Stable, Unstable and Adaptive Stock Markets: A Tale of Market References

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Abstract

Purpose of the Study: The present study explores if the linear CAPM vis-à-vis its autoregressive distributed lag (ARDL) augmentation model stands up to expectations at the stable, unstable and adaptive references of the NSE stock market in India.
Study design/methodology/approach: With a sample of the NSE Nifty stocks in India during April 3, 2000 and January 14, 2019, methodologically, this study firstly considers if the CAPM and its ARDL augmentation can explain stocks' returns at the full-length data, and then, it considers the same at the market references of the pre-2008-09 financial crisis (stable market), during the financial crisis (unstable market) and the post-financial crisis (adaptive market).
Findings: With the data of nine stocks from the Nifty, this study shows that the linear CAPM has little explanatory powers at the both cases of use of the full-length data and the different market references while the ARDL augmentation of the same has better explanatory powers in all the cases.
Implications of the study: The mutual fund managers can identify effects of investors' reference-dependence of market situations along with the overall market impacts. This study shows the extents of such reference dependencies with the data of Nifty stocks.
Originality/value: With the ARDL model, the static CAPM view is calibrated with the dynamic reference-dependence perspectives along with their behavioral applicative values.

Keywords: *Efficient Market Hypothesis; Fractal Market Hypothesis; Chaos Theory; Behavioral Economics; Adaptive Market Hypothesis.*

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Introduction: In the financial markets, investors always have many stories to tell about their success, failure, passion, greed, fear etc. Such stories also include learnings from their live-experiences and interactions with others as well (Hong, Kubik, & Stein, 2004). These tales are very often behaviorally biased (Bondia, Biswal, & Panda, 2019). Asks and Them (2014) have explained the same tales for their two-states' proposition at stable and unstable stock markets respectively with the efficient market hypothesis (EMH) and fractal market hypothesis (FMH), and they have opined that the stock market transits over the stable and unstable states. In essence, the adjective "stable" has a timestamp perspective of data used (Caporale, Gil-Alana, & Plastun, 2018). With the US S&P 500 Composite Stock Index data since 1948, Renshaw (1995) finds a stable stock market for the mid-90s. The stocks' returns do not show stable relationships with the macroeconomic variables rather the relationships are at reversals across the stocks and the time-periods as well (Panetta, 2002). With data from the same market for 1960-2014, Asks and Them (2014) find a sequence of stable periods followed by unstable periods and vice-versa.

With the different perspectives of human evolution in their economic interactions, the adaptive market hypothesis (AMH) in Lo (2004, 2005) provides a reconciliatory view between the standard finance and behavioral finance propositions about market efficiency. Lo (2004, 2005) argues that the stock market's information efficiency is conditioned by the environment and economic ecology. With the INR-USD exchange rates data, Khuntia and Pattanayak (2019) comment that the exchange market has time-varying adaptation at changes in the environments viz., the regimes of exchange rates, financial turbulence, interventions by the countries' central banks and trade volume, and therefore, the proposition of market efficiency is a time-varying phenomenon. Very recently, the AMH is found valid for the Tunisian stock market (Obalade & Muzindutsi, 2020), Turkish stock market (Kılıç, 2020), Vietnamese stock market (Trung & Quang, 2019), and Moroccan stock market (Lekhal & Oubani, 2020).

Is the AMH valid for the Indian stock markets? This query becomes relevant in financial economics in the presence of cointegrations amongst the emerging stock markets. It is also appearing as a research trend in the contemporary empirical literature (Hiremath & Narayan, 2016; Hiremath & Kumari, 2014; Kumar & Nandamohan, 2018). Akhter and Yong (2019) have explored the same in the context of the Dhaka Stock Exchange in Bangladesh. Over the different time-lines, these studies have found positive but restrictive supports for their propositions on the AMH in the emerging cases of stock-markets in India or Bangladesh. To identify the time-varying property of market efficiency, these studies either have used the measure of generalized Hurst exponent (GHE) or have explored the degree of the randomness – if there is uniformity or trend over the data periods.

In exploring the afore-mentioned research query, this study applies a direct methodology and it explores if the National Stock Exchange (NSE) in India has the odds of the AMH. This study contrasts with the above-mentioned studies as well. It has the tale of empirical exploration of nine stocks over three different states of the economic environment – before the 2008 financial crisis, during the crisis and after the crisis. It covers the anonymous investors' journey over the three states of the NSE stock market - stable, unstable and adaptive. It also extends the two-states' proposition in Asks and Them (2014) for the stable and unstable stock markets. The flow of this study is maintained as below.

The study briefly reviews the literature of EMH, FMH and AMH in Section-2. It lays out the empirical data and methodology in Section-3 and demonstrates the results and findings briefly in Section-4. It concludes and identifies further research needs in Section-5.

Literature Review: In financial economics, the prices of financial assets have become the central focus for discussion theoretically, experimentally and empirically. What do the prices proxy for – the streams of information, changes in environment, dynamics of efficiency, adaptation to the market's ecology or a combination of all these? On this query, the exact literatures have been divided under three types of hypotheses - the efficient market hypothesis, fractal market hypothesis and adaptive market hypothesis.

The efficient market hypothesis (EMH) is dated long back to the studies of Fama (1965, 1970). It argues that the "security prices fully reflect all available information" (Fama, 1991; p.1575). At its core, the EMH proposes that the markets are hard to beat with new information. On critics against the persistency issue of the EMH, Malkiel (2003) finds a few consolatory notes "…with the passage of time and with the increasing sophistication of our databases and empirical techniques, we will document further apparent departures from efficiency and further patterns in the development of stock returns" while in Malkiel (2005), the influence of the EMH has remained persistent. In critics of standard finance, Statman (2018) argues that the EMH is unfocused in distinguishing between the *price equals value* hypothesis and *hard to beat market* hypothesis. He suggests that the stock markets are behaviourally efficient, where a stock's price does not equal its intrinsic value but it is hard to beat without "…exclusive or narrowly available information" (Statman, 2018; p. 85).

In contrast, the fractal market hypothesis (FMH) of Peters (1991) is much younger than the EMH. It argues that the stocks' prices in the capital markets are fractal in dimensions and these follow a biased random walk. Their fractal time series are leptokurtic in distribution, and these characterize a long-memory process and show the presence of deterministic chaos (Peters, 1991). The first empirical support for the FMH can be found in Corazza, Malliaris, and Nardelli (1997). They have showed that the returns of agricultural futures follow a fractal process that involves statistical self-similarity, fractal structure and long-term dependency. The FMH also assumes varying information impacts for different investment horizons while market stability depends largely on the demand and supply in matching the markets' liquidity (Weron & Weron, 2000). The said time-varying demand-supply in the FMH is originated at the agents' heterogeneous long/short investment horizons and in essence, the same bring in liquidity in the stock markets (Vácha & Vosvrda, 2005). Hence, the fractal market dynamics depict stability that depends on the nature of market liquidity over the different time-horizons (Van Quang, 2005).

Since the global financial crisis in 2008, the FMH has received huge academic interests in the studies conducted by Blackledge (2008, 2010), Onali and Goddard (2009), Bohdalová and Greguš (2010), Mulligan (2010), Günay(2014), Caporale, Gil-Alana, Plastun, and Makarenko (2016), and Dar, Bhanja, and Tiwari (2017) and many more. More or less, all of them have opined that the FMH has good predictive powers in explaining the stock indices of various stock markets taken for the study, and their comments are equally applicable to the forex markets also.

The duality of efficiency and inefficiency in the EMH and FMH on assets' pricing over investment-horizons is generalized in the AMH. The assumptions in the AMH in Lo (2004) fill the missing links in Simon's (1955) satisficing theory and places the AMH as an alternative to the EMH as well (Lo, 2005). Individuals are motivated by self-interests but they commit mistakes, learn from past experiences and adapt to the market ecology. Their self-satisficing behaviors compel on to the competition and motivate them for innovations while natural selection reshapes the market ecology and evolution fixes the market dynamics. Besides the presence of human greed and fear, human emotion performs critical roles in the above-stated framework of the AMH in Lo (2005). The global financial crisis in 2008 has led the contemporary academics' world in putting their focuses on the empirical explorations of the AMH (Todea & Lazar, 2012; Urquhart & McGroarty, 2016; Tripathi, Vipul, & Dixit, 2020).

With the set of six Asia-Pacific stock markets data from 1997 to 2008 in Australia, Hong Kong, India, Malaysia, Singapore and Japan, Todea, Ulici,

& Silaghi (2009) have depicted that the performance of a trading strategy (viz., moving average) is non-linear and it has cyclical episodes over time. Khuntia and Pattanayak (2016) have also found supports for the AMH with the Indian stock and forex market data for 1997-2015. On the factor-driven causal dynamics, Mahdavi and Namazi (2017) find supports for the AMH for the Tehran Stock Exchange during 2005-2015. Rojas, Coronado, and Venegas-Martínez (2017) have documented that the Mexican stock exchange index data behave episodically where its periods of random walk are followed by the periods of non-linear adaptability. Nonetheless, using different sub-samples with the Nigerian stock markets during 1987-2016, Ndubuisi and Okere (2018) have discovered that the sub-samples depict nonlinear dependence and they exhibit time-varying inefficiency.

