Does the type of settlement matter?
Evidence from Indian Derivatives Market.

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Abstract

The study investigates whether the mode of settlement of futures contract- cash settlement or physical delivery has any significant role in determining the prominent constructs in the Indian financial market. The study employs a sample of 46 treatment stocks that were moved from cash settlement to a physical delivery mode of futures-settlement from April, 2019 expiry onwards following a mandate by Securities Exchange Board of India. High-frequency intra-day data is used to estimate multiple proxies gauging the spot market volatility, hedging efficiency and price-discovery efficiency of futures contracts. A difference in difference analysis reveals a significant decline in volatility accompanied with a significant increase in hedging ratio as well as price-discovery efficiency of futures contracts upon the adoption of physical mode of delivery. However, we find that the effects are likely to be short-lived until markets acclimatize to the intervention. The study weighs the costs and benefits associated with the alternate modes of settlement that need to be considered for the welfare of the market and concludes that shifting to physical mode of settlement benefits the markets by bringing down the volatility without any adverse impact on hedging efficiency of price-discovery process.

1 Introduction

Derivative contracts derive their value from the underlying assets, but what make the trade more exciting are the characteristics of the derivatives. Characteristics such as the price of the underlying in the spot market, the time to expiration, the hedging effectiveness, and the mode of settlement render their uniqueness to a derivative contract. Of all the salient features, literature has been least illustrative about the impact of mode of settlement of a derivative contract on the spot and futures markets. A derivative contract has two modes of settlement- physical delivery or cash settlement. Under a settlement through physical delivery, the trader with a short-position is obliged to deliver the underlying asset at a specified location. The mode of physical delivery opens conversation about the quality of asset, the location of the asset, the storage, transportation and the insurance costs. The addition of several contractual specifications makes the contract lose its tradability in the market, especially in case of commodities. Under the alternative mode of cash settlement, a cash transfer is conducted by squaring off the difference between the prevailing market price and the agreed exercise price. As per conventional wisdom, cash settlement system leaves little scope for market manipulation techniques such as – market cornering or market squeezes, which otherwise have been rampant under the physical delivery mode of settlement.

Historically, fewer shifts in the settlement mechanisms have been observed in the global markets. The same might be the reason for the sparse attention spared on the impact of a delivery mode. One such rare event of a shift in settlement mechanisms was observed in 1986, when the feeder cattle future contracts traded on the Chicago Mercantile Exchange witnessed a shift from a physical delivery mode to cash settlement. Similarly, in February 1997, live hog contracts were converted to lean hog contracts with a switch from physical delivery mode to cash settlement. However, the first such change for equity assets was witnessed in the year 2000, when 10 Australian individual futures share contracts were moved from a cash settlement to physical delivery. In all the three cases, the exchange claimed that the change would be beneficial. The shifts have been discussed in literature but the evidence has largely been contradictory and limited to the context of developed economies.

A latest switch in settlement mechanism occurred recently in Indian markets upon the issuance of a mandate by the Securities Exchange Board of India (SEBI) on April 11, 2018 imposing a phased shift of all stock futures and options contracts from a cash settlement to a physical delivery system. The circular updated on December 31, 2018 prescribed the phased transition in two steps- 1) Stocks which were being cash settled shall be ranked in descending order based on daily market capitalization averaged for the month of December 2018; 2) Based on the ranking arrived above, the bottom 50 stocks shall move to physical settlement from April 2019 expiry , the next 50 stocks from the bottom shall move to physical settlement from July 2019 expiry , and the remaining stocks shall move to physical settlement from October 2019 expiry.

This move by SEBI was aimed at curbing the excessive speculation which creates severe volatility in the market especially during the settlement week. With mandatory physical settlement of contracts, the traders would no more be able to set off their positions in the market by transferring cash. They will have to roll-over their position ahead of expiry day, averting the lumping of roll-over positions on expiry day that leads to excess volatility. However, the need for owning/borrowing the stocks before indulging into a short position is likely to induce relatively higher activity and volatility in spot markets. If the said increase in volatility is large enough, it may even exceed the decline in volatility towards the expiry, hence reflecting as an increase in overall volatility in the spot market.

Another important purpose that is intended to be served upon a switch towards a physical settlement system is an improvement in the hedging efficiency. With physical delivery of contracts upon expiry, a call option writer is redeemed from purchasing the contracts in spot market to deliver them to the buyer. Instead, he would transfer the shares he received at an agreed price to the respective option buyers, hence mitigating his hedging risk exposure (Lien and Yang, 2004). At the same time however, physical deliveries may reduce short-selling as short-sellers would now be required to borrow stocks under the Securities Lending and Borrowing (SLB) mechanism which remains a shallow space in India. With higher cost of borrowing under the SLB mechanism, cost of hedging is also raised, lowering the efficiency of hedging in the market.

Further, the distinction between futures and spot markets is removed upon introduction of physical settlement in the spot markets. This convergence in prices may enhance the information dissemination between spot and futures. On the other hand, a consequent shift in traded volumes from equity spot and futures market to cash-settled equity-indices may dry up the stock futures and options market. A drop in volume may exacerbate the bid-ask spread and adversely impact the price-discovery mechanism.

Having said so, a switch in settlement mechanism may even have no significant impact on market mechanisms. With most of the positions squared off before expiry, physical settlement would be applicable to a small percentage of positions left to expiry. Besides, high minimum-lot-size requirements build unnecessary pressure and volatility, including rollovers which are reflected through bogus increase in volumes. The impact of minimum-lot size requirement may be huge enough to overcompensate the impact induced by a switch in the delivery mechanisms in the market.

Amidst several active hypotheses, the mandate serves as an excellent opportunity of complementing the literature by illustrating the role of futures-settlement system in a market. More than a decade later, the study intends to revive the debate in literature and settle it with robust empirical evidence. With about 46 future contracts trading that were switched to a physical settlement system from April 2019 onwards, a promising sample becomes available to evaluate the impact of settlement systems. This is considerably larger than the 10 Australian Individual stock futures studied previously by Lien and Yang (2004). The study further marks an integral milestone by exploring the question in an emerging market context of India.

The study investigates if the settlement mechanism has any significant impacts on the three important constructs of a market- i) volatility, ii) hedging effectiveness and iii) efficiency in price discovery function of futures contracts. The study employs intra-day data for spot and near-month future contracts at 5-minute intervals procured from National Stock Exchange, India. Each of the three constructs is measured through multiple proxies to ensure robustness. Series of student's t-tests have been run to gauge significant changes in the distribution of proxies before and after the adoption of physical settlement system. Further, a Difference in Difference analysis is undertaken to ensure causal inference. The stocks that switched to physical settlement in April, 2019 (hereon,treatment firms) were compared with the control group of stocks that switched to physical settlement in July(hereon, control firms).

To sum it up, upon a shift to physical settlement system, the Indian market not only experiences mitigation of spot market volatility but also a significant rise in hedging ratio and price-discovery efficiency. However, the documented impact may be short-lived. The findings are an essential guiding tool for policy-makers and market-regulators into assessing how a physical futures-settlement system might suit their purpose. The remaining paper proceeds as follows: section 2 briefly summarises the literature. Section 3 entails a concise discussion about Indian Derivatives market. Section 4 explains the data and variables used in the analysis. Section 5 illustrates the empirical strategy employed. Section 6 delineates the findings and discussion of results, section 7 checks for robustness, and section 8 concludes.

2 Review of Literature

The derivatives market can be efficient in its economic function only when the market is competitive with little or no scope for manipulations. Amidst market manipulations such as "squeezes" or "corners", the derivatives market loses its appeal as a signalling-tool for the spot market. As Chaherli and Hauser (1995) put it, at the heart of such manipulations is the settlement system associated with derivatives. Thereon, the authors analyse the impact of settlement system on the hedging effectiveness of two commodity contracts viz-soybean and corn. The primary objectives of the study included the comparison of physical-settlement systems and cash-settlement systems in stimulating higher hedging effectiveness of respective contracts. The authors find that a cash settlement system served better than a physical settlement system as a better device for hedging by allowing up to 6 % risk-reduction than physical delivery of corn or soybean. The study is corroborated by the evidences presented by Elam (1988) and Schroeder et al. (1988) who captured a significant decline in hedging risk with the introduction of cash-settlement in the feeder cattle market.

However, a contradiction was raised by Kenyon et al. (1991) suggesting that there was no statistically significant difference in the standard deviations of feeder cattle basis in Oklahoma City and South-West Virginia auction markets upon a switch to cash-settlement mode. Further, there was no reduction in basis risk for feeder cattle hedgers as a result of conversion to cash-settlement. Kenyon et al. (1991) argues to have provided a rather robust analysis as it employs actual future prices after cash settlement in contrast with the estimated proxy (U.S. Feeder Steer Price reported by Cattle-Fax) used for cash-settled future prices used by Elam (1988) and Schroeder et al. (1988).

A rejuvenated attention to the domain was then spared towards the turn of the century by Garbade and Silber (2000). The authors highlighted the importance of physical delivery as it enhances the convergence of futures and spot markets and thereby promotes risk-transfer and price-discovery functions of the futures market. At the same time, a cash settlement system is free of the costs and uncertainties of physical delivery. Through its extensive discussion on the alternate mechanisms on delivery, the article illustrates two major problems with a physical delivery system. First, high delivery costs are likely to interrupt the convergence of prices in the spot and futures market, and second, manipulations in the market such as squeezes or dumping may drive the cash market prices farther from the actual commercial value. Both the problems are done away with in a cash-settlement system- in absence of the need for physical delivery, squeezing and dumping vanish, and through riskless transfers in futures, the cash system enables convergence between the futures prices and the settlement index. However, for the arguments to be true, the choice of settlement index must be a reliable indicator of true commercial value of the commodity. The claims advocated by Garbade and Silber (2000) are contended by Pirrong (2001). The author defies the idea that cash-settlement system is relatively less vulnerable to manipulation than delivery- settlement. The primary arguments presented suggest that while the probability of manipulation by short-traders is higher in a physical settlement contract, in case of a cash settled contract, the manipulation is more likely from the long-traders end. For instance, in a delivery settlement system, the long-trader tries to run up the prices by forcing short to make excessive deliveries, the short can choose to deliver a number of varieties, varieties that are relatively inelastic to demand. In case of cash-settlement however, the long-trader may buy excess quantity of the variety whose price is most sensitive to maximise the effect on the settlement index. The author emphasizes that the appropriate settlement mechanism is contingent on the type of manipulation prevalent in a market- “an exchange’s efficient contract choice for a given commodity depends on which problem is more acute.”

The apparent divergence in theory is also visible in empirical evidences presented in literature. Chan and Lien (2001) adopt the Gweke feedback measure to investigate the impact of cash settlement system on the price-discovery function of futures market. The authors establish that feeder cattle futures traded in Chicago Mercantile Exchange (CME), improve in their price-discovery function and the futures market became more integrated with the spot market upon introduction of a cash settlement system in August, 1986. The conclusion is drastically different in the case of cash-settled lean-hog future contracts (CME) replacing the physically-settled live hog futures in December, 1996. The authors find that upon shifting to cash-settled contracts, the futures market becomes less efficient in price-discovery and the futures and spot market become more segmented. Lien and Tse (2006) offer some plausible explanations for these contradictions- in the transition from physically-settled live hogs to cash-settled lean hogs, several confounding factors arise. These factors include- 1) a small sample size with only 152 observations for the lean hog futures contract, plausibly leading to unreliable Gweke measures, 2) a change in weighing scheme of the live and lean hog contracts from live weight to carcass weight respectively while the spot market was still priced on the basis of live weight, and 3) the simultaneous change in contract name might have made the traders perceive both contracts as two different contracts.

Chan and Lien (2002) adopt multivariate stochastic volatility model to look for changes in basis and basis variance upon a shift to cash-settlement method in feeder cattle futures contract. The authors find that the cash-settlement certainly improved the hedging effectiveness of the feeder-cattle futures contract and made markets not only more integrated but also more stable, thus, benefiting all the market participants. With a concentrated focus on market volatility, Lien and Tse (2002) apply a bivariate GARCH model to find that volatility of futures prices declined upon a switch from physical to cash-settlement in case of feeder-cattle contracts traded on CME. The results were corroborated by Chan and Lien (2003) who found a reduction in volatility of future prices and an improvement in hedging effectiveness of feeder-cattle contracts upon the adoption of cash-settlement.

Though elaborate, the above studies are concerned with commodity future contracts only. Little has been said about the change in settlement format for stock futures. Stock-futures are not heterogeneous in nature like commodities. The concern regarding the grade of deliverable therefore does not arise in case of stock futures. Further, the delivery costs are negligible in the new digital era. With the two major problems with physical settlement curbed, a cash settlement system loses its lucrativeness as a remedial solution, in case of stock-futures. Hence, it would be interesting to investigate which settlement mechanism serves better for stock-futures. Lien and Yang (2004) present one of the first studies to look into the change in settlement format in Australian Individual Stock Futures (ISFs). ISF contracts were introduced as cash-settled contracts in 1994. In 1996, cash settlement was replaced by physical delivery of contracts. The authors adopted a bivariate error correction GARCH model to find that upon switch to physical settlement, the future prices, spot prices and basis all became more volatile. Even though a significant rise in volatility was recorded, it was observed that physically settled contracts were more effective tools of hedging. To the best of our knowledge, this has been the only study concerned with stock-futures, however the sample size of 10 contracts seems too small to be fully relied upon without corroboration.

