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INVESTORS' BEHAVIOR AND FUTURES MARKETS: A Dynamic CAPM Augmented GJR-GARCH Process Approach with Non-Normal Distribution

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During the market turmoil, and later in the year 2008, the Securities and Exchange Commission of Pakistan (SECP) decided to discontinue the trading in single stock futures (SSFs) at the Karachi Stock Exchange (KSE). On 27th July 2009, trading in SSFs were re-launched in those stocks which passed the stringent criteria set by the SECP. While the overall market is in a transitional stage, there is a need to assess this new situation in order to improve and regulate the available futures contracts, as well as, the upcoming options contracts. In this vein, this study attempts to investigate the impact of parallel SSFs markets on the underlying spot market by examining whether the introduction of futures has played a role in destabilizing the market. The results suggest an insignificant change in coefficients used to gauge the market inefficiencies, feedback trading, trading volume, and volatility. This may imply that stringent contract specifications have helped to mitigate the potential destabilizing ability of SSFs.

I. Introduction

The concern that whether futures markets destabilize the underlying spot markets has received a great deal of attention from the stakeholders and researchers. Antoniou and Holmes (1995) claim that this concern predates the introduction of futures. Conceptual arguments regarding the specific effect of futures on spot markets are present in favor of both the stabilizing and destabilizing hypotheses. According to Friedman (1953), the rational trader takes his investment decisions based upon the fundamental analysis, which in turn seems to stabilize the market. As long as the futures markets attract rational traders, asset prices should move toward their intrinsic or fundamental values, which should result in stability in the market. The reasons why futures markets attract more traders are that futures trading has low margin requirements and low transaction costs [Cox (1976)]. These features, make the futures markets an additional route for information flow to the spot market and results in their stability. However, Chau, Holmes and Paudyal (2008) argue that luring features of futures markets attract noise traders who destabilize securities'

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prices. Even if noise traders are not attracted, Ross (1989) argues that spot market is bound to experience more volatility, after the introduction of futures trading due to more trading and more information flow. There is a lack of clear consensus in the extant literature on whether futures markets stabilize the spot market. This debate intensifies the following market crashes. Similar situations have been seen several times in Pakistan, where the SECP went back and forth, on allowing the trading of single stock futures in the KSE, after the market crashes.

Futures of the individual stocks were introduced in KSE in July 2001. In the beginning, one month's SSFs were introduced in ten stocks, where this number kept on changing as the market went through phases of developments. The SECP has formulated stringent eligibility criteria for analyzing the performance of already available futures contracts, which is conducted after every six months. Upon aforementioned intervals, SECP analyzes the performance of listed/unlisted futures contracts for potential delisting/listing of individual stocks. When the financial crisis of 2007-08 hit the global economy, Pakistan's financial market also felt its effects. The KSE 100-Index lost more than 50 per cent of its value, following which it was declared frozen for downward movements for several months. During this period, trading in futures contracts was also banned. In KSE, futures markets were also blamed as one of the sources of market de-stability [Khan (2006), Naz (2011)]. Later, the trading in SSFs was resumed on 27th July 2009 in the eighteen[1] stocks with improved contract regulations.

The objective of this study is to investigate whether the SSFs have played any role in stabilizing the spot market of KSE. This study is conducted for the resumption episode where SSFs were resumed in KSE on 27th July 2009 in eighteen stocks, with improved regulatory framework.[2] Although, several studies[3] have been conducted in Pakistan's context, but none of them has used the data for resumption episode, which is characterized by improved and stringent regulatory work. This paper contributes to the extant literature on several counts:

1. The KSE crash of 2008 provides a natural experiment to test the stabilizing vs destabilizing effects of futures trading on the spot market.

[1] SSFs are Adamjee Insurance (AJI), Azgard Nine (AN), Bank Al-Falah (BAF), D.G. Khan Cement (DGKC), Engro Chemical (EC), Fauji Fertilizer Bin Qasim (FFBQ), Fauji Fertilizer Company (FFC), Hub Power Company (HUBCO), Lucky Cement (LUCK), Muslim Commercial Bank (MCB), National Bank of Pakistan (NBP), Nishat Mills Limited (NML), Oil & Gas Development Corporation (OGDC), Pakistan Oilfields Limited (POL), Pakistan Petroleum Limited (PPL), Pakistan State Oil Company Limited (PSO), Pakistan Telecommunication Limited (PTCL) and United Bank Limited (UBL).

[2] Differences in regulations for resumed SSFs from, initially issued SSFs contracts back in 2001. (1) Increase in bank or cash margin from 50 to 100 per cent to make trading in SSFs controlled. (2) Applicability of concentration margin instead of special margin, and (3) Retainment of the mark to market profit with regulated exchange instead of distributing it to stakeholders.

[3] For example, Malik and Khan (2012), Khan, Shah and Abbas (2011), Khan (2006) and Siddiqi et al. (2012), etc.

2. The SSFs have attracted relatively little attention of researchers, specifically when evidence from individual countries are considered. Study of an individual country provides an excellent opportunity to analyze and interpret results in light of the given institutional settings. While the existing studies have focused more on the industrialized countries and cross-country analysis with mixed results,[4] there is a need to test destabilizing the hypothesis in context to an emerging economy.
3. The study contributes to the economic literature by modifying Sentana and Wadhwani (1992) model[5] by using dynamic Capital Asset Pricing Model (CAPM) instead of the mean variance equation and adding trading volume as a control variable. CAPM adds two assumptions (i.e., complete agreement between investors regarding distribution of returns and borrowing, and lending at risk-free rate) to the risk - return relationship. In addition, this study also makes use of student's t and Generalized Error Distribution (GED) along with Gaussian normal distribution. Since the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family of models does not take care of fat tails, which is an attribute of financial time series data, this study makes use of student's t[6] and GED.[7]

Following that, this study makes use of closing prices of six months data for pre- and post-period for SSFs and non-SSFs for resumption episode and employs derived rational-irrational trading model augmented with Glosten Jaganathan and Runkle Generalized Autoregressive Conditional Autoregressive Heteroskedasticity (GJR-GARCH) (1, 1) process with simultaneous use of Gaussian normal, students' t, and the GED. To avoid endogeneity bias, a carefully selected non-SSFs sample is also selected. The results report statistically, insignificant coefficients used to measure the market inefficiencies, feedback trading, volume and volatility. Thereby, it could be stated that any alleged change in these dynamics could not be attributed to futures markets, but overall contemporaneous changes in the sector or the economy.

The rest of the study is organized as follows. Section II discusses the relevant literature regarding feedback trading, autocorrelation, volume and volatility. Section III describes data and econometric methodology. Section IV elaborates the results and analysis, and Section V concludes the study.