The AMH has reference dependence to both the macroeconomic market conditions and microeconomic firm-specifications (Lo, 2012). The markets also show multi-fractal dynamic properties (Patil & Rastogi, 2020). How do the prices of individual stocks in the Indian stock markets adapt to their episodic journey over the periods of stable, unstable and adaptive market dynamics? In examining this query, the present study has the following theoretical proposition and it explores the same empirically.

P_0*: *The stocks' returns in the NSE of India show dynamic cointegration for short-run and long-run effects and these depict their episodic journey over the periods of stable, unstable and adaptive market dynamics.

Research design & Methodology: The study uses the daily prices of only those nine stocks which stand included in the NSE Nifty in India in January 2019 and also have been persistently remained listed in the NSE Nifty for mostly about twenty years' time period from April 3, 2000 to January 14, 2019. Besides using the data for the aforesaid period, the data have been grouped over three different sub-periods – a stable period, unstable period and adaptive period. The sub-period from September 14, 2008 to July 6, 2009 in 2008-09 financial years is assumed to be the unstable period, and the sub-period in the full-length data period that it precedes viz., 02.04.2001 to 13.09.2008 (that it follows viz., 07.07.2009 to 14.01.2019) is assumed to be the stable (adaptive) time-period. A comparative analysis of their results over these three different states might show the firms' evolution dynamics.

The nine stocks are Tata Steel (TISC), Tata Motors (TAMO), State Bank of India (SBI), Reliance Industries Ltd (RIL), ITC Ltd (ITC), ICICI Bank (ICBK), Housing Development Finance Corporation (HDFC), HDFC Bank (HDBK) and Grasim India (GRAS). To proxy for the risk-free rate of return

(R_f), the study uses the ten years' Government bonds' yield data. It is used as the reference rate of return for investors in the stock markets. The concerned secondary data are collected from the website of www.investing.com and these are processed in Microsoft Excel. In deriving their return data; the study has used daily percentage change in the closing value of the stocks' price or market index. It has followed the same method to derive the rate of return for the stocks and NSE Nifty as well.

Since stocks' prices have macroeconomic and microeconomic impacts and multi-fractal dynamic properties, the study proposes that individual stock's returns (R_i) include these dynamics at their statistical distributions. These dynamics can be traced with the explanatory variables (X_i) – individual stock's systematic risk (B_t) and the reference risk-free rate of return (R_f). That is, R_i has the cointegration effects of B_t and R_f. It hypothesizes that the multi-fractal properties of stocks' return involve short-run and long-run dynamics. The study uses the capital asset pricing model (CAPM) in *Eq*-1 in its derived version for a stock's dynamic security market line (DSML), its unrestricted specification in the Auto-regressive Distributed Lagged (ARDL) framework is given in *Eq*-2. To be specific to the stated objectives, it makes a restrictive use of the respective conditional long-run form (LRF) and conditional error correction form (ECF) as given in *Eq*-3 and *Eq*-4. The study uses the data with the said models in EViews 10 statistical system and so, it proceeds for the linear as well as ARDL explorations of *Eq*-1 and *Eq*-2 as well. Future researchers may explore both conditional models in detail and they may generalize thereof.

$$R_{it} = \alpha_0 + \alpha_{1r}R_{ft} + \beta_{is}B_{it} + \dot{r}_t \dots\dots\dots\dots (Eq - 1)$$

$$R_{it} = \alpha_0 + [\sum_{r=1}^{r}\sum_{t=1}^{n}\alpha_{1r}R_{it-r} + \sum_{s=1}^{s}\sum_{i=1}^{R}\sum_{t=1}^{n}\beta_{is}X_{it-s} + \sum_{i=1}^{R}\sum_{t=1}^{n}\beta_i X_{it}] + \varepsilon_t \dots\dots\dots\dots (Eq - 2)$$

$$\Delta \mathrm{R}_{it} = \alpha_0 + [\sum_{r=1}^{r}\sum_{t=1}^{n}\alpha_{jr}\Delta \mathrm{R}_{it-r} + \sum_{s=1}^{s}\sum_{i=1}^{R}\sum_{t=1}^{n}\beta_{is}\Delta X_{it-s} + \sum_{r=1}^{r}\sum_{t=1}^{n}\alpha_{kr}R_{it-r} + \sum_{s=0}^{s}\sum_{i=1}^{R}\sum_{t=1}^{n}\beta_{iq}X_{it-s}] + \xi_t \dots\dots\dots (Eq - 3)$$

$$\Delta \mathrm{R}_{it} = \alpha_0 + [\sum_{r=1}^{r}\sum_{t=1}^{n}\alpha_{jr}\Delta \mathrm{R}_{it-r} + \sum_{s=1}^{s}\sum_{i=1}^{R}\sum_{t=1}^{n}\beta_{is}\Delta X_{it-s} + \eta Z_{t-1}] + \varphi_t \dots\dots\dots\dots (Eq - 4)$$

In the ARDL specifications in *Eq-1*, *Eq-2*, and *Eq-3,* a_0 represents the intercept and ε_t, ξ_t, and φ_t are the residual error terms. The regressand ΔR_{it} in *Eq-2* and *Eq-3* is the 1st difference of the regressand R_{it} in *Eq-1*. The study has used R_{it} as the general notation and regress the sample stocks' returns data separately. The regressor ΔX_{it} denotes the 1st difference of the regressor X_{it}, and X_{it} is the *i*-th data of the variables of R_f, and B_t in the array of investors' dynamic references *R*. Since it applies the ARDL cointegration model set up finally, the dynamic reference array has the arrays of values for the variables of X_{it} and ΔX_{it} along with their lags as well, i.e., *R*. In *Eq-1*, the regressors within the bracket are the endogenous variable at *r* lags, independent variables at *s* lags, and the independent regressors at the current time *t* as well. In *Eq*-2, the regressors within the bracket include the endogenous 1st difference variable at *r* lags, the 1st difference of independent attention variables at *s* lags, endogenous variables at *r* lags, and the level data of independent variables at lags of $s \geq 0$ as well. In *Eq-2*, the 1st difference variables represent short-run effects while the rest two show long-run effects. In *Eq-3,* the 1st difference variables show short-run effects and the third one, Z_{t-1} is the co-integrating equation factor at its 1st lag. The regression system derives the data array of Z_{t-1} as the error correction (EC) factor at the levels' specification of the data towards regressing R_{it}.

Even if the sample data for the relevant variables are of I(0) stationary in nature, the study does not apply the Johansen Cointegration test and Granger causality test to explore the nature of cointegration amongst the variables since none of these models directly include both the short-run and long-run dynamics within the regression system framework. Rather, in examining their short-run and long-run dynamics, it firstly employs the unrestricted short-run forms (SRFs) of the ARDL models for the sample stocks' data at the different episodic sub-periods separately, then in perusing robustness checks, it uses their respective conditional long-run forms (LRFs) for the F-bound-tests (Pesaran, Shin, & Smith, 2001), and thereafter, it uses the conditional error correction forms (ECFs) of the ARDL model to get the error correction terms (ECTs) i.e., the long-run adjustment multipliers. The study reports those results along with the SRFs of the ARDL models. Besides, it shows the results with the *Eq*-1 and reports them briefly.

<u>*Lag selection*</u>: Even if an Augmented Dicky Fuller (ADF) test for the unit root of the variables shows the I(0) stationarity of the data both at the level and 1st difference with or without trend effects, in examining the cointegration dynamics, the study uses to identify the appropriate lag lengths (*r*,*s*) for the variables in the regression models. At *Var Estimation* with the endogenous the stock's return variable and the six independent regressor variables, it finds that the methods of "LR", "FPE", "AIC", "SC" and "HQ" suggest for use

of different lags for the different sub-sample study periods. However, the AIC (SC) method is biased towards over (under)-identification of the appropriate lag-lengths. It has followed the AIC method if its lag-length is less than 12 and otherwise the SC method. For the explanatory variables, in EViews10 system, it selects a lag of 1 and chooses the automatic lag selection method for the variables if the same increases the explanatory power in the regression model/s.

Empirical hypothesis of the study: With the individual stock's returns in the NSE market in India for the aforementioned four data sets at the full-length period, stable sub-period, unstable sub-period and adaptive sub-period, it puts forward the following null hypotheses of H_{01}, H_{02}, H_{03} and H_{04} against their respective alternative hypotheses of H_{11}, H_{12}, H_{13} and H_{14} for the regression models in *Eq*-1, *Eq*-2, *Eq*-3, and *Eq*-4.

***H_{01}*:** In the dynamic security market line (DSML), stocks' return (R_{it}) has no effect of the stocks' alpha component (α), systematic risk (B_t) and the risk-free rate of return (R_f).