Therefore, our study aims at complementing the literature by employing a promising sample of 46 Indian stock futures that were mandated to move to a physical settlement system in a phased manner starting April, 2019 by SEBI. In the same vein,the study tests the following hypotheses:

- H_1 : Spot-market volatility declines upon adoption of Physical mode of delivery of futures contracts.
- H_2 : Hedging ratio of Futures Contracts improves upon adoption of Physical mode of delivery of futures contracts.
- H_3 : Efficiency of price-discovery function of Futures Contracts improves upon adoption of Physical mode of delivery of futures contracts.

3 Indian Derivatives Market

Even though the oldest stock exchange in Asia, the Bombay Stock Exchange (BSE) has an Indian origin, the history of the modern security market in India starts from 1991. During this period, India got its first demutualised stock exchange- National Stock Exchange (NSE), which became the first to employ satellite-based communication technology for a securities transaction. NSE further introduced straight-through processing in securities transactions. With rock bottom global rankings in the state of capital markets in the 1990s, the Indian capital market buckled its shoe up to surprise the world by achieving radically high standards of market quality within less than a decade. In 2007, NSE emerged as the second-largest stock exchange in terms of market capitalization in South Asia and has grown exponentially ever since to become the third-largest stock exchange in terms of the amount of transactions across the world today. In 2019, NSE was ranked as the the stock exchange with the largest traded volume in derivative contracts, as per the World Federation of Exchange rankings.

In a report published by SEBI for the Financial Year 2017-18, a 44 % increase was witnessed in the total turnover of equity derivatives over the previous year. The ratio of turnover in equity derivatives to that in cash segment was found to have increased from 20 times in 2017-18 to 27 times in 2018-19. As the market activities has been experiencing tremendous growth, the regulators have been trying to rein in the excess enthusiasm in the market to ensure smooth and efficient market practices. In one such initiative, SEBI mandated the phased movement of then cash settled stock derivatives to physical settlement (for April 2019 expiry, July 2019 expiry and October 2019 expiry) on the basis of average daily market capitalisation of the stocks. It was also specified that derivatives introduced on new stocks, meeting the enhanced eligibility criteria after the date of concerned circular, shall also be physically settled. Shifting of stocks to physical settlement was expected to help reduce speculation and hence excessive intra-day volatility in such stock.

The study however, expands its scope to market constructs beyond volatility and investigates the benefits and costs associated with a switch towards physical mode of futures settlement.

4 Data and Variables Estimation Method

4.1 Sample Data

The study primarily focuses on a list of 46 stocks that were moved from cash to physical-delivery mode of settlement from April, 2019 expiry onwards [1]. These 46 stocks were then compared against a control group of 45 stocks that moved to physical settlement mode from July, 2019 expiry onwards. The list of of all the stocks in treatment and control group, along with their month of expiry from when they were mandated to be settled in physical mode has been provided in Table 1. The left side enlists the 46 securities whose mode of settlement was changed to physical settlement from April, 2019 expiry onwards and the right side delineates all securities for which the switch happened from July, 2019 expiry. A better insight on the differences between the two groups of stocks is presented in Table 2. The market capital is averaged for the month of December, 2018. These values were employed by SEBI as a cutoff-criterion such that the first 50 firms with lower average market capital for the month of December, 2018 were mandated to transition earlier from April, 2019 onwards, followed by subsequent 50 stocks from July, 2019, and the rest from October, 2019 onwards. Therefore, a significantly lower market capital for the treated stocks when compared with the control group is evident in Table 2. Interestingly, there is no significant difference in the daily average number of shares traded for both the groups during the sample period.

The study is based on high frequency data with 5 -minute intervals of price and volume dimensions of all relevant (treatment and control) stocks in spot and derivatives market. The sample starts on January 28, 2019 and ends on May 27, 2019 that is 60 calendar days before the switch on March 28, 2019 until 60 calendar days post [2]. The data includes spot price, futures price from the nearby contracts since it is the most actively traded contract, and spot market trading volumes for each security in the treatment and control group. The required data has been sourced from National Stock Exchange of India. The descriptive statistics for spot and futures return series of all the concerned stocks for the period before and after intervention by SEBI have been presented in Panels A(treated stocks) and B (control-group stocks) of Table 3 and 4 respectively. All the return series are found to be stationary with a majority of stocks-returns having high kurtosis in both spot and futures market.

[1] A set of 46 stocks was shifted to physical settlement in April, 2018 (https://archives.nseindia.com/content/circulars/FAOP37594.pdf). However the set does not offer any randomisation supremacy over current sample, since the stocks converted also had lowest market capitalisation. Several stocks were also delisted from Futures market within next 6 months.

[2] The sample period is constrained as the control group is exposed to treatment in the subsequent months, leaving a small window to use it as a control in the experiment

Table 1: Indian Individual share future contracts

Company Name	Code	Switching Date	Company Name	Code	Switching Date
Adani Enterprises Limited	ADANIENT	April 2019	ACC Limited	ACC	July 2019
Amara Raja Batteries Limited	AMARAJABAT	April 2019	Ambuja Cements Limited	AMBUJACEM	July 2019
Apollo Hospitals Enterprise Limited	APOLLOHOSP	April 2019	Ashok Leyland Limited	ASHOKLEY	July 2019
Apollo Tyres Limited	APOLLOTYRE	April 2019	Aurobindo Pharma Limited	AUROPHARMA	July 2019
Arvind Limited	ARVIND	April 2019	Bank Of Baroda	BANKBARODA	July 2019
Bata India Limited	BATAINDIA	April 2019	Bharat Forge Limited	BHARATFORG	July 2019
Bharat Electronics Limited	BEL	April 2019	Bharat Heavy Electricalslimited	BHEL	July 2019
Bharat Financial Inclusion Limited	BHARATFIN	April 2019	Biocon Limited	BIOCON	July 2019
Canara Bank	CANBK	April 2019	Cadila Healthcare Limited	CADILAHC	July 2019
Castrol India Limited	CASTROLIND	April 2019	Cipla Limited	CIPLA	July 2019
Century Textiles & Industries Limited	CENTURYTEX	April 2019	Colgate Palmolive (India) Limited	COLPAL	July 2019
Cesc Limited	CESC	April 2019	Container Corporation Of India Limited	CONCOR	July 2019
Cholamandalam Investmentand Finance Company Limited	CHOLAFIN	April 2019	Cummins India Limited	CUMMINSIND	July 2019
Dewan Housing Financecorporation Limited	DHFL	April 2019	Divi'S Laboratories Limited	DIVISLAB	July 2019
Dish Tv India Limited	DISHTV	April 2019	Dlf Limited	DLF	July 2019
Engineers India Limited	ENGINERSIN	April 2019	Grasim Industries Limited	GRASIM	July 2019
Equitas Holdings Limited	EQUITAS	April 2019	Havells India Limited	HAVELLS	July 2019
Escorts Limited	ESCORTS	April 2019	Hindalco Industries Limited	HINDALCO	July 2019
Exide Industries Limited	EXIDEIND	April 2019	Hindustan Petroleum Corporation Limited	HINDPETRO	July 2019
The Federal Bank Limited	FEDERALBNK	April 2019	ICICI Prudential Life Insurance Company Limited	ICICIPRULI	July 2019
Glenmark Pharmaceuticals Limited	GLENMARK	April 2019	Vodafone Idea Limited	IDEA	July 2019
Gmr Infrastructure Limited	GMRINFRA	April 2019	Interglobe Aviation Limited	INDIGO	July 2019
Indraprastha Gas Limited	IGL	April 2019	Bharti Infratel Limited	INFRATEL	July 2019
Jindal Steel & Power Limited	JINDALSTEL	April 2019	L&T Finance Holdings Limited	L&TFH	July 2019
Jubilant Foodworks Limited	JUBLFOOD	April 2019	LIC Housing Finance Limited	LICHSGFIN	July 2019
Kajaria Ceramics Limited	KAJARIACER	April 2019	Lupin Limited	LUPIN	July 2019
Manappuram Finance Limited	MANAPPURAM	April 2019	Mahindra & Mahindra Financial Services Limited	M&MFIN	July 2019
Multi Commodity Exchange Of India Limited	MCX	April 2019	Marico Limited	MARICO	July 2019
Max Financial Services Limited	MFSL	April 2019	United Spirits Limited	MCDOWELL-N	July 2019
Mindtree Limited	MINDTREE	April 2019	Motherson Sumi Systems Limited	MOTHERSUMI	July 2019
Muthoot Finance Limited	MUTHOOTFIN	April 2019	MRF Limited	MRF	July 2019
National Aluminium Company Limited	NATIONALUM	April 2019	NMDC Limited	NMDC	July 2019
NBCC (India) Limited	NBCC	April 2019	Page Industries Limited	PAGEIND	July 2019
NCC Limited	NCC	April 2019	Piramal Enterprises Limited	PEL	July 2019
Raymond Limited	RAYMOND	April 2019	Petronet Lng Limited	PETRONET	July 2019
REC Limited	RECLTD	April 2019	Power Finance Corporation Limited	PFC	July 2019
Reliance Capital Limited	RELCAPITAL	April 2019	Pidilite Industries Limited	PIDILITIND	July 2019
Reliance Infrastructure Limited	RELINFRA	April 2019	Punjab National Bank	PNB	July 2019
Steel Authority Of India Limited	SAIL	April 2019	RBL Bank Limited	RBLBANK	July 2019
Tata Chemicals Limited	TATACHEM	April 2019	Shriram Transport Finance Company Limited	SRTRANSFIN	July 2019
Tata Elxsi Limited	TATAELXSI	April 2019	Sun Tv Network Limited	SUNTV	July 2019
Tata Global Beverages Limited	TATAGLOBAL	April 2019	Tata Steel Limited	TATASTEEL	July 2019
Tata Motors Limited	TATAMTRDVR	April 2019	Torrent Pharmaceuticalslimited	TORNTPHARM	July 2019
Tata Power Company Limited	TATAPOWER	April 2019	TVS Motor Company Limited	TVSMOTOR	July 2019
Ujjivan Financial Services Limited	UJJIVAN	April 2019	UPL Limited	UPL	July 2019
Voltas Limited	VOLTAS	April 2019			

Table 1 enlists the name of securities, their NSE symbols and their month of switching to physical delivery mode of settlement. 46 stocks with the least daily market-capitalisation that were mandated to move to physical settlement from April 2019 expiry onwards have been enlisted towards the left hand side of Table 1. The next 45 stocks from the bottom were mandated to move to physical settlement from July 2019 expiry onwards are listed in the right hand side of Table 1.

Table 2: Market capital and number of traded shares for sample firms

Treatment Group	Market Value (Rs million) average for the month December 2018	Daily average of number of shares traded (thousands) during the sample period.	Control Group	Market Value (Rs million) average for the month December 2018	Daily average of number of shares traded (thousands) during the sample period.
ADANIENT	173850	7173	ACC	278042	794
AMARAJABAT	124327	703	AMBUJACEM	432126	3006
APOLLOHOSP	172171	706	ASHOKLEY	307430	24315
APOLLOTYRE	133347	2644	AUROPHARMA	436869	2289
ARVIND	25819	3015	BANKBARODA	296117	18710
BATAINDIA	139697	937	BHARATFORG	241862	1420
BEL	206047	12026	BHEL	252342	12665
BHARATFIN	141252	770	BIOCON	369702	3280
CANBK	191908	5562	CADILAHC	356195	1485
CASTROLIND	148332	1527	CIPLA	421532	2345
CENTURYTEX	101251	1351	COLPAL	348751	402
CESC	91460	3656	CONCOR	323408	902
CHOLAFIN	194575	1673	CUMMINSIND	223834	530
DHFL	69925	26984	DIVISLAB	392989	632
DISHTV	67964	24542	DLF	317474	11361
ENGINERSIN	75174	2388	GRASIM	543323	1437
EQUITAS	40417	2104	HAVELLS	431843	1243
ESCORTS	82196	2066	HINDALCO	499769	7842
EXIDEIND	220476	2336	HINDPETRO	358413	6240
FEDERALBNK	177623	12585	ICICIPRULI	457373	2470
GLENMARK	187391	601	IDEA	314811	69434
GMRINFRA	95070	24542	INDIGO	416189	1805
IGL	181316	2154	INFRATEL	475783	3722
JINDALSTEL	152997	11135	L&TFH	294548	6829
JUBLFOOD	167416	2099	LICHSGFIN	232896	1815
KAJARIACER	73162	532	LUPIN	383757	1947
MANAPPURAM	73880	3807	M&MFIN	276024	3532
MCX	36699	408	MARICO	475835	1893
MFSL	117445	602	MCDOWELLS-N	372951	1531
MINDTREE	141559	1283	MOTHERSUMI	512748	7207
MUTHOOTFIN	191149	1103	MRF	282969	7
NATIONALUM	120569	13226	NMDC	298757	4379
NBCC	97335	9386	PAGEIND	275220	46
NCC	50503	9520	PEL	405148	593
RAYMOND	50673	833	PETRONET	326601	2877
RECLTD	213610	9500	PFC	249986	7563
RELCAPITAL	54752	18568	PIDILITIND	581593	621
RELINFRA	80263	15948	PNB	270680	27637
SAIL	218861	21675	RBLBANK	240822	1717
TATACHEM	176888	2411	SRTRANSFIN	267947	1208
TATAELXSI	63096	632	SUNTV	230359	2394
TATAGLOBAL	134283	2833	TATASTEEL	583512	9013
TATAMTRDVR	47085	4209	TORNTPHARM	296310	262
TATAPOWER	212269	6741	TVSMOTOR	266415	1448
UJJIVAN	29815	1741	UPL	383881	2681
VOLTAS	184467	1546			
Average	124573	6126	Average	355670	5901
Standard Deviation	58875	7221	Standard Deviation	96561	11278
t-stat ($market\_cap_{treatment} - market\_cap_{control}$)		**-13.60*** **	**t-stat(traded_ shares**$_{treatment}$ $- traded\_shares_{control}$)		**0.11**

Table 2 presents the average monthly market capital for the month of December 2018 for the sample firms. The average monthly market capital for treated stocks is significantly lower than the monthly market capital for the control group stocks for the month of December, 2018. The table also displays the daily average of number of shares traded for each of the sample firms. No significant difference is found in the number of shares traded of the treatment stocks and the control stocks.

