determinant of the futures trading volume.

[Table 4.18 about here.]

4.7.4. Cross Elasticities for Relevant Variables of the Structural Model

In general, previous investigations argued that a decrease (increase) in the contract lot size increases (decreases) customer's total cost of trading, attracts (or drives-out) trading in futures-contracts (or other hedging instruments or markets) more intensively, and therefore overall trading volume may increase (or decline) and price volatility is also expected to decline (or increase). Previous studies however, have failed to empirically establish whether the effects of the cost of execution (BAS) on TV and PV is relatively more substantial than the effects of changes in trading volume and price volatility on the liquidity costs. As suggested in Wang et al. (2014), cross elasticities for the nearby and first deferred futures based on the estimated elasticity of relevant variables from the structural model are reported in this section. Tables 4.19 and 4.20 list the percentage increase in the significant coefficients from the three equations of simultaneous structural model corresponding to the three primary market quality variables.

In general, the daily effects of the contemporaneous coefficients of trading volume and price volatility are small in magnitude (or insignificant) in the liquidity cost equation. For example, in period I, a 1% increase in trading volume reduces the nearby BAS by only -0.046% (Table 4.19), and the deferred BAS by -0.210% (Table 4.20). Similarly, a 1% increase in the price volatility leads to an insignificant change in both nearby and deferred BAS series. As discussed above, negligible trading volume and price volatility effect on BAS is well recognized in Copeland and Galai (1983) and Ho and Stoll (1983) respectively. These findings demonstrate that the smaller contract lot sizes for a substantial duration in the futures markets not only offers accessibility but also fuels growth in market participation and dealer competition. As a consequence, effects of trading volume and price volatility on the liquidity costs remains either negligible (nearby) or moderate (deferred) following the increase in the size of Nifty 50 futures contract.

This is identified from Tables 4.19 and 4.20 that the effects of BAS on TV and PV are relatively more substantial. That is, trading volume and price volatility are more sensitive to changes in liquidity costs than liquidity costs are to the changes in trading volume and price volatility. For example, in period III, a 1% increase in BAS results in a decline of TV by -0.141% (Table 4.12) in nearby contracts and -0.523% (Table 4.13) in deferred contracts; whereas TV plays negligible role in the bid-ask spread equation. Likewise, in period III, a 1% increase in BAS increases PV by 7.351% (5.50%) in the nearby (deferred) model; whereas PV plays an insignificant role in the nearby bid-ask spread equation, and for the deferred contracts a 1% increase in PV increases BAS by only 0.002%. The finding that trading volume and price volatility are relatively more sensitive to changes in the transaction costs was also encountered by Wang and Yau (2000) and Wang et al. (2014). As suggested by Smidt (1971) and Garman (1976), liquidity providers tend to reduce or increase BAS in adjusting their inventory positions to dispose-off or accumulate their inventories of stocks; and behaviour of market makers are likely to affect both trading volume and price volatility.

In summary, effects of liquidity costs on trading volume and price volatility suggests two noteworthy findings:

4.7.4A. The impact of contract size changes on TV i.e., the magnitude of decrease (increase) in the post-contract-modification volume depends on the relative importance of transaction cost (BAS) to the total fixed trading cost and the elasticity of trading volume with respect to bid-ask spreads.

4.7.4B. The net effect of the contract size changes on PV could be decreasing or increasing. The means of daily price volatility in period III and IV (after the decreases in the lot sizes: 100-50 and 50-25) are higher than the means in the pre-modification periods. These results clearly demonstrate support in favour of smooth trading hypothesis by Huang and Stoll (1998); which suggests, if the decrease in contract size results in smoother trading and decline in bid-ask spreads, then the price volatility is also expected to decline. However, it is interesting to observe that average price volatility decreases even after the contract size was increased in the period V (25-75). These results confirm that the impact of contract size changes on the price volatility will vary. For example, results from empirical tests indicate that an increase in the contract lot size has decreased the trading volume and increased the bid-ask spread. In case of cross elasticities, the estimates show that the net impact of the contract size increase on the price volatility could be increasing or decreasing. Thus, the final implication of decrease in contract lot sizes on the price volatility depends on the relative magnitude and interaction of changes in trader’s composition and costs of reduced liquidity.

[Tables 4.19 and 4.20 about here.]

4.8. SUMMARY AND CONCLUDING REMARKS

The growth in the turnover of the Indian equity derivatives markets measured by compounded annual growth rate (CAGR) has outpaced the growth in the equity cash segment. Between the period FY 2004-05 to FY 2016-17, the notional turnover of equity derivatives has grown at a CAGR of 35.10%, while the turnover in the cash market have experienced only 11.39% CAGR.[90] Considering three downward revisions in the minimum contract size since its introduction, the Nifty 50 index futures contracts have become increasingly accessible to the individual investor.[91] With regard to the significant retail investors' participation in the equity derivatives markets, the regulator, academic research institutions and market participants are concerned about whether the setting of minimum contract sizes can be used as a tool to constrain participation by small sized investors and for creating more balanced participation of hedgers and speculators. This study, by using the unique dataset, examined the impact of changes in contract sizes on the market quality of the Nifty 50 futures contracts from the period June 2000 - November 2018. This time period is extremely informative because it offers a rare event of multiple revisions in the minimum contract size, which enables this paper to trace the major determinants of the trading activity, bid-ask spreads and price

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[90] The data presented in Table No. 2 in the SEBI discussion paper shows the growth of turnover in the equity cash market and derivatives market for the period FY 2004 to FY 2017. The CAGR differential between the cash and derivatives segments has been reported alongside in Paragraph 18. Source: SEBI Discussion Paper on Growth and Development of Equity Derivatives Markets in India dated July 12, 2017.

[91] In this context data presented by SEBI in Table No. 5 and Chart No. 2 in the discussion paper shows client category-wise contribution in terms of turnover and product-wise segregation of participants in the equity derivatives segment. Three broad categories of participants profile in the equity derivative markets are represented in: Institutions, Proprietary Trades and Non Institutional Non Proprietary (NINP) category, which include individual investors. Product-wise profiling of investors are available for four product categories in the equity derivatives segment: Index Futures, Index Options, Stock Futures and Stock Options. This data points to the fact that, in case of futures (both index and stock futures) the NINP investors, including trades by individuals, dominate trading in index futures and stock futures. It is also observed from Chart No. 2 that trading by individual investors is concentrated in the index futures category. Source: SEBI Discussion Paper on Growth and Development of Equity Derivatives Markets in India dated July 12, 2017.

volatility, and document the relationship between these three endogenous variables for the pre- and post-contract redesign periods. The dataset obtained from NSE also offers the advantage of a natural experimental environment to directly compare the effect of three decreases (in 2005, 2007 and 2014) and the final increase in the size of index futures contract, when the minimum tick and other cost factors remained unchanged. In addition, it provides an opportunity to evaluate whether changes in contract lot sizes are an appropriate tool for achieving regulatory objectives in the particular futures market. Several important conclusions emerged from the study which have not been found in the previous literature on futures contract size and are described below.

4.8.1. Overview of speculative activity and univariate statistical analysis indicate that the market trading activity, both TV and OI, is concentrated in the nearby month in contrast to the first deferred contracts, which implies that relative to hedging needs there is more demand for speculation-oriented trading in the Nifty 50 index futures. The means of trading volume and speculative ratios are lower while the open interest is higher after the increase in the contract size (in period V), which is in line with the regulator's objective to discourage retail investors by increasing the contract size. Results regarding the reduction (increase) in trading volume after the increase (decrease) in contract's multiplier is consistent with the previous findings of Karagozoglu and Martell (1999) from Australian market.

Furthermore, empirical results from the three-equation structural model with $Amihud^T$ reaffirm the positive impact of the increase in the contract size on open interest in the trading volume equation, after other factors are controlled. The coefficient of OI lagged one period in Period V is high relative to the other periods of study and statistically significant at the 1% level for the nearby futures. Lagged OI have relatively larger influence on trading volume because hedgers’ activity became of much larger influence.

These results suggest that although increasing (decreasing) the multiplier in the index futures contract may lower (increase) total trading cost, it will also increase (decrease) the monetary value of the contract and therefore will have impact on the upfront initial margin requirements. For example, when the market lot of futures on Nifty 50 index is 75 (in the Vth period) and if the index level is around 5000, then the value of single Nifty 50 futures contract would be Rs. 375,000 (i.e., 5000*75 units). This is reasonably higher in contrast to the value of the single index futures contract for the earlier periods; for example, it would imply the value of Rs. 250,000 (for period III) and Rs. 125,000 (for period IV) on the similar index level and on an open position of the respective minimum lot sizes. The contract value is used for calculating the initial margins requirement by the Clearing Corporations. Thus for the aforementioned example, the investor of the futures contract will have to pay approximately 8% (including both minimum span and exposure margins) of the contract value of Rs. 375,000 = Rs. 30,000 as initial margin to the NSCCL. Clearly, a trader purchasing the Nifty 50 index contract after the upward redenomination in period V will have to pay higher upfront margins. Therefore, individual investors may avoid trading in the market because of the large contract size and increased margin requirements, which in effect will reduce the proportion of speculative activity in the equity derivatives market.

4.8.2. Changes in the contract lot size has raised concerns from market opponents that increase in the multiplier would reduce liquidity (i.e., widen bid-ask spreads) of the contract. In case of the Nifty 50 futures, the contract multiplier was lowered thrice by a factor of 2 and was finally raised by a factor of 3, while the minimum tick size was held constant.[92] Tables

[92] Minimum tick size in respect of Nifty 50 futures contract is set in multiples of Rs. 0.05 and has remained unchanged across all periods of contract size modifications. The minimum tick size rules sets the limit for the minimum allowable variations in quoting the security. For example, if Last Trade Price (LTP) of the Nifty 50 futures contract was 500, then the NSE will accept orders to trade at Rs. 499.95 (bid-prices) and Rs. 500.05 (ask-prices). In these instances, the bid-price and ask price cannot be at Rs. 499.87 and Rs. 500.075 respectively, as it does not meet the minimum tick size of Rs. 0.05. Continuing from

4.1 and 4.3 outline that, all else being equal, a decrease (increase) in the contract size decreases (increases) the monetary value of minimum tick and the bid-ask spreads respectively. The results of decrease (increase) in the INR value of minimum tick and spreads should not be too surprising because: (i) the monetary value of tick size is calculated as per the existing rule of minimum tick size times the minimum lot size, depending on the number of dwelling units[93] and (ii) the size effect appears in the monetary value of spread, estimated by $Amihud^{O}$ measure.[94]

The minimum tick rule for quotes on NSE puts a lower bound of Rs. 0.05 on the spread in the futures contract. Therefore, any increase (decrease) in the size of the tick (in level) is expected to have direct effect of corresponding increase (decrease) on the quoted bid-ask spreads (in level). The empirical evidence in this paper however indicates that monetary value of the bid-ask spreads decline (increases) following a reduction (increase) in the contract lot size, while the levels of minimum tick was held constant. It reflects the fact that even when the current tick size is retained with the changes (increase or decrease) in the contract size, market makers can adjust (widen or narrow) their bid-ask spread, as a means for adjusting their revenue. These results echo the findings reported in the scalping behaviour study of Working (1967), Silber (1984) and Kuserk and Locke (1993), who find that bid-ask spread is an important part of revenue for market makers (either engaged as direct scalpers or short-term speculators, like day traders). Prior studies have often argued that, in addition to their

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the similar example, the five consecutive bid-ask prices, which could only be quoted on grid that is Rs. 0.05 wide, are: (i) Rs. 499.95, Rs. 499.90, Rs. 499.85, Rs. 499.80, Rs. 499.75 and (ii) Rs. 500.05, Rs. 500.10, Rs. 500.15, Rs. 500.20, Rs. 500.25 respectively.

[93] If the trading is for one future contract (i.e., for a minimum lot size) of the Nifty 50 index, then the single move in the index value would imply a resultant gain or loss of Rs. 3.75, in period V, (i.e., Rs. 0.05 X 75), while the monetary value of the minimum tick in the previous periods (I-IV) were Rs. 10, Rs. 5, Rs.2.5 and Rs. 1.25.

[94] $Amihud^{O}$ illiquidity measure by construction computes daily price response per unit (INR) of market size $(TV_t \times SP_t)$. Unlike stock market, the market size component in the index futures markets is affected by both factors, growth (or decline) in the equity market and increase (increase) in the contract lot sizes.

quoted bid-ask spread, market makers derive their revenue from frequent trading in small quantities by earning small income per traded contract. Therefore, market makers may desire high trading volume in the futures contract to earn high revenue, in providing liquidity to the market. However, when the trading volume tends to decrease in response to the increase in the contract size, liquidity may decrease by widening the bid-ask spreads, because of the incentive of income that arises directly from the wider spreads.

Consistent with the literature, results from the three-equation structural model show that bid-ask spread has an inverse relationship with trading volume and a positive relationship with price volatility, in pre- and post- contract modification periods. However, the effect of trading volume and trading volatility on the bid-ask spreads are small in magnitude. In contrast, trading volume and price volatility have large response to the changes in liquidity costs. These results suggest that smaller contract size for substantial duration (i.e., between 2005-2014) has been beneficial for boosting investors' participation and for expanding the liquidity supply. Overall, these findings reveal that the benefit of lowering the contract lot sizes that has fuelled market participation; which in effect imply that if markets have substantial level of trading volume and number of liquidity providers, an increase in the contract size may not necessarily have larger impact on the bid-ask spreads.

4.8.3. The average price volatility in both nearby and deferred contracts indicate that price volatilities decline after the contract size is decreased (in period III and IV); but the reverse was not true after the contract size was increased in the fifth period. Hence, there is some evidence to support the smooth volatility hypothesis by Huang and Stoll (1998), which suggest that small contract size results in attracting small traders to the markets who will smoothen out price fluctuations and provide additional liquidity (i.e., narrowing the bid-ask spreads) that can decrease price volatility. Considering that the larger contract size in period V has increased the bid-ask spreads, but the reduced liquidity did not result in higher price volatility; this evidence lends support for the relevance of structural model framework used in this paper for studying the dynamic interaction among trading volume, bid-ask spreads and price volatility. Given the simultaneity nature of market quality variables, the impact of contract size changes on each of the variables cannot be interpreted separately.

Furthermore, the structural equation estimates indicate that impact of contract size modifications on price volatility could be increasing or decreasing since both trading volume and bid-ask spreads have positive impact on price volatility. The final result of change in contract size on price volatility will depend on the net effects of increase (decrease) in trading volume and decrease (increase) in bid-ask spread, following the decrease (increase) in the size of the futures contract.

In conclusion, the combined results indicate that increase (decrease) in the contract size will reduce (enhance) trading volume, drive up (decrease) the bid-ask spread, and may have a decreasing or increasing effect on the market price volatility. Consistent with the literature, statistical analysis reveals that BAS responds negatively to changes in TV and positively to changes in PV. However, the responses on percentage basis are negligible. Larger responses emerge when examining the effects of changes in BAS on TV and PV. These findings demonstrate that market participants are indeed sensitive to how transaction cost changes influence their TV and returns, and also indicate that maintaining BAS at low and stable levels can moderate daily PV. Importantly, these findings also confirm that the anticipated decrease in retail investor participation (i.e., lower trading volume) with larger contract size will not reduce the market liquidity (i.e., higher bid-ask spreads) in similar proportions and may not necessarily decrease the excessive price volatility. Overall, from the policymaker's point of view, the analysis provides valuable empirical evidence that the increase in the contract lot size may have reduced the impact of individual day traders while only marginally reducing the market liquidity, for a market with many suppliers of liquidity. Thus, revisions in the minimum contract size appear to be a promising avenue for creating balanced participation between the retail and institutional investors.