***H_{11}*:** In the dynamic security market line (DSML), stocks' return (R_{it}) has significant effects of the stocks' alpha component (α), systematic risk (B_t) and the risk-free rate of return (R_f).

***H_{02}*:** In the unrestricted ARDL augmented CAPM model, the stocks' return (R_{it}) has no effect of the stocks' endogenous lag-returns (R_{it-r}), systematic risk (B_t) and the risk-free rate of return (R_f).

***H_{12}*:** In the unrestricted ARDL augmented CAPM model, the stocks' return (R_{it}) has the short-run and long-run dynamics with the stocks' endogenous lag-returns (R_{it-r}), systematic risk (B_t) and the risk-free rate of return (R_f).

***H_{03}*:** In the conditional long-run forms of the ARDL augmented CAPM models, the stocks' return (R_{it}) has an insignificant cointegrating relationship in terms of F-bound test statistics with the stocks' endogenous lag-returns (R_{it-r}), systematic risk (B_t) and the risk-free rate of return (R_f).

***H_{13}*:** In the conditional long-run forms of the ARDL augmented CAPM models, stocks' return (R_{it}) has a significant cointegrating relationship in terms of F-bound test statistics with the stocks' endogenous lag-returns (R_{it-r}), systematic risk (B_t) and the risk-free rate of return (R_f).

***H_{04}*:** In the error correction forms of the ARDL augmented CAPM models, the stocks' return (R_{it}) has insignificant long-run cointegration multiplier effects for the stocks' systematic risk (B_t) and the risk-free rate of return (R_f).

***H_{14}*:** In the error correction forms (ECFs) of the ARDL augmented CAPM models, the stocks' return (R_{it}) has significant long-run cointegration multiplier effects for the stocks' systematic risk (B_t) and risk-free rate of return (R_f).

Robustness Check: At observation of supportive results for the above four research hypotheses H_{11}, H_{12}, H_{13} and H_{14}, the study performs robustness tests for comparative analysis. It examines if the results over the different states show the sample firms' evolution at the market references. In doing so, the study performs comparisons of coefficients for their intercepts, systematic risk (B_t) and risk-free rate of return (R_f) in the DSML models and unrestricted ARDL models as well. Here, in finding out the t-statistics values for the differences between the two intercepts (or two slopes of the said variables) in these models, the study follows the statistical equation (Eq-5) in determining the relevant t-statistics values for the difference in the respective coefficients. The readers can find the same in the statistical calculator at https://www.danielsoper.com/statcalc/formulas.aspx?id=103. For further critical analysis of its statistical procedure and limitations as well, interested readers may follow Andrade and Estévez-Pérez (2014).

$$t = \frac{b_1 - b_2}{\sqrt{s_{b_1}^2 + s_b^2 2}} \ldots\ldots\ldots.(Eq-5), df = n_1 + n_2 - 4$$

In the above t-test statistics, b_1 and b_2 are two coefficients of similar nature either of the intercept coefficients or slope coefficients. $S^2 b_1$ and $S^2 b_2$ are the standard errors of the measures for b_1 and b_2, n_1 and n_2 are their respective sample sizes, and *df* is the degree of freedom of the *t*-test statistic. Since the study has the datasets of large sample sizes (viz., N_S = 2722, N_U = 296, N_A = 3480 and N_F = 6497 where $_S$ refers to stable data sets, $_U$ to unstable data sets, $_A$ to adaptive data sets and $_F$ for full-length data sets) in the empirical investigation, the t-test statistic is assumed to follow the normal distribution. In exploring the reference dependencies, the study has the following null hypothesis H_{05} against the relevant alternative research hypothesis H_{15}.

H_{05}: In the unrestricted ARDL augmented CAPM models vis-à-vis the DSML models, there is no disparity in their relationship of stock's returns (R_{it}) for their intercept (C_0), the coefficient of systematic risk (B_t) and that of the risk-free rate of return (R_f) across the three different sub-periods and the full-length of the sample data as well.

H_{15}: In the unrestricted ARDL augmented CAPM models vis-à-vis the DSML models, there is a disparity in their relationship of stock's returns (R_{it}) for their intercept (C_0), the coefficient of systematic risk (B_t) and that of the risk-free rate of return (R_f) across the three different sub-periods and the full-length of the sample data as well.

Data analysis & Findings of the study: All available results of the study have been shown in tables 1 to 10. In the study, at first, for making the investigation critically, the general outlook with the full-length data has been presented, and then over the three period's namely stable, unstable and adaptive data-set periods, pin-point analyses have been made.

Table1: Stocks' Returns with the Modified CAPM in the SML Setup for the Full-Length Data Sets

Regression Model	$R_{it} = \alpha_0 + \alpha_{1r}R_{ft} + \beta_{is}B_{it} + \dot{r}_t$								
Variables	GRAS	HDBK	HDFC	ICBK	ITC	RIL	SBI	TAMO	TISC
R_f	-**0.095965** (0.031642) (0.0024)	-**0.251497** (0.029427) (0.001)	-**0.228742** (0.034733) (0.001)	-**0.337828** (0.041829) (0.001)	-**0.118006** (0.028605) (0.001)	-**0.267187** (0.033362) (0.001)	-**0.359071** (0.036082) (0.001)	-**0.240806** (0.112932) (0.033)	**-0.22458** (0.042403) (0.001)
β	0.000571 (0.000907) (0.5292)	0.000364 (0.000949) (0.7011)	-0.000094 (0.001068) (0.9301)	**0.001787** (0.000925) (0.0535)	0.000195 (0.000838) (0.8156)	0.000082 (0.000725) (0.9097)	0.000376 (0.000985) (0.7031)	**0.009929** (0.002487) (0.0001)	0.001456 (0.000954) (0.1268)
C	0.000634 (0.000439) (0.1487)	**0.001021** (0.000402) (0.0112)	**0.001096** (0.000452) (0.0153)	0.000495 (0.00051) (0.3321)	**0.000802** (0.000343) (0.0193)	**0.000909** (0.000409) (0.0265)	**0.000917** (0.000544) (0.0917)	-0.001303 (0.001357) (0.337)	0.000623 (0.000546) (0.2538)
R^2 (Aj. R^2)	0.0015 (0.0012)	0.0112 (0.011)	0.0066 (0.00633)	0.0107 (0.0104)	0.0026 (0.0023)	0.0098 (0.0095)	0.0151 (0.0148)	0.0032 (0.00292)	0.00474 (0.00443)
Reg. F-stat (Prob.)	**4.880** (0.008)	**36.67** (0.001)	**21.686** (0.001)	**35.002** (0.001)	**8.567** (0.001)	**32.158** (0.001)	**49.794** (0.001)	**10.513** (0.001)	**15.453** (0.001)
Durbin Watson	**1.321**	**1.397**	**1.305**	**1.177**	**1.392**	**1.258**	**1.277**	**1.984**	**1.290**
HTBPG F-stat (Prob.)	0.761 (0.467)	**6.369** (0.002)	**11.15** (0.001)	0.8035 (0.45)	**6.772** (0.001)	**3.994** (0.019)	**7.804** (0.001)	**22.989** (0.001)	**13.852** (0.001)
BGSCLM F-stat (Prob.)	**843.00** (0.001)	**645.00** (0.001)	**887.00** (0.001)	**1318** (0.001)	**648** (0.001)	**1032** (0.001)	**972** (0.001)	0.393 (0.531)	**931** (0.001)
JB Norm (Prob.)	**8139** (0.001)	**33515** (0.001)	**10037** (0.001)	**8738** (0.001)	**3789** (0.001)	**13247** (0.001)	**12705** (0.001)	**55717** (0.001)	**2759** (0.01)

General Outlook: With the full-length data, in Table 1, the study finds that the variable of stocks' risk-free rate (R_f) of return has negatively significant coefficients in the DSML setup across all the nine stocks while the variable of the systematic riskβ (the constant coefficient C) is positively significant only for two (five) stocks viz., *ICBK* and *TAMO* (*HDBK*, *HDFC*, *ITC*, *RIL*, and *SBI*). It finds β and C are significant for two stocks *GRAS* and *TISC*. Even if the regression models across the stocks have highly significant goodness of model fit in terms of F-statistic values, the models have fewer explanatory powers at their respective R^2 (Adj. R^2) values ranging from 0.0015 (0.0012) to 0.0151 (0.0148). Nonetheless, the Durbin-Watson WD statistics, mostly far lesser than the customary target value of 2, hints at the presence of non-normality of the regression residuals except TAMO. The Jerco-Bera (JB) normality test confirms the said non-normality across the stocks. At residual diagnosis of these models, the study also finds the presence of heteroskedasticity (serial correlation) in all stocks except two (one) stocks viz., *GRAS* and *ICBK*(TAMO). Hence, the study finds a lot of inconsistency with the DSML setup for the sample stocks where the models' coefficients are unbiased but inefficient ones.