Table 3: Descriptive statistics : Spot returns

Panel A										
treatment Firms	**Pre-Period**					**Post-Period**				
	Mean	**Std. Dev.**	**Skewness**	**Kurtosis**	**Dickey-Fuller**	**Mean**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Dickey-Fuller**
ADANIENT	0.0012	0.3510	0.05	16.49	-13.84	0.0050	0.4123	7.23	202.47	-12.39
AMARAJABAT	-0.0014	0.1711	1.19	21.21	-14.26	-0.0046	0.1939	1.06	38.60	-12.41
APOLLOHOSP	-0.0031	0.2251	0.53	33.48	-13.18	0.0010	0.2154	0.70	29.26	-14.55
APOLLOTYRE	0.0012	0.2018	0.20	21.17	-13.12	-0.0031	0.1938	1.65	58.69	-12.84
ARVIND	0.0003	0.2766	0.24	20.12	-13.20	-0.0054	0.2322	0.93	16.22	-12.54
BATAINDIA	0.0078	0.1709	2.55	49.51	-13.72	-0.0007	0.1514	0.58	12.02	-13.41
BEL	0.0055	0.2387	0.69	20.69	-14.05	0.0078	0.2431	3.85	67.05	-13.29
BHARATFIN	0.0077	0.1884	2.13	130.63	-12.94	-0.0036	0.2635	3.57	163.08	-14.19
CANBK	0.0058	0.2292	0.44	12.13	-13.92	-0.0008	0.2721	5.16	106.09	-13.74
CASTROLIND	0.0010	0.2302	1.78	63.99	-15.17	-0.0033	0.1642	-0.51	16.76	-13.77
CENTURYTEX	0.0043	0.2072	0.31	18.91	-13.97	0.0049	0.2142	1.69	43.94	-13.39
CESC	0.0018	0.2004	0.08	36.96	-14.06	0.0012	0.1953	3.53	74.26	-13.00
CHOLAFIN	0.0078	0.2223	3.13	45.85	-14.18	0.0017	0.2314	0.64	37.85	-13.47
DHFL	-0.0109	0.6360	3.26	145.49	-13.58	-0.0045	0.5903	-8.81	272.47	-14.18
DISHTV	0.0154	0.5744	-2.82	69.27	-15.08	-0.0049	0.4280	0.63	19.07	-13.41
ENGINERSIN	0.0002	0.2328	0.61	30.49	-13.95	0.0019	0.2015	2.21	46.67	-13.23
EQUITAS	0.0049	0.3011	-1.42	35.13	-13.02	0.0010	0.2684	-0.98	34.38	-14.81
ESCORTS	0.0066	0.2334	-2.80	73.80	-13.20	-0.0084	0.2507	-8.99	302.79	-14.36
EXIDEIND	0.0012	0.2084	0.19	20.41	-13.91	-0.0012	0.1735	-0.35	27.55	-12.57
FEDERALBNK	0.0030	0.1957	0.88	21.58	-13.85	0.0056	0.2217	3.10	47.46	-14.64
GLENMARK	0.0010	0.2167	-4.26	127.64	-13.87	-0.0051	0.1776	-0.25	11.83	-13.82
GMRINFRA	0.0088	0.3551	-1.41	37.46	-14.46	-0.0048	0.2867	1.55	22.79	-14.57
IGL	0.0043	0.2432	-1.05	56.73	-12.83	0.0029	0.2297	7.31	152.54	-12.70
JINDALSTEL	0.0084	0.3165	0.64	21.53	-14.17	-0.0010	0.3369	-3.13	128.18	-12.67
JUBLFOOD	0.0071	0.2610	-1.04	48.46	-14.93	-0.0033	0.1970	1.35	33.33	-13.51
KAJARIACER	0.0026	0.2144	2.14	34.27	-14.78	0.0023	0.2126	-0.87	35.29	-13.87
MANAPPURAM	0.0093	0.2544	1.40	23.45	-14.20	0.0038	0.2413	2.18	34.06	-13.81
MCX	0.0041	0.1996	1.93	26.15	-13.89	0.0023	0.2017	1.60	20.74	-13.09
MFSL	0.0034	0.2874	-0.04	24.02	-14.98	-0.0009	0.2730	2.79	76.49	-14.24
MINDTREE	0.0031	0.1727	0.27	23.73	-15.12	0.0013	0.1008	0.20	30.26	-15.93
MUTHOOTFIN	0.0056	0.2316	0.63	16.19	-13.94	0.0031	0.2246	3.89	66.05	-14.17
NATIONALUM	-0.0040	0.3201	-2.32	109.51	-12.67	-0.0021	0.1946	1.62	51.64	-13.46
NBCC	0.0052	0.2900	0.49	47.58	-12.74	-0.0011	0.2396	4.14	74.79	-12.66
NCC	0.0128	0.2476	0.47	11.82	-13.67	0.0006	0.2817	3.00	47.88	-13.59
RAYMOND	0.0025	0.2604	3.61	79.47	-15.45	0.0023	0.2073	-0.15	49.62	-13.14
RECLTD	0.0085	0.3053	-5.49	182.85	-13.08	-0.0015	0.2358	3.19	80.00	-12.64
RELCAPITAL	0.0006	0.6000	0.50	51.33	-13.19	-0.0157	0.4644	-1.82	60.21	-12.82
RELINFRA	-0.0235	0.7052	-4.50	176.20	-12.80	-0.0065	0.4141	-0.88	83.65	-13.34
SAIL	0.0040	0.2764	2.46	44.11	-12.90	0.0014	0.2641	1.02	31.00	-12.97
TATACHEM	-0.0046	0.2096	-10.79	349.12	-13.23	0.0031	0.2035	7.85	174.06	-14.67
TATAELXSI	0.0035	0.2006	1.82	38.80	-14.04	-0.0033	0.1599	1.32	24.48	-13.84
TATAGLOBAL	-0.0020	0.2221	0.62	16.68	-13.49	0.0061	0.2195	0.85	16.96	-14.00
TATAMTRDVR	-0.0011	0.3786	-28.93	1257.32	-12.72	0.0011	0.2855	1.18	50.38	-12.92
TATAPOWER	0.0006	0.2197	0.64	12.85	-13.92	-0.0017	0.2423	9.54	257.35	-13.13
UJJIVAN	0.0070	0.2823	-0.65	23.14	-13.46	0.0015	0.2793	2.48	38.54	-14.14
VOLTAS	0.0058	0.1960	0.69	32.54	-12.66	-0.0020	0.2025	-3.98	119.67	-15.00

Table 3 Panel A provides mean, standard deviation, skewness, Kurtosis, Dickey-Fuller statistic of return-series for each stock in the treatment group. Spot returns are calculated as log differences of spot closing prices multiplied by 100. Pre-period spans from January 28, 2019 till March 27, 2019. Post-period spans from March 28, 2019 till May 27,2019. All the return series are stationary.

Table 3: Descriptive Statistics : Spot return (contd)

Panel B										
Control Firms	**Pre-Period**					**Post-Period**				
	Mean	**Std. Dev.**	**Skewness**	**Kurtosis**	**Dickey-Fuller**	**Mean**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Dickey-Fuller**
ACC	0.0062	0.1822	2.32	43.12	-13.46	0.0029	0.1905	-4.18	158.20	-13.10
AMBUJACEM	0.0062	0.1966	1.92	26.47	-14.48	0.0004	0.1993	1.74	52.69	-13.31
ASHOKLEY	0.0018	0.2421	1.18	63.93	-13.62	0.0023	0.2300	-2.23	65.79	-12.73
AUROPHARMA	0.0014	0.2008	0.54	48.59	-13.99	-0.0049	0.2234	-3.90	119.65	-13.92
BANKBARODA	0.0041	0.2123	0.09	20.50	-13.94	0.0045	0.2963	1.48	126.84	-13.37
BHARATFORG	0.0019	0.2246	1.44	55.69	-13.55	-0.0004	0.2126	-4.09	110.15	-14.03
BHEL	0.0041	0.2397	0.71	53.63	-13.92	0.0000	0.2494	1.33	28.25	-12.89
BIOCON	-0.0022	0.1478	-0.02	17.04	-13.20	-0.0032	0.1850	-3.62	72.98	-13.34
CADILAHC	0.0004	0.1919	1.90	23.94	-14.39	-0.0097	0.2037	-1.61	32.30	-12.99
CIPLA	0.0027	0.1491	0.73	33.27	-15.35	0.0035	0.1795	0.99	38.37	-15.22
COLPAL	0.0000	0.1481	1.50	28.71	-14.24	-0.0027	0.1322	0.20	17.74	-13.83
CONCOR	-0.0086	0.4809	-35.76	1615.62	-14.21	0.0000	0.1922	-0.17	19.82	-13.15
CUMMINSIND	-0.0033	0.2465	-2.32	72.32	-14.12	0.0008	0.2056	0.03	29.81	-13.38
DIVISLAB	0.0054	0.1979	0.12	60.35	-12.64	-0.0005	0.2078	-11.32	401.25	-13.70
DLF	0.0064	0.2988	2.23	35.84	-14.25	-0.0009	0.3068	-1.40	93.66	-13.98
GRASIM	0.0049	0.1899	0.04	20.99	-13.43	0.0041	0.1917	0.43	31.43	-12.98
HAVELLS	0.0032	0.1699	-0.40	19.57	-13.21	-0.0006	0.1536	-2.62	39.07	-14.84
HINDALCO	0.0016	0.1958	-0.81	34.98	-13.61	-0.0018	0.2281	1.53	101.55	-13.83
HINDPETRO	0.0050	0.2497	-0.79	38.69	-12.98	0.0043	0.3151	1.12	112.78	-13.47
ICICIPRULI	0.0063	0.2963	5.83	119.23	-12.64	0.0039	0.2326	3.39	57.01	-12.94
IDEA	-0.0034	0.3476	-0.86	32.96	-12.99	-0.0291	0.8541	-33.42	1509.63	-13.29
INDIGO	0.0067	0.2336	-0.05	34.81	-13.71	0.0055	0.2690	1.62	59.33	-13.62
INFRATEL	0.0032	0.2622	-0.18	35.78	-14.13	-0.0043	0.2394	-1.17	66.04	-14.54
L&TFH	0.0060	0.2352	0.77	32.90	-13.28	-0.0062	0.2323	1.27	80.92	-13.62
LICHSGFIN	0.0073	0.2151	1.90	25.91	-14.47	0.0008	0.1953	1.73	41.50	-13.86
LUPIN	-0.0057	0.2061	-4.55	105.47	-14.07	0.0006	0.2376	-3.44	121.05	-14.37
M&MFIN	0.0018	0.2297	0.53	19.89	-14.77	-0.0013	0.2274	4.91	136.63	-14.34
MARICO	-0.0025	0.1884	-2.46	54.07	-13.60	0.0029	0.2042	11.19	330.29	-14.48
MCDOWELL-N	0.0005	0.2122	-0.58	25.71	-13.69	-0.0005	0.1763	-0.12	20.99	-13.49
MOTHERSUMI	0.0003	0.2957	1.79	53.11	-13.37	-0.0067	0.2609	-2.13	54.91	-13.71
MRF	-0.0038	0.1422	-0.01	47.25	-13.57	0.0008	0.1338	1.12	17.58	-11.70
NMDC	0.0049	0.2307	-4.22	121.61	-14.57	-0.0005	0.1959	3.96	54.30	-12.94
PAGEIND	0.0037	0.2147	-0.39	48.47	-13.08	-0.0077	0.2500	-18.41	674.48	-10.45
PEL	0.0075	0.2288	-0.16	33.72	-13.17	-0.0063	0.2338	2.03	61.97	-13.07
PETRONET	0.0026	0.1921	3.07	40.07	-13.74	0.0011	0.1674	1.37	23.91	-12.56
PFC	0.0061	0.2459	1.89	37.82	-14.01	-0.0009	0.2122	3.19	56.68	-12.47
PIDILITIND	0.0039	0.1949	3.35	73.36	-14.11	0.0001	0.1673	-0.30	14.34	-14.74
PNB	0.0076	0.2600	1.42	43.80	-12.94	-0.0016	0.2452	2.70	67.12	-13.38
RBLBANK	0.0061	0.1853	0.52	29.68	-13.35	0.0004	0.1880	1.98	76.95	-14.04
SRTRANSFIN	0.0057	0.2351	3.16	52.38	-14.40	-0.0049	0.2718	1.57	61.07	-15.00
SUNTV	0.0042	0.2501	2.46	46.19	-14.29	-0.0036	0.2438	4.10	97.26	-13.04
TATASTEEL	0.0055	0.2055	0.86	30.01	-14.25	-0.0014	0.2377	1.04	62.27	-13.17
TORNTPHARM	0.0011	0.1529	0.98	21.03	-13.96	-0.0083	0.2356	-13.64	430.11	-14.99
TVSMOTOR	-0.0011	0.2152	0.19	20.05	-14.28	0.0026	0.2314	-7.72	270.43	-14.37
UPL	0.0063	0.1536	0.92	23.23	-14.97	0.0048	0.1541	0.00	22.49	-12.67

Table 3 Panel B provides mean, standard deviation, skewness, Kurtosis, Dickey-Fuller statistic of return-series for each stock in the control group. Spot returns are calculated as log differences of spot closing prices multiplied by 100. Pre-period spans from January 28, 2019 till March 27, 2019. Post-period spans from March 28, 2019 till May 27,2019. All the return series are stationary.