Table 4.1 - Changes to contract specification - Revision of market lot for the Nifty 50 Index futures contract traded on the National Stock Exchange

S.No.	Particulars	Mar-2005	Feb-2007	Sep-2014	Aug-2015
1	Security description	FUTIDX			
2	Underlying	S&P CNX Nifty Index	S&P CNX Nifty Index	CNX Nifty Index	CNX Nifty Index[1]
3	Revised/Permitted lot size (in units)[2]	From 200 to 100[3]	From 100 to 50	From 50 to 25	From 25 to 75
4	Revised implementation w.e.f contract month	July 2005 expiry	May 2007 expiry	November 2014 expiry	November 2015 expiry
5	Contract size/value[4]	Minimum value of Rs. 2 lakhs[5] at the time of introduction			Minimum value of Rs. 5 lakhs at the time of introduction
6	Price steps (Minimum tick size)	Rs. 0.05			
7	Value of minimum tick	Rs. 5	Rs. 2.5	Rs. 1.25	Rs. 3.75
8	Settlement basis	All futures contracts on index and individual securities are settled in cash			
9	Settlement mechanism	Daily mark-to-market settlement on T+0 & T+1 basis and final settlement on T+1 basis			
10	Contract months & Expiration period	At any point there are only 3 contract months available for trading, with 1 month, 2 months and 3 months to expiry			
11	Trading cycle	A maximum of three month trading cycle - the near month (one), the next month (two) and the far month (three)			
12	Last Trading/Expiration Day	Last Thursday of the expiry month or the preceding trading day, if last Thursday is a trading holiday			
13	Exchange fees and charges	In addition to the application processing fees and admission fees, members are required to pay transaction charges on trades undertaken by them			
13.1	Exchange transaction charges	Fixed at the rate of 0.002% (Rs. 2 per Rs. 1 lakh[6] of the turnover) subject to minimum of Rs. 1,00,00 p.a		Changed to a slab-based structure w.e.f October 2009. Rate of 0.0019% each side (Rs. 1.90 per Rs. 2500 crore[7] of the turnover) subject to minimum of Rs. 1,00,00 p.a	
13.2	Brokerage charges	Brokerage charges negotiable between trading members and clients. However, maximum brokerage chargeable by a trading member is fixed at 2.5% of the contract value			
14	Initial margin	NSCCL[8] charges an upfront initial margin on daily basis ; Initial Margin = SPAN Margin + Exposure Margin			
14.1	SPAN margin	99% VaR-based margining over a two-day time horizon, computed through SPAN, subject to a minimum margin percentage of 5%			
14.2	Exposure margin	3% of the notional-value[9] of a index futures contract			

Notes:

1 With effect from November 9, 2015 CNX Nifty Index was rebranded as Nifty 50
2 Permitted Units of lot Size and multiples thereof
3 From June 2000, i.e. since the commencement of trading in Nifty 50 index futures contract, to March 2005 the permitted lot size was 200 units
4 The minimum value of the contract as on particular day is determined by multiplying the market lot by the closing price of the underlying security on that day
5 One lakh is equivalent to one tenth of a million
6 INR 1 lakh = 0.1 million
7 INR 2500 crore = 25,000 million
8 The National Securities Clearing Corporation Ltd. (NSCCL), a wholly owned subsidiary of NSE, acts as legal counter-party to all deals on NSE's F&O segment and guarantees settlement
9 The notional value for a futures contract for this purpose means, the contract value at last traded price / closing price

Source: National Stock Exchange of India Ltd. (NSE)

Table 4.3: Summary Statistics of Log Transformed Daily Data Used in the Analysis of Nifty 50 Index Futures

Panel A: Nearby Series

Variables	Full Sample Contracts from Jun 00 - Oct 18	Period I - 200 Lot Size Contracts from Jun 00 - Jul 05	Period II - 100 Lot Size Contracts from Jul 05 - May 07	Period III - 50 Lot Size Contracts from May 07 - Nov 14	Period IV - 25 Lot Size Contracts from Nov 14 - Nov 15	Period V - 75 Lot Size Contracts from Nov 15 - Oct 18
1. Ln (TV)						
N = Sample size	4396	1220	444	1784	236	712
Mean	10.9333	8.4483	11.6797	12.1732	12.3494	11.1495
Median	11.5784	8.5447	11.9952	12.4355	12.8396	11.5172
STD. Dev.	2.1879	2.2575	1.1331	1.1045	1.1000	1.0386
2. Ln (BAS)						
Mean	0.0122	0.0183	0.0108	0.0097	0.0090	0.0099
Median	0.0101	0.0167	0.0104	0.0093	0.0086	0.0095
STD. Dev.	0.0057	0.0080	0.0012	0.0010	0.0009	0.0010
3. Ln (PV)						
Mean	0.0168	0.0172	0.0207	0.0191	0.0127	0.0095
Median	0.0135	0.0142	0.0171	0.0153	0.0115	0.0084
STD. Dev.	0.0128	0.0125	0.0141	0.0141	0.0062	0.0052
4. Ln (OI)						
Mean	15.7219	13.9237	16.4409	16.4835	16.1926	16.2901
Median	16.4246	13.8368	16.9111	16.7545	16.6339	16.7624
STD. Dev.	1.6304	1.7517	0.9563	0.8378	0.9482	0.9050
5. Ln (SP)						
Mean	8.2451	7.1906	8.0573	8.5541	9.0357	9.1326
Median	8.5021	7.1299	8.0631	8.5789	9.0354	9.1396
STD. Dev.	0.7457	0.2553	0.1843	0.2192	0.0357	0.1319
6. Ln (3MIBOR)						
Mean	2.0201	1.9291	2.0035	2.1084	2.1027	1.9375
Median	2.0541	1.8229	1.9762	2.1872	2.1138	1.9344
STD. Dev.	0.2436	0.2839	0.1712	0.2535	0.0540	0.0716

Table 4.3, continued: Summary Statistics of Log Transformed Daily Data Used in the Analysis of Nifty 50 Index Futures

Panel B: First Deferred Series

Variables	Full Sample Contracts from Jul 00 - Nov 18	Period I - 200 Lot Size Contracts from Jul 00 - Aug 05	Period II - 100 Lot Size Contracts from Aug 05 - Jun 07	Period III - 50 Lot Size Contracts from Jun 07 - Dec 14	Period IV - 25 Lot Size Contracts from Dec 14 - Dec 15	Period V - 75 Lot Size Contracts from Dec 15 - Nov 18
1. Ln (TV)						
N = Sample size	4396	1220	444	1784	236	712
Mean	7.4791	4.9479	7.5576	8.6944	9.0987	8.1855
Median	8.0125	5.1533	7.6942	8.8768	9.1934	8.2705
STD. Dev.	2.0045	1.6609	1.1847	0.9788	0.7886	0.7418
2. Ln (BAS)						
Mean	0.0188	0.0315	0.0169	0.0137	0.0123	0.0135
Median	0.0143	0.0269	0.0161	0.0132	0.0120	0.0132
STD. Dev.	0.0132	0.0198	0.0031	0.0019	0.0011	0.0013
3. Ln (PV)						
Mean	0.0163	0.0158	0.0207	0.0188	0.0123	0.0092
Median	0.0125	0.0123	0.0160	0.0149	0.0112	0.0081
STD. Dev.	0.0137	0.0140	0.0168	0.0146	0.0058	0.0052
4. Ln (OI)						
Mean	12.8339	11.0732	13.0237	13.5790	13.4723	13.6541
Median	13.1892	11.2759	13.1209	13.7102	13.4848	13.7509
STD. Dev.	1.4694	1.2424	0.9398	0.8811	0.6541	0.7194
5. Ln (SP)						
Mean	8.2469	7.1919	8.0549	8.5564	9.0410	9.1357
Median	8.5027	7.1365	8.0588	8.5814	9.0410	9.1398
STD. Dev.	0.7466	0.2541	0.1861	0.2207	0.0361	0.1314
6. Ln (3MIBOR)						
Mean	2.0201	1.9291	2.0035	2.1084	2.1027	1.9375
Median	2.0541	1.8229	1.9762	2.1872	2.1138	1.9344
STD. Dev.	0.2436	0.2839	0.1712	0.2535	0.0540	0.0716

Notes: (a) Panel A and Panel B of this table reports the descriptive statistics of the variables used in the analysis of Nearby and First Deferred Nifty 50 futures
(b) The definition of each variable is as follows:
TV trading volume is measured as the number of traded nearby (first deferred) futures contracts ; *BAS* bid-ask spread is the daily liquidity proxy estimated by the Amihud (2002) procedure ; *PV* price volatility measured by the daily price range (i.e. high price minus low price) ; *OI* open interest is the total number of outstanding contracts per day ; *SP* daily settlement price of the futures contract ; and *3MIBOR* risk-free proxy for short-term interest rate

Table 4.4: Empirical Results of Augmented Dickey-Fuller Tests on the Stationarity of Time Series Data

	Ln (TV)		Ln (BAS)		Ln (PV)		Ln (OI)		Ln (SP)		Ln (3MIBOR)	
	k	*ADF statistics*	*k*	*ADF statistics*	*k*	*ADF statistics*	*k*	*ADF statistics*	*k*	*ADF statistics*	*k*	*ADF statistics*
Full Sample												
Nearby	23	-3.62**	30	-6.33***	13	-8.10***	27	-4.90***	25	-0.75	10	-2.53
First Deferred	23	-3.78**	30	-5.93***	20	-7.12***	24	-4.15***	26	-0.73		
Period I - 200 Lot Size												
Nearby	22	-3.37*	21	-4.49***	5	-8.24***	22	-2.96**	4	-0.37	2	-1.30
First Deferred	18	-3.71**	21	-3.28**	4	-10.39***	21	-3.40**	4	-0.38		
Period II - 100 Lot Size												
Nearby	16	-4.65***	16	-3.48***	6	-3.82***	10	-9.26***	0	-1.32	6	-0.10
First Deferred	7	-9.04***	17	-2.75*	4	-5.56***	0	-6.60***	0	-1.31		
Period III - 50 Lot Size												
Nearby	24	-6.50***	23	-4.98***	10	-5.14***	24	-3.56***	18	-1.38	10	-1.94
First Deferred	18	-6.20***	19	-4.94***	10	-5.20***	24	-5.04***	18	-1.38		
Period IV - 25 Lot Size												
Nearby	12	-7.63***	13	-7.42***	3	-5.00***	11	-7.32***	5	-1.90	3	-0.54
First Deferred	0	-7.51***	0	-7.62***	3	-4.77***	0	-4.47***	0	-2.14		
Period V - 75 Lot Size												
Nearby	18	-5.38***	18	-5.81***	6	-5.23***	19	-6.21***	0	-0.93	2	-1.41
First Deferred	18	-4.27***	19	-4.27***	7	-4.93***	19	-4.01***	1	-0.96		

Notes: (a) The test examines the null hypothesis that y_t contains unit root against the alternative that the series is stationary

(b) *ADF statistics* , reports the *t* -statistics of the coefficient β_1 from the regression model of the ADF test in Eq. (4.12)

(c) *k* , the number of lags are determined by using the information criterion - AIC

(d) The critical values of the ADF test without a time trend at the 1%, 5% and the 10% levels are -3.43, -2.86 and -2.57, respectively

(e) The critical values of the ADF test with a time trend at the 1%, 5% and the 10% levels are -3.96, -3.41 and -3.12, respectively

(f) * , ** , *** indicate statistical significance at 10%, 5% and 1% levels

(g) The regressions are estimated with a time trend in the cases of TV measure

Table 4.5: Hausman's Specification Test in TV Equation

Contract	*(1) F Test*	*(2) χ^2*	*(3) χ^2*
Panel A: Nearby Series			
Period I - 200 Lot Size	168.82***	1427.17***	20.77***
Period II - 100 Lot Size	950.33***	2358.03***	1.12
Period III - 50 Lot Size	1673.69***	9017.30***	2.33
Period IV - 25 Lot Size	42.68***	448.00***	0.65
Period V - 75 Lot Size	476.92***	302.41***	21.32***
Panel B: First Deferred Series			
Period I - 200 Lot Size	13.76***	1140.78***	14.042***
Period II - 100 Lot Size	134.05***	1282.79***	0.02
Period III - 50 Lot Size	83.21***	2169.31***	30.58***
Period IV - 25 Lot Size	25.65***	74.11***	0.55
Period V - 75 Lot Size	334.30***	221.67***	3.83

Notes: (a) The table reports *F* -statistics for Hausman's specification test.

(b) For Case 1, in the null hypothesis H_0 the bid-ask spread (BAS) and price-volatility (PV) are exogenous in the trading volume (TV) equation (Eq. 4.1); in the alternative hypothesis H_A neither of them are an exogenous variable. For Case 2, in the null hypothesis H_0 the BAS is exogenous if the PV is endogenous in the TV equation; in the alternative hypothesis H_A BAS is endogenous. For Case 3, in the null hypothesis H_0 the PV is exogenous if the BAS is endogenous in the TV equation; in the alternative hypothesis H_A PV is endogenous.
(c) Critical values for *F* -distribution with (2, ∞) degrees of freedom for significance levels =0.05 and =0.01 are 3.0 and 4.61 respectively.
(d) *Chi-* squared critical values statistics with 1 degrees of freedom for significance levels =0.05 and =0.01 are 3.84 and 6.63, respectively.
(e) *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively.

Table 4.6: Hausman's Specification Test in BAS Equation			
Contract	*(1) F Test*	*(2)* χ^2	*(3)* χ^2
Panel A: Nearby Series			
Period I - 200 Lot Size	136.21***	13.05***	717.93***
Period II - 100 Lot Size	345.64***	0.18	9877.04***
Period III - 50 Lot Size	1780.16***	26.96***	6349.34***
Period IV - 25 Lot Size	10.81***	0.59	122.63***
Period V - 75 Lot Size	353.93***	0.36	11088.96***
Panel B: First Deferred Series			
Period I - 200 Lot Size	2.72*	3.50	4.62**
Period II - 100 Lot Size	149.26***	0.26	13925.49***
Period III - 50 Lot Size	98.18***	5.23**	995.30***
Period IV - 25 Lot Size	5.52***	0.01	40.78***
Period V - 75 Lot Size	340.40***	21.44***	982.79***

Notes: (a) The table reports *F* -statistics for Hausman's specification test.

(b) For Case 1, in the null hypothesis H_0 the trading volume (TV) and price-volatility (PV) are exogenous in the bid-ask spread (BAS) equation (Eq. 4.2); in the alternative hypothesis H_A neither of them are an exogenous variable. For Case 2, in the null hypothesis H_0 the PV is exogenous if the TV is endogenous in the BAS equation; in the alternative hypothesis H_A PV is endogenous. For Case 3, in the null hypothesis H_0 the TV is exogenous if the PV is endogenous in the BAS equation; in the alternative hypothesis H_A TV is endogenous.

(c) Critical values for *F* -distribution with (2, ∞) degrees of freedom for significance levels =0.05 and =0.01 are 3.0 and 4.61 respectively.

(d) *Chi-* squared critical values statistics with 1 degrees of freedom for significance levels =0.05 and =0.01 are 3.84 and 6.64, respectively.