Table2: Stocks' Returns with the Modified CAPM in the ARDL Model Setup for the Full-Length Data Sets

Regression Model	$R_{it} = \alpha_0 + [\sum_{r=1}^{r}\sum_{t=1}^{n}\alpha_{1r}R_{it-r} + \sum_{s=1}^{s}\sum_{i=1}^{A}\sum_{t=1}^{n}\beta_{is}X_{it-s} + \sum_{i=1}^{A}\sum_{t=1}^{n}\beta_i X_{it}] + \varepsilon_t \dots\dots\dots (ARDL-1)$								
Variables	GRAS (6,*1*)	HDBK (4,*1*)	HDFC *(10,1)*	ICBK (11,1)	ITC (*7,1*)	RIL (*4,1*)	SBI (*8,1*)	TAMO *(12,1)*	TISC (*6,1*)
R_t(-1)	**0.324731** (0.012341) (0.001)	**0.300506** (0.01233) (0.001)	**0.338029** (0.012431) (0.001)	**0.397630** (0.012439) (0.001)	**0.285692** (0.012411) (0.001)	**0.351105** (0.012296) (0.001)	**0.341770** (0.012364) (0.001)	**0.052642** (0.012318) (0.001)	**0.331738** (0.012395) (0.001)
R_t(-2)	**0.065347** (0.012987) (0.001)	**0.048278** (0.012751) (0.001)	**0.033398** (0.013069) (0.0106)	**0.059389** (0.013351) (0.001)	**0.084088** (0.012911) (0.001)	**0.093697** (0.012991) (0.001)	**0.069004** (0.013071) (0.001)	**0.204549** (0.012356) (0.001)	**0.103581** (0.013045) (0.001)
R_t(-3)	- **0.058777** (0.013008) (0.001)	- **0.038686** (0.012756) (0.001)	- **0.059681** (0.013079) (0.001)	- **0.051897** (0.01337) (0.001)	- **0.052284** (0.012948) (0.001)	**-0.077648** (0.0123) (0.001)	**-0.034296** (0.013103) (0.0089)	**-0.109697** (0.012568) (0.001)	**-0.046719** (0.013105) (0.001)
R_t(-4)	0.000219 (0.013008) (0.9866)	- **0.039539** (0.012247) (0.0013)	- **0.020638** (0.013079) (0.1146)	-0.018366 (0.013382) (0.17)	- **0.033889** (0.01295) (0.0089)		**-0.020083** (0.013112) (0.1257)	**0.097019** (0.012616) (0.001)	**-0.025380** (0.013057) (0.052)
R_t(-5)	**0.023598** (0.012978) (0.0691)		-0.003840 (0.013084) (0.7692)	0.008834 (0.013388) (0.5094)	0.011618 (0.012914) (0.3684)		0.019447 (0.013109) (0.138)	**0.141338** (0.012625) (0.001)	**0.024910** (0.012394) (0.0445)
R_t(-6)	**0.028544** (0.01233) (0.0207)		-0.000542 (0.013085) (0.967)	0.013014 (0.013388) (0.331)	**0.022330** (0.012416) (0.0721)		-0.000786 (0.013107) (0.9522)	**0.117404** (0.012644) (0.001)	
R_t(-7)			- **0.058240** (0.013087) (0.001)	0.002968 (0.013387) (0.8246)			-0.019708 (0.013077) (0.1319)	**-0.145935** (0.012644) (0.001)	
R_t(-8)			-0.006723 (0.01308) (0.6073)	- **0.023627** (0.013382) (0.0775)			**-0.020755** (0.01235) (0.0929)	**0.102190** (0.012613) (0.001)	
R_t(-9)			- **0.028341** (0.013082) (0.0303)	- **0.029629** (0.013376) (0.0268)				**-0.058873** (0.012621) (0.001)	
R_t(-10)			- **0.029239** (0.012404) (0.0184)	-0.005650 (0.013359) (0.6724)				**-0.038707** (0.01257) (0.0021)	

$R_t(-11)$				**0.029333** (0.012401) (0.018)				**0.077409** (0.012303) (0.001)	
$R_t(-12)$								**-0.119035** (0.01232) (0.001)	
R_f	- **0.086236** (0.029478) (0.0035)	- **0.230600** (0.029558) (0.001)	- **0.218777** (0.034474) (0.001)	- **0.297989** (0.040467) (0.001)	- **0.094515** (0.02718) (0.001)	**-0.221680** (0.030795) (0.001)	**-0.296683** (0.033623) (0.001)	**-0.253152** (0.103698) (0.0147)	**-0.176784** (0.039444) (0.001)
$R_f(-1)$		**0.062104** (0.029704) (0.0366)	**0.058111** (0.034606) (0.0932)	0.059016 (0.040665) (0.1467)					
β	- **0.244787** (0.027894) (0.001)	- **0.302029** (0.027704) (0.001)	- **0.109218** (0.028613) (0.001)	0.001048 (0.000844) (0.2147)	- **0.072417** (0.028937) (0.0124)	**-0.184813** (0.028045) (0.001)	**-0.106262** (0.030015) (0.001)	**0.312085** (0.062539) (0.001)	**-0.155887** (0.031149) (0.001)
B (-1)	**0.245093** (0.027891) (0.001)	**0.302373** (0.0277) (0.001)	**0.109218** (0.028612) (0.001)		**0.072506** (0.028932) (0.0122)	**0.184860** (0.028043) (0.001)	**0.106502** (0.030011) (0.001)	**-0.305871** (0.062521) (0.001)	**0.156729** (0.031142) (0.001)
C	0.000373 (0.000409) (0.3618)	**0.000702** (0.00038) (0.0647)	**0.000889** (0.000423) (0.0353)	0.000326 (0.000464) (0.4824)	**0.000555** (0.000326) (0.0887)	0.000568 (0.000377) (0.1326)	0.000610 (0.000506) (0.2272)	-0.000629 (0.001247) (0.6142)	0.000387 (0.000507) (0.4457)
R^2 (Aj. R^2)	0.1325 (0.1313)	0.121 (0.121)	0.13856 (0.1367)	0.1847 (0.1829)	0.1026 (0.1013)	0.1609 (0.1602)	0.1515 (0.15011)	0.1637 (0.1618)	0.1431 (0.1421)
Reg. F-stat (Prob.)	**109.00** (0.001)	**112.00** (0.001)	**74.356** (0.001)	**104.71** (0.001)	**82.299** (0.001)	**207.40**(0.001)	**105.17** (0.001)	**84.43** (0.001)	**135.00**(0.001)
Durbin Watson Stat	**2.001**	**1.985**	**1.98**	**1.999**	**1.9987**	**1.993**	**1.994**	**1.999**	**1.995**
HTBPG F-stat (Prob.)	**2.023** (0.033)	**41.23** (0.001)	**5.568** (0.001)	**6.39** (0.001)	**3.0497** (0.001)	**3.325** (0.003)	**3.001** (0.001)	**13.98** (0.001)	**9.325** (0.001)
BGSCLM F-stat (Prob.)	**16.124** (0.001)	**14.77** (0.001)	**3.752** (0.053)	**4.1397** (0.042)	0.710 (0.399)	**2.481** (0.115)	**2.565** (0.109)	0.008 (0.93)	1.7804 (0.182)
JB Norm (Prob.)	**7121** (0.001)	**37778** (0.001)	**9.0158** (0.001)	**10874** (0.001)	**5136** (0.001)	**12341** (0.001)	**18850** (0.001)	**55645** (0.001)	**3664** (0.001)
F-Bound F-Stat	**210** (0.01)	**377** (0.01)	**208.08** (0.01)	**144.14** (0.01)	**233** (0.01)	**427** (0.01)	**215** (0.01)	**131** (0.01)	**258.00** (0.01)
ECT	- **0.616338** (0.001)	**-0.72944** (0.001)	- **0.835817** (0.001)	- **0.618001** (0.001)	- **0.682445** (0.001)	**-0.632846** (0.001)	**-0.665406** (0.001)	**-0.679697** (0.001)	**-0.61187** (0.001)

In Table 2 with the ARDL augmented modified CAPM, the study shows that the endogenous stocks' return has significant impacts at the different lag lengths and these suggest a presence of stock-specific long-memory effects. The risk-free rate of return (R_f) is negatively significant across the stocks and the magnitudes of its coefficient range within -0.086236 and -0.297989. These observations are confirmatory to the earlier stated observations in the DSML setup. Nonetheless, it finds some positively significant lag effects of R_f for two stocks viz., *HDBK* and *HDFC,* and these show dynamic effects of R_f from their respective previous years. Besides the above, with the systematic risk variable β the table shows negatively (positively) significant coefficients for all stocks (*TAMO*) except the ICBK, where it shows an insignificant coefficient for β. Nonetheless, the respective coefficients of β at its first lag show significant coefficients but these are all in opposite signs to those as obser

ved significant for β. These observations are somewhat new and innovative towards the limited observations in the DSML model. These demonstrate the long-memory dynamics of systematic risk included in stocks' returns. Furthermore, the study can locate positively significant magnitudes for the intercept in the ARDL model setup for three stocks viz., *HDBK*, *HDFC*, and *ITC*. These confirm the presence of arbitrage opportunity for investors in these stocks in the NSE stock market.