Table 4: Descriptive Statistics : Futures Return

Panel A										
treatment Firms	Pre-Period					Post-Period				
	Mean	Std. Dev.	Skewness	Kurtosis	Dickey-Fuller	Mean	Std. Dev.	Skewness	Kurtosis	Dickey-Fuller
ADANIENT	0.0011	0.3787	-0.07	15.37	-13.92	0.0050	0.3983	7.97	217.85	-12.25
AMARAJABAT	-0.0013	0.1714	0.35	21.84	-14.18	-0.0045	0.1970	0.95	36.80	-12.48
APOLLOHOSP	-0.0032	0.2290	0.26	26.09	-13.13	0.0010	0.2165	1.90	41.30	-14.85
APOLLOTYRE	0.0013	0.2018	0.07	21.12	-12.97	-0.0032	0.1965	1.83	58.20	-12.65
ARVIND	0.0004	0.2832	-0.07	21.99	-13.32	-0.0053	0.2384	0.86	15.45	-12.63
BATAINDIA	0.0076	0.1549	1.50	33.86	-14.01	-0.0007	0.1460	0.05	11.51	-13.81
BEL	0.0054	0.2492	0.53	19.51	-14.00	0.0077	0.2539	3.58	62.69	-13.57
BHARATFIN	0.0077	0.1602	2.85	59.61	-12.65	-0.0036	0.2632	3.46	159.07	-14.16
CANBK	0.0059	0.2401	0.34	13.24	-13.87	-0.0008	0.2844	4.21	87.50	-13.75
CASTROLIND	0.0007	0.2277	0.67	55.95	-15.06	-0.0032	0.1770	-0.74	22.22	-14.26
CENTURYTEX	0.0043	0.2085	0.13	19.12	-13.97	0.0049	0.2140	1.72	43.31	-13.56
CESC	0.0017	0.1961	0.16	29.32	-14.02	0.0012	0.1982	3.67	76.92	-13.19
CHOLAFIN	0.0078	0.2218	2.65	41.86	-14.20	0.0018	0.2393	0.89	37.98	-13.81
DHFL	-0.0108	0.6735	2.02	119.59	-13.94	-0.0046	0.6484	-10.66	331.05	-14.49
DISHTV	0.0155	0.5932	-2.81	64.16	-15.15	-0.0048	0.4445	0.63	16.90	-13.69
ENGINERSIN	0.0003	0.2416	0.42	34.91	-13.89	0.0020	0.2061	1.68	31.76	-13.35
EQUITAS	0.0048	0.3038	-1.42	33.49	-13.10	0.0010	0.2809	-0.50	41.20	-14.94
ESCORTS	0.0064	0.2384	-3.22	85.92	-13.42	-0.0084	0.2552	-9.12	303.58	-14.45
EXIDEIND	0.0011	0.2038	-0.25	18.10	-14.06	-0.0012	0.1839	-0.26	27.23	-12.90
FEDERALBNK	0.0030	0.1975	0.59	16.76	-13.87	0.0055	0.2339	3.65	60.64	-14.86
GLENMARK	0.0012	0.2106	-4.21	123.32	-13.92	-0.0051	0.1837	0.24	16.25	-14.19
GMRINFRA	0.0091	0.3434	-1.27	41.74	-14.77	-0.0046	0.2792	1.58	23.94	-14.70
IGL	0.0042	0.2370	-1.03	56.96	-12.79	0.0030	0.2132	7.16	158.61	-12.33
JINDALSTEL	0.0084	0.3250	0.55	19.88	-14.22	-0.0009	0.3507	-1.50	111.28	-12.69
JUBLFOOD	0.0071	0.2594	-0.76	45.50	-14.95	-0.0033	0.1996	1.18	33.55	-13.81
KAJARIACER	0.0026	0.2110	1.48	29.19	-14.74	0.0025	0.2092	-0.75	29.19	-13.91
MANAPPURAM	0.0094	0.2547	1.46	21.62	-14.17	0.0039	0.2499	2.03	33.38	-13.62
MCX	0.0041	0.2038	1.99	26.49	-14.00	0.0024	0.2051	0.99	12.55	-13.30
MFSL	0.0034	0.2859	0.07	24.96	-15.32	-0.0009	0.2792	3.45	87.07	-14.45
MINDTREE	0.0030	0.1751	0.21	24.43	-15.33	0.0012	0.0920	1.12	27.52	-15.50
MUTHOOTFIN	0.0055	0.2183	0.00	12.99	-13.69	0.0031	0.2218	3.30	53.32	-14.26
NATIONALUM	-0.0039	0.3358	-4.59	165.74	-12.56	-0.0020	0.2119	1.86	55.34	-13.55
NBCC	0.0052	0.3014	0.12	45.13	-12.76	-0.0011	0.2570	3.97	66.21	-13.09
NCC	0.0130	0.2517	0.36	11.99	-13.56	0.0006	0.2832	2.90	50.77	-13.83
RAYMOND	0.0027	0.2588	3.24	71.69	-15.59	0.0023	0.2152	-1.06	62.28	-13.45
RECLTD	0.0082	0.2850	-4.04	124.14	-13.12	-0.0014	0.2301	3.16	76.23	-12.66
RELCAPITAL	0.0001	0.6174	0.30	44.32	-13.17	-0.0157	0.5236	-1.42	44.66	-12.97
RELINFRA	-0.0237	0.7223	-3.91	153.68	-12.93	-0.0064	0.4738	-1.28	69.48	-13.57
SAIL	0.0039	0.2884	3.37	69.53	-13.06	0.0015	0.2813	1.81	45.08	-13.11
TATACHEM	-0.0048	0.2125	-10.61	345.95	-13.40	0.0031	0.2021	7.01	150.65	-14.68
TATAELXSI	0.0034	0.1997	1.75	32.66	-14.21	-0.0033	0.1670	0.80	20.60	-14.46
TATAGLOBAL	-0.0019	0.2208	0.43	14.85	-13.33	0.0062	0.2213	0.94	17.86	-13.78
TATAMTRDVR	-0.0011	0.3843	-29.05	1260.74	-12.59	0.0011	0.2941	0.83	51.75	-13.05
TATAPOWER	0.0006	0.2228	0.66	12.69	-13.90	-0.0017	0.2473	9.00	241.60	-13.32
UJJIVAN	0.0068	0.2816	-0.45	18.07	-13.31	0.0016	0.2920	2.42	40.43	-14.34
VOLTAS	0.0058	0.2018	0.74	47.11	-12.92	-0.0019	0.1936	-2.12	74.91	-15.21

Table 4 Panel A provides mean, standard deviation, skewness, Kurtosis, Dickey-Fuller statistic of return-series for each stock in the treatment group. Future returns are calculated as log differences of Future closing prices multiplied by 100. Pre-period spans from January 28, 2019 till March 27, 2019. Post-period spans from March 28, 2019 till May 27,2019. All the return series are stationary.

Table 4: Descriptive statistics: Futures Return (contd)

Panel B										
Control Firms	**Pre-Period**					**Post-Period**				
	Mean	**Std. Dev.**	**Skewness**	**Kurtosis**	**Dickey-Fuller**	**Mean**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Dickey-Fuller**
ACC	0.0062	0.1816	1.86	35.97	-13.67	0.0029	0.1944	-3.91	157.13	-13.30
AMBUJACEM	0.0063	0.1973	2.72	44.31	-14.31	0.0004	0.2035	1.49	48.63	-13.34
ASHOKLEY	0.0018	0.2533	1.13	60.52	-13.72	0.0023	0.2414	-1.63	62.72	-13.06
AUROPHARMA	0.0014	0.2002	0.08	44.62	-14.03	-0.0050	0.2196	-3.17	132.86	-14.11
BANKBARODA	0.0041	0.2245	0.10	23.31	-14.10	0.0045	0.3071	0.96	120.33	-13.45
BHARATFORG	0.0019	0.2187	1.16	54.69	-13.46	-0.0004	0.2111	-3.06	100.07	-14.00
BHEL	0.0040	0.2468	0.37	50.12	-13.93	0.0000	0.2608	1.74	36.49	-13.00
BIOCON	-0.0022	0.1498	-0.36	23.37	-13.28	-0.0033	0.1836	-2.92	60.76	-13.59
CADILAHC	0.0005	0.1908	1.71	25.11	-14.16	-0.0097	0.2103	-1.16	30.14	-13.42
CIPLA	0.0027	0.1446	0.89	31.71	-14.82	0.0034	0.1783	1.26	36.47	-15.24
COLPAL	-0.0001	0.1424	1.17	29.57	-13.99	-0.0027	0.1324	0.43	16.29	-13.80
CONCOR	-0.0085	0.4875	-36.10	1632.22	-14.44	0.0000	0.1950	0.34	26.74	-13.29
CUMMINSIND	-0.0032	0.2386	-2.65	69.02	-14.33	0.0007	0.1979	0.00	19.59	-13.31
DIVISLAB	0.0054	0.1916	0.02	57.76	-12.57	-0.0005	0.2065	-9.89	403.04	-13.56
DLF	0.0065	0.3090	1.76	31.09	-14.21	-0.0008	0.3006	1.54	35.65	-13.77
GRASIM	0.0050	0.1905	0.27	23.74	-13.53	0.0041	0.1916	0.34	30.98	-13.10
HAVELLS	0.0032	0.1676	-0.84	19.05	-13.18	-0.0006	0.1556	-2.03	34.84	-15.00
HINDALCO	0.0016	0.1954	-0.77	33.82	-13.60	-0.0018	0.2334	1.47	93.58	-14.04
HINDPETRO	0.0050	0.2395	0.16	27.17	-13.11	0.0043	0.3139	0.92	109.48	-13.40
ICICIPRULI	0.0064	0.2858	5.93	125.11	-12.75	0.0038	0.2235	3.36	56.11	-13.09
IDEA	-0.0037	0.3888	0.49	36.64	-12.67	-0.0289	1.0944	-38.59	1817.72	-13.40
INDIGO	0.0067	0.2265	-0.45	31.17	-13.62	0.0056	0.2621	1.11	59.70	-13.56
INFRATEL	0.0033	0.2531	-0.33	33.21	-14.26	-0.0043	0.2397	-1.19	60.78	-14.27
L&TFH	0.0061	0.2434	0.73	32.68	-13.35	-0.0063	0.2408	1.23	77.34	-13.59
LICHSGFIN	0.0073	0.2200	2.43	38.78	-14.48	0.0007	0.1975	1.59	37.57	-14.12
LUPIN	-0.0056	0.2133	-5.04	119.30	-14.18	0.0006	0.2432	-3.17	124.99	-14.51
M&MFIN	0.0018	0.2318	0.72	21.51	-14.61	-0.0012	0.2298	4.45	124.41	-14.50
MARICO	-0.0026	0.1791	-2.50	50.50	-13.59	0.0029	0.1985	10.83	303.97	-14.55
MCDOWELL-N	0.0005	0.2143	-0.23	25.15	-13.79	-0.0005	0.1804	0.35	31.46	-13.67
MOTHERSUMI	0.0003	0.2947	1.38	43.00	-13.55	-0.0066	0.2619	-2.04	51.98	-13.76
MRF	-0.0038	0.1526	-0.84	40.88	-14.07	0.0007	0.1466	0.71	15.93	-12.32
NMDC	0.0049	0.2081	-1.52	61.17	-15.55	-0.0005	0.2063	5.26	81.27	-12.97
PAGEIND	0.0036	0.2211	-0.62	53.70	-13.09	-0.0076	0.2583	-16.09	585.32	-11.65
PEL	0.0076	0.2344	-0.51	29.50	-13.11	-0.0062	0.2393	2.10	58.66	-13.15
PETRONET	0.0026	0.1839	2.73	37.57	-13.85	0.0012	0.1652	1.60	28.73	-12.65
PFC	0.0059	0.2554	2.06	39.47	-13.82	-0.0008	0.2188	2.99	55.60	-12.48
PIDILITIND	0.0037	0.1868	3.39	75.48	-14.16	0.0002	0.1661	-0.28	13.91	-14.83
PNB	0.0077	0.2681	1.08	36.80	-12.97	-0.0016	0.2618	2.56	62.32	-13.62
RBLBANK	0.0061	0.1817	0.44	27.43	-13.39	0.0005	0.1837	2.35	72.92	-13.75
SRTRANSFIN	0.0057	0.2379	2.69	46.18	-14.29	-0.0049	0.2676	1.47	58.37	-14.94
SUNTV	0.0042	0.2479	1.95	33.76	-14.36	-0.0036	0.2449	3.55	80.77	-12.90
TATASTEEL	0.0054	0.2037	0.68	29.05	-14.32	-0.0014	0.2433	1.57	78.72	-13.22
TORNTPHARM	0.0011	0.1524	0.44	13.39	-14.02	-0.0082	0.2320	-13.32	428.06	-14.42
TVSMOTOR	-0.0012	0.2118	-0.31	19.61	-14.35	0.0026	0.2228	-7.24	239.24	-14.16
UPL	0.0064	0.1482	0.77	21.92	-15.01	0.0045	0.1491	-0.16	17.59	-12.70

Table 4 Panel B provides mean, standard deviation, skewness, Kurtosis, Dickey-Fuller statistic of return-series for each stock in the control group. Future returns are calculated as log differences of futures closing prices multiplied by 100. Pre-period spans from January 28, 2019 till March 27, 2019. Post-period spans from March 28, 2019 till May 27,2019. All the return series are stationary.