(e) *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively.

Table 4.7: Hausman's Specification Test in PV Equation			
Contract	*(1) F Test*	*(2)* χ^2	*(3)* χ^2
Panel A: Nearby Series			
Period I - 200 Lot Size	6.98***	0.03	2908.28***
Period II - 100 Lot Size	7.50***	1.11	14.51***
Period III - 50 Lot Size	25.11***	10.17***	129.49***
Period IV - 25 Lot Size	28.36***	5.02**	19.78***
Period V - 75 Lot Size	17.43***	2.26	36.62***
Panel B: First Deferred Series			
Period I - 200 Lot Size	2.80*	25.23***	3.76
Period II - 100 Lot Size	3.67**	90.11***	615.55***
Period III - 50 Lot Size	22.01***	0.10	117.95***
Period IV - 25 Lot Size	13.57***	0.96	6.10**
Period V - 75 Lot Size	1.14	X^a	X^a

Notes: (a) The table reports *F* -statistics for Hausman's specification test.

(b) For Case 1, in the null hypothesis H_0 the bid-ask spread (BAS) and trading volume (TV) are exogenous in the price-volatility (PV) equation (Eq. 4.3); in the alternative hypothesis H_A neither of them are an exogenous variable. For Case 2, in the null hypothesis H_0 the BAS is exogenous if the TV is endogenous in the PV equation; in the alternative hypothesis H_A BAS is endogenous. For Case 3, in the null hypothesis H_0 the TV is exogenous if the BAS is endogenous in the PV equation; in the alternative hypothesis H_A TV is endogenous.

(c) Critical values for *F* -distribution with (2, ∞) degrees of freedom for significance levels =0.05 and =0.01 are 3.0 and 4.61 respectively.

(d) *Chi-* squared critical values statistics with 1 degrees of freedom for significance levels =0.05 and =0.01 are 3.84 and 6.64, respectively.

(e) *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively.

(f) X^a indicate that if the null hypothesis of joint significance is not rejected, then two-step test is not required.

Table 4.8 : Regression Results for the Nearby Model using GMM

	Period I - 200 Lot Size		Period II - 100 Lot Size		Period III - 50 Lot Size		Period IV - 25 Lot Size		Period V - 75 Lot Size	
	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)
Panel A: Trading Volume (TV) equation: Dependent Variable = ln(TV_t)										
Constant	-1.813	(-2.54)**	5.752	(3.34)***	3.295	(1.95)*	18.260	(20.72)***	11.867	(12.65)***
ln(BAS_t)	-1.540	(-0.25)	-212.619	(-3.11)***	-163.348	(-1.88)*	-934.823	(-17.60)***	-513.585	(-10.52)***
ln(PV_t)	10.753	(3.42)***	7.313	(3.45)***	12.505	(5.51)***	12.766	(5.78)***	23.709	(7.45)***
Δln($MIBOR_t$)	0.969	(0.48)	-2.475	(-1.87)*	-0.572	(-0.69)	-0.314	(-0.19)	-0.335	(-0.22)
ln(OI_{t-1})	0.304	(4.42)***	0.208	(2.01)**	0.347	(5.61)***	0.025	(1.13)	0.039	(1.46)
ln(TV_{t-1})	0.697	(14.32)***	0.398	(4.27)***	0.370	(5.99)***	0.160	(4.56)***	0.316	(7.52)***
R^2	0.872		0.724		0.688		0.981		0.895	
Panel B: Bid-Ask spread (BAS) equation: Dependent Variable = ln(BAS_t)										
Constant	0.011	(4.11)***	-0.005	(-0.77)	0.007	(3.70)***	0.022	(10.09)***	-0.004	(-0.32)
ln(TV_t)	-0.001	(-3.37)***	0.000	(1.20)	-0.000	(-2.08)**	-0.001	(-8.43)***	0.000	(0.59)
ln(PV_t)	-0.006	(-0.86)	-0.008	(-1.78)*	0.002	(0.83)	0.010	(2.21)**	-0.037	(-1.53)
Δln(SP_t)	-0.005	(-0.91)	0.002	(0.59)	0.005	(3.73)***	0.001	(0.54)	0.017	(1.38)
ln(BAS_{t-1})	0.684	(10.80)***	1.020	(4.34)***	0.546	(6.98)***	-0.129	(-1.41)	0.977	(2.13)**
R^2	0.795		0.102		0.647		0.989		0.110	
Panel C: Price Volatility (PV) equation: Dependent Variable = ln(PV_t)										
Constant	0.014	(3.89)***	-0.069	(-1.67)*	-0.282	(-5.85)***	-0.353	(-2.3)**	-0.150	(-4.36)***
ln(TV_t)	0.002	(3.25)***	0.004	(1.80)*	0.016	(6.47)***	0.018	(2.57)**	0.009	(5.24)***
ln(BAS_t)	-0.105	(-1.83)*	3.054	(1.71)*	14.049	(5.75)***	18.539	(2.31)**	7.159	(4.41)***
ln(TV_{t-1})	-0.002	(-4.10)***	0.000	(-0.41)	-0.003	(-5.76)***	-0.002	(-2.99)***	-0.001	(-4.11)***
ln(PV_{t-1})	0.408	(9.43)***	0.520	(9.32)***	0.393	(8.57)***	0.153	(1.84)*	0.240	(4.18)***
R^2	0.269		0.361		0.462		0.259		0.242	

Notes: (a) The table reports the parameter estimates of the trading volume, bid-ask spread, and price volatility in the three equation model specified in equations (4.1) to (4.3) using GMM estimator.
(b) All variables are in log form.
(c) The definition of each variable is as follows: TV = trading volume; BAS = bid-ask spread; PV = price volatility; OI = open interest; MIBOR = three-month short-term rate; SP = settlement price; and the subscript t - 1 denotes one period lagged variables. Δ is the difference operator.

(d) Standard errors of the coefficients are computed using Newey-West (1987) heteroskedasticity-and autocorrelation- consistent (HAC) covariance matrix.
(e) Numbers in parentheses denote t -statistics. *** , ** , and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 4.10 : Regression Results for the Deferred Model using GMM

	Period I - 200 Lot Size		Period II - 100 Lot Size		Period III - 50 Lot Size		Period IV - 25 Lot Size		Period V - 75 Lot Size	
	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)
Panel A: Trading Volume (TV) equation: Dependent Variable = ln(TV_t)										
Constant	-6.616	(-1.57)	6.526	(5.45)***	6.184	(5.30)***	14.119	(17.49)***	6.665	(5.55)***
ln(BAS_t)	44.845	(1.07)	-149.336	(-4.67)***	-195.188	(-4.38)***	-551.529	(-13.98)***	-222.690	(-4.75)***
ln(PV_t)	17.378	(3.87)***	3.365	(1.57)	12.087	(6.36)***	15.124	(4.62)***	30.609	(7.92)***
Δln($MIBOR_t$)	0.478	(0.15)	-1.376	(-1.04)	-0.771	(-1.17)	2.101	(1.45)	-0.817	(-0.55)
ln(OI_{t-1})	0.590	(2.62)***	0.011	(0.32)	0.138	(3.89)***	0.038	(2.79)***	0.168	(5.21)***
ln(TV_{t-1})	0.678	(5.46)***	0.442	(6.97)***	0.355	(7.85)***	0.115	(3.10)***	0.238	(5.85)***
R^2	0.283		0.810		0.779		0.977		0.814	
Panel B: Bid-Ask spread (BAS) equation: Dependent Variable = ln(BAS_t)										
Constant	0.065	(10.26)***	0.033	(37.46)***	0.025	(9.38)***	0.028	(9.85)***	0.021	(10.03)***
ln(TV_t)	-0.007	(-7.65)***	-0.002	(-25.94)***	-0.001	(-7.44)***	-0.002	(-7.72)***	-0.001	(-7.13)***
ln(PV_t)	0.041	(0.88)	0.002	(0.72)	0.021	(6.49)***	0.015	(1.40)	-0.015	(-2.06)**
Δln(SP_t)	-0.011	(-0.49)	0.000	(0.08)	0.013	(7.03)***	0.000	(-0.23)	0.004	(1.84)*
ln(BAS_{t-1})	-0.043	(-0.61)	0.047	(2.38)**	0.067	(0.90)	-0.085	(-0.98)	0.179	(3.03)***
R^2	0.357		0.934		0.836		0.983		0.909	
Panel C: Price Volatility (PV) equation: Dependent Variable = ln(PV_t)										
Constant	0.006	(0.95)	-0.102	(-2.75)***	-0.212	(-5.31)***	-0.192	(-1.96)*	-0.113	(-3.02)***
ln(TV_t)	0.002	(0.95)	0.010	(3.52)***	0.018	(5.74)***	0.014	(2.40)**	0.010	(3.95)***
ln(BAS_t)	0.035	(0.50)	2.910	(2.85)***	7.401	(5.48)***	7.501	(1.90)*	3.988	(2.97)***
ln(TV_{t-1})	-0.001	(-0.73)	-0.001	(-2.13)**	-0.004	(-6.48)***	-0.002	(-2.74)***	-0.001	(-4.47)***
ln(PV_{t-1})	0.192	(3.74)***	0.434	(7.70)***	0.489	(9.79)***	0.147	(2.06)**	0.236	(3.94)***
R^2	0.123		0.231		0.455		0.311		0.277	

Notes: (a) The table reports the parameter estimates of the trading volume, bid-ask spread, and price volatility in the three equation model specified in equations (4.1) to (4.3) using GMM estimator.

(b) All variables are in log form.

(c) The definition of each variable is as follows: TV = trading volume; BAS = bid-ask spread; PV = price volatility; OI = open interest; MIBOR = three-month short-term rate; SP = settlement price; and the subscript *t* - 1 denotes one period lagged variables. Δ is the difference operator.

(d) Standard errors of the coefficients are computed using Newey-West (1987) heteroskedasticity-and autocorrelation- consistent (HAC) covariance matrix.

(e) Numbers in parentheses denote *t* -statistics. *** , ** , and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 4.12 : Pairwise Correlation Coefficients for Estimates of Liquidity Costs, Market Size and Trading Volume - Nearby Contracts

	Return-to-Volume (Amihud^{O})				Return-to-Turnover (Amihud^{T})		
	BAS^{O}	MKSZ	TV		BAS^{T}	MKSZ	TV
Period I - 200 Lot Size							
BAS^{O}	1			BAS^{T}	1		
MKSZ	-0.97	1		MKSZ	-0.69	1	
TV	-0.99	0.97	1	TV	-0.82	0.97	1
Period II - 100 Lot Size							
BAS^{O}	1			BAS^{T}	1		
MKSZ	-0.89	1		MKSZ	-0.20	1	
TV	-0.95	0.79	1	TV	-0.66	0.79	1
Period III - 50 Lot Size							
BAS^{O}	1			BAS^{T}	1		
MKSZ	-0.85	1		MKSZ	-0.35	1	
TV	-0.92	0.78	1	TV	-0.78	0.78	1
Period IV - 25 Lot Size							
BAS^{O}	1			BAS^{T}	1		
MKSZ	-0.68	1		MKSZ	0.17	1	
TV	-0.99	0.65	1	TV	-0.51	0.65	1
Period V - 75 Lot Size							
BAS^{O}	1			BAS^{T}	1		
MKSZ	-0.70	1		MKSZ	0.20	1	
TV	-0.95	0.57	1	TV	-0.56	0.57	1

Notes: This table presents the pairwise correlation coefficients of the three series: bid-ask spread by traditional Amihud ratio (BAS^{O}) or turnover-based Amihud measure (BAS^{T}), market size (= open interest x contract lot size x futures settlement price) (MKSZ) and the trading volume (TV).

Table 4.13 : Pairwise Correlation Coefficients for Estimates of Liquidity Costs, Market Size and Trading Volume - Deferred Contracts

	Return-to-Volume (Amihud^{O})				Return-to-Turnover (Amihud^{T})		
	BAS^{O}	MKSZ	TV		BAS^{T}	MKSZ	TV
Period I - 200 Lot Size							
BAS^{O}	1			BAS^{T}	1		
MKSZ	-0.79	1		MKSZ	-0.39	1	
TV	-0.87	0.90	1	TV	-0.70	0.90	1
Period II - 100 Lot Size							
BAS^{O}	1			BAS^{T}	1		
MKSZ	-0.79	1.00		MKSZ	-0.01	1	
TV	-0.99	0.74	1.00	TV	-0.63	0.74	1
Period III - 50 Lot Size							
BAS^{O}	1			BAS^{T}	1		
MKSZ	-0.83	1		MKSZ	0.17	1	
TV	-0.96	0.75	1	TV	-0.43	0.75	1
Period IV - 25 Lot Size							
BAS^{O}	1			BAS^{T}	1		
MKSZ	-0.52	1		MKSZ	0.29	1	
TV	-1.00	0.52	1	TV	-0.60	0.52	1
Period V - 75 Lot Size							
BAS^{O}	1			BAS^{T}	1		
MKSZ	-0.72	1		MKSZ	0.31	1	
TV	-0.98	0.71	1	TV	-0.35	0.71	1

Notes: This table presents the pairwise correlation coefficients of the three series: bid-ask spread by traditional Amihud ratio (BAS^{O}) or turnover-based Amihud measure (BAS^{T}), market size (= open interest x contract lot size x futures settlement price) (MKSZ) and the trading volume (TV).

Table 4.14 : Regression Results for the Nearby Model using GMM

	Period I - 200 Lot Size		Period II - 100 Lot Size		Period III - 50 Lot Size		Period IV - 25 Lot Size		Period V - 75 Lot Size	
	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)
Panel A: Trading Volume (TV) equation: Dependent Variable = ln(TV $_t$)										
Constant	-4.770	(-4.08)***	-1.591	(-0.54)	-1.788	(-2.16)**	-5.534	(-3.47)***	-12.123	(-10.70)***
$\ln(BAS_t)^a$	-10.764	(-2.62)***	-8.224	(-0.80)	-7.305	(-2.79)***	-18.107	(-5.15)***	-43.829	(-10.85)***
$\ln(PV_t)$	5.684	(2.13)**	5.733	(1.20)	4.236	(1.89)*	15.797	(0.84)	-25.923	(-1.82)*
$\Delta\ln(MIBOR_t)$	0.485	(0.29)	-2.559	(-1.56)	-0.669	(-0.85)	2.494	(0.40)	-1.451	(-0.75)
$\ln(OI_{t-1})$	0.520	(5.47)***	0.501	(2.40)**	0.529	(7.06)***	0.780	(5.31)***	1.073	(14.17)***
$\ln(TV_{t-1})$	0.460	(4.75)***	0.272	(1.29)	0.284	(3.87)***	0.023	(0.19)	-0.229	(-3.47)***
R^2	0.905		0.607		0.664		0.688		0.755	
Panel B: Bid-Ask spread (BAS) equation: Dependent Variable = ln(BAS $_t$) ^{b}										
Constant	0.011	(4.11)***	-0.005	(-0.77)	0.007	(3.70)***	0.022	(10.09)***	-0.004	(-0.32)
$\ln(TV_t)$	-0.001	(-3.37)***	0.000	(1.20)	-0.000	(-2.08)**	-0.001	(-8.43)***	0.000	(0.59)
$\ln(PV_t)$	-0.006	(-0.86)	-0.008	(-1.78)*	0.002	(0.83)	0.010	(2.21)**	-0.037	(-1.53)
$\Delta\ln(SP_t)$	-0.005	(-0.91)	0.002	(0.59)	0.005	(3.73)***	0.001	(0.54)	0.017	(1.38)
$\ln(BAS_{t-1})$	0.684	(10.80)***	1.020	(4.34)***	0.546	(6.98)***	-0.129	(-1.41)	0.977	(2.13)**
R^2	0.795		0.102		0.647		0.989		0.110	
Panel C: Price Volatility (PV) equation: Dependent Variable = ln(PV $_t$)										
Constant	0.014	(3.89)***	-0.069	(-1.67)*	-0.282	(-5.85)***	-0.353	(-2.3)**	-0.150	(-4.36)***
$\ln(TV_t)$	0.002	(3.25)***	0.004	(1.80)*	0.016	(6.47)***	0.018	(2.57)**	0.009	(5.24)***
$\ln(BAS_t)^b$	-0.105	(-1.83)*	3.054	(1.71)*	14.049	(5.75)***	18.539	(2.31)**	7.159	(4.41)***
$\ln(TV_{t-1})$	-0.002	(-4.10)***	0.000	(-0.41)	-0.003	(-5.76)***	-0.002	(-2.99)***	-0.001	(-4.11)***
$\ln(PV_{t-1})$	0.408	(9.43)***	0.520	(9.32)***	0.393	(8.57)***	0.153	(1.84)*	0.240	(4.18)***
R^2	0.269		0.361		0.462		0.259		0.242	

Notes: (a) BAS is estimated by the Turnover version of Amihud Ratio (*Amihud* ^{T}) as specified in Brennan et al. (2013).