The above results are unbiased with the good fit of the model at significant F-statistics across the stocks along with explanatory powers ranging 0.1026 (0.1013) and 0.1847 (0.1829) in terms of R^2 (Adj. R^2). The statistics for the WD statistics are mostly equal to the customary target value of 2 and these show absence of severe non-normality of the regression residuals. However, the robustness tests for the residual non-normality with the JB test statistics confirm residual non-normality. The paper finds a significant presence of heteroscedasticity with the nine sample stocks but significant residual serial correlation only with *GRAS* and *HDBK* (*HDFC* and *ICBK*) at 0.1% (6%) level of significance. That is, the residual non-normality is not caused by the presence of residual serial correlations of the ARDL model. The presence of heteroscedasticity, that is, the other explanatory variables might cause the residual non-normality problem. Nonetheless, the significant values for the F-bound test statistics in the table across the nine stocks confirm the cointegrating relationship of their risk-free return, systematic risk, and endogenous returns. Besides the above, the coefficient of the long-run cointegration multiplier in the ARDL model (i.e., ECT) shows that across the nine stocks, there is a strong presence of negatively significant coefficients (ranging from -0.61187 to -0.835817) suggesting for the presence of higher long-run speed of adjustments in their return dynamics.

In brief, the above general outlook in the study suggests for greater explanatory power in terms of the coefficient estimates of the ARDL model than those of the DSML model and the methodological superiority of the ARDL model in terms of capturing their long-run vis-à-vis short-run dynamics.

Table3: Stocks' returns with the CAPM in the SML setup for the Stable Data Sets

Regression	$R_{it} = \alpha_0 + \alpha_{1r}R_{ft} + \beta_{is}B_{it} + \dot{r}_t$								
Variables	GRAS	HDBK	HDFC	ICBK	ITC	RIL	SBI	TAMO	TISC
R_f	**-0.176464** (0.057889) (0.0023)	**-0.234204** (0.057614) (0.001)	**-0.254393** (0.062172) (0.001)	**-0.355879** (0.071909) (0.001)	**-0.127758** (0.053686) (0.0174)	**-0.327476** (0.05802) (0.001)	**-0.368895** (0.060479) (0.001)	**-0.271129** (0.277073) (0.3279)	**-0.21654** (0.07013 5) (0.002)
β	0.000009 (0.00123) (0.994)	-0.001595 (0.001655) (0.3351)	-0.002003 (0.001705) (0.2402)	0.000955 (0.001204) (0.4279)	0.000717 (0.001185) (0.5455)	-0.001227 (0.000887) (0.1666)	-0.000823 (0.001191) (0.4894)	**0.012111** (0.004329) (0.0052)	-0.00072 (0.00107 3)
C	**0.001387** (0.000697) (0.0466)	**0.001594** (0.000701) (0.023)	**0.001852** (0.000689) (0.0073)	0.001011 (0.000774) (0.1915)	0.000738 (0.000556) (0.1845)	**0.001973** (0.000629) (0.0017)	**0.001804** (0.000712) (0.0113)	-0.000070 (0.002823) (0.9804)	**0.00275 9** (0.00075
R^2 (Aj. R^2)	0.003435 (0.0027)	0.0062 (0.00543)	0.0064 (0.00565)	0.0095 (0.00874)	0.0023 (0.0016)	0.01184 (0.0111)	0.0135 (0.0128)	0.00345 (0.0027)	0.00355 (0.0028)
Reg. F-stat (Prob.)	**4.686** (0.0093)	**8.423** (0.001)	**8.730** (0.001)	**12.997** (0.001)	**3.162** (0.043)	**16.29** (0.001)	**18.60** (0.001)	**4.735** (0.0091)	**4.84** (0.008)
DW Stat.	**1.32**	**1.47**	**1.362**	**1.169**	**1.364**	**1.301**	**1.32**	**2.0562**	**1.3003**
HTBPG F-stat. (Prob.)	2.080 (0.125)	**7.230** (0.001)	**18.99** (0.001)	**5.71** (0.001)	**9.462** (0.001)	**4.268** (0.014)	**9.712** (0.001)	**12.088** (0.001)	**4.628** (0.0098)
BGSCLM F-stat. (Prob.)	**352.8** (0.001)	**205.08** (0.001)	**306.56** (0.001)	**556.02** (0.001)	**306.33** (0.001)	**377.92** (0.001)	**358.07** (0.001)	2.165 (0.1413)	**377.08** (0.001)
JB Norm (Prob.)	**7.410** (0.001)	**13313** (0.001)	**933.80** (0.001)	**874.87** (0.001)	**1155** (0.001)	**2231.8** (0.001)	**1397** (0.001)	**57274** (0.001)	**301.02** (0.001)

***Stable Outlook*:** In Table 3, the study shows the results of the DSML model for the stable data period. It shows that the coefficients of the risk-free rate of return R_f are significant across the sample stocks at an α level of significance of 0.001 except that for TAMO at α of 0.3279 while, it is interesting to find that, the coefficient of systematic risk β is significant only for TAMO at an α of 0.0052. It shows positive coefficients for the constant intercept in the DSML model and these are strongly significant for the sample stocks viz., HDFC, RIL, SBI, and TISC at α of 0.01, GRAS, and HDBK at α of 0.05 while those for ICBK, ITC, and TAMO are insignificant. As observed in the general outlook, the stable data-set also shows the goodness of the DSML model fit with the magnitudes of the model's F-statistics but with a low degree of explanatory power ranging between 0.0023 (0.0016) and 0.0135 (0.0128) in terms of R^2 (Adj. R^2) of the respective models. Besides, there is the presence of the models' residual non-normality, heteroskedasticity, and serial-autocorrelation problems. Therefore, even with the stable data sets of the stocks, it finds inconsistent findings for the efficiency of the DSML model even if the estimates are unbiased. Hence, the cause behind the inefficiency of the DSML model is not rooted in the presence of mixed data – stable, unstable, and adaptive data sets – in the full-length data-sets. As envisaged in the latter, the DSML model itself is not an efficient one and this causes inefficiency in terms of explanatory powers.

Table 4: Stocks' Returns with the Modified CAPM in the ARDL Model Setup for the Stable Data Sets

Regression Model	$R_{it} = \alpha_0 + [\sum_{r=1}^{r}\sum_{t=1}^{n}\alpha_{1r}R_{it-r} + \sum_{s=1}^{s}\sum_{i=1}^{A}\sum_{t=1}^{n}\beta_{is}X_{it-s} + \sum_{i=1}^{A}\sum_{t=1}^{n}\beta_i X_{it}] + \varepsilon_t \ldots\ldots\ldots (ARDL-1)$								
Variables	GRAS (6,1)	HDBK (5,1)	HDFC (8,1)	ICBK (8,1)	ITC (7,1)	RIL (4,1)	SBI (8,1)	TAMO (13,1)	TISC (4,1)
R_t (-1)	**0.334001** (0.01882) (0.001)	**0.272768** (0.018831) (0.001)	**0.308649** (0.018983) (0.001)	**0.401460** (0.019141) (0.001)	**0.305455** (0.019116) (0.001)	**0.326097** (0.018852) (0.001)	**0.323785** (0.019037) (0.001)	0.021138 (0.019032) (0.267)	**0.336119** (0.018984) (0.001)
R_t (-2)	**0.040261** (0.01987) (0.0428)	**0.065483** (0.0193) (0.001)	**0.040915** (0.019879) (0.0397)	**0.071639** (0.020639) (0.001)	**0.078384** (0.019974) (0.001)	**0.112622** (0.019768) (0.001)	**0.072342** (0.020067) (0.001)	**0.193068** (0.01913) (0.001)	**0.089147** (0.019972) (0.001)
R_t (-3)	**-0.077083** (0.01983) (0.001)	**-0.045586** (0.019301) (0.0183)	**-0.068264** (0.019909) (0.001)	**-0.055770** (0.020676) (0.007)	**-0.055300** (0.02) (0.006)	**-0.082989** (0.018859) (0.001)	-0.026531 (0.020102) (0.187)	**-0.106003** (0.019363) (0.001)	**-0.090156** (0.018954) (0.001)
R_t (-4)	0.018604 (0.01985) (0.3487)	**-0.046546** (0.018727) (0.013)	-0.007000 (0.01995) (0.726)	**-0.045229** (0.020685) (0.0289)	**-0.031955** (0.019996) (0.1101)		-0.005148 (0.020085) (0.798)	**0.114021** (0.019415) (0.001)	
R_t (-5)	***0.032398*** (0.01877) (0.0845)		-0.004703 (0.019891) (0.813)	0.027316 (0.020675) (0.1865)	0.024151 (0.019962) (0.2264)		0.022536 (0.020082) (0.262)	**0.166210** (0.019496) (0.001)	
R_t (-6)			-0.007507 (0.0199) (0.706)	0.030557 (0.02067) (0.1394)	**0.064313** (0.019111) (0.001)		0.005403 (0.020053) (0.788)	**0.134226** (0.019674) (0.001)	
R_t (-7)			**-0.074722** (0.019015) (0.001)	**-0.042418** (0.01917) (0.027)			**-0.052202** (0.019025) (0.006)	**-0.140048** (0.019634) (0.001)	