[4] See for example, Antoniou et al. (2005), Chau et al. (2008), Siklos (2008).

[5] Hou and Li (2014), Xie, Zhu and Yu (2013), Tokie (2011), Antoniou et al. (2011), Salm and Schuppli (2010), Chau et al. (2008), Bohl and Siklos (2008), Laopodis (2005) and Antoniou et al. (2005), Pierdzioch (2004), Koutmos (2002), and Koutmos (1997), have also used this model.

[6] A number of studies have proposed to use students t if the time series has fait tales, see e.g., Bollerslev (1987), Baillie and Bollerslev (1989), Kaiser (1996) and Beine, Laurent and lecourt (2000).

[7] Use of GED is suggested by Nelson (1991), and Kaiser (1996) for handling fat tails in the time series data.

II. Literature Review

Several studies have been conducted all over the world, to identify the impact of the introduction of futures markets upon the underlying markets. These studies discuss the theoretical aspects regarding impact on different dynamics of the underlying markets, as well as, provide empirical evidences to confirm or refute their respective claims. Along with progress in theoretical explanations, advancement in econometric methodologies have also been recognized and used in these studies, while attempting to provide empirical evidences. Following are some of the studies which discuss different aspects that constitute the development of conceptual and empirical framework, used in this study.

In the financial markets, stock prices depict the information set held by two types of investors, i.e., rational expected utility maximizers (who trade on information), and noise traders (who assume noise, e.g., trend patterns) to be informative [see, Black (1986))]. According to Friedman (1953) rational traders takes their investment decisions based upon the fundamental analysis, which in turn seems to stabilize the market. It also reduces hyper oscillations in the prices of stocks. If the introduction of futures markets attracts rational traders, then the prices should move toward their intrinsic or fundamental values, which should result in stability in the market. Similar to this, Cox (1976) stated that the introduction of futures markets provides an additional route of information to the market, because trading in futures markets is relatively much easier in terms of cheaper transaction costs, and lesser margin requirements. Also, he argued that the introduction of new markets increases the number of trader/investor in the overall market. In this vein, Ross (1989) stated that increase in rapid and highly processed information is directly related to volatility. Following the studies by Cox (1976) and Ross (1989), it is plausible to interpret that the introduction of futures markets may attract rational traders who use futures for arbitraging, thereby stabilizing the market. On the other hand, Black (1986) stated that noise traders assume noise to be relevant information regarding stocks, and base their decisions on it. Leading to this, Delong et al. (1991) proposed a model to show that activities of noise traders are the reason for deviation of prevailing stock prices from their actual intrinsic or the fundamental values. The literature supports the hypothesis that noise trading destabilizes the spot market. In relevance to the futures markets, the explanation that introduction of the derivative markets enhances speculative activity, specifically the noise trading, because of cheaper and easier way of trading. As a result, noise traders make the assets prices deviate away from their fundamental values and the cause de-stability. One form of noise trading is feedback trading (positive and negative feedback). In a positive feedback trading strategy, the trader buys when the asset prices move up, and sells when they move down, and vice versa in the negative feedback trading strategy. This strategy is adopted in the following cases:

portfolio insurance, stop-loss order, help of technical analysis and extrapolative expectations. In the short-run, the interaction of rational and feedback trader may move the asset prices away from their intrinsic values. In accordance with this, Delong et al. (1990b) argue that as a result of traders' response to such situation, the asset prices will move towards their intrinsic values. In a short-run, positive serial correlation in stock return could be observed as a result of positive feedback trading activities, because positive feedback traders react to increase in prices. Moreover, the serial correlation turns negative in the long-run, because the assets prices move back to their intrinsic values. If it is hypothesized the introduction of futures markets attract the noise trading, then there is a possibility that in the short-run, the market would observe de-stability, which eventually make regulators to step in. Thus, depending upon the dominance of the rational or noise trader in the market, the stability or de-stability could be associated with introduction of futures markets, accordingly. This discussion leads to answer the destabilizing ability of the futures markets in relevance to noise trading. On similar lines, Sentana and Wadhwani (1992) proposed a heterogeneous trading model to check the presence of feedback trading strategies. They used the US index returns and provided evidence that during tranquility, returns are positively correlated, which turn negative in volatile periods. This notion is consistent with presence of positive feedback traders in the market.

Liquidity is the positive aspect by the noise trading to the financial markets, but at the same time, it enhances the inherent risk. Consequently, the probability that rational speculators may hesitate to take positions which is necessary to eradicate arbitrage chances. Thaler (1999) argues that quasi-rational traders (i.e., Noise traders also affect the stock prices along with the rational speculators. Shiller (1990) in his series of papers, tried to establish the fact that stock price volatility could not only be determined by the fundamentals [(e.g., Income, and Divided Per Share (DPS)]. Furthermore, Delong et al. (1990) argued that noise trading drag the stock prices away from their intrinsic values. Ironically, it enhances the volatility which makes the rational risk-averse arbitragers who hesitate to take advantage of opportunities created. Under such circumstances, noise traders benefit themselves by earning abnormal returns by only bearing disparate amount of risk. In such a case, it would be ideal for rational speculators to join the trend.

In the past, the impact of noise traders on the volatility of the underlying market, after the introduction of futures markets has been investigated. In this regard, Antoniou et al. (1998) examined the asymmetric response of volatility on arrival of new information. Antoniou et al (2005) added feedback trading aspect to their work and studies the change in the first and second order moment after introduction of the futures. They conclude that the introduction of futures markets helps to stabilize the market because they reduce the impact of feedback traders and attract rational speculators who eventually enhance the efficiency of the market.

Several feedback trading frameworks have been used in the past to capture the autocorrelation in the stock returns. Each model has its own explanation. The feedback trading used by Shiller et al. (1984) results positive autocorrelation in stock returns in the short-run. The model used by Cutler et al. (1991) also had the similar implications. Feedback trading models could not be assumed to superior alternatives for traditional martingale models for stock returns, since they also predict small positive autocorrelations. However, a study by Shiller (1990) revealed that feedback trading models can also depict negative autocorrelations. Still, the autocorrelation pattern in stock returns is a complicated issue. For example, LeBaron (1992) used the first order autocorrelation pattern with a GARCH model to capture the short-run features of stocks and index returns. It has been concluded that there are inverse relationship between autocorrelation and volatility; and also report statistically significant non-linear interdependence in the first moment. In other words the autocorrelation pattern is different for volatile and tranquil periods. These patterns are low in volatility periods and higher in tranquil periods. Also, Capmbell et al. (1993) reported an inverse relationship between the autocorrelation in stock returns and their respective traded volumes. For low volume days, the autocorrelation is positive and vice-versa. Their results are stable with their claim that risk-averse utility maximizers accommodate market pressures (i.e. selling or buying) created by noise traders.