4.2 Proxies for Volatility

Three proxies of volatility are proposed as under, in order to gauge the presence of any significant change in volatility when the settlement system shifts from cash-settlement to physical delivery.

4.2.1 Garman-Klass Volatility

Garman Klass is a volatility estimator that incorporates open, low, high, and close prices of a security. As markets are most active during the opening and closing of a trading session, it makes volatility estimation more accurate. Garman and Klass also assumed that the process of price change is a process of continuous diffusion (geometric Brownian motion).

Garman-Klass Volatility Formula

$$\sigma_{GK} = \sqrt{(1/N)\sum_{i=1}^{N}\frac{1}{2}log(\frac{H_i}{L_i})^2 - \frac{1}{N}\sum_{i=1}^{N}(2log(2)-1)log(\frac{C_i}{C_i-1})^2)} \tag{1}$$

where , N = Number of 5-minute trading intervals

O_i = Open price in interval i

H_i = High price in interval i

L_i = Low price in interval i

C_i = Close price in interval i

4.2.2 Parkinson Volatility

Parkinson volatility is a volatility measure that uses the stock's high and low price of the day. The main difference between regular volatility and Parkinson volatility is that the latter uses high and low prices for a day, rather than only the closing price. That is useful as close to close prices could show little difference while large price movements could have happened during the day. Thus Parkinson's volatility is considered to be more precise and requires less data for calculation than the close-close volatility.

Parkinson Volatility Formula

$$\sigma_p = \sqrt{\frac{1}{4Nlog2}\sum_{i=1}^{N}log(\frac{H_i}{L_i})^2} \tag{2}$$

where, N =Number of 5-minute trading intervals

H_i = High price in interval i

L_i = Low price in interval i

4.2.3 GARCH based Volatility

GARCH models describe financial markets in which volatility can change, becoming more volatile during periods of financial crises or world events and less volatile during periods of relative calm and steady economic growth. The first step in GARCH modelling of the returns series,is to remove any predictability associated with lagged returns by accommodating AR and MA terms in the mean equation as shown in equation 3.The ARMA order for each stock in the study has been derived by minimising the AIC selection criterion. This is followed by estimation of a variance equation for GARCH (1,1) is by represented in equation 4.

GARCH mean equation

$$r_t = \alpha_0 + \sum_{i=1}^{l} \beta_i r_{t-i} + \sum_{j=1}^{m} \gamma_j \xi_{t-j} + \epsilon_t \tag{3}$$

GARCH variance equation

$$\sigma^2_{garch} = \theta_0 + \phi\xi^2_{t-1} + \mu\sigma^2_{t-1} \tag{4}$$

4.3 Proxies for Hedging ratio

Two proxies prominently used in literature have been estimated to gauge any significant deviation in hedging ratios of futures contract upon introduction of physical settlement.

4.3.1 Ederington's OLS Hedge Ratio

Based upon portfolio theory approach, Ederington (1979) suggested minimum-variance hedge ratio, which presumes strong and stable long-run relationship between two markets. Optimal hedge ratio henceforth, is classically estimated as ratio of co-variance of cash and futures market returns and variance of futures market returns and hedging effectiveness will depend upon the coefficient of R^2.

$$R_{s,t} = \alpha_0 + \beta_1 R_{f,t} + \epsilon_t \tag{5}$$

where, $R_{s,t}$ =Returns from spot market
$R_{f,t}$ =Returns from futures market
α_0 = Intercept
ϵ_t = Error.

4.3.2 DCC-GARCH Hedge Ratio

Recent developments suggest that if the joint distribution of futures and spot prices changes over time, the classical constant hedge-ratio may deem inappropriate. Hence, for a better insight into structural changes in the hedging effectiveness of future contracts upon introduction of physical settlement mode of delivery, a time-varying hedge ratio is constructed by using a DCC-GARCH model.

DCC-GARCH is based on the decomposition of the conditional covariance matrix into two time-varying parts: First, conditional standard deviations matrix and second into correlations matrix (Engle III and Sheppard, 2001; Engle, 2002). The DCC-GARCH model can be written as:

$$H_t = D_t \Gamma_t D_t \tag{6}$$

$$D_t = diag(h_{11,t}^{\frac{1}{2}}, h_{22,t}^{\frac{1}{2}}) \tag{7}$$

$$h_{ii,t} = \omega_i + \beta_i h_{ii,t-1} + \gamma_i \epsilon_{i,t-1}^2, \qquad i = 1, 2 \tag{8}$$

$$\Gamma_t = diag(Q_t)^{\frac{-1}{2}} Q_t diag(Q_t)^{\frac{-1}{2}} \tag{9}$$

$$Q_t = (1 - \delta_1 - \delta_2)\bar{Q} + \delta_1 \mu_{t-1} \mu_{t-1} + \delta_2 Q_{t-1} \tag{10}$$

,where ϵ_t denotes a vector of unexpected returns and $\mu_{i,t} = (\mu_{1t}, \mu_{2t}) = \epsilon_{i,t}/\sqrt{h_{ii,t}}$ denotes a vector of standardized unexpected returns. $h_{ii,t}$ can be defined as a standard GARCH process and Q_t denotes a 2×2 symmetric positive-definite matrix. $\bar{Q} = E[\mu_t \mu_t^{'}]$ is a 2×2 unconditional variance matrix of u_t. δ_1 and δ_2 are scalar parameters, and $\delta_1 \geq 0$,$\delta_2 \geq 0$, and $\delta_1 + \delta_2 < 1$ guarantee positive definiteness of the conditional correlation matrix during the optimization. Given the bivariate model of the spot and futures prices changes, the time-varying hedge ratio can be expressed with the variance–covariance estimates for the DCC models, respectively, as:

$$\hat{\beta_{t-1}} = \frac{\hat{h_{sf,t}}}{\hat{h_{f,t}}} \tag{11}$$

An appropriate ARMA order based on AIC selection criteria was chosen while modelling the spot as well as future price series to estimate the hedging ratio of each stock under scrutiny.

4.4 Proxies for measuring efficiency of Price-Discovery

Three proxies are employed to determine the degree of new information processed in the futures market. Before estimating these proxies, presence of co-integration between spot and futures prices for all the contracts under scrutiny has been tested through an Auto-regressive Distributed Lag (ARDL) bounds test proposed by Pesaran et al. (1999) and Pesaran et al. (2001). The test for each stock was conducting by picking the most suitable ARDL order structure based on AIC selection criterion.

All the treatment securities except CESC and Engineers India Limited, and all control stocks but Hindustan Petroleum, Idea, NMDC and UPL are found to be significantly co-integrated. These exceptions are excluded from dataset while constructing measures of futures-pricing efficiency.

Henceforth, bi-variate Vector Error Correction model is run for the remaining 43 treatment stocks and 41 control group stocks, as specified in equations 12 and 13.

$$\Delta s_t = \mu_{s,0} + \alpha_s ec_{t-1} + \sum_{i=1}^{p} \delta_{ss,i} \Delta s_{t-i} + \sum_{j=1}^{q} \delta_{sf,j} \Delta f_{t-j} + \epsilon_{s,t} \tag{12}$$

$$\Delta f_t = \mu_{f,0} + \alpha_f ec_{t-1} + \sum_{i=1}^{p} \delta_{fs,i} \Delta s_{t-i} + \sum_{j=1}^{q} \delta_{ff,j} \Delta f_{t-j} + \epsilon_{f,t} \tag{13}$$

(12)

where $\mu_{s,0}$ and $\mu_{f,0}$ denote intercepts, $\epsilon_{s,t}$ and $\epsilon_{f,t}$ are error terms assumed to be serially uncorrelated with zero mean and covariance matrix Ω. The error correction term ec_{t-1} corresponds to the lagged residual from the cointegrating equation of futures and spot returns.

4.4.1 Hasbrouk's Information Share

According to Hasbrouck (1995), a market's relative contribution to price discovery is defined as the proportion of the variance of the common efficient equilibrium price that can be attributed to this particular market. By denoting $\Psi\Omega\Psi'$as the variance of the common efficient equilibrium price, the information share of market j can be expressed as follows:

$$IS_j = \frac{[(\Psi(F))_j]^2}{\Psi\Omega\Psi'}, j = 1, 2 \tag{14}$$

where F is the Cholesky factorization of the estimated VECM variance–covariance matrix Ω (i.e., the lower triangular (2 × 2) matrix such that Ω = FF') and Ψ represents the long-run impact matrix of dimension (1 × 2). By construction, $IS_1 + IS_2 = 1$. Simply interpreted, price discovery occurs predominantly in the market for which the information share exceeds the value of 0.5.

4.4.2 Gonzalo and Granger's Component Share

The approach given by Gonzalo and Granger (1995) uses the relative magnitude of the adjustment coefficients in the VECM to assess each market's contribution to price discovery. Accordingly, we compute the common factor weights of the futures (θ_f) and the spot market (θ_s) as follows:

$$\theta_f = \frac{|\alpha_s|}{|\alpha_s| + |\alpha_f}, \qquad \theta_s = \frac{|\alpha_f|}{|\alpha_s| + |\alpha_f} \tag{15}$$

Since the denominator represents the total adjustment of both markets to any difference between spot and futures prices, the common factor weights measure the relative portion of total adjustment. The values of the common factor weights are restricted to the interval between zero and one. Their interpretation is straightforward, if $\theta_f = 1$, price discovery occurs entirely in the futures market, as the adjustment reaction falls completely on the spot market.

4.4.3 Time-varying Common Factor Weights

The above-outlined measures of price discovery only indicate where price discovery occurs on average and are not able to detect structural changes in the price discovery process. To overcome this drawback, we apply the Kalman filtering technique (Durbin et al., 2001) to obtain time-varying parameters. The measure of time-varying price-discovery efficiency was first introduced by Adämmer et al. (2016). The state–space form of the VECM of Equations 12 and 13 reads as follows:

$$y_t = Z_t\xi_t + \epsilon_t, \epsilon_t\tilde{\ }N(0, R) \tag{16}$$

$$\xi_t = F\xi_{t-1} + \eta_t, \eta_t\tilde{\ }N(0, Q) \tag{17}$$

where Equation 16 represents the measurement equation and Equation 17 is the transition equation. Time-varying parameters are assumed to evolve according to a random walk and are represented by the vector ξ_t. F is an identity matrix. The multivariate normally distributed error terms ϵ_t and η_t are serially uncorrelated with zero mean and diagonal co-variance matrices R and Q, respectively.

After having filtered the optimal states,time-varying common factor weights are calculated as:

$$\theta_{f,t} = \frac{|\alpha_{s,t}|}{|\alpha_{s,t}| + |\alpha_{f,t}}, \qquad \theta_{s,t} = \frac{|\alpha_{f,t}|}{|\alpha_{s,t}| + |\alpha_{f,t}} \tag{18}$$

5 Empirical Strategy

Firstly, we undertake a simple comparative analysis between pre and post-intervention outcome variables for treatment and control group stocks by employing a student's t-test.

Subsequently, the study employs a quasi-experimental setup to ensure the causal implication of conversion in settlement mode. A Difference in Difference technique is employed by estimating the following OLS regression equation:

$$\Delta Y_t = \alpha + \beta treat_t + \epsilon_t \tag{19}$$

where, t indexes the time after the intervention for treated and control firms. The ΔY_t are the difference in the outcome variables of interest pre and post the transition to physical settlement. *treat* is a dummy variable that takes the value 1 for group of stocks that shifted to physical-delivery mode of settlement from April, 2019 onwards and 0 otherwise. Further, we ensure the robustness of our estimates by employing heteroskedasticity robust standard errors for the DID regression on the panel data (Long and Ervin, 2000).

6 Results and Discussion

The findings from the student's t-test for each outcome variables are presented in subsequent panels of Table 5. Firstly, the variables to measure spot-volatility are reported in Panel A of Table 5. A significant decline in all the three proxies is detected for treatment stocks. This implies a significant decline in spot-market volatility post the adoption of physical settlement for treatment stocks. In contrast, the deviations in pre versus post intervention averages of Garman-Klass and Parkinson volatility estimates are insignificant for the control group stocks. A significant drop in GARCH-based volatility is witnessed for control group, however, the magnitude of this decline is approximately 2 times lower than the decline witnessed by the treatment group.

Moving onto the measures of hedging ratio, Panel B in Table 5 reports a comparative analysis of post versus pre time-invariant hedging ratio given by Ederington (1979) and DCC-GARCH based hedge ratio. Time-invariant

Ederington's hedge ratio does not record any significant change in the pre versus post hedge ratio for either of the two groups. In contrast, a different story is revealed by the estimates of hedge-ratio derived by running a DCC-GARCH model. A significant increase in hedge ratio is captured for the treatment whereas the control group stocks witness a highly significant decline in hedge ratio. Supremacy of a DCC-GARCH hedge ratio over time-invariant Ederington's hedge Ratio has been established by Ku et al. (2007). The authors claim that frequent fluctuations between spot and futures market are captured upon inclusion of dynamic conditional correlations in the GARCH model. Under this purview, reliance on a DCC-GARCH based hedge over time-invariant Ederington's hedge ratio for accurate judgements stands justified.