R_t (-8)								**0.100796** (0.019448) (0.001)	
R_t (-9)								**-0.066963** (0.019426) (0.001)	
R_t (-10)								**-0.053872** (0.01938) (0.006)	
R_t (-11)								**0.070775** (0.018999) (0.001)	
R_t (-12)								**-0.129849** (0.019031) (0.001)	
R_f	**-0.156812** (0.053228) (0.0032)	**-0.207246** (0.054285) (0.001)	**-0.207211** (0.058278) (0.001)	**-0.304961** (0.065311) (0.001)	**-0.097314** (0.050529) (0.0542)	**-0.272412** (0.053532) (0.001)	**-0.311826** (0.056641) (0.001)	-0.257055 (0.251634) (0.307)	**-0.159730** (0.064973) (0.014)
β	**-0.469544** (0.04654) (0.001)	**-0.526568** (0.047798) (0.001)	**-0.343565** (0.050864) (0.001)	0.000467 (0.001093) (0.6692)	**-0.230656** (0.05273) (0.001)	**-0.382902** (0.050916) (0.001)	**-0.225873** (0.050599) (0.001)	**0.540551** (0.119251) (0.001)	**-0.291510** (0.049852) (0.001)
B (-1)	**0.469501** (0.04654) (0.001)	**0.525302** (0.047784) (0.001)	**0.342132** (0.050868) (0.001)		**0.230997** (0.052721) (0.001)	**0.382087** (0.050919) (0.001)	**0.225216** (0.050598) (0.001)	**-0.532828** (0.119221) (0.001)	**0.291050** (0.049851) (0.001)
C	0.000793 (0.000641) (0.2164)	**0.001137**(0.000661) (0.0854)	**0.001431** (0.000648) (0.0274)	0.000675 (0.000701) (0.3354)	0.000429 (0.000523) (0.412)	**0.001188** (0.000581) (0.041)	**0.001178** (0.000666) (0.0773)	0.000491 (0.002562) (0.848)	**0.001734** (0.000703) (.0137)
R^2 (Adj. R^2)	0.1573 (1548)	0.1222 (0.12)	0.1327 (0.1295)	0.1905 (0.1878)	0.1219 (0.1189)	0.164 (0.162)	0.144 (0.1411)	0.187 (0.1824)	0.148 (0.146)
Reg. F-stat (Prob.)	**63.24** (0.001)	**53.13** (0.001)	**41.37** (0.001)	**70.73** (0.001)	**41.74** (0.001)	**88.42** (0.001)	**45.588** (0.001)	**41.28** (0.001)	**78.59** (0.001)
Durbin Watson Stat	**1.96**	**1.957**	**1.98**	**2.003**	**1.986**	**1.976**	**1.989**	**2.003**	**1.981**
HTBPG F-stat (Prob.)	1.27 (0.254)	**20.63** (0.001)	**7.03** (0.001)	**4.136** (0.001)	**4.665** (0.001)	**4.71** (0.001)	**8.66** (0.001)	**6.39** (0.001)	**4.159** (0.001)
BGSCLM F-	**28.17** (0.001)	**26.26** (0.001)	**5.41** (0.020)	0.756 (0.38)	**10.41** (0.0013)	**10.59** (0.001)	**4.011** (0.045)	0.313 (0.576)	**10.438** (0.0012)
JB Norm (Prob.)	**1164** (0.001)	**5211** (0.001)	**978** (0.001)	**1450** (0.001)	**1131** (0.001)	**1875** (0.001)	**1049** (0.001)	**66014** (0.001)	**567** (0.001)
F-Bound F-Stat	**113.5** (0.01)	**164.4** (0.01)	**118.5** (0.01)	**94.37** (0.01)	**82.98** (0.01)	**183.28** (0.01)	**96.84** (0.01)	**56.85** (0.01)	**184.97** (0.01)
ECT	**-0.65182** (0.001)	**-0.75388** (0.001)	**-0.812631** (0.001)	**-0.612445** (0.001)	**-0.614951** (0.001)	**-0.644271** (0.001)	**-0.659815** (0.001)	**-0.696502** (0.001)	**-0.66489** (0.001)

In Table 4, the study finds that stock's endogenous returns have significant long-run impacts across the sample scripts and the ranges of lag-lengths vary from scripts to scripts – for example, it finds the least lag-length of three for *RIL* and *TISC* while there is a maximum of twelve lags in the case of *TAMO*. The coefficients of these endogenous lag returns are dynamically significant, positive in some cases and negative in some other cases. Besides, with all of the sample stocks except for TAMO, it shows the presence of negatively significant coefficients for the risk-free rate of return, R_f. This observation reiterates the results it has for the full-length data sets. In contrast to the presence of lag-effects of R_f in the full-length data sets, here it does not find any such impacts. However, it finds dynamic impacts of systematic risk β and its first lag significant across the stocks except for *ICBK*. Nonetheless, it shows five cases viz., *HDBK*, *HDFC*, *RIL*, *SBI*, and *TISC* where there are significant coefficients for the constant intercept *C* and these infer the presence of arbitrage opportunities in the stock markets. The table also confirms that the ARDL augmentation of the CAPM setup has a good fit of the data along with the explanatory powers ranging within 0.1210 (0.1189) and 0.187 (0.1824). The DW statistic approximates to 2 in all cases and it can be accepted that the model is free from any autocorrelation in terms of the while noise factor of the model residuals. But there is a presence of other short of residual noises and so, it can trace residual heteroscedasticity (serial correlation) for all stocks except for *GRAS* (*ICBK*, *SBI*, and *TAMO*) at an α value of 0.01 and the residuals are non-normal across the stocks as well. With the F-bound F-statistics and coefficients of the ECT, the ARDL augmentation further shows the presence of long-run co integrations of the stocks' returns with the variables of R_f and β and their dynamic adjustments towards the long-run relationships. These results reiterate the earlier findings with the full-length data sets.

In a synoptic view of the above observations with the stable data sets, therefore, the study confirms the presence of greater explanatory power with the ARDL model than DSML model vis-à-vis the long-run and short-run impacts in the former models, but both results show that the models' estimates lack efficiency even if these are unbiased estimates.

Table5: Stocks' Returns with the CAPM in the SML Setup for the Unstable Data Sets

Regression Model		$R_{it} = \alpha_0 + \alpha_{1r}R_{ft} + \beta_{is}B_{it} + \dot{r}_t$							
Variables	GRAS	HDBK	HDFC	ICBK	ITC	RIL	SBI	TAMO	TISC
R_f	-0.069741 (0.110266) (0.5276)	**-0.365174** (0.099164) (0.0003)	**-0.247768** (0.137656) (0.0729)	**-0.526520** (0.173259) (0.0026)	**-0.115600** (0.072823) (0.1135)	**-0.501216** (0.133269) (0.0002)	**-0.426340** (0.116529) (0.0003)	**-0.307432** (0.155144) (0.0485)	**-0.3575** (0.167886) (0.0341)

β	**0.109971** (0.032522) (0.0008)	**0.063832** (0.018258) (0.0005)	**0.098245** (0.028207) (0.0006)	**0.126683** (0.030573) (0.001)	0.004231 (0.016492) (0.7977)	**0.078265** (0.019241) (0.0001)	**0.053119** (0.015631) (0.0008)	**0.100761** (0.021906) (0.001)	**0.111237** (0.021317) (0.001)
C	**-0.028868** (0.008932) (0.0014)	**-0.023519** (0.007504) (0.0019)	**-0.027992** (0.009641) (0.004)	**-0.052788** (0.013774) (0.0002)	-0.001318 (0.004965) (0.7909)	**-0.021730** (0.006392) (0.0008)	**-0.019787** (0.006627) (0.0031)	**-0.027398** (0.006916) (0.0001)	**-0.0356** (0.007624) (0.001)
R^2 (Aj. R^2)	0.0376 (0.0309)	0.0694 (0.063)	0.0447 (0.0382)	0.0712 (0.0649)	0.0085 (0.0018)	0.0811 (0.0748)	0.068 (0.0616)	0.0723 (0.0659)	0.0897 (0.0835)
Reg. F-stat (Prob.)	**5.717** (0.004)	**10.922** (0.001)	**6.855** (0.001)	**11.235** (0.001)	1.259 (0.285)	**12.925** (0.001)	**10.69** (0.001)	**11.42** (0.001)	**14.434** (0.001)
Durbin Watson Stat	**1.276**	**1.3325**	**1.1401**	**1.106**	**1.663**	**1.145**	**1.26**	**1.1896**	**1.212**
HTBPG F-stat (Prob.)	1.089 (0.338)	**7.285** (0.001)	1.733 (0.179)	**7.098** (0.001)	0.401 (0.669)	**8.109** (0.001)	0.333 (0.717)	0.163 (0.849)	**5.873** (0.003)
BGSCLM F-stat (Prob.)	**43.44** (0.001)	**35.87** (0.001)	**65.04** (0.001)	**71.72** (0.001)	**8.247** (0.004)	**64.45** (0.001)	**44.90** (0.001)	**56.74** (0.001)	**52.44** (0.001)
JB Norm (Prob.)	**67.93** (0.001)	**65.44** (0.001)	**115.93** (0.001)	**23.92** (0.001)	**48.19** (0.001)	**67.17** (0.001)	**63.06** (0.001)	**10.78** (0.005)	**2759** (0.001)