III. Data & Methodology

On July 27, 2009, SECP resumed SSFs trading in 18 stocks with improved risk management mechanisms. This study makes use of the data for resumption episode to investigate whether SSFs has played a role in destabilizing the underlying markets. To avoid the endogeneity bias, a control sample methodology is employed, for which a relatively matched sample (i.e., size, volume and sector) consisting of sixteen[8] stocks is selected. Six months' daily closing prices of all stocks are collected from online sources (i.e., Business recorder), and daily observations of three months' T bills rates are used as a proxy for RFR, which are obtained from website of the State Bank of Pakistan.

Following the study of Sentatna and Wadhwani (1982), this study models the demand for stocks by feedback traders as follows:

$$F_t = \gamma R_{t-1} \quad (1)$$

[8] Non-SSFs are Allied Bank Limited (ABL), Askari Commercial Bank Limited (ACBL), Attock Petroleum Limited (APL), Attock Refinary Limited (ARL), Bank Al-Habib Limited (BAHL), Dawood Hereculues Corporation Limited (DHC), EFU Insurance Company Limited (EFU), Fauji Cement Compnay Limited (FCCL), Habib Bank Limited (HBL), Kot Addu Power Company (KAPC), Kohinoor Textile Mills (KTM), Mari Gas Company Limited (MGCL), Maple Leaf Cement Factory (MLCF), Nishat Chunian Limited (NCL), National Refinary Limited (NRL) and Telecard Limited (TELE).

On the other hand, unlike the Sentana and Wadhwani (1982) framework, this study uses the following dynamic CAPM model instead of mean variance equation.

$$E_{t-1}(R_{it}) = R_f + \beta_t (E_{t-1}(R_{mt}) - (R_f) \quad (2)$$

In the presence of rational and noise traders the market equilibrium would be achieved, if demand of these traders follows the following notion:

$$F_t + S_t = 1 \quad (3)$$

After incorporating the first and second equation in the third equation, this study derives[9] the following form of framework which lends itself for empirical testing:

$$ER_{it} + \alpha + \beta_1 VarER_{it} + \{\varphi_{0,1} + \varphi_{0,2}(D_t)\} ER_{it-1} + \{\varphi_{1,1} + \varphi_{1,2}(D_t)$$
$$VarER_{it} ER_{it-1} + \{\varphi_{2,1} + \varphi_{2,2}(D_t)\} Vol_{it} + \varepsilon_t; \varepsilon_t \sim N, t, or GED (0, \sigma_t^2) \quad (4)$$

where, ER_{it} is the excess return for each individual stock at time i, $\varphi_{0,1}$ measures the lagged excess returns for pre-SSFs period, and $\varphi_{0,2}$ measures the same for change in excess returns, which is used to measure market inefficiencies. The sum of $\varphi_{0,1}$ and $\varphi_{0,2}$ measures the significance of market inefficiencies in the post-SSFs period. In addition, $\varphi_{1,1}$ is used to measure feedback trading in the pre-SSF period and $\varphi 1,2$ measures the change in feedback trading post-SSFs period. Similarly, $\varphi_{2,1}$ measures the significance of control variable volume for pre-SSFs period and $\varphi_{2,2}$ for post-SSFs period. This model is designed to use the whole data set which would improve the informational efficiency of the sample.

To capture changes in the volatility dynamics, Glosten et al. (1993) GJR-GARCH (1, 1) process is utilized as variance equation.

$$\sigma_t^2 = \alpha_{0,1} + \alpha_{0,2} D_t + \alpha_1 \varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta X_{t-1}\varepsilon_{t-1}^2 \quad (5)$$

where, $\alpha_{0,1}$ measure the unconditional variance in pre-SSF period, and $\alpha_{0,2}$ checks the change in unconditional variance due to introduction of SSFs. The sum of $\alpha_{0,1}$ and $\alpha_{0,2}$ measures the unconditional variance in the post-SSF period. Maximum likelihood estimates are used to estimate Equations (4) and (5). Following that non-parametric Wilcoxen Signed Rank Test (WSRT) is used to compare the pre- and post-SSFs coefficients, while Mann-Whitney U Test (MWUT) is used to compare changes across SSFs to non-SSFs.

[9] Derivation of model lies with the authors of the study.

IV. Results and Analysis

To answer the main research question, Equations (4) and (5) are estimated for 18 SSFs and 16 non-SSFs. To draw the conclusion regarding promotion or inhibitions ability of SSFs in their underlying counterparts, the descriptive, as well as, inferential statistics are provided in the respective tables as follows. Tables 1 and 2 depict the descriptive statistics of excess returns. These tables include the summary statistics of mean, standard deviation, skewness, kurtosis, Augmented Dicky Fuller Test (ADF), Jarque-berra (JB) test to check the normality assumption, Breusch-Godfrey Serial Correlation LM Test (BGLM), and the Autoregressive conditional (ARCH) test to check the potential presence of conditional variance as it is considered to be the main attribute of financial time series data.

Tables 3 and 4 summarize the outcome of maximum likelihood estimates of the derived empirical version of the feedback trading framework for both the SSFs and non-SSFs. These tables depict estimation output of the coefficients α, β_1, $\varphi_{0,1}$ $\varphi_{0,2}$, $\varphi_{1,1}$, $\varphi_{1,2}$, $\varphi_{2,1}$, $\varphi_{2,2}$ from the mean equation and $\alpha_{0,1}$, $\alpha_{0,2}$, α_1, β, δ and their respective p-values from the variance equation. The detailed analysis of the estimation output of SSFs and non-SSFs could be observed. In all cases the variables of interest are stationary, and the level of skewedness and peakedness of the stock returns vary, accordingly. This affirms the need for use of non-normal distribution (i.e., students' t and GED) functions alongside Gaussian distribution. Additionally, the presence of strong heteroscedastic patterns confirms the choice of GARCH models over others.