Table 5: **Comparison of outcome variables prior to and post the adoption of physical settlement system.**

Panel A : Volatility	**Treatment stocks**			**Control Stocks**		
Outcome Variables	**Pre-period**	**Post-period**	**t-stat(post-pre)**	**Pre-period**	**Post-period**	**t-stat(post-pre)**
Graman Klass Volatility	0.0179	0.0165	-8.22*	0.0142	0.0144	1.27
Parkinson Volatility	0.0226	0.0210	-8.23*	0.0181	0.0180	-0.06
Garch-based Volatility	0.2895	0.2625	-7.82*	0.2408	0.2346	-4.26*
Panel B : Hedging ratio	**Treatment stocks**			**Control Stocks**		
Outcome Variables	**Pre-period**	**Post-period**	**t-stat(post-pre)**	**Pre-period**	**Post-period**	**t-stat(post-pre)**
Ederington's Hedge ratio	0.8720	0.8963	1.60	0.8931	0.9061	0.95
DCC-GARCH Based Hedge ratio	0.8840	0.8880	2.95*	0.9608	0.9073	-13.56*
Panel C : Price-Discovery Measure	**Treatment stocks**			**Control Stocks**		
Outcome Variables	**Pre-period**	**Post-period**	**t-stat(post-pre)**	**Pre-period**	**Post-period**	**t-stat(post-pre)**
Hasbrouk's Information Share	0.4813	0.5188	1.74*	0.4737	0.5063	1.64
Gonzalo and Granger's Component Share	0.4820	0.5393	1.04	0.4616	0.5316	1.30
Time-Varying Common Factor Weights	0.4996	0.5003	1.99*	0.4997	0.5003	2.31*
Panel D : Liquidity	**Treatment stocks**			**Control Stocks**		
Control Variable	**Pre-period**	**Post-period**	**t-stat(post-pre)**	**Pre-period**	**Post-period**	**t-stat(post-pre)**
Spot-market Trading Volume	11813164.36	10335424.72	-8.77*	14652991.27	16282537.41	6.15*

Table 5 presents a comparison between the sample period before the adoption of physical settlement system (January 28, 2019 to March 27, 2019) and the sample period post-adoption (March 28, 2019 to May 27, 2019) for treatment and control group stocks. All the eight outcome variables have been sequentially listed in different panels of table 4. A significant decrease in volatility is gauged for treatment stocks post-intervention across panels A. Panel B suggests a significant decline in hedge ratios in the post period for both the groups. Similarly, Panel C demonstrates a significant decline in the degree of new information processed in the futures market for both the groups.

A DID analysis with standard errors clustered across time and groups allows us a better insight into causal effect of the shift from cash-settlement to physical-delivery mode of futures-settlement. The difference in pre and post-intervention outcomes for treatment group is compared with the same difference in the control group stocks. The results from equation 19 for all the outcome variables have been collated in Panels A to H of Table 6.

As is evident from Panel A in Table 6, the treated group has witnessed a significant decline in Garman-Klass volatility in the spot-markets in comparison with control group upon a switch towards physical delivery system. Panel B closely resembles Panel A in the measure of estimates and the findings as well. The coefficient of *treat* is negative and significant for Parkinson and GARCH based volatility also. One plausible explanation for the observed decline in volatility is the reduction in speculation that SEBI targeted for. When stocks cannot be settled by squaring-off cash-differences, traders are likely to refrain from excess speculation wherein an over-ambitious trade-position could multiply their risk several times. Therefore, traders have to be wary while trading in the derivatives segment, as they may end up paying the full contract value besides the margin money. As a result, traders are cautioned to roll-over their positions ahead of the expiry week when settlement can only be done through physical delivery. This mitigates the lumping of roll-over positions on expiry day curbing volatility in the market.

Panels D and E record the changes in hedge-ratios when measured as time-invariant ratio (Ederington, 1979) and a time-varying DCC-GARCH based ratio. Ederington's Hedge ratio records no significant change in hedging efficiency of futures contracts. On the other hand, the hedge ratio determined from DCC-GARCH model demonstrates a significant increase in the hedging-efficiency of the futures contracts. Taking cue from Ku et al. (2007), we rely on DCC-GARCH based hedge ratio to formulate an appropriate decision-judgement. The results therefore lead us to believe that hedging ratio of futures contracts increased significantly upon introduction of physical settlement.

The time-invariant proxies used to measure the efficiency of price-discovery in the market do not suggest any significant difference as shown in Panel F and G of Table 6. However, the coefficient for *treat* is significantly positive for time varying common weights. A similar inconsistency in variables was experienced by Adämmer et al. (2016) in their study. The authors recommended reliance on time-varying parameters as ignoring time-variance could lead to misleading results since price-discovery process in the markets is subject to strong fluctuations, which remain latent when assessed through time-invariant proxies. Even though investor's attention is likely to shift towards the cash settled indices, the significant rise in the convergence of the spot and futures market reflects as a rise in informativeness of futures contracts.

The results from the DID analysis closely resemble the findings from a student's t-test discussed in Table 5. However, some incoherence exists with the change in time-varying common factor weights over two period. While in Table 5 the rise in time varying common factor weights for control group stocks rises more significantly than for treatment group, we note a significant rise in time varying common factor weights of treated group in Table 6. However, a student's t-test does not imply causal inference like a DID analysis depicted in Table 6.

Table 6 : DID results to examine the impact of settlement change.

Results from equation : $\Delta Y_t = \alpha + \beta treat_t + \epsilon_t$, where, t indexes the time after the intervention for treated and control firms. ΔY_i are the difference in the outcome variables of interest pre and post the transition to physical settlement. *treat* is a dummy variable that takes the value 1 for group of stocks that shifted to physical-delivery mode of settlement from April, 2019 onwards and 0 otherwise.

Panel A: Garman Klass Volatility

Variable	Estimate	Std. Error	t-statistic	p-value
Intercept	0.000222	0.000159	1.40	0.16
treat	-0.001402	0.000090	-15.63	0.00
Number of Observations	5425			
Adjusted R-square	0.0056			
F-statistic	244.386			

Panel B: Parkinson Volatility

Variable	Estimate	Std. Error	t-statistic	p-value
Intercept	0.000211	0.000187	1.13	0.26
treat	-0.001572	0.000094	-16.70	0.00
Number of Observations	5469			
Adjusted R-square	0.0048			
F-statistic	278.973			

Panel C: GARCH Volatility

Variable	Estimate	Std. Error	t-statistic	p-value
Intercept	-0.006516	0.001484	-4.39	0.00
treat	-0.007545	-0.007544	-8.72	0.00
Number of Observations	5719			
Adjusted R-square	0.0015			
F-statistic	76.0879			

Panel A, B and C of Table 6 depict the results from DID analysis with heteroskedasticity robust standard errors, to determine the causal impact of a switch to physical settlement on the spot-market volatility of treated stocks. Volatility is measured through three proxies, Garman-klass Volatility, Parkinson volatility, and GARCH-based volatility presented in Panel A, B and C respectively. A significant decline in volatility is recorded across all three panels.

Table 6 : DID results to examine the impact of settlement change (contd.)

Results from equation : $\Delta Y_t = \alpha + \beta treat_t + \epsilon_t$, where, t indexes the time after the intervention for treated and control firms. ΔY_i are the difference in the outcome variables of interest pre and post the transition to physical settlement. *treat* is a dummy variable that takes the value 1 for group of stocks that shifted to physical-delivery mode of settlement from April, 2019 onwards and 0 otherwise.

Panel D: Ederington's hedge ratio

Variable	Estimate	Std. Error	t-statistic	p-value
Intercept	-0.000537	0.012056	-0.045	0.96
treat	-0.0237	0.0169571	-1.398	0.166
Number of Observations	91			
Adjusted R-square	0.01048			
F-statistic	1.953			

Panel E: DCC GARCH Hedge ratio

Variable	Estimate	Std. Error	t-statistic	p-value
Intercept	-0.020972	0.001546	-13.56	0.00
treat	0.025063	0.001223	20.49	0.00
Number of Observations	5718			
Adjusted R-square	0.0264			
F-statistic	419.97			

Panel D and E of Table 6 depict the results from DID analysis with standard errors clustered across time and groups, to determine the causal impact of a switch to physical settlement on the hedging ratio of the futures contracts of the treated stocks. Hedging ratio is measured through two proxies, time-invariant Ederington's Hedge ratio and time-varying DCC-GARCH based hedge ratio presented in Panel D and E of Table 6 respectively. Although, no significant deviation is captured through Ederington's hedge ratio, a significant improvement in hedge ratio is captured when measured through a DCC-GARCH model.

Table 6 : DID results to examine the impact of settlement change (contd.)

Results from equation : $\Delta Y_t = \alpha + \beta treat_t + \epsilon_t$, where, t indexes the time after the intervention for treated and control firms. ΔY_i are the difference in the outcome variables of interest pre and post the transition to physical settlement. *treat* is a dummy variable that takes the value 1 for group of stocks that shifted to physical-delivery mode of settlement from April, 2019 onwards and 0 otherwise.

Panel F: Hasbrouk's Information share

Variable	Estimate	Std. Error	t-statistic	p-value
Intercept	-0.033464	0.022915	-1.46	0.148
treat	-0.001355	0.03223	-0.042	0.967
Number of Observations	91			
Adjusted R-square	-0.01			
F-statistic	244.386	0.0017		

Panel G: Gonzalo and Granger Component share

Variable	Estimate	Std. Error	t-statistic	p-value
Intercept	-0.02939	0.05368	-0.547	0.585
treat	-0.02462	0.0755	-0.326	0.745
Number of Observations	91			
Adjusted R-square	-0.01			
F-statistic	0.1064			

Panel H: Time varying common factor weights

Variable	Estimate	Std. Error	t-statistic	p-value
Intercept	0.000575	0.000021	26.832500	0.00
treat	0.000110	0.000021	5.1988	0.00
Number of Observations	5715			
Adjusted R-square	0.0048			
F-statistic	27.02			

Panel F, G and H of Table 6 depict the results from DID analysis with standard errors clustered across time and groups to determine the causal impact of a switch to physical settlement on the efficiency of price-discovery in the market. Efficiency of price-discovery is measured through three proxies, time-invariant Hasbrouk's Infromation share, time-invariant Gonzalo and Granger's component share and time-varying Common Factor weights presented in Panel F, G and H of Table 5 respectively. Although, no significant deviation is captured through time-invariant proxies in panel F and G, a significant deterioration in price-discovery by futures contract of treated stocks is captured when measured through time-varying common-factor weights.

The results from Table 6 can be visualised in Figure 1. The orange bar indicates the change in outcome variables for the control group and the green bars indicate the corresponding changes in the treated stocks.

As is evident is Fig. 1(a), the volatility measured as Garman Klass volatility, Parkinson volatility, or GARCH based volatility is declining significantly in comparison with control group. The coinciding error bars for Ederington Hedge ratio in Fig. 1(b) indicate no significant differences in the change of hedge ratio for treated and control group stocks upon adoption of physical settlement. The same does not stand true when hedge ratio is measured through the DCC-GARCH based method where hedge ratio is significantly higher for the treated group. Finally, in Fig. 1(c) we record an insignificant variation in the changes of information share and component share between treated and control group. However, changes in time varying common factor weights appear very small. It is important to note that while Information share and Component share are estimated for entire pre and post periods, Time varying common factor weights have been estimated at a 5-min frequency. Therefore, for convenience, TVCS has been individually plotted in fig A in appendix. We note an evident rise in Time varying common factor weights for treated group.