(b) BAS is measured by the Original Amihud Ratio (*Amihud* ^{o}) as specified in Amihud (2002).

(c) The table reports the parameter estimates of the trading volume, bid-ask spread, and price volatility in the three equation model specified in equations (4.11) to (4.13) using GMM estimator.

(d) All variables are in log form.

(e) The definition of each variable is as follows: TV = trading volume; BAS = bid-ask spread; PV = price volatility; OI = open interest; MIBOR = three-month short-term rate; SP = settlement price; and the subscript *t* - 1 denotes one period lagged variables. Δ is the difference operator.

(f) Standard errors of the coefficients are computed using Newey-West (1987) heteroskedasticity-and autocorrelation- consistent (HAC) covariance matrix.

(g) Numbers in parentheses denote *t* -statistics. *** , ** , and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 4.16 : Regression Results for the Deferred Model using GMM

	Period I - 200 Lot Size		Period II - 100 Lot Size		Period III - 50 Lot Size		Period IV - 25 Lot Size		Period V - 75 Lot Size	
	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)
Panel A: Trading Volume (TV) equation: Dependent Variable = ln(TV_t)										
Constant	-6.055	(-1.21)	-8.369	(-3.37)***	-6.474	(-4.93)***	-3.451	(-1.25)	-4.697	(-1.73)*
ln(BAS_t)[a]	-19.179	(-0.90)	-29.229	(-3.71)***	-21.938	(-6.06)***	-18.520	(-2.99)***	-17.877	(-2.12)**
ln(PV_t)	-8.045	(-1.45)	0.364	(0.25)	-5.192	(-2.64)***	18.111	(0.92)	17.577	(1.43)
Δln($MIBOR_t$)	-1.106	(-0.65)	-0.629	(-0.56)	-0.250	(-0.32)	-1.695	(-0.31)	-1.141	(-0.69)
ln(OI_{t-1})	0.586	(2.07)**	0.803	(4.48)***	0.760	(7.96)***	0.748	(3.08)***	0.590	(3.72)***
ln(TV_{t-1})	0.299	(0.88)	0.005	(0.03)	0.046	(0.55)	-0.116	(-0.56)	0.169	(1.54)
R^2	0.815		0.789		0.696		0.664		0.661	
Panel B: Bid-Ask spread (BAS) equation: Dependent Variable = ln(BAS_t) [b]										
Constant	0.065	(10.26)***	0.033	(37.46)***	0.025	(9.38)***	0.028	(9.85)***	0.021	(10.03)***
ln(TV_t)	-0.007	(-7.65)***	-0.002	(-25.94)***	-0.001	(-7.44)***	-0.002	(-7.72)***	-0.001	(-7.13)***
ln(PV_t)	0.041	(0.88)	0.002	(0.72)	0.021	(6.49)***	0.015	(1.40)	-0.015	(-2.06)**
Δln(SP_t)	-0.011	(-0.49)	0.000	(0.08)	0.013	(7.03)***	0.000	(-0.23)	0.004	(1.84)*
ln(BAS_{t-1})	-0.043	(-0.61)	0.047	(2.38)**	0.067	(0.90)	-0.085	(-0.98)	0.179	(3.03)***
R^2	0.357		0.934		0.836		0.983		0.909	
Panel C: Price Volatility (PV) equation: Dependent Variable = ln(PV_t)										
Constant	0.006	(0.95)	-0.102	(-2.75)***	-0.212	(-5.31)***	-0.192	(-1.96)*	-0.113	(-3.02)***
ln(TV_t)	0.002	(0.95)	0.010	(3.52)***	0.018	(5.74)***	0.014	(2.40)**	0.010	(3.95)***
ln(BAS_t)[b]	0.035	(0.50)	2.910	(2.85)***	7.401	(5.48)***	7.501	(1.90)*	3.988	(2.97)***
ln(TV_{t-1})	-0.001	(-0.73)	-0.001	(-2.13)**	-0.004	(-6.48)***	-0.002	(-2.74)***	-0.001	(-4.47)***
ln(PV_{t-1})	0.192	(3.74)***	0.434	(7.70)***	0.489	(9.79)***	0.147	(2.06)**	0.236	(3.94)***
R^2	0.123		0.231		0.455		0.311		0.277	

Notes: (a) BAS is estimated by the Turnover version of Amihud Ratio (*Amihud* ^{T}) as specified in Brennan et al. (2013).

(b) BAS is measured by the Original Amihud Ratio (*Amihud* ^{o}) as specified in Amihud (2002).

(c) The table reports the parameter estimates of the trading volume, bid-ask spread, and price volatility in the three equation model specified in equations (4.11) to (4.13) using GMM estimator.

(d) All variables are in log form.

(e) The definition of each variable is as follows: TV = trading volume; BAS = bid-ask spread; PV = price volatility; OI = open interest; MIBOR = three-month short-term rate; SP = settlement price; and the subscript *t* - 1 denotes one period lagged variables. Δ is the difference operator.

(f) Standard errors of the coefficients are computed using Newey-West (1987) heteroskedasticity-and autocorrelation- consistent (HAC) covariance matrix.

(g) Numbers in parentheses denote *t* -statistics. *** , ** , and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 4.18 : A Comparison of the Estimated BAS Coefficients in the Trading-Volume Equation in the Nearby and Deferred Series - by Generalized Method of Moment (GMM) and Ordinary Least-Squares (OLS) Procedures

	Nearby Contracts				Deferred Contracts			
	GMM Procedure		*OLS Procedure*		*GMM Procedure*		*OLS Procedure*	
Period I - 200 Lot Size								
Original model - $\ln(BAS_t)^O$	-1.54	(-0.25)	-81.74	(-19.81)***	44.85	(1.07)	-20.35	(-14.03)***
New model - $\ln(BAS_t)^T$	-10.76	(-2.62)***	-40.61	(-34.80)***	-19.18	(-0.90)	-30.94	(-35.80)***
Period II - 100 Lot Size								
Original model - $\ln(BAS_t)^O$	-212.62	(-3.11)***	-810.71	(-62.99)***	-149.34	(-4.67)***	-344.32	(-60.10)***
New model - $\ln(BAS_t)^T$	-8.22	(-0.80)	-39.06	(-18.16)***	-29.23	(-3.71)***	-37.71	(-25.24)***
Period III - 50 Lot Size								
Original model - $\ln(BAS_t)^O$	-163.35	(-1.88)*	-949.90	(-115.05)***	-195.19	(-4.38)***	-405.32	(-84.40)***
New model - $\ln(BAS_t)^T$	-7.30	(-2.79)***	-32.76	(-47.11)***	-21.94	(-6.06)***	-27.20	(-37.09)***
Period IV - 25 Lot Size								
Original model - $\ln(BAS_t)^O$	-934.82	(-17.60)***	-1135.65	(-133.68)***	-551.53	(-13.98)***	-650.97	(-101.60)***
New model - $\ln(BAS_t)^T$	-18.11	(-5.15)***	-24.57	(-11.09)***	-18.52	(-2.99)***	-24.57	(-11.09)***
Period V - 75 Lot Size								
Original model - $\ln(BAS_t)^O$	-513.58	(-10.52)***	-909.59	(-122.47)***	-222.69	(-4.75)***	-529.11	(-110.31)***
New model - $\ln(BAS_t)^T$	-43.83	(-10.85)***	-49.75	(-25.84)***	-17.88	(-2.12)**	-28.53	(-20.64)***

Notes: (a) Original Model - Regression (4.1) estimated with BAS^O, the Original Amihud Ratio ($Amihud^o$) as specified in Amihud (2002).

(b) New Model - Regression (4.1) is estimated with the Turnover version of Amihud Ratio ($Amihud^T$) as specified in Brennan et al. (2013).

(c) Numbers in parentheses denote *t*-statistics. *** , ** , and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 4.19 : Estimated Cross Elasticities for the Nearby Structural Model

Equation	$\ln(TV_t)$	$\ln(BAS_t)$	$\ln(PV_t)$	$\ln(OI_{t-1})$	$\Delta\ln(SP_t)$
Period I - 200 Lot Size					
$\ln(TV_t)$	-	-0.236	0.012	0.857	-
$\ln(BAS_t)$	-0.046	-	-	-	-
$\ln(PV_t)$	0.985	-0.110	-	-	-
Period II - 100 Lot Size					
$\ln(TV_t)$	-	-	-	0.705	-
$\ln(BAS_t)$	-	-	-0.001	-	-
$\ln(PV_t)$	2.253	1.620	-	-	-
Period III - 50 Lot Size					
$\ln(TV_t)$	-	-0.141	0.007	0.716	-
$\ln(BAS_t)$	0.000	-	-	-	0.183
$\ln(PV_t)$	10.192	7.351	-	-	-
Period IV - 25 Lot Size					
$\ln(TV_t)$	-	-0.387	-	1.023	-
$\ln(BAS_t)$	-0.047	-	0.000	-	-
$\ln(PV_t)$	17.536	13.163	-	-	-
Period V - 75 Lot Size					
$\ln(TV_t)$	-	-0.770	-0.022	1.568	-
$\ln(BAS_t)$	-	-	-	-	-
$\ln(PV_t)$	10.552	7.528	-	-	-

Notes: The elasticities corresponds to the primary variable with significant coefficients in table 4.14.

Table 4.20 : Estimated Cross Elasticities for the Deferred Structural Model

Equation	$\ln(TV_t)$	$\ln(BAS_t)$	$\ln(PV_t)$	$\ln(OI_{t-1})$	$\Delta\ln(SP_t)$
Period I - 200 Lot Size					
$\ln(TV_t)$	-	-	-	1.311	-
$\ln(BAS_t)$	-0.210	-	-	-	-
$\ln(PV_t)$	-	-	-	-	-
Period II - 100 Lot Size					
$\ln(TV_t)$	-	-0.720	-	1.384	-
$\ln(BAS_t)$	-0.081	-	-	-	-
$\ln(PV_t)$	3.654	2.392	-	-	-
Period III - 50 Lot Size					
$\ln(TV_t)$	-	-0.523	-0.011	1.187	-
$\ln(BAS_t)$	-0.042	-	0.002	-	0.537
$\ln(PV_t)$	8.307	5.500	-	-	-
Period IV - 25 Lot Size					
$\ln(TV_t)$	-	-0.477	-	1.108	-
$\ln(BAS_t)$	-0.078	-	-	-	-
$\ln(PV_t)$	10.350	7.314	-	-	-
Period V - 75 Lot Size					
$\ln(TV_t)$	-	-0.403	-	0.984	-
$\ln(BAS_t)$	-0.044	-	-0.001	-	0.198
$\ln(PV_t)$	8.888	5.629	-	-	-

Notes: The elasticities corresponds to the primary variable with significant coefficients in table 4.16.

Figure 4.4 : Monthly Volume of Nifty 50 Futures

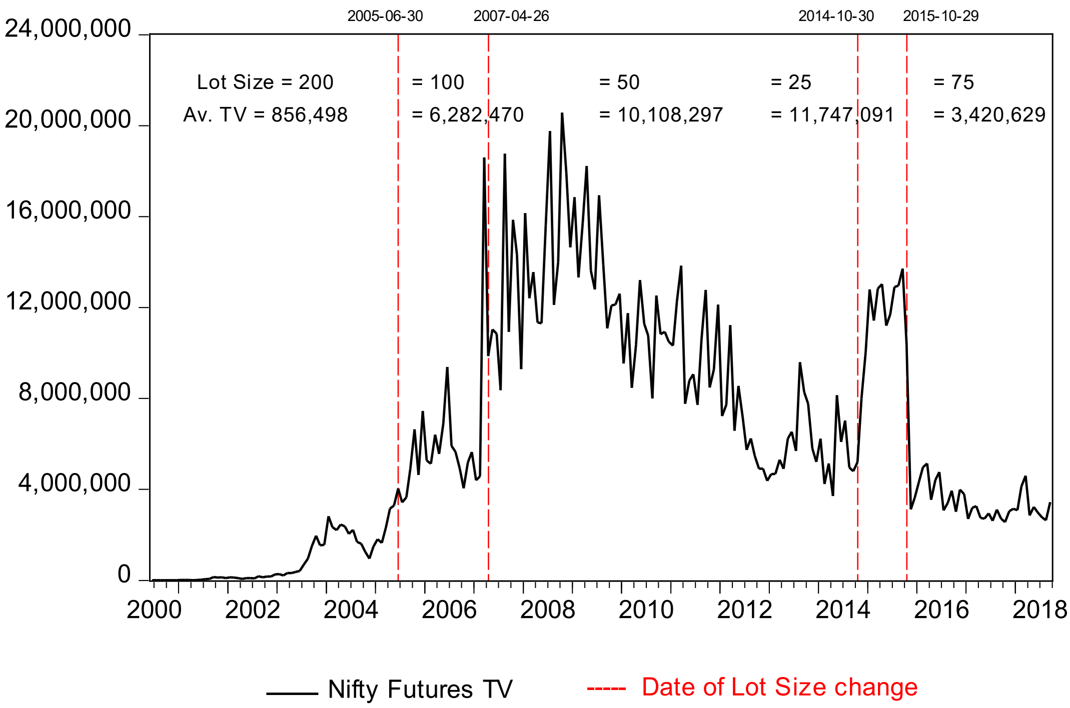


Figure 4.5 : Concentration of Volume in Contracts with Different Maturities (Monthly)