The summarized results are separated in Panel-A (for SSFs) and Panel-B (for non-SSFs) in Table 5. In this table along with mean and median of the important coefficients, results of WSRT and MWUT are also presented. For the sample as a whole, non-parametric WSRT examine whether coefficients in the post-SSFs are significantly different from the pre-SSFs period at 5 per cent level of significance, while non-parametric MWUT checks if change in SSFs to non-SSFs is significantly different or not. In Panel-A, $\varphi_{0,1}$ measures the presence of market inefficiencies for pre-period of SSFs, and $\varphi_{0,2}$ measures the potential change in the same attribute for SSFs after their introduction. Mean and median of coefficients $\varphi_{0,1}$ and $\varphi_{0,2}$ of SSFs are -0.088 (-0.059) and -0.152 (-0.166), respectively. This suggests that mean and median of SSFs have reduced after their introduction. Further, $\varphi_{0,1}$ is statistically insignificant at 5 per cent for all SSFs with negative, sign and $\varphi_{0,2}$ is only significant for PPL. This shows that these stocks are not affected by market inefficiencies. Z and p-value of WSRT for coefficients $\varphi_{0,1}$ and $\varphi_{0,1} + \varphi_{0,2}$ are -1.764 (0.078), suggesting that there is insignificant change at 5 per cent level of significance in the coefficient used to measure the change due to market frictions. This suggests that introduction of SSFs have not affected the the market frictions. Similarly, in Panel-B of Table 5, descriptive statistics for non-SSFs are presented. For non-SSFs, mean

TABLE 1

Descriptive statistics for SSFs

Sr.		Variables		Residuals				Variables		Residuals			
#	Stock	Mean	Std. Dev.	Skewness	Kurtosis	Normality test		Unit Root test		BGLM		ARCH test	
1.	AJI	0.001	0.015	-0.225	2.711	2.952	0.229	-12.856	0.000	7.486	0.001	5.296	0.000
2.	AN	0.000	0.015	-0.221	2.874	2.188	0.335	-11.996	0.000	0.206	0.814	4.008	0.000
3.	BAF	0.000	0.014	-0.007	3.512	2.716	0.257	-14.940	0.000	1.666	0.191	5.398	0.000
4.	DGKC	0.001	0.014	-0.090	2.374	4.384	0.112	-13.137	0.000	8.135	0.000	4.303	0.000
5.	EC	0.000	0.012	0.120	3.511	3.294	0.193	-12.746	0.000	9.774	0.000	8.032	0.000
6.	FFBQ	0.001	0.011	0.011	-0.600	0.000	51.932	-17.765	0.000	6.862	0.001	2.018	0.033
7.	FFC	0.000	0.012	-0.108	3.018	0.481	0.786	-13.110	0.000	2.653	0.072	1.613	0.104
8.	HUBCO	0.001	0.009	-0.226	4.835	36.896	0.000	-15.214	0.000	2.847	0.060	2.930	0.002
9.	LUCK	0.001	0.012	-0.134	2.529	3.026	0.220	-13.620	0.000	7.447	0.001	4.582	0.000
10.	MCB	0.001	0.013	-0.245	2.597	4.171	0.124	-13.664	0.000	0.333	0.717	2.560	0.006
11.	NBP	0.000	0.013	-1.531	12.788	1086.854	0.000	-13.786	0.000	1.183	0.308	0.408	0.942
12.	NML	0.001	0.013	-0.192	2.265	7.119	0.028	-14.777	0.000	0.305	0.737	3.200	0.001
13.	OGDC	0.001	0.010	-0.152	2.761	1.545	0.462	-12.494	0.000	0.669	0.513	3.994	0.000
14.	POL	0.001	0.011	0.071	2.527	2.516	0.284	-14.131	0.000	0.118	0.889	5.103	0.000
15.	PPL	0.000	0.011	-2.001	17.131	2228.827	0.000	-17.188	0.000	5.346	0.005	0.072	1.000
16.	PSO	0.001	0.011	0.100	2.657	1.629	0.443	-14.351	0.000	0.317	0.729	5.627	0.000
17.	PTCL	0.000	0.012	-0.108	3.018	0.481	0.786	-13.110	0.000	2.653	0.072	1.613	0.104
18.	UBL	0.001	0.012	-0.245	2.951	2.508	0.285	-14.631	0.000	2.749	0.066	4.532	0.000

Note: The Table depict descriptive statistics of the excess returns for SSFs. These tables include the summary statistics of mean, median, skewness, kurtosis, Augmented Dicky Fuller Test (ADF), Jarque Berra (JB) test to check the normality assumption, Breusch-Godfrey Serial Correlation LM Test (BGLM) and Autoregressive conditional heteroskedasticity (ARCH) test to check the potential presence of conditional variance as is considered to be the main attribute of financial time series data.

TABLE 2

Descriptive statistics for Non-SSFs

Sr.		Variables		Residuals				Variables		Residuals			
#	Stock	Mean	Std.Dev.	Skewness	Kurtosis	Normality test		Unit Root test		BGLM		ARCH test	
1.	ABL	0.00	0.01	-0.40	3.45	8.72	0.01	-13.33	0.00	0.93	0.40	4.268	0.000
2.	ACBL	0.00	0.01	-1.62	12.96	1133.47	0.00	-15.38	0.00	1.19	0.31	1.103	0.361
3.	APL	0.00	0.02	-3.67	63.45	38316.36	0.00	-18.05	0.00	14.43	0.00	3.391	0.000
4.	ARL	0.00	0.01	-0.26	2.35	7.21	0.03	-12.19	0.00	3.03	0.05	2.905	0.002
5.	BAHL	0.00	0.01	-5.52	62.56	37908.86	0.00	-17.25	0.00	1.45	0.24	0.027	1.000
6.	DHC	0.00	0.01	-0.13	2.77	1.19	0.55	-12.49	0.00	3.43	0.03	5.152	0.000
7.	EFU	0.00	0.01	-0.11	2.25	6.41	0.04	-12.05	0.00	10.56	0.00	2.384	0.011
8.	FCCL	0.00	0.01	0.14	7.35	195.88	0.00	-17.99	0.00	6.79	0.00	2.427	0.009
9.	HBL	0.00	0.01	-1.54	13.66	1272.48	0.00	-15.09	0.00	1.47	0.23	0.260	0.989
10.	KAPC	0.00	0.01	-0.15	4.16	14.82	0.00	-15.51	0.00	0.28	0.76	3.043	0.001
11.	KTM	0.00	0.03	-4.24	48.02	21685.66	0.00	-12.60	0.00	0.76	0.47	0.409	0.941
12.	MGCL	0.00	0.02	-8.90	116.70	136861.80	0.00	-13.87	0.00	3.53	0.03	0.007	1.000
13.	MLCF	0.00	0.02	-0.57	6.24	122.15	0.00	-17.09	0.00	13.73	0.00	2.311	0.013
14.	NCL	0.00	0.02	0.23	3.03	2.16	0.34	-14.91	0.00	4.42	0.01	2.587	0.006
15.	NRL	0.00	0.01	-0.01	2.86	0.20	0.91	-13.92	0.00	7.63	0.00	5.495	0.000
16.	TELE	0.00	0.03	-0.68	13.71	1204.46	0.00	-18.43	0.00	2.63	0.07	0.551	0.853

Note: The Table depict descriptive statistics of the excess returns for SSFs. These tables include the summary statistics of mean, median, skewness, kurtosis, Augmented Dicky Fuller Test (ADF), Jarque Berra (JB) test to check the normality assumption, Breusch-Godfrey Serial Correlation LM Test (BGLM) and Autoregressive conditional heteroskedasticity (ARCH) test to check the potential presence of conditional variance as is considered to be the main attribute of financial time series data.