***Unstable Outlook*:** In Table 5, the study depicts the results for DSML model with the stocks' returns during the unstable data period and here it shows that the variable R_f has negatively significant coefficients for *HDBK*, *RIL*, and *SBI* (*ICBK*) at an α level of 0.001 (0.01) while *TAMO* and *TISC* (*HDFC*) are significant at the level of significance i.e., α value of 0.05 (0.10) and with the case of *GRAS*, the same has an insignificant coefficient. That is, as it was earlier showed, here it cannot generalize the presence of significant negative impacts of the risk-free rate of return on the sample stocks' returns in the unstable data period rather the impacts are stock specific. Apart from the above, it finds significantly positive impacts of systematic risk across the stocks except for *ITC*. The magnitudes of intercept vary across the scripts but these all are negatively significant except for *ITC* at α value of 0.02. These results show that the investors' attraction in the stock market at positive impacts of systematic risk should be read along with the presence of underlying risk for arbitrage. But why there is a risk for arbitrage losses instead of arbitrage profit at times of unstable stock market conditions? Even if the concerned models are of good fit and these have better explanatory powers in terms of R^2 (Adj. R^2) with magnitudes ranging within 0.0085 (0.0018) and 0.0897 (0.0835), the said DSML models have the least explanations on the said query, and observed sustained findings of non-normal and correlated return residuals of the stocks in the models provide us no clues about the same.

Table 6: Stocks' Returns with the Modified CAPM in the ARDL Model Setup for the Unstable Data Sets

Regression Model	$R_{it} = \alpha_0 + [\sum_{r=1}^{r}\sum_{t=1}^{n}\alpha_{1r}R_{it-r} + \sum_{s=1}^{s}\sum_{i=1}^{A}\sum_{t=1}^{n}\beta_{is}X_{it-s} + \sum_{i=1}^{A}\sum_{t=1}^{n}\beta_i X_{it}] + \varepsilon_t \ldots\ldots\ldots (ARDL-1)$								
Varia-bles	GRAS (2,1)	HDBK (3,1)	HDFC (3,1)	ICBK (1,1)	ITC (2,1)	RIL (2,1)	SBI (2,1)	TAMO (5,1)	TISC (2,1)
R_t (-1)	**0.363081** (0.05385) (0.001)	**0.351867** (0.057634) (0.001)	**0.456431** (0.059168) (0.001)	**0.442068** (0.052028) (0.001)	**0.163896** (0.057491) (0.005)	**0.423918** 0.051992) (0.001)	**0.352918** (0.053933) (0.001)	**0.367456** (0.058822) (0.001)	**0.391155** (0.053867) (0.001)
R_t (-2)		-0.081632 (0.057716) (0.158)	-0.084736 (0.059812) (0.1577)					**0.149540** (0.062626) (0.0176)	
R_t (-3)								-0.054142 (0.062479) (0.387)	
R_t (-4)								**-0.102337** (0.058812) (0.0829)	
R_f	0.016864 (0.103873) (0.8711)	**-0.252872** (0.098944) (0.011)	**-0.299780** (0.125342) (0.0174)	**-0.426870** (0.155997) (0.007)	-0.067548 (0.075026) (0.369)	**-0.420444** (0.121061) (0.001)	**-0.300068** (0.110817) (0.007)	**-0.228359** (0.141898) (0.1087)	**-0.348038** (0.157986) (0.0284)
β	**-0.872634** (0.292697) (0.003)	**-0.506751** (0.244112) (0.0388)	**0.708910** (0.263466) (0.0075)	**0.074444** (0.028127) (0.009)	**-0.418756** (0.218998) (0.0568)	**0.04837** (0.017809) (0.007)	**-0.618032** (0.270449) (0.023)	**0.067325** (0.021355) (0.002)	**0.534065** (0.313369) (0.0894)
B (-1)	**0.942474** (0.291215) (0.002)	**0.551446** (0.242632) (0.023)	**-0.646411** (0.262548) (0.0144)		**0.421404** (0.217591) (0.0538)		**0.65236** (0.269552) (0.0161)		**-0.465365** (0.312356) (0.1373)
C	**-0.018000** (0.008373) (0.0324)	**-0.016047** (0.00722) (0.027)	**-0.018301** (0.008818) (0.0388)	**-0.031229** (0.01263) (0.014)	-0.000605 (0.004924) (0.902)	**-0.01365** (0.005881) (0.021)	**-0.012191** (0.006227) (0.0512)	**-0.018684** (0.006668) (0.005)	**-0.022788** (0.007305) (0.002)
R^2 (Aj. R^2)	0.1939 (0.1827)	0.1901 (0.1761)	0.244 (0.2307)	0.2549 (0.2473)	0.0487 (0.0356)	0.2511 (0.2433)	0.216 (0.205)	0.255 (0.239)	0.237 (0.226)
Reg. F-stat (Prob.)	**17.43** (0.001)	**13.523** (0.001)	**18.57** (0.001)	**33.19** (0.001)	**3.716** (0.006)	**32.52** (0.001)	**19.98** (0.001)	**16.246** (0.001)	**22.51** (0.001)
Durbin Watson Stat	**2.001**	**1.94**	**1.991**	**1.912**	**2.019**	**1.961**	**1.948**	**1.9667**	**2.004**
HTBPG F-stat (Prob.)	1.0727 (0.370)	**2.001** (0.077)	1.429 (0.214)	**6.15** (0.001)	0.368 (0.636)	**2.78** (0.041)	0.205 (0.94)	0.637 (0.70)	**4.815** (0.001)
BGSC LM F-stat	0.0199 (0.888)	**2.761** (0.098)	0.605 (0.437)	1.784 (0.183)	1.102 (0.295)	0.300 (0.584)	0.378 (0.539)	0.153 (0.696)	0.236 (0.627)

JB Norm (Prob.	**57.92** (0.001)	**120.0** (0.001)	**100** (0.001)	**120.5** (0.001)	**80.68** (0.001)	**101.37** (0.001)	**63.37** (0.001)	**45.17** (0.001)	**3.893** (0.143)
F-Boun d F-	**35.00** (0.01)	**32.17** (0.01)	**27.40** (0.01)	**29.72** (0.01)	**52.99** (0.01)	**32.38** (0.01)	**37.16** (0.01)	**17.81** (0.01)	**32.56** (0.01)
ECT	**-0.636919** (0.001)	**-0.729765** (0.001)	**-0.628305** (0.001)	**-0.557932** (0.001)	**-0.836104** (0.001)	-0.576082 (0.001)	**-0.647082** (0.001)	**-0.639484** (0.001)	**-0.608845** (0.001)

In Table 6, with the ARDL augmented data sets, the study finds a presence of lesser lag-effect/s for the endogenous stock return variable across the scripts. *HDBK* and *HDFC* have insignificant effects of their second lags, and TISC has positively (negatively) significant effects its second (fourth) lag while the sample stocks show positively significant effects for their first lags. These suggest the presence of lesser effects of stocks' past footprints on the present market conditions and thus, investors' memory comes up with lesser usability. The presence of a negatively significant coefficient of R_f here also confirms that be it a stable situation or unstable situation, the bond market possesses a negative source of attention attraction to investors and it diminishes possible arbitrage opportunities for the stocks. Nonetheless, with the explanatory variable of systematic risk β, it is found that is has positively (negatively) significant coefficient impacts for *HDFC*, *ICBK*, *RIL*, *TAMO* and *TISC* (*GRAS*, *HDBK*, *ITC* and *SBI*) and interestingly, at the first lag of β, it finds a reverse sign at their coefficient magnitudes for *HDFC*, *TISC, GRAS*, *HDBK*, *ITC* and *SBI*. These confirm the dynamic nature of impacts of systematic risk at times of unstable market conditions. However, with the constant intercept, it demonstrates that the same for *TAMO* and *TISC* (*GRAS*, *HDBK*, *HDFC*, *ICBK*, *RIL* and *SBI*) are negatively significant at an α value of 0.01 (0.05). Besides the above, it shows persistency in the sign of the intercept coefficients across the stocks in both the ARDL and DSML models setup for unstable data sets. Nonetheless, with the ARDL models, the study identifies higher explanatory powers within the range of 0.0487 (0.0356) and 0.2549 (0.2473) in terms of R^2 (Adj. R^2) along with goodness of the model fit with the significant F-statistics values for the respective models.