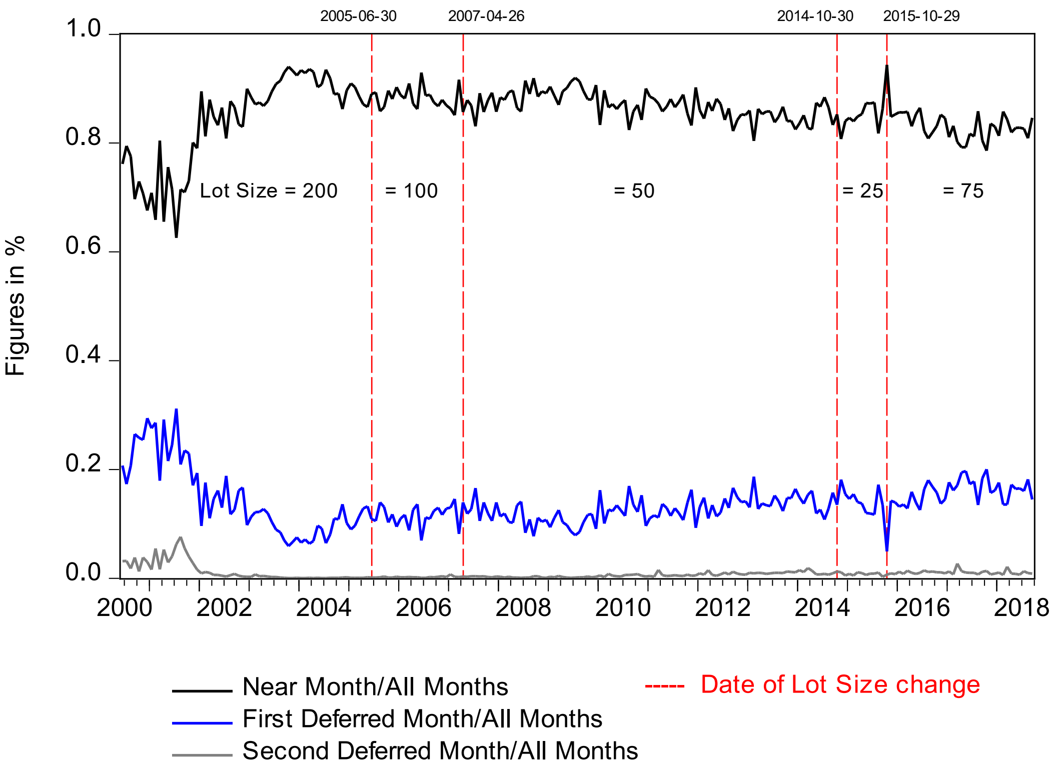


Figure 4.6 : Concentration of Open Interest in Contracts with Different Maturities (Monthly)

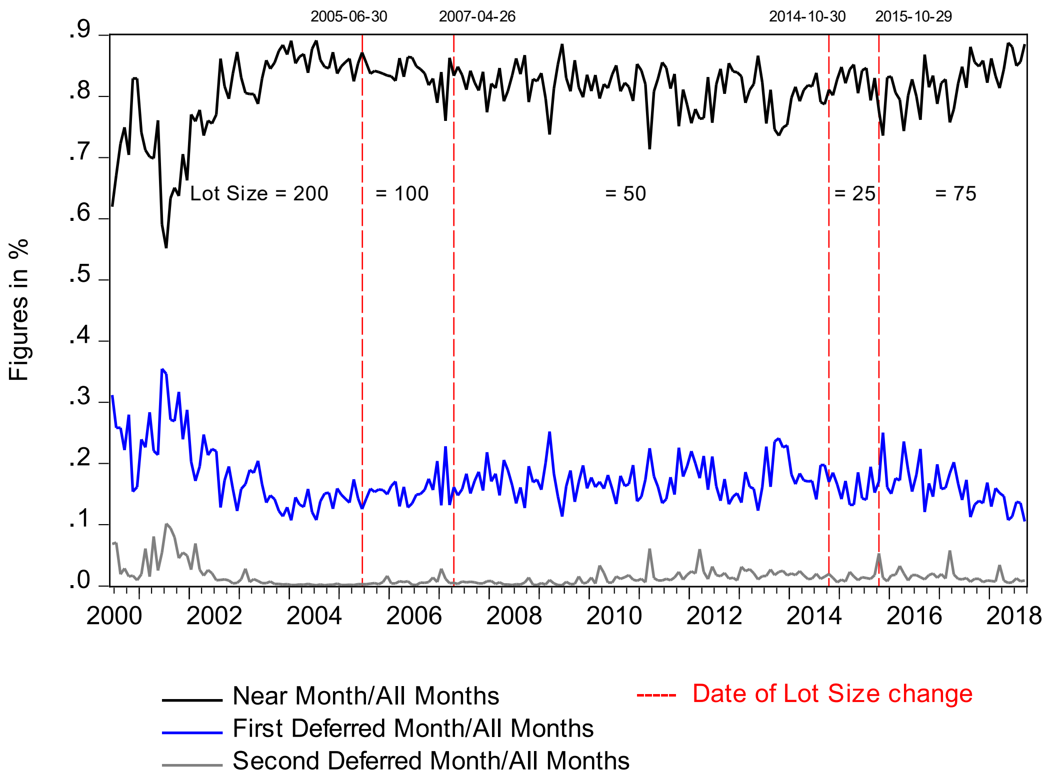


Figure 4.7 : Daily Speculative Ratio for the Nearby Series

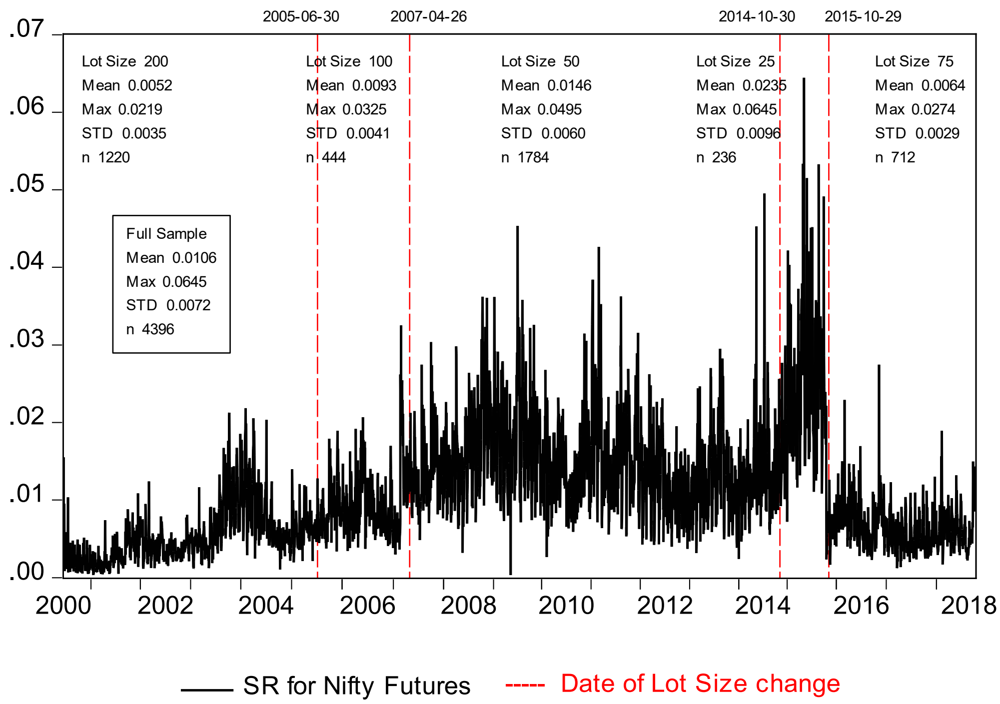
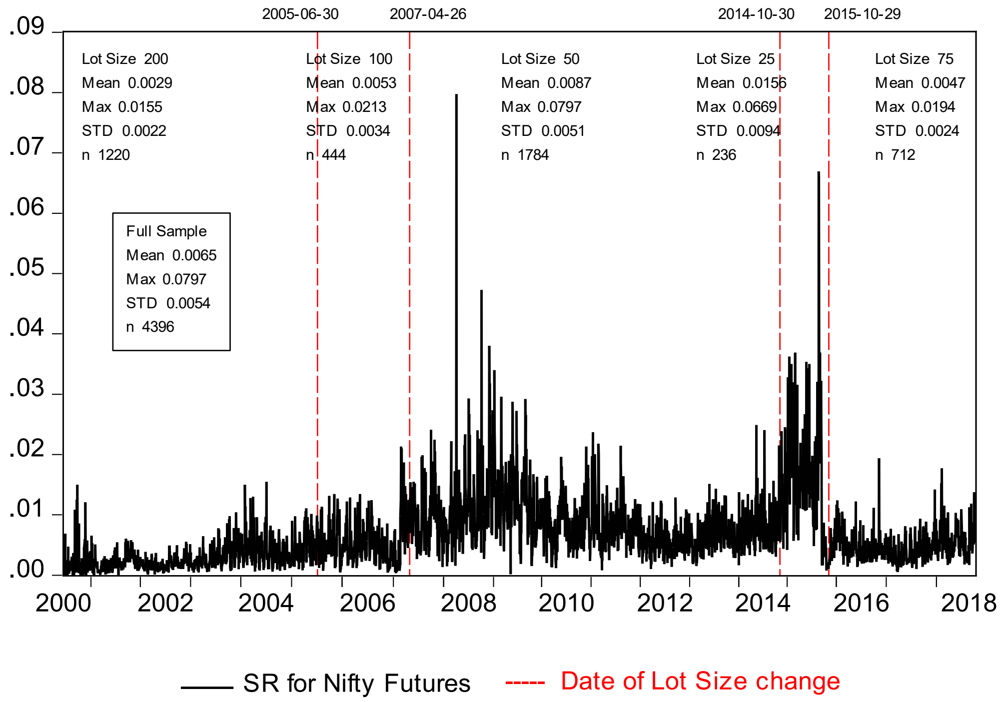


Figure 4.8 : Daily Speculative Ratio for the First Deferred Series



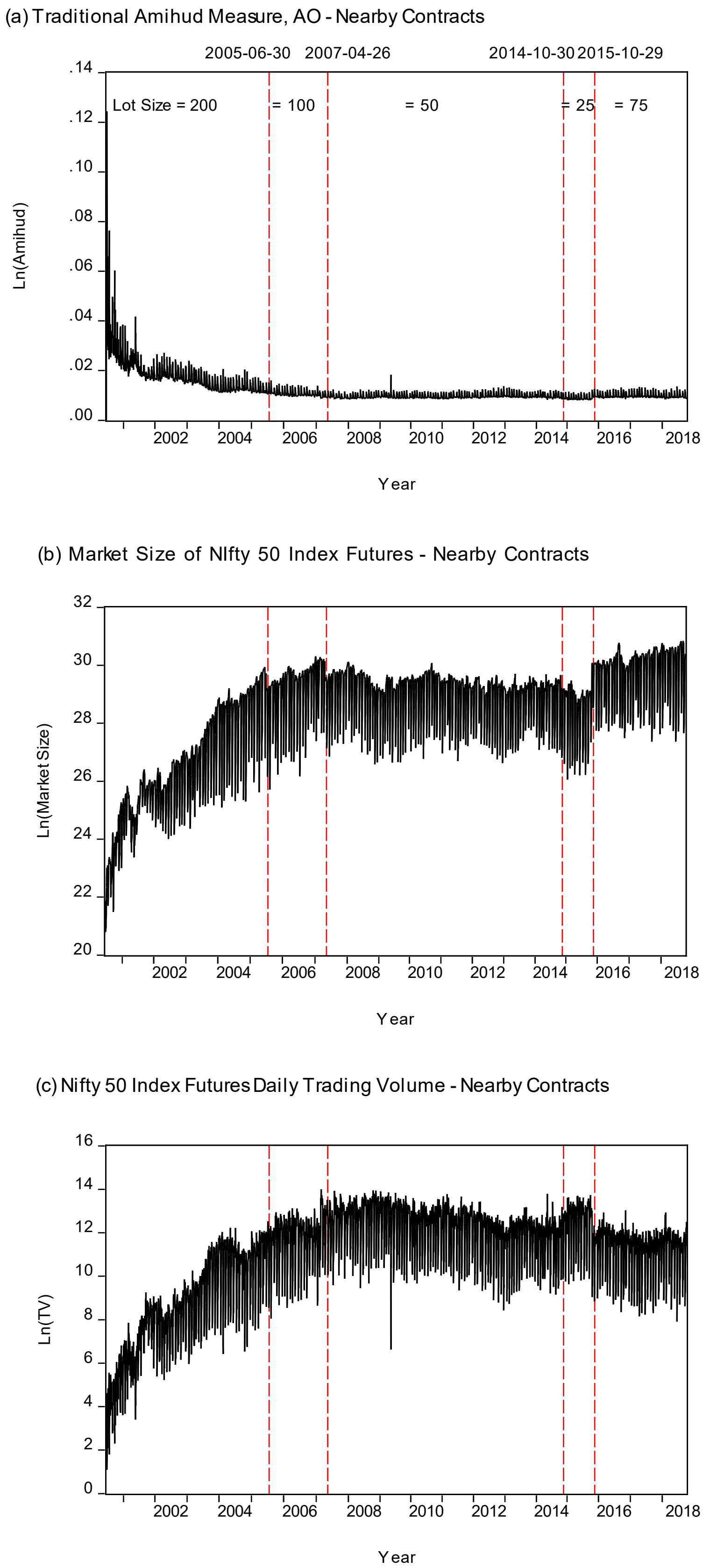


FIGURE 4.9 - Evolution of Nifty 50 index futures market illiquidity by traditional Amihud measure (a) market size (b) and trading volume (c)

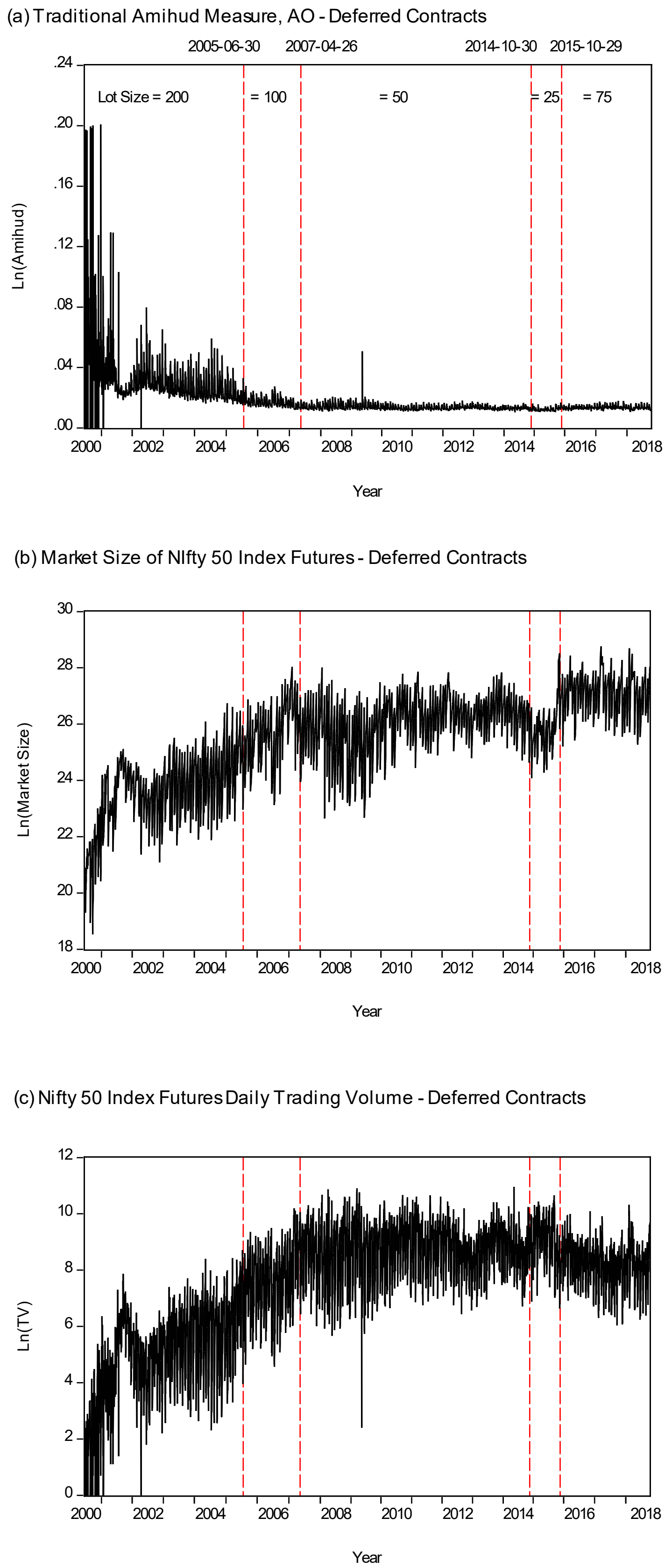


FIGURE 4.10 - Evolution of Nifty 50 index futures market illiquidity by traditional Amihud measure (a) market size (b) and trading volume (c)

Appendix A: Most Actively Traded Maturity

Volume Shift in Nifty 50 Index Futures

Figure 4.1 shows daily volume for April 2018 Nifty futures (top) and May 2018 Nifty futures (bottom). April Nifty volume is negligible until mid-March 2018, at which point it increases rapidly towards the end-of-March and maintains a high level through the first-week of April (the contract expires on April, 26, 2018). Meanwhile, May Nifty's volume is minimal until mid-April, at which point it increases suddenly and becomes the more actively traded contract in the last-week of April - even though the April Nifty contract is still a week from expiration at that point. The volume shift across two contract suggests the near month Nifty futures is likely to be the most liquid contract month for index contracts on NSE.