TABLE 3

Maximum Likelihood Estimates for SSFs

Sr. #	Stock	α	Prob.	β_1	Prob.	φ 0,1	Prob.	φ 0,2	Prob.	φ 1,1	Prob.	φ 1,2	Prob.	φ 2,1	Prob.	φ 2,2	Prob.
1.	AJI	-0.008	0.003	16.577	0.191	-0.101	0.713	0.252	0.610	146.095	0.945	-24.414	0.992	0.000	0.000	0.000	0.462
2.	AN	-0.009	0.001	24.938	0.037	-0.572	0.159	0.636	0.245	4996.947	0.108	-4295.442	0.192	0.000	0.000	0.000	0.468
3.	BAF	-0.005	0.000	-0.028	0.997	0.163	0.587	-0.339	0.340	-4426.060	0.153	4967.617	0.112	0.000	0.000	0.000	0.926
4.	DGKC	-0.003	0.189	8.070	0.308	0.721	0.099	-0.786	0.152	-4561.015	0.177	5019.363	0.152	0.000	0.332	0.000	0.347
5.	EC	-0.002	0.133	-11.552	0.305	-0.338	0.256	-0.168	0.668	2965.144	0.405	239.856	0.948	0.000	0.000	0.000	0.893
6.	FFBQ	0.001	0.447	-21.034	0.052	-0.129	0.446	0.092	0.723	1425.369	0.376	-2715.936	0.156	0.000	0.000	0.000	0.421
7.	FFC	0.000	0.773	-22.707	0.102	-0.436	0.223	-0.007	0.986	6111.735	0.075	-3611.678	0.307	0.000	0.004	0.000	0.094
8.	HUBCO	-0.001	0.140	-16.277	0.229	-0.257	0.269	0.021	0.941	1354.235	0.681	844.785	0.812	0.000	0.000	0.000	0.137
9.	LUCK	-0.003	0.151	3.042	0.821	-0.615	0.108	0.441	0.363	5751.643	0.067	-4808.112	0.164	0.000	0.003	0.000	0.444
10.	MCB	-0.008	0.000	20.246	0.008	-0.234	0.379	-0.165	0.669	1087.350	0.644	849.344	0.731	0.000	0.000	0.000	0.000
11.	NBP	-0.006	0.000	17.285	0.018	0.042	0.962	-0.311	0.734	-2344.563	0.790	4379.559	0.621	0.000	0.000	0.000	0.002
12.	NML	-0.005	0.082	19.440	0.234	-0.018	0.959	-0.203	0.704	590.814	0.770	39.535	0.988	0.000	0.012	0.000	0.766
13.	OGDC	-0.002	0.202	-22.423	0.037	0.192	0.591	-0.649	0.109	-3351.522	0.528	6435.971	0.234	0.000	0.000	0.000	0.198
14.	POL	-0.002	0.235	-10.374	0.388	0.078	0.784	-0.267	0.473	-950.885	0.776	2100.314	0.556	0.000	0.000	0.000	0.442
15.	PPL	0.000	0.567	-28.951	0.001	0.053	0.739	-0.617	0.006	-1473.156	0.282	3686.452	0.024	0.000	0.000	0.000	0.492
16.	PSO	-0.003	0.142	14.316	0.177	0.061	0.844	-0.164	0.668	-2183.815	0.488	2892.562	0.374	0.000	0.057	0.000	0.405
17.	PTCL	0.000	0.773	-22.707	0.102	-0.436	0.223	-0.007	0.986	6111.735	0.075	-3611.678	0.307	0.000	0.004	0.000	0.094
18.	UBL	-0.004	0.034	3.442	0.781	0.226	0.586	-0.498	0.351	-2599.061	0.476	3731.842	0.341	0.000	0.000	0.000	0.076

(Contd.)

TABLE 3

(contd.)

Sr.	Stock	$\alpha 0,1$	Prob.	$\alpha 0,2$	Prob.	$\alpha 1$	Prob.	β	Prob.	δ	Prob.	Method and Distribution
1.	AJI	0.000	0.546	0.000	0.741	-0.010	0.770	1.007	0.000	0.015	0.764	Method: ML - ARCH (Marquardt) - Normal distribution
2.	AN	0.000	0.222	0.000	0.285	0.045	0.796	0.389	0.378	0.191	0.437	Method: ML - ARCH (Marquardt) - Normal distribution
3.	BAF	0.000	0.715	0.000	0.272	0.053	0.098	0.989	0.000	-0.082	0.011	Method: ML - ARCH (Marquardt) - Normal distribution
4.	DGKC	0.000	0.302	0.000	0.414	0.053	0.650	0.725	0.001	0.070	0.578	Method: ML - ARCH (Marquardt) - Normal distribution
5.	EC	0.000	0.011	0.000	0.008	0.228	0.046	0.417	0.001	0.251	0.221	Method: ML - ARCH (Marquardt) - Normal distribution
6.	FFBQ	0.000	0.418	0.000	0.962	0.169	0.017	0.905	0.000	-0.173	0.015	Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
7.	FFC	0.000	0.810	0.000	0.500	0.095	0.046	0.967	0.000	-0.117	0.016	Method: ML - ARCH (Marquardt) - Normal distribution
8.	HUBCO	0.000	0.390	0.000	0.816	0.100	0.090	0.896	0.000	-0.043	0.594	Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
9.	LUCK	0.000	0.345	0.000	0.757	0.090	0.307	0.907	0.000	-0.053	0.539	Method: ML - ARCH (Marquardt) - Normal distribution
10.	MCB	0.000	0.663	0.000	0.163	0.107	0.064	0.906	0.000	-0.042	0.538	Method: ML - ARCH (Marquardt) - Normal distribution
11.	NBP	0.000	0.304	0.000	0.316	-0.049	0.535	0.857	0.000	0.126	0.299	Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
12.	NML	0.000	0.442	0.000	0.786	0.087	0.383	0.867	0.000	0.000	1.000	Method: ML - ARCH (Marquardt) - Student's t distribution
13.	OGDC	0.000	0.263	0.000	0.273	0.160	0.141	0.772	0.000	-0.036	0.735	Method: ML - ARCH (Marquardt) - Normal distribution
14.	POL	0.000	0.324	0.000	0.684	0.075	0.238	0.853	0.000	0.080	0.341	Method: ML - ARCH (Marquardt) - Normal distribution
15.	PPL	0.000	0.407	0.000	0.862	0.104	0.134	0.892	0.000	-0.075	0.161	Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
16.	PSO	0.000	0.458	0.000	0.549	0.064	0.082	0.983	0.000	-0.086	0.013	Method: ML - ARCH (Marquardt) - Normal distribution
17.	PTCL	0.000	0.810	0.000	0.500	0.095	0.046	0.967	0.000	-0.117	0.016	Method: ML - ARCH (Marquardt) - Normal distribution
18.	UBL	0.000	0.657	0.000	0.762	0.086	0.119	0.895	0.000	-0.002	0.977	Method: ML - ARCH (Marquardt) - Normal distribution