Fig. 1(a): Changes in volatility for treated group versus control group

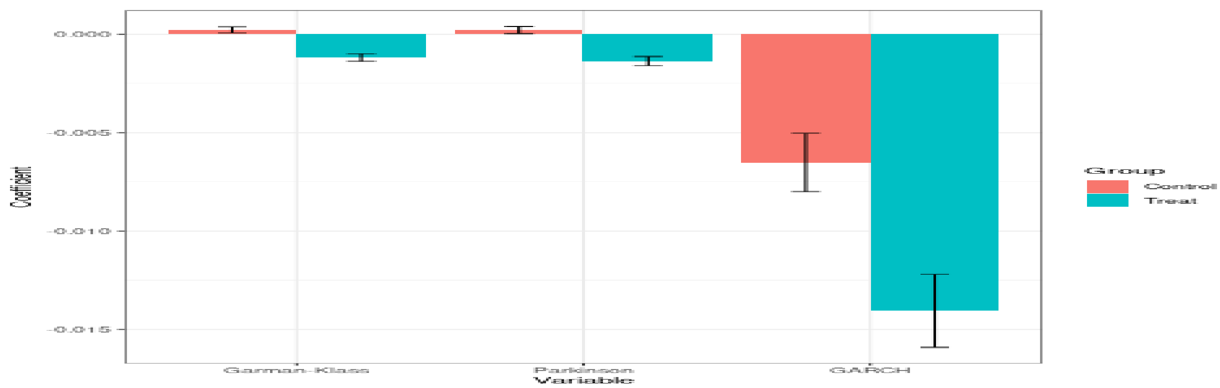


Fig. 1(b): Changes in hedge ratios for treated group versus control group

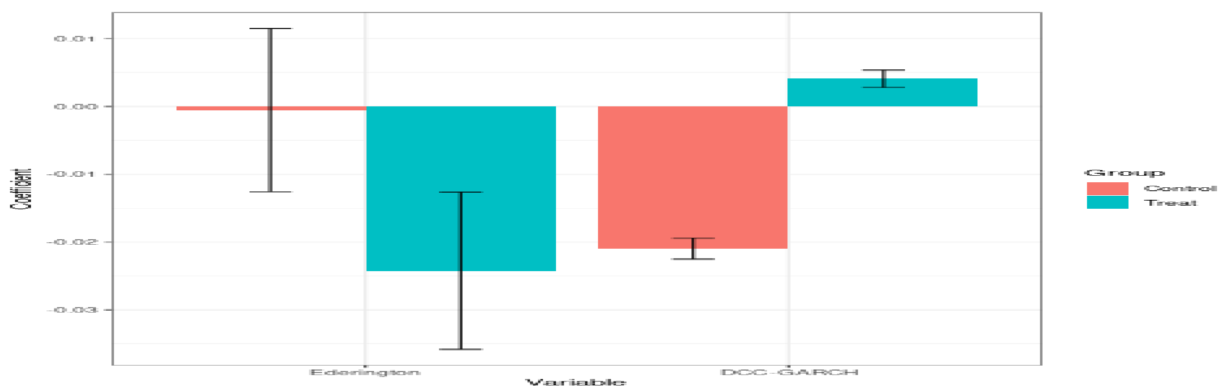
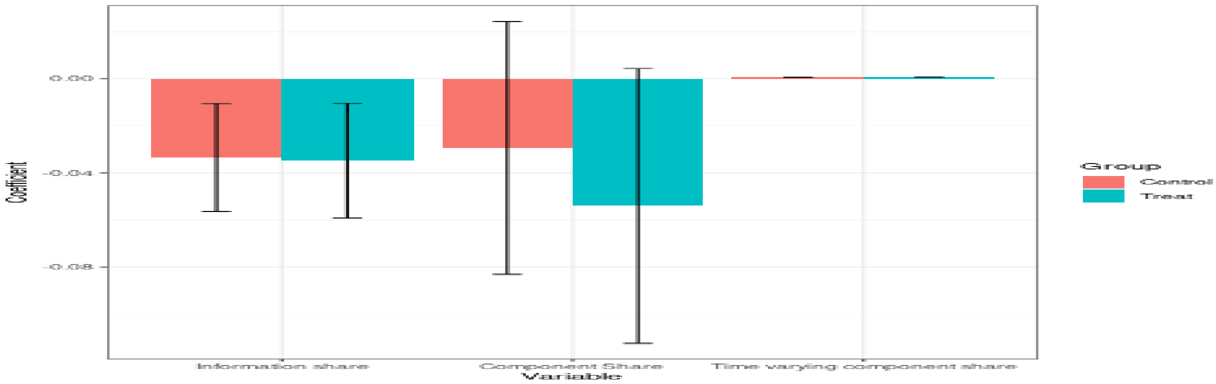


Fig. 1(c): Changes in price discovery efficiency for treated group versus control group[3]



The plots provide a visual representation of the difference in the changes of outcome variables for treated group and control group. The bars represent α (estimated impact on control group stocks) and $\alpha + \beta$(estimated impact on treated group of stocks). Error bars represent 95% confidence intervals using robust standard errors.

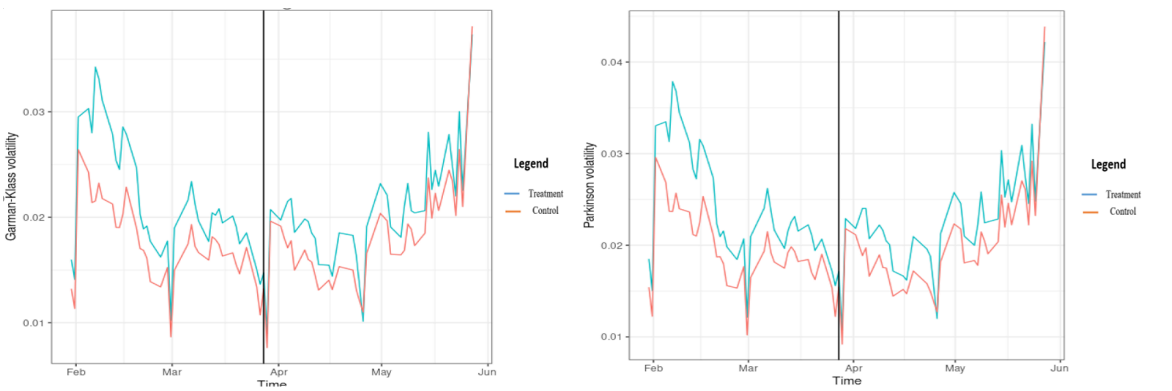
7 Robustness check

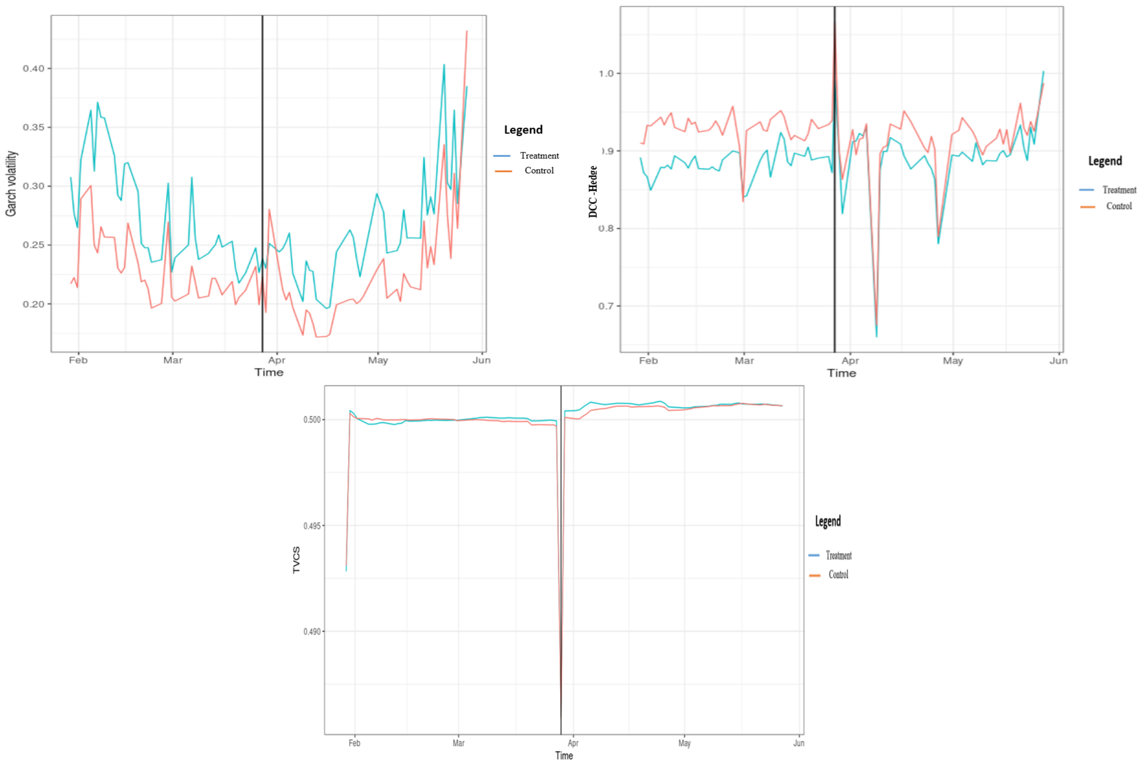
7.1 Classic Difference in Difference analysis

In this section, we change equation 19 to measure the impact of intervention by distinctly comparing significant deviations in outcome variables in post period from pre period and treated stocks from control group stocks. For this purpose, we firstly check for the common trends between treated and control group stocks by plotting the movement of time-varying outcome variables in Fig. 2. The outcome variables for all the treatment group stocks and control group stocks are averaged for the entire sample period and are presented through green and red lines respectively.

We find that the movements of the outcome variables for both the groups are mostly parallel during the period prior to the shift mandated by SEBI, indicated by the black vertical line. Hence, a DID analysis is a well-suited empirical tool in the given context.

Fig. 2: Movement of outcome variables across the sample period [4]





The figures indicate a parallel movement between the outcome variables for the treatment and control variable prior to the intervention by SEBI. The green lines represent the movements in treatment groups, the red line indicates the movements in the control group, and the black vertical line marks the time of intervention in the markets.

Thereon, the difference in pre and post-intervention outcomes for treatment group is compared with the same difference in the control group stocks in line with equation 20.

$$Y_{it} = \alpha + \beta_1 time + \beta_2 treat + \beta_3 treat * time + \beta_4 * volume + \epsilon_t \tag{20}$$

where, Y_{it} is the outcome variable of interest, $time$ is the dummy variable that takes the value 1 for the period post the intervention and 0 otherwise, and $treat$ is a dummy variable that takes the value 1 for stocks that shifted to physical-delivery mode of settlement from April and 0 otherwise. Since, SEBI introduced the shift in settlement-mode in a phased manner such that stocks with lowest market capital for the month of December, 2018 had to convert first, we try to mitigate the inherent bias between the size of treated and control stocks by employing spot trading volume as a control variable. Hence, log of $volume$ been added to the model to control for variations that arise due to differences in spot-market liquidity. Moreover, to ensure robust estimated, the standard errors for the DID regression on the panel data have been clustered across time as well as groups (Bertrand et al., 2004).

The results from equation 20 for all the outcome variables have been collated in Table 7. As is evident from Panel A in Table 7, the treated group has witnessed a significant decline in Garman-Klass volatility in the spot-markets in comparison with control group upon a switch towards physical delivery system. Panel B closely resembles Panel A in the measure of estimates and the findings as well. The coefficient of $treat * time$ is negative and significant for Parkinson volatility also. The coefficient is also negative when volatility is estimated by using a GARCH model, but the difference between treatment stocks upon switching relative to the control group stocks loses significance when estimated through a GARCH-based as depicted in Panel C of Table 7. However, since the range-based estimators are more efficient estimators of volatility (Li and Weinbaum, 2001; Pandey, 2005), we rely on Garman Klass and Parkinson estimates to derive our conclusions. Volume maintains a positive and significant influence on the volatility in the spot markets evidenced across panel A, B and C. This sits in line with the findings of Brailsford (1996).

Panels D and E record the changes in hedge-ratios when measured as time-invariant ratio (Ederington, 1979) and a time-varying DCC-GARCH based ratio. Ederington's Hedge ratio records no significant change in hedging efficiency of futures contracts. Similarly, the hedge ratio determined from DCC-GARCH model has a positive $treat * time$ coefficient but the deviation is insignificant. The results therefore partly corroborate with our previous findings.

Similarly, the proxies used to measure the efficiency of price-discovery in the market do not suggest any significant difference as shown in Panel F, G, and H. Although, the coefficient for $time * treat$ is positive for all the three proxies, the indicated rise in informativeness of futures contracts is not significant. Time varying common factor weights lose their significance when estimated through conventional DID method, providing partial support to our analysis.

Table 7 : Classic DID results to examine the impact of settlement change.

Results from equation : $Y_{it} = \alpha + \beta_1 time + \beta_2 treat + \beta_3 treat * time + \beta_4 * volume + \epsilon_t$, where Y_{it} is the outcome variable. 'treat' is a dummy variable that takes value 1 for treated stocks and zero otherwise. 'time' is a dummy variable that takes value 1 for the period post-intervention and zero otherwise. The sign and significance of the interaction term 'treat*time' denotes the additional impact of physical settlement on treated stocks over the control group stocks.

Panel A : Garman-Klass Volatility				
Variables	Estimate	Std. Error	t-statistic	p-value
Intercept	-0.04690	0.00625	-7.50	0.00
Volume	0.00390	0.00039	9.82	0.00
treat	0.00536	0.00113	4.74	0.00
time	0.00018	0.00034	0.52	0.60
treat*time	-0.00112	0.00039	-2.80	0.00
Number of observations	518471			
Adjusted R-square	0.17448			
F-statistic	25.36			
Panel B : Parkinson Volatility				
Variables	Estimate	Std. Error	t-statistic	p-value
Intercept	-0.05635	0.00778	-7.24	0.00
Volume	0.004752	0.00049	9.92	0.00
treat	0.00680	0.00140	4.84	0.00
time	-0.00028	0.00042	-0.06	0.00
treat*time	-0.00137	0.00049	-2.75	0.00
Number of observations	518471			
Adjusted R-square	0.10702			
F-statistic	10.42			
Panel C : Garch-Based Volatility				
Variables	Estimate	Std. Error	t-statistic	p-value
Intercept	-0.3243	0.09010	-3.59	0.00
Volume	0.03474	0.00570	6.09	0.00
treat	0.06170	0.01514	4.07	0.00
time	-0.00698	0.00679	-1.03	0.30
treat*time	-0.0039	0.0087	-0.44	0.65
Number of observations	520415			
Adjusted R-square	0.10702			
F-statistic	10.42			

Panel A, B and C of Table 7 depict the results from DID analysis with standard errors clustered across time and groups, to determine the causal impact of a switch to physical settlement on the spot-market volatility of treated stocks. Volatility is measured through three proxies, Garman-klass Volatility, Parkinson volatility, and GARCH-based volatility presented in Panel A, B and C respectively. A decline in volatility is recorded across all three panels. The decline is significant for Garman-Klass and Parkinson volatility.

Table 7 : Classic DID results to examine the impact of settlement change (contd.)

Results from equation : $Y_{it} = \alpha + \beta_1 time + \beta_2 treat + \beta_3 treat * time + \beta_4 * volume + \epsilon_t$, where Y_{it} is the outcome variable. 'treat' is a dummy that takes value 1 for treatment stocks and zero otherwise. 'time' is a dummy variable that takes value 1 for the period post-intervention and zero otherwise. The sign and significance of the interaction term 'treat*time' denotes the additional impact of physical settlement on treated stocks over the control group stocks.