[Figure 4.1 about here.]

Behaviour of Open Interest for the Individual Contract Months

Figure 4.2 shows the behaviour of open interest of a single month futures contract, before and after the contract size modifications in Nifty 50 Index futures. The expiration dates for these contracts are three months hence from their introduction. For the initial days when the exchange listed these contracts for trading, the open interest in these individual contract months is almost zero. Open interest slowly begins to increase, but the number of open positions in distant months are relatively low because they are not the nearby contract.

Nifty 50 Index futures have a 3-month expiration cycle, the March future becomes the lead month with the arrival of February of that expiration year. Open interest in the March 2005 contract escalates dramatically during mid-Feb, 2005. In the expiration month, open interest in the March 2015 future drops back to zero. These patterns in open interest are similar across all contracts shown in Figure 2 below and no changes are observed in the shape of single contract open interest plots, before and/or after the contract size modifications.

[Figure 4.2 about here.]

Series of Nifty 50 Index Futures Expirations - Individual Contracts Open Interest

Figure 4.3 exhibits a series of Nifty 50 expirations between the October 2016 to October 2018 contracts. The open interest curves in Figure 4.3 resemble the behaviour of individual contract month plot in Figure 4.2.

The volume and open interest patterns shown in this section are similar to those patterns observed in the established futures markets. A month prior to contract expiration, volume (in Figure 4.1) and open interest (in Figure 4.2 and 4.3) are relatively large. As contract expiration approaches, both volume and open interest decline. This is an almost universal phenomenon that the near month always has more trading activity than any of the more distant months, at least until contract expiration draws near and people who want positions but not delivery will roll into the next month out.

[Figure 4.3 about here.]

Concentration of Volume and Open Interest in the Near, the First Deferred and the Second Deferred Month

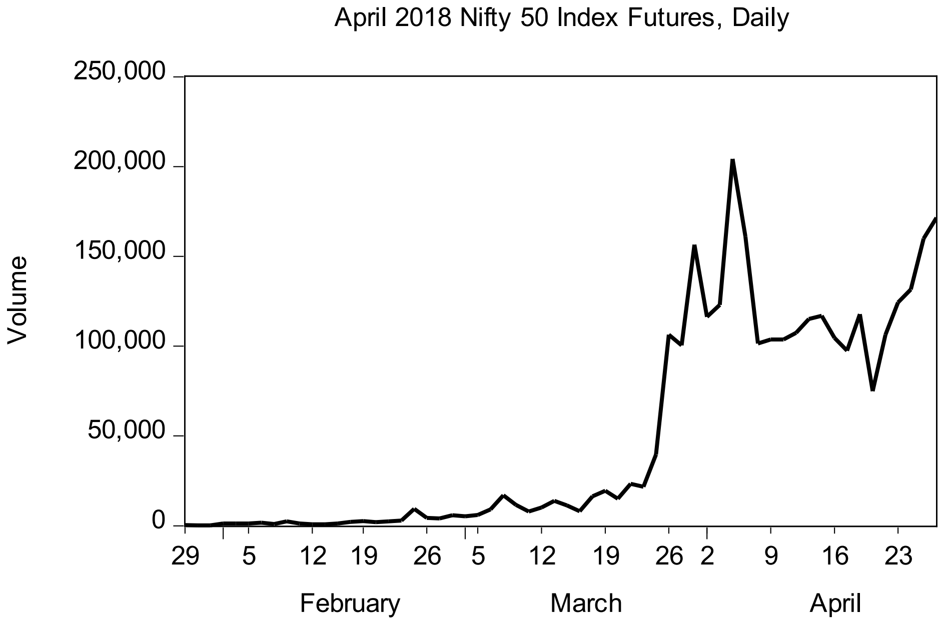
Table 4.2 shows these ratios of volume and open interest in the near month as a percentage of volume and open interest in all months combined, for all contract maturities in 2016. The ratios are also shown in the context of first and second deferred contracts. Foreign exchange and equity futures worldwide tend to have most of their trading and open interest concentrated in the nearby month. Similar to the global trend, the concentration of volume and open interest in the Nifty 50 Index futures market is quite high, typically around 84% and 80% respectively in the nearby contract month; while the first and second deferred months on average had only 15% and 1% of the total volume, and 18% and 2% of the total open interest respectively.

As noted in Shah et al. (2008), Nifty 50 Index future is actively traded in near contract months followed by first deferred months and almost inactively traded in the second deferred contract months. Following authors (Karagozoglu and Martell, 1999; Bollen et al., 2003; Aitken, Frino, Hill and Jarnecic, 2004; Atesand Wang, 2005.a, 2005.b; Chung and Chiang, 2006; Wang et al., 2007.a; Chou et al., 2015.a) either applied the two/three structural equation framework or examined different issues in the equity index futures by employing variables such as bid-ask spread and volume while selecting only the nearby contracts in their studies. In general, they found that the nearby month is the *most actively traded*[95] contract in the equity index futures market.

[Table 4.2 about here.]

[95] Most liquid contracts, in terms of trading volume.

Figure 4.1 - Volume Shift in Index Futures



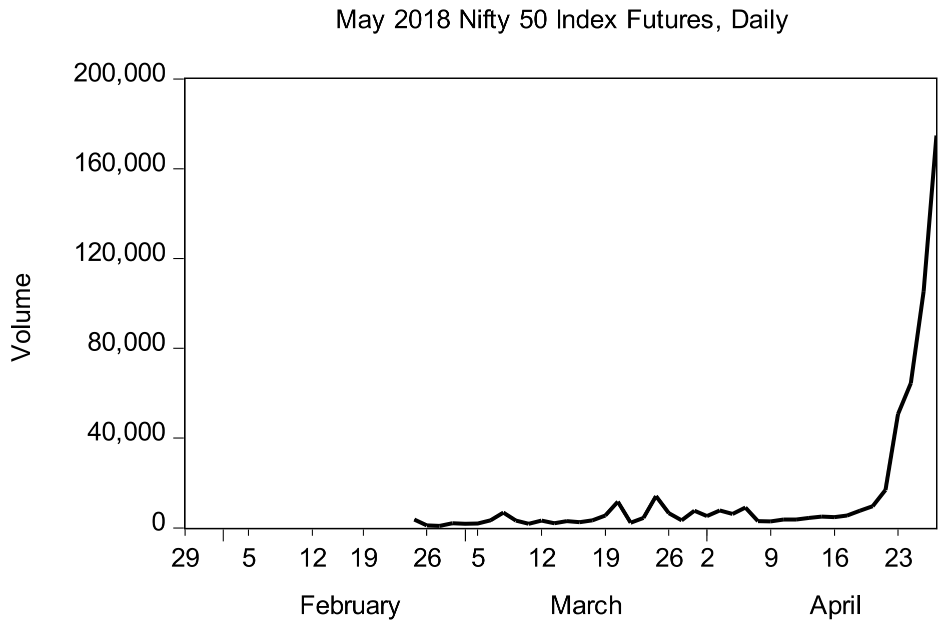


Figure 4.2 - Open Interest for Individual Contract Months
Before and After Contract Size Modifications in Nifty 50 Index Futures

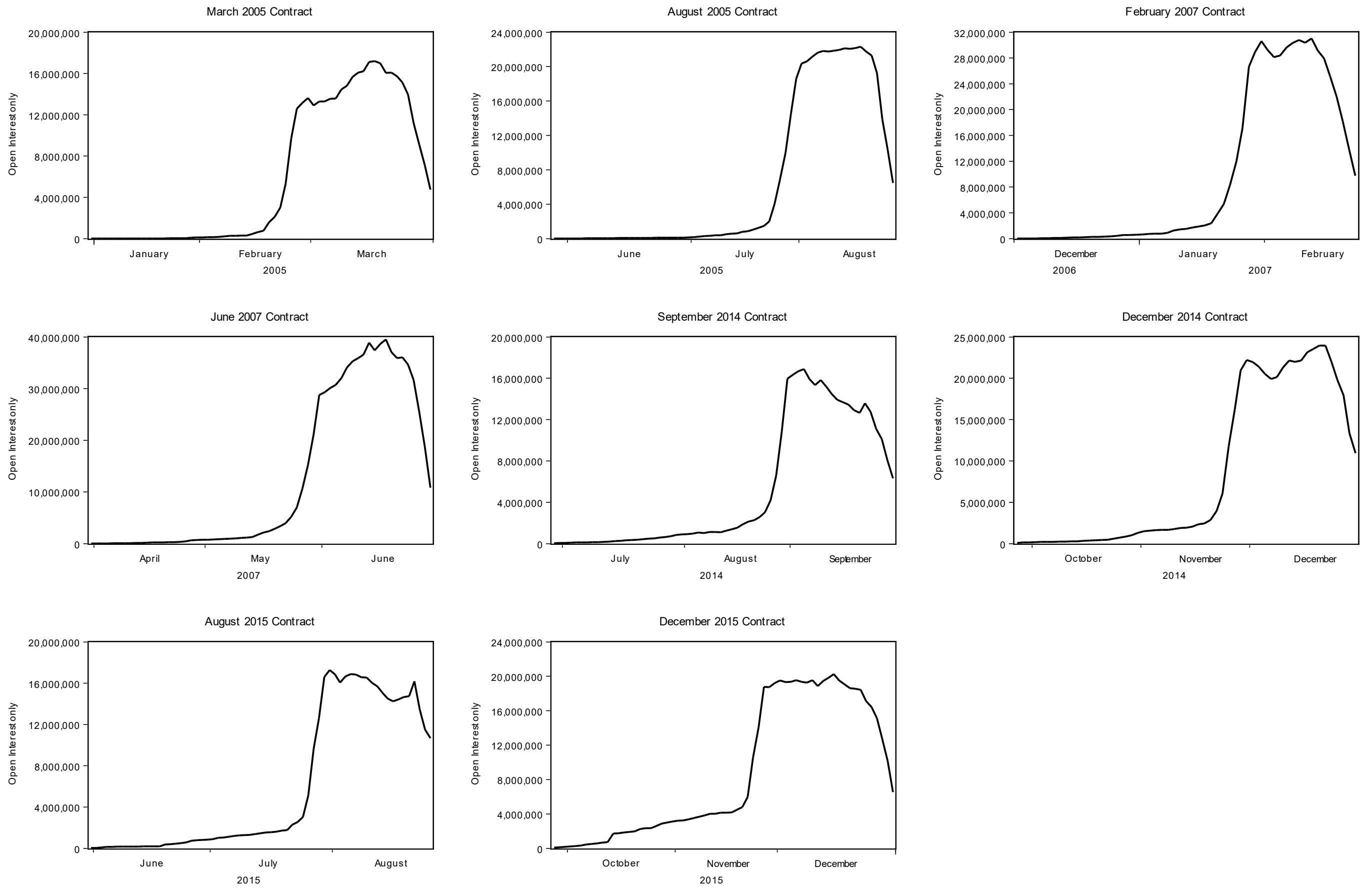


Figure 4.3 - Nifty 50 Index Futures
Open Interest 07/29/2016 to 10/25/2018

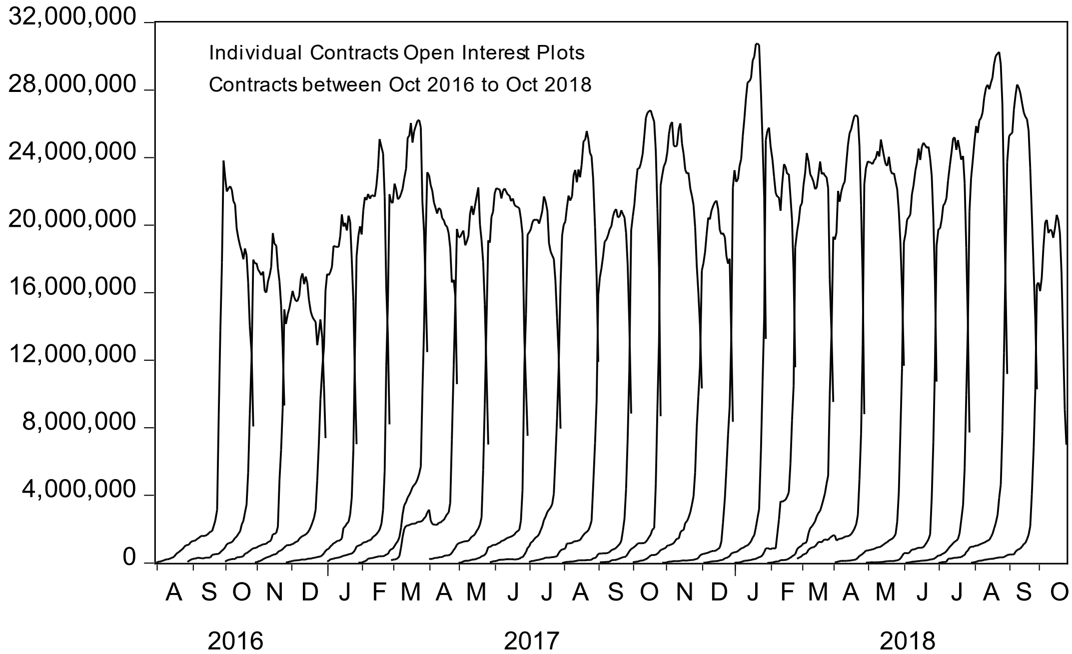


Table 4.2 - Pattern in Nearby, First Deferred and Second Deferred Contracts - for the Year 2016						
	Near Month / All Months		*First Deferred / All Months*		*Second Deferred / All Months*	
Expiry Month	TV	OI	TV	OI	TV	OI
Jan-16	85.65%	83.21%	13.16%	15.08%	1.19%	1.71%
Feb-16	85.62%	80.58%	13.58%	17.60%	0.80%	1.81%
Mar-16	85.77%	79.45%	12.85%	17.27%	1.38%	3.28%
Apr-16	83.09%	74.35%	15.90%	23.63%	1.02%	2.03%
May-16	85.34%	80.13%	13.88%	18.97%	0.78%	0.90%
Jun-16	86.47%	82.79%	12.56%	15.42%	0.98%	1.79%
Jul-16	82.18%	80.02%	16.39%	18.19%	1.42%	1.79%
Aug-16	80.84%	76.18%	18.03%	22.40%	1.14%	1.42%
Sep-16	81.94%	86.81%	16.83%	12.10%	1.23%	1.09%
Oct-16	83.14%	81.45%	15.76%	16.78%	1.10%	1.76%
Nov-16	85.20%	83.39%	13.71%	14.56%	1.09%	2.04%
Dec-16	84.60%	78.77%	14.50%	19.88%	0.89%	1.35%

Note: Traded Volumes (TV) and Open Interest (OI) in each Traded Maturities as a percentage of TV and OI in All Months combined

Appendix B: Unit Root Test

The ADF test involves fitting the regression model:

$$\Delta y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 t + \sum_{i=1}^{p} \delta_i \, \Delta y_{t-i} + \varepsilon_t \tag{4.12}$$

Table 4.4 reports the *t*-statistics of the coefficient β_1 from the Equation (4.12), where y_t refers to any of the variables used in this study. The optimal number of lag lengths for ADF equation was selected using Akaike's (1974) Information Criterion (AIC). For the information criterion method, the upper bound, i.e. the maximum lag length, p_{max}, for p in Equation (4.12) is determined by using the Schwert (1989) procedure suggested as:

$$p_{max} = int\left[12\,.\left(\frac{T}{100}\right)^{1/4}\right] \tag{4.13}$$

where T is the sample size and $[x]$ denote the integer part of x ; here this is the highest integer contained in $12 \times (T/100)^{1/4}$.