Note: The Table summarize the outcome of maximum likelihood estimates of the derived empirical version of the feedback trading framework for both SSFs. These tables depict estimation output of the coefficients α, β_1, $\varphi_{0,1}$, $\varphi_{0,2}$, $\varphi_{1,1}$, $\varphi_{1,2}$, $\varphi_{2,1}$, $\varphi_{2,2}$ from the mean equation and$\alpha_{0,1}$, $\alpha_{0,2}$, $\alpha 1$, β, δ and their respective p-values from the variance equation.

TABLE 4

Maximum Likelihood Estimates for Non-SSFs

Sr. #	Stock	α	Prob.	β_1	Prob.	φ 0,1	Prob.	φ 0,2	Prob.	φ 1,1	Prob.	φ 1,2	Prob.	φ 2,1	Prob.	φ 2,2	Prob.
1.	ABL	-0.002	0.062	5.004	0.568	-0.303	0.160	0.258	0.353	1464.593	0.320	-1213.264	0.446	0.000	0.000	0.000	0.795
2.	ACBL	-0.004	0.000	-12.281	0.073	-0.220	0.131	-0.050	0.795	269.439	0.842	-208.970	0.880	0.000	0.000	0.000	0.851
3.	APL	-0.002	0.000	2.422	0.291	-0.121	0.225	0.026	0.847	-251.903	0.390	242.378	0.403	0.000	0.000	0.000	0.200
4.	ARL	-0.006	0.055	16.355	0.235	-0.227	0.484	-0.270	0.578	2018.595	0.306	888.805	0.713	0.000	0.045	0.000	0.740
5.	BAHL	0.000	0.729	-16.016	0.062	0.149	0.511	-0.365	0.150	-2107.217	0.437	2854.496	0.307	0.000	0.000	0.000	0.255
6.	DHC	0.000	0.872	-16.156	0.083	-0.262	0.159	0.156	0.543	1488.761	0.258	-938.247	0.535	0.000	0.000	0.000	0.328
7.	EFU	-0.003	0.016	-4.321	0.598	-0.181	0.422	-0.128	0.728	356.525	0.769	1772.246	0.260	0.000	0.000	0.000	0.570
8.	FCCL	-0.003	0.032	-2.148	0.820	-0.709	0.053	0.523	0.193	4587.001	0.169	-4904.728	0.149	0.000	0.002	0.000	0.024
9.	HBL	-0.006	0.001	12.580	0.207	-0.189	0.385	0.264	0.305	108.152	0.926	-66.791	0.956	0.000	0.000	0.000	0.795
10.	KAPC	0.001	0.227	-41.256	0.028	0.013	0.946	0.384	0.162	-1859.872	0.530	-2653.445	0.463	0.000	0.276	0.000	0.573
11.	KTM	0.001	0.627	-3.480	0.008	-0.295	0.018	0.113	0.464	177.768	0.008	-141.188	0.051	0.000	0.665	0.000	0.452
12.	MGCL	-0.002	0.028	-0.758	0.000	-0.036	0.674	0.166	0.260	-2.481	0.001	135.674	0.041	0.000	0.000	0.000	0.101
13.	MLCF	0.000	0.832	-22.323	0.000	-0.049	0.727	-0.340	0.088	195.184	0.816	119.688	0.895	0.000	0.041	0.000	0.000
14.	NCL	-0.004	0.239	-0.883	0.909	-0.851	0.006	0.551	0.192	2557.264	0.000	-2383.704	0.005	0.000	0.004	0.000	0.000
15.	NRL	-0.002	0.252	-3.078	0.834	-0.513	0.075	0.281	0.502	5131.758	0.136	-3965.518	0.303	0.000	0.009	0.000	0.004
16.	TELE	-0.002	0.037	-2.677	0.024	-0.042	0.666	-0.204	0.138	-34.602	0.608	9.206	0.899	0.000	0.000	0.000	0.000

(Contd.)

TABLE 4

(contd.)

Sr.	Stock	α0,1	Prob.	α0,2	Prob.	α1	Prob.	β	Prob.	δ	Prob.	Method and Distribution
1.	ABL	0.000	0.207	0.000	0.785	0.334	0.004	0.707	0.000	-0.143	0.320	Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
2.	ACBL	0.000	0.136	0.000	0.181	0.145	0.038	0.874	0.000	-0.081	0.271	Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
3.	APL	0.000	0.136	0.000	0.256	0.236	0.233	0.587	0.001	0.049	0.873	Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
4.	ARL	0.000	0.457	0.000	0.879	0.087	0.356	0.881	0.000	-0.026	0.775	Method: ML - ARCH (Marquardt) - Student's t distribution
5.	BAHL	0.000	0.117	0.000	0.156	0.187	0.093	0.639	0.000	-0.194	0.085	Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
6.	DHC	0.000	0.006	0.000	0.231	0.306	0.058	0.590	0.000	0.148	0.414	Method: ML - ARCH (Marquardt) - Normal distribution
7.	EFU	0.000	0.037	0.000	0.114	0.338	0.081	0.466	0.001	0.025	0.902	Method: ML - ARCH (Marquardt) - Student's t distribution
8.	FCCL	0.000	0.354	0.000	0.178	0.019	0.541	0.995	0.000	-0.056	0.220	Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
9.	HBL	0.000	0.026	0.000	0.134	0.431	0.040	-0.034	0.918	-0.167	0.558	Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
10.	KAPC	0.000	0.133	0.000	0.786	0.106	0.237	0.785	0.000	0.091	0.606	Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
11.	KTM	0.000	0.118	0.000	0.638	0.375	0.113	0.666	0.000	-0.339	0.186	Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
12.	MGCL	0.000	0.997	0.000	0.110	0.258	0.055	0.940	0.000	-0.262	0.052	Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
13.	MLCF	0.000	0.219	0.000	0.458	0.008	0.167	1.001	0.000	-0.050	0.005	Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)
14.	NCL	0.000	0.085	0.000	0.569	-0.029	0.493	0.703	0.000	0.211	0.112	Method: ML - ARCH (Marquardt) - Normal distribution
15.	NRL	0.000	0.215	0.000	0.647	0.121	0.155	0.846	0.000	-0.039	0.695	Method: ML - ARCH (Marquardt) - Normal distribution
16.	TELE	0.000	0.323	0.000	0.407	0.222	0.055	0.784	0.000	-0.058	0.655	Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)