Panel D : Ederington's Hedge Ratio				
Variables	Estimate	Std. Error	t-statistic	p-value
Intercept	-0.10079	0.10945	-0.92100	0.36
Volume	0.06150	0.00666	9.22780	0.00
treat	0.01227	0.01217	1.00770	0.32
time	-0.01430	0.01200	-1.19090	0.24
treat*time	-0.00338	0.01690	-0.19970	0.84
Number of observations	182			
Adjusted R-square	0.33176			
F-statistic	23.46			
Panel E : DCC-GARCH based Hedge Ratio				
Variables	Estimate	Std. Error	t-statistic	p-value
Intercept	0.59654	0.10826	5.5102	0.00
Volume	0.02093	0.00637	3.2815	0.00
treat	-0.03546	0.03049	-1.1632	0.24
time	-0.02123	0.04082	-0.5271	0.59
treat*time	0.02707	0.05057	0.5353	0.59
Number of observations	520323			
Adjusted R-square	0.01456			
F-statistic	3.90			

Panel D and E of Table 7 depict the results from DID analysis with standard errors clustered across time and groups, to determine the causal impact of a switch to physical settlement on the hedging ratio of the futures contracts of the treated stocks. Hedging ratio is measured through two proxies, time-invariant Ederington's Hedge ratio and time-varying DCC-GARCH based hedge ratio presented in Panel D and E of Table 7 respectively. Although, no significant deviation is captured through Ederington's hedge ratio, a significant improvement in hedge ratio is captured when measured through a DCC-GARCH model.

Table 7 : Classic DID results to examine the impact of settlement change (contd.)

Results from equation : $Y_{it} = \alpha + \beta_1 time + \beta_2 treat + \beta_3 treat * time + \beta_4 * volume + \epsilon_t$, where Y_{it} is the outcome variable. 'treat' is a dummy that takes value 1 for treatment stocks and zero otherwise. 'time' is a dummy variable that takes value 1 for the period post-intervention and zero otherwise. The sign and significance of the interaction term 'treat*time' denotes the additional impact of physical settlement on treated stocks over the control group stocks.

Panel F : Hasbrouk's Information Share				
Variables	Estimate	Std. Error	t-statistic	p-value
Intercept	0.40403	0.19212	2.10300	0.04
Volume	0.00590	0.01170	0.50500	0.61
treat	0.01755	0.02137	0.82100	0.41
time	-0.03225	0.02107	-1.53000	0.13
treat*time	0.00046	0.02967	0.01600	0.99
Number of observations	170			
Adjusted R-square	0.01128			
F-statistic	1.52			
Panel G : Gonzalo and Granger's Component Share				
Variables	Estimate	Std. Error	t-statistic	p-value
Intercept	0.09415	0.47379	0.19900	0.84
Volume	0.02620	0.02885	0.90800	0.37
treat	0.02302	0.05270	0.43700	0.66
time	-0.06628	0.05196	-1.27500	0.20
treat*time	0.02504	0.07318	0.34200	0.73
Number of observations	170			
Adjusted R-square	-0.00216			
F-statistic	0.90			
Panel H : Time-Varying Common Factor Weights				
Variables	Estimate	Std. Error	t-statistic	p-value
Intercept	0.5024	0.00174	288.92	0.00
Volume	-0.00017	0.00011	-1.65	0.09
treat	-0.00008	0.00044	-0.19	0.84
time	0.00058	0.00044	1.30	0.19
treat*time	0.00011	0.00048	0.24	0.80
Number of observations	520493			
Adjusted R-square	0.00077			
F-statistic	3.75			

Panel F, G and H of Table 7 depict the results from DID analysis with standard errors clustered across time and groups to determine the causal impact of a switch to physical settlement on the efficiency of price-discovery in the market. Efficiency of price-discovery is measured through three proxies, time-invariant Hasbrouk's Information share, time-invariant Gonzalo and Granger's component share and time-varying Common Factor weights presented in Panel F, G and H of Table 7 respectively. No significant deviation is captured through proxies of price discovery efficiency in panel F,G, and H.

7.2 Learning effects

In this section, we explore if there have been any learning effects over the period in the Indian financial markets upon the introduction of physical settlement of derivative contracts. For this purpose, we disintegrate a 60 day pre-post sample period into sub-periods of 10 days each. The sub-periods thereon are individually exposed to the DID analysis as specified in equation 19. The β coefficient for $treat_t$ that is estimated for each sample period is plotted in Fig. 3.

We find that Garman Klass volatility in Fig. 3(a) for the treated stock in comparison with the control group declines steeply from period 1 to period 2. However, from period 2 onwards β starts to rise until period 6, albeit it remains negative. This indicates that markets may have become attuned to the intervention and the decline in volatility is likely to be short-lived.

Fig. 3: Learning effects visualisation for time-varying outcome variables

We run regressions as per equation 19: $\Delta Y_t = \alpha + \beta treat_t + \epsilon_t$, after segregating the sample period into 6 equal sub-periods (10 days pre and post each). Thereon, we plot the β for each sub-periods.

Fig. 3(a): Learning effects visualisation for Garman Klass volatility

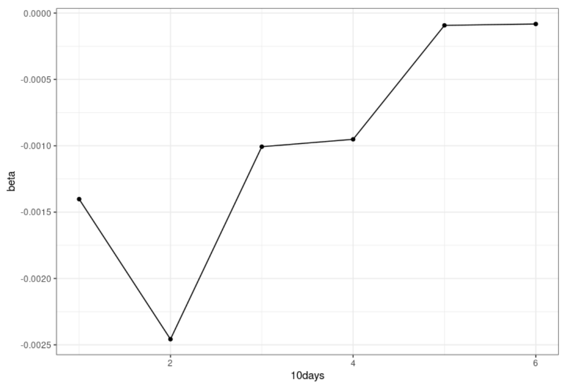


Fig. 3(b): Learning effects visualisation for Parkinson volatility

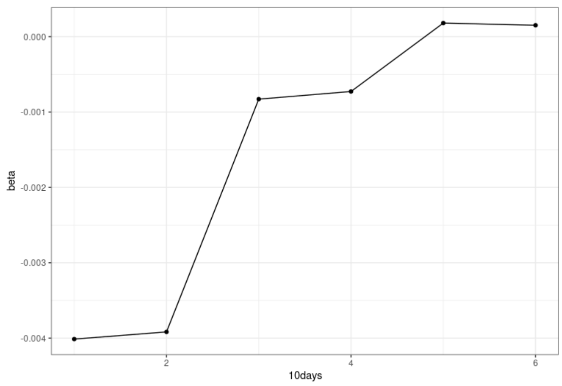


Fig. 3(c): Learning effects visualisation for GARCH based volatility

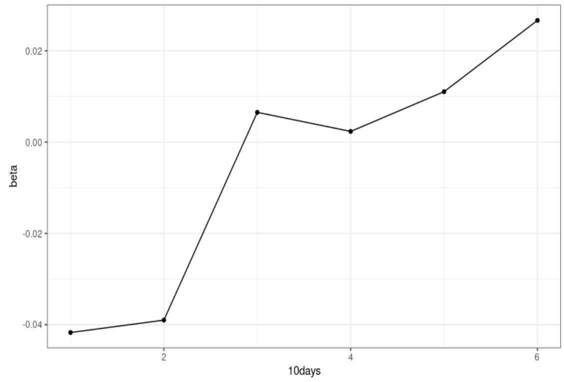


Fig. 3(d): Learning effects visualisation for DCC-GARCH based hedge ratio

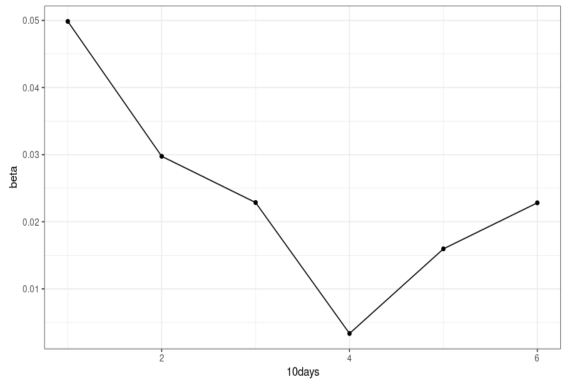
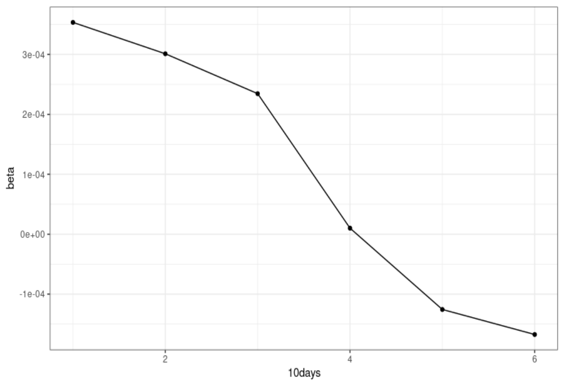


Fig. 3(e): Learning effects visualisation for time varying common factor weights



The figures indicate the movement of betas across subsequent sub-periods(10 days each). We detet presence of learning effects for all the proxies of volatility. The movement of betas for DCC GARCH hedge ratio is inconclusive. Learning effects are evident for time varying common factor weights. Similar visualisation cannot be conducted for time-invariant proxies- Ederington's hedge ratio, Hasbrouk's information share, and Gonzalo and Granger's component share.

Similar patterns are observed for other proxies of volatility in Fig. 3(b) and Fig. 3(C). The pattern of the movement of betas across sub-periods remains inconsistent for DCC-GARCH based hedge ratio depicted in Fig. 3(d). While some learning effect is evident as β witnesses decline from period 1 to period 4, a rise in β thereon until period 6 makes it difficult to reach a conclusion due to the restrained sample period. Finally, in Fig. 3(e) we again note a steeply declining curve reaching to even negative values. This suggests that even though informativeness increased for treated stocks than control group stocks upon adoption of physical settlement, the benefits were mostly short-lived as markets started acclimatising to the intervention.

8 Conclusion

The study investigates if the mode of settlement of futures contract - cash or physical-delivery has any significant influence on the volatility in the spot market, the hedging efficiency of futures, and the price-discovery function of futures contracts. With a treatment sample of 46 stocks that were moved to physical delivery system by SEBI from April, 2019 expiry and a control group of 45 stocks that were mandated to switch to a physical settlement mode from July, 2019. The analysis takes onto a Difference in Difference approach to look for significant deviations in the market upon the said intervention by SEBI. The empirical evidence suggests a significant decline in spot-market volatility. At the same time, hedging ratio is recorded to rise accompanied with improvement in price discovery efficiency. However, the effect of intervention on the market is likely to fade away with time as markets adjust to the newness.

The study not only brings back to surface an important policy questions almost a decade later, but also investigates it in an emerging market context of India. The analysis puts under the scanner a promising sample of 46 treatment stocks, and uses intra-day historical data to empirically prove the relative impact of physical delivery system when compared with cash-settlement system, making it an important contribution to the literature. Moreover, it serves as an imminent guiding tool for market-regulators, and policy-makers by illustrating the role played by a futures-settlement system in determination of important market constructs such as volatility, hedging efficiency and price-discovery.

The study is limited in its scope as it leaves the context of options contracts unexplored. The analysis further ignites the need to look at the changes in the markets near to and on the expiry days. The study also offers the potential to corroborate the findings by comparing stocks that were shifted to physical settlement July to those that were shifted October.

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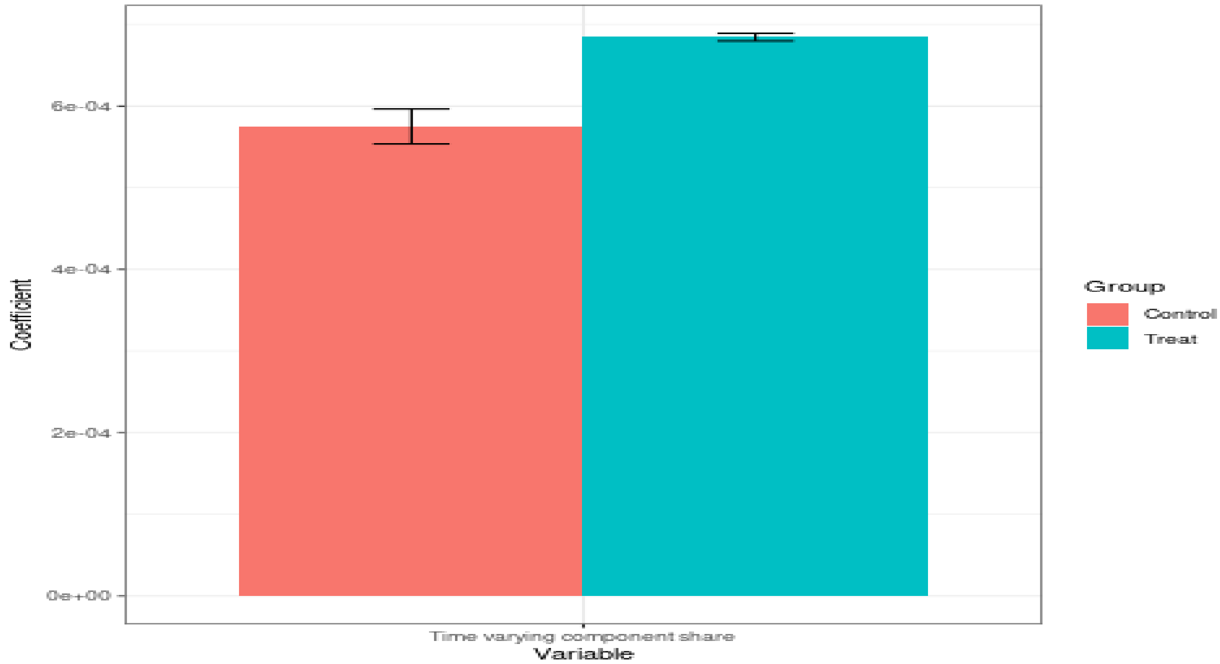
Appendix

Fig. A: Time varying common factor weights



A significant rise in time varying common factor weights for treated stocks is evident in the given plot.

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