All variables in the data are also tested for possible unit roots by the second unit root test based on PP method. The calculation of PP method is based on estimating the non-augmented DF test equation:

$$\Delta y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 t + \varepsilon_t \tag{4.14}$$

One advantage of the PP test over ADF tests is that it modifies the t-ratio of the β_1 coefficeint to correct for any serial correlation and heteroskedasticity in the errors ε_t of the DF test regression. The number of bandwith in the PP test is controlled by using the Newey-West (1994) method.

Appendix C: Estimation using OLS Method

Table 4.9 : Regression Results for the Nearby Model using OLS

	Period I - 200 Lot Size		Period II - 100 Lot Size		Period III - 50 Lot Size		Period IV - 25 Lot Size		Period V - 75 Lot Size	
	Coefficient	(*t*-stat)	Coefficient	(*t*-stat)	Coefficient	(*t*-stat)	Coefficient	(*t*-stat)	Coefficient	(*t*-stat)
Panel A: Trading Volume (TV) equation: Dependent Variable = $ln(TV_t)$										
Constant	3.416	(7.68)***	19.140	(45.18)***	18.417	(76.56)***	21.320	(122.86)***	19.407	(101.79)***
$ln(BAS_t)$	-81.744	(-19.81)***	-810.706	(-62.99)***	-949.903	(-115.05)***	-1135.648	(-133.68)***	-909.588	(-122.47)***
$ln(PV_t)$	2.896	(1.81)*	2.984	(3.24)***	10.948	(25.40)***	7.923	(8.55)***	12.593	(10.82)***
$\Delta ln(MIBOR_t)$	2.549	(1.38)	-1.252	(-1.48)	-0.842	(-2.13)**	-0.538	(-0.58)	-0.912	(-1.00)
$ln(OI_{t-1})$	0.071	(1.50)	-0.041	(-1.05)	0.070	(3.18)***	0.050	(3.62)***	-0.046	(-2.99)***
$ln(TV_{t-1})$	0.650	(18.03)***	0.160	(4.82)***	0.131	(7.77)***	0.031	(2.37)**	0.126	(8.82)***
R^2	0.907		0.953		0.949		0.994		0.979	
Panel B: Bid-Ask spread (BAS) equation: Dependent Variable = $ln(BAS_t)$										
Constant	0.022	(24.47)***	0.022	(62.93)***	0.020	(117.65)***	0.020	(135.68)***	0.021	(121.78)***
$ln(TV_t)$	-0.002	(-22.36)***	-0.001	(-57.94)***	-0.001	(-106.54)***	-0.001	(-122.35)***	-0.001	(-111.13)***
$ln(PV_t)$	-0.010	(-1.27)	0.003	(3.22)***	0.011	(23.80)***	0.007	(7.38)***	0.013	(10.32)***
$\Delta ln(SP_t)$	0.005	(0.73)	0.000	(0.22)	0.003	(7.67)***	0.001	(2.48)**	0.001	(1.15)
$ln(BAS_{t-1})$	0.521	(26.78)***	0.044	(2.70)***	0.017	(1.96)*	-0.054	(-6.52)***	-0.016	(-1.78)*
R^2	0.825		0.945		0.929		0.993		0.974	
Panel C: Price Volatility (PV) equation: Dependent Variable = $ln(PV_t)$										
Constant	0.009	(2.58)**	-0.088	(-2.07)**	-0.281	(-14.97)***	-0.566	(-7.09)***	-0.191	(-9.25)***
$ln(TV_t)$	0.001	(3.37)***	0.006	(2.70)***	0.015	(16.81)***	0.028	(7.74)***	0.011	(10.55)***
$ln(BAS_t)$	-0.060	(-0.85)	4.075	(2.22)**	13.960	(14.70)***	29.612	(7.05)***	9.126	(9.22)***
$ln(TV_{t-1})$	-0.001	(-3.76)***	-0.001	(-1.89)*	-0.003	(-7.64)***	-0.003	(-5.74***	-0.001	(-5.53)***
$ln(PV_{t-1})$	0.532	(21.83)***	0.587	(15.29)***	0.483	(24.52)***	0.142	(2.43)**	0.238	(6.84)***
R^2	0.290		0.373		0.470		0.297		0.252	

Notes: (a) The table reports the parameter estimates of the trading volume, bid-ask spread, and price volatility in the three equation model specified in equations (4.1) to (4.3) using OLS estimator.
(b) All variables are in log form.
(c) The definition of each variable is as follows: TV = trading volume; BAS = bid-ask spread; PV = price volatility; OI = open interest; MIBOR = three-month short-term rate; SP = settlement price; and the subscript *t* - 1 denotes one period lagged variables. Δ is the difference operator.
(d) Numbers in parentheses denote *t*-statistics. *** , ** , and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 4.11 : Regression Results for the Deferred Model using OLS

	Period I - 200 Lot Size		Period II - 100 Lot Size		Period III - 50 Lot Size		Period IV - 25 Lot Size		Period V - 75 Lot Size	
	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)
Panel A: Trading Volume (TV) equation: Dependent Variable = $ln(TV_t)$										
Constant	0.039	(0.10)	13.458	(46.25)***	12.135	(65.84)***	15.973	(94.80)***	14.132	(95.38)***
$ln(BAS_t)$	-20.350	(-14.03)***	-344.323	(-60.10)***	-405.321	(-84.40)***	-650.971	(-101.60)***	-529.114	(-110.31)***
$ln(PV_t)$	11.022	(6.19)***	1.226	(1.57)	9.791	(18.32)***	8.690	(8.54)***	12.054	(12.42)***
$\Delta ln(MIBOR_t)$	-1.967	(-0.85)	-1.083	(-1.16)	-0.310	(-0.62)	1.693	(1.84)*	-1.178	(-1.57)
$ln(OI_{t-1})$	0.256	(5.88)***	-0.107	(-4.67)***	-0.008	(-0.48)	0.045	(4.61)***	0.061	(5.91)***
$ln(TV_{t-1})$	0.515	(15.91)***	0.171	(8.71)***	0.232	(15.62)***	0.043	(4.38)***	0.031	(2.86)***
R^2	0.732		0.948		0.896		0.989		0.973	
Panel B: Bid-Ask spread (BAS) equation: Dependent Variable = $ln(BAS_t)$										
Constant	0.070	(31.59)***	0.034	(59.58)***	0.030	(97.00)***	0.026	(106.07)***	0.027	(120.31)***
$ln(TV_t)$	-0.008	(-23.52)***	-0.002	(-54.85)***	-0.002	(-84.82)***	-0.001	(-91.22)***	-0.002	(-104.32)***
$ln(PV_t)$	0.083	(2.47)**	0.003	(1.52)	0.024	(20.66)***	0.011	(6.22)***	0.016	(8.72)***
$\Delta ln(SP_t)$	-0.009	(-0.29)	0.000	(-0.18)	0.011	(10.92)***	0.001	(1.21)	0.001	(1.29)
$ln(BAS_{t-1})$	-0.067	(-2.48)**	0.055	(3.28)	-0.031	(-2.77)***	-0.037	(-3.48)***	0.000	(-0.05)
R^2	0.363		0.940		0.870		0.986		0.966	
Panel C: Price Volatility (PV) equation: Dependent Variable = $ln(PV_t)$										
Constant	0.001	(0.51)	-0.020	(-0.59)	-0.139	(-13.99)***	-0.342	(-6.23)***	-0.151	(-7.97)***
$ln(TV_t)$	0.003	(7.31)***	0.003	(1.36)	0.012	(16.42)***	0.024	(7.39)***	0.012	(9.77)***
$ln(BAS_t)$	0.069	(2.94)***	0.756	(0.83)	4.941	(14.70)***	13.449	(6.16)***	5.263	(7.56)***
$ln(TV_{t-1})$	-0.002	(-3.96)***	-0.001	(-1.31)	-0.003	(-8.35)***	-0.003	(-5.97)***	-0.001	(-4.40)***
$ln(PV_{t-1})$	0.319	(11.72)***	0.486	(11.60)***	0.570	(31.87)***	0.195	(3.33)***	0.231	(6.49)***
R^2	0.142		0.247		0.480		0.349		0.287	

Notes: (a) The table reports the parameter estimates of the trading volume, bid-ask spread, and price volatility in the three equation model specified in equations (4.1) to (4.3) using OLS estimator.

(b) All variables are in log form.

(c) The definition of each variable is as follows: TV = trading volume; BAS = bid-ask spread; PV = price volatility; OI = open interest; MIBOR = three-month short-term rate; SP = settlement price; and the subscript *t* - 1 denotes one period lagged variables. Δ is the difference operator.

(d) Numbers in parentheses denote *t* -statistics. *** , ** , and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 4.15 : Regression Results for the Nearby Model using OLS

	Period I - 200 Lot Size		Period II - 100 Lot Size		Period III - 50 Lot Size		Period IV - 25 Lot Size		Period V - 75 Lot Size	
	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)
Panel A: Trading Volume (TV) equation: Dependent Variable = $ln(TV_t)$										
Constant	-12.592	(-29.39)***	-10.459	(-10.71)***	-9.957	(-24.23)***	-7.869	(-6.09)***	-13.557	(-17.77)***
$ln(BAS_t)^a$	-40.607	(-34.80)***	-39.063	(-18.16)***	-32.758	(-47.11)***	-24.567	(-11.09)***	-49.754	(-25.84)***
$ln(PV_t)$	-5.719	(-4.27)***	-9.570	(-3.98)***	-6.647	(-7.38)***	-19.900	(-2.38)**	-49.934	(-9.86)***
$\Delta ln(MIBOR_t)$	-0.507	(-0.34)	-0.097	(-0.05)	-0.834	(-1.09)	-0.594	(-0.09)	-1.852	(-0.60)
$ln(OI_{t-1})$	1.088	(24.74)***	1.159	(11.03)***	1.212	(26.56)***	0.985	(7.36)***	1.143	(17.18)***
$ln(TV_{t-1})$	-0.183	(-4.70)***	-0.427	(-4.57)***	-0.443	(-11.88)***	-0.159	(-1.38)	-0.285	(-4.91)***
R^2	0.939		0.733		0.809		0.711		0.763	
Panel B: Bid-Ask spread (BAS) equation: Dependent Variable = $ln(BAS_t)^b$										
Constant	0.022	(24.47)***	0.022	(62.93)***	0.020	(117.65)***	0.020	(135.68)***	0.021	(121.78)***
$ln(TV_t)$	-0.002	(-22.36)***	-0.001	(-57.94)***	-0.001	(-106.54)***	-0.001	(-122.35)***	-0.001	(-111.13)***
$ln(PV_t)$	-0.010	(-1.27)	0.003	(3.22)***	0.011	(23.80)***	0.007	(7.38)***	0.013	(10.32)***
$\Delta ln(SP_t)$	0.005	(0.73)	0.000	(0.22)	0.003	(7.67)***	0.001	(2.48)**	0.001	(1.15)
$ln(BAS_{t-1})$	0.521	(26.78)***	0.044	(2.70)***	0.017	(1.96)*	-0.054	(-6.52)***	-0.016	(-1.78)*
R^2	0.825		0.945		0.929		0.993		0.974	
Panel C: Price Volatility (PV) equation: Dependent Variable = $ln(PV_t)$										
Constant	0.009	(2.58)**	-0.088	(-2.07)**	-0.281	(-14.97)***	-0.566	(-7.09)***	-0.191	(-9.25)***
$ln(TV_t)$	0.001	(3.37)***	0.006	(2.70)***	0.015	(16.81)***	0.028	(7.74)***	0.011	(10.55)***
$ln(BAS_t)^b$	-0.060	(-0.85)	4.075	(2.22)**	13.960	(14.70)***	29.612	(7.05)***	9.126	(9.22)***
$ln(TV_{t-1})$	-0.001	(-3.76)***	-0.001	(-1.89)*	-0.003	(-7.64)***	-0.003	(-5.74***	-0.001	(-5.53)***
$ln(PV_{t-1})$	0.532	(21.83)***	0.587	(15.29)***	0.483	(24.52)***	0.142	(2.43)**	0.238	(6.84)***
R^2	0.290		0.373		0.470		0.297		0.252	

Notes: (a) BAS is estimated by the Turnover version of Amihud Ratio ($Amihud^T$) as specified in Brennan et al. (2013).

(b) BAS is measured by the Original Amihud Ratio ($Amihud^o$) as specified in Amihud (2002).

(c) The table reports the parameter estimates of the trading volume, bid-ask spread, and price volatility in the three equation model specified in equations (4.11) to (4.13) using OLS estimator.

(d) All variables are in log form.

(e) The definition of each variable is as follows: TV = trading volume; BAS = bid-ask spread; PV = price volatility; OI = open interest; MIBOR = three-month short-term rate; SP = settlement price; and the subscript t - 1 denotes one period lagged variables. Δ is the difference operator.