Note: The Table summarize the outcome of maximum likelihood estimates of the derived empirical version of the feedback trading framework for Non- SSFs. These tables depict estimation output of the coefficients α, β_1, $\varphi_{0,1}$, $\varphi_{0,2}$, $\varphi_{1,1}$, $\varphi_{1,2}$, $\varphi_{2,1}$, $\varphi_{2,2}$ from the mean equation and $\alpha_{0,1}$, $\alpha_{0,2}$, $\alpha 1$, β, δ and their respective p-values from the variance equation.

TABLE 5

Results of WSRT and MWUT for SSFs and Non-SSFs

Mean (Median)	Panel A: SSFs	Panel B: Non-SSFs
φ0,1	-.0889 (-.059)	-.240 (-.204)
φ0,2	-.152 (-.166)	.085 (.134)
WSRT Z value (P-value)	-1.764 (.078)	-1.034 (.301)
Number of stocks with 5% significant φ0,1	0	2
Number of stocks with 5% significant φ0,2	1	0
5% Significantly positive (negative) φ0,1	0 (0)	0 (2)
5% Significantly positive (negative) φ0,2	0 (1)	0 (0)
MWUT Z value (P-value)		-1.932 (.053)
φ1,1	4.806E2 (3.684E2)	8.811E2 (2.323E2)
φ1,2	8.955E2 (8.471E2)	-6.533E2 (-1.040E2)
WSRT Z value (P-value)	-1.328 (.184)	-1.034 (.301)
Number of stocks with 5% significant φ1,1	0	3
Number of stocks with 5% significant φ1,2	1	2
5% Significantly positive (negative) φ1,1	0 (0)	2 (1)
5% Significantly positive (negative) φ1,2	1 (0)	1 (1)
MWUT Z value (P-value)		-1.656 (.098)
φ2,1	.000 (.000)	.000 (.000)
φ2,2	.000 (.000)	.000 (.000)
WSRT Z value (P-value)	.000 (1.000)	.000 (1.000)
Number of stocks with 5% significant φ2,1	16	14
Number of stocks with 5% significant φ2,2	2	5
5% Significantly positive (negative) φ2,1	16 (0)	14 (0)
5% Significantly positive (negative) φ2,2	2 (0)	5 (0)
MWUT Z value (P-value)		.000 (1.000)
φ0,1	.000 (.000)	.000 (.000)
φ0,2	.000 (.000)	.000 (.000)
WSRT Z value (P-value)	.000 (1.000)	.000a (1.000)
Number of stocks with 5% significant φ0,1	1	3
Number of stocks with 5% significant φ0,2	1	0
5% Significantly positive (negative) φ0,1	1 (0)	3 (0)
5% Significantly positive (negative) φ0,2	1 (0)	0 (0)
MWUT Z value (P-value)		.000 (1.000)

Note: The summarized results are separated in Panel A (for SSFs) and Panel B (for Non-SSFs). In Table 5 along with mean and median of the important coefficients for SSFs and Non-SSFs, results of WSRT and MWUT are presented. For the sample as a whole, non-parametric WSRT examine that whether coefficients in post SSFs are significantly different from Pre SSFs period at 5% level of significance, while non-parametric MWUT checks that whether change in SSFs to Non-SSFs is significantly different or not.

and median of coefficients $\varphi_{0,1}$ and $\varphi_{0,2}$ of SSFs are -0.239 (-0.204) and 0.085 (0.134), respectively. Like SSFs, it appears that introduction of SSFs have reduced their mean values. Further, $\varphi_{0,1}$ is significant at 5 per cent for 2 non-SSF stocks with negative signs, which are KTM and NCL, while $\varphi_{0,2}$ is insignificant for all stocks. The findings are similar to that of SSFs. Z and p-value of WSRT for coefficients $\varphi_{0,1}$ and $\varphi_{0,1} + \varphi_{0,2}$ are -1.034 (0.301) suggesting that there is insignificant change at 5 per cent level of significance in the coefficient used to measure the change due to market frictions. This suggests that introduction of SSFs have not affected the market frictions. Finally, MWUT Z (p-value) for comparison of change across introduction SSFs is -1.932 (0.053) which confirms that change in coefficient used to measure the market inefficiency/friction is same for both the SSFs and non-SSFs at 5 per cent level of significance. Therefore, it can be interpreted that introduction of SSFs do not seem to significantly affect the intensity of market frictions from pre to post period.

In Panel-A of Table 5, to capture the effect of feedback trading activities, the coefficients $\varphi_{1,1}$ and $\varphi_{1,2}$ are used. For SSFs, the mean and median of $\varphi_{1,1}$ and $\varphi_{1,2}$ are 4.806E2 (3.684E2) and 8.955E2 (8.470E2), respectively. The mean and median values have increased a bit after introduction of SSFs. To separate positive feedback trading activities from the negative feedback trading activities, results are reported separately for positive feedback trading activities (negative values of $\varphi_{1,1}$) and negative feedback trading activities (positive values of $\varphi_{1,1}$). A main feature of these results is low level of feedback trading activities, both in pre- and post-SSFs period, which is evident from the following results. All SSFs show insignificant $\varphi_{1,1}$ and, only PPL depict significant $\varphi_{1,2}$. Z (p-value) for comparison between pre- and post-futures coefficients $\varphi_{1,1}$, and $\varphi_{1,1}$, + $\varphi_{1,2}$ obtained from WSRT is -1.328 (0.184), which suggests that the introduction of SSFs have neither promoted nor inhibited feedback trading for SSFs underlying stocks. These results are in contrast to Antoniou et al. (2005). In their cross-country analysis, they reported that five out of six markets show significant presence of feedback trading activities in pre futures period. Further, they find that in the post-futures period, only one market depicts presence of feedback traders. Moreover, Panel-B of Table 5 relates to the statistics of non-SSFs. For non-SSFs, mean and median for $\varphi_{1,1}$ and $\varphi_{1,2}$ are 8.811E2 (2.323E2) and -6.533E2 (-1.039E2), respectively. Only one of the non-SSFs have significant $\varphi_{1,1}$ with negative signs, which is MGCL, on the other hand, KTM and NCL depict significant and positive signs. Only one non-SSFs depict significant and positive $\varphi_{1,2}$, which is MGCL. Similarly, only one non-SSF show significant and negative $\varphi_{1,2}$ which is NCL. Z (p-value) for comparison between pre- and post-futures coefficients $\varphi_{1,1,}$ and $\varphi_{1,1,}$ + $\varphi_{1,2}$ obtained from WSRT is -1.034 (0.301), which also suggest that the introduction of SSFs have neither promoted nor inhibited feedback trading for non-SSFs underlying stocks. Finally, Z (p-value) obtained by employing MWUT is -1.656

(0.098), which is insignificant at 5 per cent level of significance. Given that the notion that introduction of SSFs promotes or inhibits feedback trading could not be confirmed by this evidence.

In Panel-A of Table 5 the descriptive statistics of control variable i.e., trading volume is also presented. The significant change in trading volume could be interpreted as movement of feedback traders to or from the underlying market upon introduction of futures markets. Mean and median of the coefficients $\varphi_{2,1}$ and $\varphi_{2,2,}$ (which are used for trading volume) are 0.000 (0.000) and 0.000 (0.000). This suggests that introduction of SSFs does not change the mean and median of trading volume. Z (p-value) of WRST for $\varphi_{2,1}$ and $\varphi_{2,1} + \varphi_{2,2}$ is 0.000 (1.000), which confirms that both coefficients can be assumed to belong to the same distribution. Further, 89 per cent of the SSF stock show positive and statistically significant $\varphi_{2,1,}$ which are AJI, AN, BAF, EC, FFBQ, FFC, HUBCO, LUCK, MCB, NBP, NML, OGDC, POL, PPL, PTCL and UBL. On the other hand, only two SSFs depict significant $\varphi_{2,2,}$ which are MCB and NBP. For non-SSFs, mean and median of the coefficients $\varphi_{2,1}$ and $\varphi_{2,2}$ are 0.000 (0.000) and 0.000 (0.000) and 88 per cent of non-SSFs show significant and positive $\varphi_{2,1,}$ which are ABL, ACBL, APL, ARL, BAHL, DHC, EFU, FCCL, HBL, MGCL, MLCF, NCL, NRL and TELE. Also, 31 per cent of non-SSFs depict positive and significant $\varphi_{2,2,}$ which are FCCL, MLCF, NCL, NRL and TELE. Z (p-value) of WRST for $\varphi_{2,1}$ and $\varphi_{2,1} + \varphi_{2,2}$ is 0.000 (1.000), which confirms that both coefficients can be assumed to belong to same distribution and that there is no significant change in trading volume from pre- to post-SSFs period for SSFs underlying stocks. Further, Z (p-value) resulted by employing MWUT is 0.000 (1.000), which is consistent with the fact that change in volume of SSFs and non-SSFs post-futures contract list is same, and cannot be attributed to introduction of SSFs. This also confirms the results of promotion or inhibition of feedback trading activity after introduction of SSFs, because this could be interpreted that introduction of futures do not encourage or discourage migration of feedback traders to or from the spot market.

For variance equation, mean and median of the coefficients of unconditional volatility $\alpha_{0,1}$ and $\alpha_{0,2}$ are 0.000 (0.000) and -0.000 (0.000), respectively. It appears that there is no change in the mean and median value of unconditional volatility after introduction of SSFs. Further, Z (p-value) obtained from WSRT to check the change between $\alpha_{0,1}$ and $\alpha_{0,1} + \alpha_{0,2}$ is 0.000 (1.000), which confirms that there is no significant change unconditional variance across pre- to post-futures period for SSFs. Only one SSFs show significant coefficient of unconditional variance, which is EC. The same SSFs stock show significant $\alpha_{0,2,}$ (i.e., EC). For non-SSFs, 19 per cent of the stocks show significant unconditional variance, which are DHC, EFU and HBL while none of the non-SSFs show significant $\alpha_{0,2}$. Z (p-value) for WSRT is 0.000 (1.000), which confirms insignificant change in volatility from pre- to post-period in non-SSFs. Furthermore, value of MWUT 0.000 (1.000) depicts insignificant change across SSFs and non-SSFs. This evidence of synonymous to the notion that introduction of SSFs has not increased or decreased volatility due to inhibition or promotion of feedback trading activities.

It is evident from the analysis that coefficients used to measure the market frictions and inefficiencies has significantly changed from pre- to post-period for SSFs, while the opposite is observed for non-SSFs. MWUT used to measure the simultaneous change across SSFs and non-SSFs suggest that this change could not be attributed to contract listings of SSFs. In addition WSRT which is used to measure feedback trading results insignificant change from pre- to post-period for both the SSFs and non-SSFs, which is further confirmed by the use of MWUT. Similar results are obtained for the coefficients measuring potential change in trading volume. Finally, the unconditional volatility coefficients also show similar results. WSRT show that introduction of SSFs contracts' listings does not result in any significant change, neither in the SSFs nor in the non-SSFs from pre- to post-period. MWUT also confirms the findings of WSRT.

These results are contrary to the findings of Chau et al. (2008), reported limited presence of feedback trading, which reduced further after introduction of the Universal Stock Futures (USFs) in UK. Antoniou et al. (2004), reported an increase in positive feedback trading after introduction of index futures in six industrialized nations.

V. Conclusion and Implications

The objective of this paper is to investigate the role of SSFs in destabilizing spot markets. With improved regulatory framework, the SSFs were resumed in eighteen stocks in KSE in July 2009, after financial crisis of 2008. The newer market is still in a transitional stage and there is a need to check the impact of SSFs on the underlying counterparts. For this purpose, the study used dynamic CAPM augmented GJR-GARCH (1,1) process along with Gaussian normal, student's t and GED distribution. To avoid endogeneity bias, this study made use of a control sample and found the results which are contrary to some of the earlier studies in developed markets. Specifically, the results suggest that SSFs have had no impact on market inefficiencies, feedback trading, trading volume and volatility. Since the futures is in its infancy stage in Pakistan and regulations for options contracts are in process, our findings might have implications for both of them. However, our findings should be interpreted carefully. There is a possibility that futures have no destabilizing effect on spot market, as our results suggest. However, it is also possible that SECP is too conservative in its approach of selection of stocks for SSF and chalking out stringent regulations for trading in SSFs; thereby, limiting the role of SSFs to destabilize the market. These two alternative explanations for no-destabilizing effect of SSFs on spot market in KSE can be explored in futures research studies. Such an analysis is important because if SSFs do not destabilize the market; then the unnecessary stringent regulations do no good, instead they limit efficiency of the market.

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