(f) Numbers in parentheses denote *t* -statistics. *** , ** , and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 4.17 : Regression Results for the Deferred Model using OLS

	Period I - 200 Lot Size		Period II - 100 Lot Size		Period III - 50 Lot Size		Period IV - 25 Lot Size		Period V - 75 Lot Size	
	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)	Coefficient	(*t* -stat)
Panel A: Trading Volume (TV) equation: Dependent Variable = ln(TV $_t$)										
Constant	-8.975	(-27.71)***	-11.015	(-17.45)***	-8.549	(-24.51)***	-7.869	(-6.09)***	-7.869	(-14.49)***
$\ln(BAS_t)^a$	-30.940	(-35.80)***	-37.714	(-25.24)***	-27.197	(-37.09)***	-24.567	(-11.09)***	-28.535	(-20.64)***
$\ln(PV_t)$	0.217	(0.16)	-0.675	(-0.44)	-5.080	(-5.39)***	-19.900	(-2.38)**	0.466	(0.13)
$\Delta\ln(MIBOR_t)$	-1.438	(-0.83)	-0.161	(-0.09)	-0.283	(-0.34)	-0.594	(-0.09)	-2.337	(-0.92)
$\ln(OI_{t-1})$	0.753	(22.10)***	0.994	(17.60)***	0.920	(27.49)***	0.985	(7.36)***	0.771	(17.87)***
$\ln(TV_{t-1})$	0.098	(3.55)***	-0.182	(-3.78)***	-0.091	(-3.07)***	-0.159	(-1.38)	0.033	(0.84)
R^2	0.849		0.804		0.705		0.711		0.688	
Panel B: Bid-Ask spread (BAS) equation: Dependent Variable = ln(BAS $_t$) ^{b}										
Constant	0.070	(31.59)***	0.034	(59.58)***	0.030	(97.00)***	0.026	(106.07)***	0.027	(120.31)***
$\ln(TV_t)$	-0.008	(-23.52)***	-0.002	(-54.85)***	-0.002	(-84.82)***	-0.001	(-91.22)***	-0.002	(-104.32)***
$\ln(PV_t)$	0.083	(2.47)**	0.003	(1.52)	0.024	(20.66)***	0.011	(6.22)***	0.016	(8.72)***
$\Delta\ln(SP_t)$	-0.009	(-0.29)	0.000	(-0.18)	0.011	(10.92)***	0.001	(1.21)	0.001	(1.29)
$\ln(BAS_{t-1})$	-0.067	(-2.48)**	0.055	(3.28)	-0.031	(-2.77)***	-0.037	(-3.48)***	0.000	(-0.05)
R^2	0.363		0.940		0.870		0.986		0.966	
Panel C: Price Volatility (PV) equation: Dependent Variable = ln(PV $_t$)										
Constant	0.001	(0.51)	-0.020	(-0.59)	-0.139	(-13.99)***	-0.342	(-6.23)***	-0.151	(-7.97)***
$\ln(TV_t)$	0.003	(7.31)***	0.003	(1.36)	0.012	(16.42)***	0.024	(7.39)***	0.012	(9.77)***
$\ln(BAS_t)^b$	0.069	(2.94)***	0.756	(0.83)	4.941	(14.70)***	13.449	(6.16)***	5.263	(7.56)***
$\ln(TV_{t-1})$	-0.002	(-3.96)***	-0.001	(-1.31)	-0.003	(-8.35)***	-0.003	(-5.97)***	-0.001	(-4.40)***
$\ln(PV_{t-1})$	0.319	(11.72)***	0.486	(11.60)***	0.570	(31.87)***	0.195	(3.33)***	0.231	(6.49)***
R^2	0.142		0.247		0.480		0.349		0.287	

Notes: (a) BAS is estimated by the Turnover version of Amihud Ratio (*Amihud* ^{T}) as specified in Brennan et al. (2013).

(b) BAS is measured by the Original Amihud Ratio (*Amihud* ^{o}) as specified in Amihud (2002).

(c) The table reports the parameter estimates of the trading volume, bid-ask spread, and price volatility in the three equation model specified in equations (4.11) to (4.13) using OLS estimator.

(d) All variables are in log form.

(e) The definition of each variable is as follows: TV = trading volume; BAS = bid-ask spread; PV = price volatility; OI = open interest; MIBOR = three-month short-term rate; SP = settlement price; and the subscript *t* - 1 denotes one period lagged variables. Δ is the difference operator.

(f) Numbers in parentheses denote *t* -statistics. *** , ** , and * denote significance at the 1%, 5% and 10% levels, respectively.

CHAPTER 5

5. Conclusion

In this thesis, both market efficiency and the price discovery function have been examined for an Indian commodity futures market dataset. The focus in Chapter 2 and 3 has been on the still relatively unexplored Indian agricultural futures markets motivated by the recent trading ban in wheat contracts. Moreover, the focus on the contract lot size of index futures in the Chapter 4 of this thesis should bring new insights on the issues of changes of contract specifications and their effects on market quality dynamics, which is still an unexplored area with respect to the futures contract design literature.

The results of testing the market efficiency hypothesis employing a cointegration model for $(s_t, f_{t-\tau})'$ presented in Chapter 2 reveals that both price series are integrated of order one at 5% level of significance for both the sub-periods in this study. As far as Johansen cointegration test results are concerned, the finding confirms the presence of cointegration between futures prices and spot prices for all forecast horizons in the post-ban period. However, the Indian commodity futures markets being in a nascent stage during the pre-ban period, only two (28- and 56-days) out of three wheat forecast horizons present such a long-run relationship. The presence of cointegration implies interdependency between the price series and suggests that Indian wheat futures markets satisfy one of the necessary conditions for market efficiency irrespective of the trading ban restrictions. The joint restrictions of unbiasedness on the cointegrating vector using the *LR* test are rejected in both the periods. Further analysis of the two sub-samples imply that the market efficiency hypothesis is supported (in 28- and 56-days forecast horizons) only for the pre-ban period. Results of the present study confirms that the wheat futures market in India was inefficient in the long-run only during the post-ban phase. These results support the hypothesis that the abrupt trading bans may play a major role in the effectiveness of futures markets. The study also tested short-term market efficiency using QECM. The statistical significant value of past prices of spot and futures confirms that some inefficiency exists in the short-run for all the forecasting horizons in the post-ban period. A further comparison of efficiency measure from both sub-periods reveal that wheat futures markets in all forecast horizons became more inefficient in the short-term during the post-ban period.

From a policy point of view, the inefficiency of futures markets in the post-ban period may indicate two things: (i) speculators demand a premium from hedgers as a compensation for assuming the risk due to the unpredictable changes in the regulatory environment (Kaminsky and Kumar, 1990; Deaves and Krinsky, 1995), and/or (ii) biases in the future price are likely to cause social loss and increase the cost of hedging (Stein, 1987; Krehbiel and Adkins, 1993; Murphy and Purcell, 1995). Therefore, policymakers and regulators should consider adopting other possible reforms/tools to curb speculative trading which would not hamper the liquidity and efficiency of the futures markets; because stringent measures such as trading suspensions to control inflation and speculation may impact the market efficiency negatively both in the long- and short-run.

A word of caution. In this study the inferences on the pre-ban phase have been derived based on a shorter sample size. An interesting extension would be to observe the impact of trading ban in the guar seed, castor seed and chickpea contracts which were suspended from trading in the period post 2012. Future studies of these contracts would allow to compare the impact of trading ban on market efficiency in two sub-periods (pre- and post-ban) over a longer sample period. It would also be meaningful to investigate the cases similar to the wheat contracts which would allow inter-contract analyses.

Chapter 3 has attempted to assess the temporal lead-lag and causality by using the cointegration model of $(s_t, f_t)'$. As a precursor to testing cointegration, data properties were envisaged to determine the order of integration for the spot and futures series. Findings from ADF, PP and KPSS tests indicated that both series are $I(1)$ in the two subsamples. The Johansen cointegration test finds the existence of a long-run association among the spot and futures markets. Thus, greater intervention by the government did not affect the market in terms of cointegration. In Chapter 2, inferences on the cointegration relationship were derived based on the shorter sample horizon. Chapter 3 overcomes the limitation of monthly data in the prior chapter by employing daily closing prices of spot and futures. Results of unbiasedness test with joint restrictions of $(1, -1, 0)$ has shown that positive constant risk premium is present in the market in the post-ban phase. The difference between the results of unbiasedness hypothesis in the two samples is an indication of risk aversion in the post-ban period arising from the regulatory uncertainty and lack of trust in continuity of trading of the agricultural futures contracts. Results of VECM model revealed the weak exogeneity of futures series in the long-run dynamics for both the sub-periods. Thus, futures prices continue to serve the role of primary market for price discovery and the imposition of ban did not change the direction of spot-futures relationship. However, the short-term prediction hypothesis applied in this study indicates that there is a unidirectional causality from futures markets to spot markets in the pre-ban period, but in the post-ban period there is a bidirectional informational flow between the two markets. Though a feedback relationship exists in the post-ban period, more information continues to flow from the futures market to the spot market. Hence, regulators may frame the policies on the agricultural futures markets on the basis that although futures markets observed loss in terms of its trading dominance in the post-ban period, price discovery in future markets still exists.

From the policy makers point of view, the decline in the futures market dominance in the post-ban period may indicate two things: (i) futures contracts remain informationally efficient in the post-ban phase which reinforces the reliable role played by the futures platform in incorporating new information faster than the spot markets (Tse, 1999; Brooks, Rew and Ritson, 2001; Floros and Vougas, 2008), and (ii) bidirectional short-run causality between two markets could be because of significant drop in the volume of trade of the futures contracts (Mattos and Garcia, 2004; Adämmer, Bohl and Gross, 2015), as it was subjected to trading ban. Hence, policy makers and regulators need to focus on adopting reforms without hampering the functioning of price discovery mechanism. Also, for a decentralized agricultural spot commodity market such as India, instead of suspending the futures trading, market regulators may take other steps to bring reforms to develop agri-futures markets. The role of agricultural commodity futures is critical given that it provides a centralized marketplace where the farmers and FPOs can get advance information about prices for their planting decisions and can also offset their commodity price risk by ensuring a pre-determined price.

Several factors may explain the lower contribution of futures markets to price discovery in the post-ban period, like reduced trading volume, change in the investor structure of the futures markets triggered by the regulatory intervention and relatively inactive trades in the wheat spot market[96] that may have decreased the needs of hedgers and speculation in the post-ban period.

[96] It has been well documented (Gulati et al., 2017; Mohanty and Mishra, 2020) that Indian agricultural commodity prices are often under severe pressure due to inaccurate weather forecasts, droughts, and unstable Government policies related to export-import, and stocking-movement-trading of commodities. If weaknesses in the commodity markets have continued during the post-ban period, then the Indian investor may take less interest in the agricultural spot market.

Only when the effects of the trading ban are examined using microstructure variables or with account-level data for individual day-traders and individual non-day traders, will deeper market insights for the reasons for lower price discovery in the post-ban period be developed. Besides this, future research studies in the field may also explore the determinants of price discovery with specific emphasis on agricultural commodities to help policy makers and exchanges in making agri-futures a successful trading instrument, i.e., a consistent, liquid, and deep futures market, in the commodities segment.

Chapter 4 of this thesis examines the potential impact of change in the contract lot size on the market quality of the Indian index futures markets. The results from the speculative ratio indicate that the degree of speculative activity increases (decreases) following the decrease (increase) in the contract lot sizes. In addition, univariate statistical analysis indicates that the trading volume has increased (decreased), while the bid-ask spread has decreased (increased) after size of a futures contract was decreased (increased); however, price volatility does not appear to have clear results affected by the downward (upward) revisions in the contract lot sizes. Further empirical analysis to investigate the effect of contract size changes on TV, BAS and PV is carried out in a three-equation structural model, using both OLS and GMM estimation procedure, to account for interdependence among the market quality variables and to control for other market factors that may impact these variables.

The results confirm that: (1) open interest has a larger influence on TV after the contract size was increased, providing empirical evidence that larger contracts would encourage hedgers' participation and increase their impact; (2) BAS is negatively related to TV, however, the TV has negligible effect on BAS, i.e., the magnitude of coefficients of TV in BAS equations are small and thus are of little economic significance. These findings support the notion that the Indian index futures market is highly liquid, since smaller contract sizes prior to 2015 have fuelled the growth by allowing wider market participation and added more liquidity suppliers to the market; hence, the cost of execution (BAS) is largely unaffected by the decrease in volume of trade of futures contracts following the increase in the contract size; and (3) PV has positive relation with TV and BAS after controlling for other variables. Although, there is some evidence for the smooth volatility hypothesis, i.e., PV decreased as a result of decline in BAS after contract sizes were reduced, however, the results do not support the hypothesis when the contract size was increased, i.e., PV did not increase as a result of increased BAS. Therefore, the results of the three equation-structural model suggests that the impact of increase (decrease) in the contract lot size on PV depends on the net effect of a decline (increase) in TV and an increase (decline) in BAS on price volatility.

From the point of view of market regulators, the respecification of the contract lot sizes are an effective policy tool for reducing the excessive speculative activity because of two implications: (i) the minimum contract value is an important factor in determining the initial margin requirements (Huang and Stoll, 1998; Ates and Wang, 2003). Therefore, increase in the margin as a consequence of increased contract value may lower the demand for futures contracts by retail traders more as opposed to the institutional traders, and (ii) increases in contract size may only have a slight impact on reducing the liquidity (Karagozoglu and Martell, 1999) and price volatility may decrease after the upward revision (Bjursell, Frino, Tse and Wang, 2010). When the contract size is increased, the institutional investors may be forced to place orders at multiples of minimum lot sizes while making small adjustments to their portfolios; whereas retail investors who potentially might prefer trading in smaller lots, may still continue to trade by placing orders exactly at the minimum lot size. Hence, the presence of both the types of investors will add more liquidity suppliers to the market, which will offset the negative impact of the increase in the contract size on BAS. Furthermore, there is evidence of a strong positive relationship between contemporaneous TV and PV, which is consistent with the previous empirical literature on futures markets. As a result, the reduction in liquidity (i.e., increased BAS) has a relatively small effect on PV compared to the effect of reduced trading activity (i.e., decreased TV) on PV, after the increase in the contract size. Overall, this study provides empirical evidence that the increase in the minimum contract size is an effective policy tool for reducing excessive participation of speculative traders.

Overall, this research chapter demonstrates that the intervention of market regulator SEBI to increase the minimum lot size of the Nifty futures contract can be viewed as successful by considering the effects of increased open interest and reduced trading volume; therefore, the objective of increasing hedger's participation and reducing speculator's activity is likely to have been achieved. However, it is unlikely that all members of the exchange (i.e., brokers and market-marker) and its customers (i.e., institutional and retail) are better off as a result of increased contract lot sizes. For example, brokers quote their commissions on a 'per contract' basis, and with decreased TV following the increase in the contract lot size, brokers revenue will decrease. Likewise, market-makers hold large number of positions to earn small amounts on each trade, but with lower turnover as a result of decreased TV following the increase in the contract lot size, the market-maker's opportunity for profits will also reduce. Also, market-maker's earnings are tied to the bid-ask spread for providing liquidity to the market, but their revenue will not increase as per expectation because the increase in the minimum contract size has not resulted in a large increase of BAS. Furthermore, with higher margin requirements induced by large contract sizes, the trading costs for both types of customers will increase. Thus, it is possible that significant transaction cost in the long-term may cause more institutional traders to exit the market, because the process of making adjustment to the portfolio with increased contracts sizes are likely to become discreet, requiring large adjustments. On the other hand, with reduced TV and larger BAS, the quality of the Nifty 50 futures market is clearly deteriorated. Combined negative consequences on the trading activity and market liquidity may influence inventor sentiment and discourage interest in the Indian index futures products at large. Thus, it would be interesting to see future empirical research on the long-term effects of the increase in the minimum lot size on the NSE members revenue and changes in the composition of different types of traders.

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