Besides the above supportive statistics in favour of the ARDL model during the unstable data periods, the study also finds significant long-run cointegrations in terms of F-bound F-statistics values and significant coefficients of the ECT for their dynamic speeds of adjustment towards their long-run relationships. Furthermore, the table shows the presence of heteroskedasticity in the ARDL models only for *ICBK* and *TISC* (*RIL*) at the value of 0.001 (0.05) while for HDBK, it is at an α value of 0.077 only. Nonetheless, it finds the absence of serial correlation for all stocks except HDBK, where the problem exists at an α value of 0.098 only. Even if it illustrates significant statistics for the JB normality tests (except for *TISC*) representing the presence of residual non-normality, the coefficients of variables in the ARDL model show overall consistency and efficiency of its estimates in the unstable data period.

Table7: Stocks' Returns with the Modified CAPM in the SML Setup for the Adaptive Data Sets

Regression Model	$R_{it} = \alpha_0 + \alpha_{1r} R_{ft} + \beta_{is} B_{it} + \dot{r}_t$								
Variables	GRAS	HDBK	HDFC	ICBK	ITC	RIL	SBI	TAMO	TISC
R_f	-**0.097424** (0.042104) (0.0207)	-**0.245283** (0.03541) (0.001)	-**0.262144** (0.044494) (0.001)	-**0.292128** (0.055167) (0.001)	-**0.104064** (0.04079) (0.0108)	-**0.114235** (0.044161) (0.0097)	-**0.366841** (0.055105) (0.001)	-**0.202442** (0.063288) (0.0014)	**-0.27328** (0.059613) (0.001)
β	-0.000320 (0.001309) (0.8071)	0.001053 (0.000934) (0.2594)	0.000665 (0.001127) (0.555)	0.001528 (0.001238) (0.2173)	-0.000959 (0.001207) (0.4266)	0.001423 (0.001249) (0.2546)	0.001291 (0.001684) (0.4432)	-0.000892 (0.001647) (0.5881)	**0.003776** (0.001919) (0.0492)
C	0.000595 (0.000554) (0.2829)	**0.000771** (0.000396) (0.0517)	0.000398 (0.000499) (0.4243)	0.000342 (0.000589) (0.562)	**0.001142** (0.000438) (0.0092)	-0.000059 (0.000547) (0.9139)	0.000176 (0.000879) (0.8416)	**0.001190** (0.00076) (0.1174)	-0.00108 (0.000879) (0.2211)
R^2 (Aj. R^2)	0.00156 (0.00098)	0.0139 (0.0133)	0.0099 (0.0094)	0.0084 (0.0078)	0.0021 (0.0015)	0.0023 (0.0017)	0.0127 (0.012)	0.0031 (0.0025)	0.0068 (0.0063)
Reg. F-stat (Prob.)	**2.71** (0.067)	**24.41** (0.001)	**17.48** (0.001)	**14.67** (0.001)	**3.64** (0.026)	**3.944** (0.019)	**22.39** (0.001)	**5.343** (0.001)	**11.99** (0.001)
Durbin Watson Stat	**1.371**	**1.306**	**1.366**	**1.2279**	**1.389**	**1.32**	**1.26**	**1.285**	**1.391**
HTBPG F-stat (Prob.)	**7.56** (0.001)	**12.86** (0.001)	**9.99** (0.001)	**6.188** (0.002)	0.342 (0.71)	1.278 (0.28)	0.219 (0.80)	1.446 (0.236)	1.739 (0.176)
BGSCLM F-stat (Prob.)	**379.05** (0.001)	**468.78** (0.001)	**379.10** (0.001)	**508** (0.001)	**355** (0.001)	**453** (0.001)	**541** (0.001)	**507** (0.001)	**350** (0.001)
JB Norm (Prob.)	**893** (0.001)	**389** (0.001)	**186** (0.001)	**781** (0.001)	**1947** (0.001)	**329** (0.001)	**17349** (0.001)	**569** (0.001)	**354** (0.001)

Adaptive Outlook: In Table 7, the study shows results for the DSML model during the adaptive data period. It depicts that the coefficients of the risk-free rate of return are as usual significantly negative across the stocks. It is not surprising to find the systematic risk variable β is significant only for *TISC* while the intercept coefficient is significant for *HDBK*, *ITC*, and *TAMO* only. The table furthermore shows those as usual results of significant F-statistics value for the DSML models along with less magnitudes for the explanatory powers with the DSML model during the adaptive data period. Nonetheless, it demonstrates non-normality and serial correlation for the respective stocks' residual return components. Despite the said limitations, it finds the absence (presence) of significant heteroskedasticity in the DSML models for ITC, RIL, SBI, TAMO, and TISC (GRAS, HDBK, HDFC, and ICBK). This case of dichotomy at heteroskedasticity is, however, new with the

DSML model and this needs further examination with the ARDL model. Nonetheless, the coefficient estimates are unbiased but these are not the efficient ones.

Table 8: Stocks' Returns with the Modified CAPM in the ARDL Model Setup for the Adaptive Data Set

Regression Model	$R_{it} = \alpha_0 + [\sum_{r=1}^{r}\sum_{t=1}^{n}\alpha_{1r}R_{it-r} + \sum_{s=1}^{s}\sum_{i=1}^{A}\sum_{t=1}^{n}\beta_{is}X_{it-s} + \sum_{i=1}^{A}\sum_{t=1}^{n}\beta_i X_{it}] + \varepsilon_t \dots\dots\dots\dots (ARDL-1)$								
Variables / Parameters	GRAS (*4,1*)	HDBK (*8,1*)	HDFC (*10,1*)	ICBK (4,1)	ITC (*6,1*)	RIL (*4,1*)	SBI (*4,1*)	TAMO (*6,1*)	TISC (*3,1*)
R_t(-1)	**0.288566** (0.016944) (0.001)	**0.336771** (0.016864) (0.001)	**0.293156** (0.01692) (0.001)	**0.335919** (0.01687) (0.001)	**0.285876** (0.016954) (0.001)	**0.313473** (0.016914) (0.001)	**0.342612** (0.016872) (0.001)	**0.336131** (0.016911) (0.001)	**0.275528** (0.016833) (0.001)
R_t(-2)	**0.105476** (0.0175) (0.001)	**0.057962** (0.017804) (0.001)	**0.076073** (0.017596) (0.001)	**0.097184** (0.017771) (0.001)	**0.090489** (0.017636) (0.001)	**0.110421** (0.01771) (0.001)	**0.093042** (0.017825) (0.001)	**0.093365** (0.017854) (0.001)	**0.118467** (0.017317) (0.001)
R_t(-3)	-0.024921 (0.016887) (0.1401)	**-0.044036** (0.017806) (0.0134)	**-0.047021** (0.017634) (0.008)	**-0.048487** (0.017725) (0.006)	**-0.056833** (0.017694) (0.0013)	**-0.056941** (0.017785) (0.0014)	**-0.036988** (0.017818) (0.038)	**-0.054106** (0.017895) (0.0025)	**-0.026498** (0.016785) (0.1145)
R_t(-4)		**-0.027608** (0.017833) (0.1217)	-0.020014 (0.017638) (0.257)	**-0.037305** (0.016774) (0.0262)	-0.023953 (0.017684) (0.1757)	**-0.032501** (0.017786) (0.0677)	**-0.026398** (0.016822) (0.1167)	-0.026568 (0.017907) (0.138)	
R_t(-5)		-0.013246 (0.017805) (0.457)	**-0.029182** (0.017629) (0.098)		0.003475 (0.017577) (0.8344)	0.006249 (0.017705) (0.7241)		-0.024563 (0.017839) (0.1686)	
R_t(-6)		**0.040127** (0.017754) (0.0239)	0.017926 (0.017627) (0.309)		**-0.042708** (0.016903) (0.0116)	**-0.043429** (0.016852) (0.01)		**0.033709** (0.016897) (0.0461)	
R_t(-7)		-0.015466 (0.017736) (0.3833)	-0.013452 (0.017635) (0.446)						
R_t(-8)		**-0.031934** (0.016755) (0.0567)	**-0.032943** (0.017606) (0.0614)						
R_t(-9)			0.000353 (0.017566) (0.984)						
R_t(-10)			**-0.032200** (0.016763) (0.0548)						
R_f	**-0.104213** (0.040028) (0.0093)	**-0.207439** (0.033392) (0.001)	**-0.223524** (0.042085) (0.001)	**-0.247173** (0.051515) (0.001)	**-0.108546** (0.038653) (0.005)	**-0.090523** (0.041421) (0.0289)	**-0.328529** (0.051079) (0.001)	**-0.176207** (0.05912) (0.003)	**-0.205844** (0.056363) (0.001)
β	**-0.065795** (0.035405) (0.063)	**-0.099188** (0.027987) (0.0004)	**-0.066075** (0.029758) (0.0265)	**-0.116425** (0.031931) (0.001)	-0.000662 (0.00114) (0.561)	**-0.125055** (0.03229) (0.001)	0.000868 (0.001556) (0.5768)	**-0.157395** (0.035239) (0.001)	**-0.196412** (0.034832) (0.001)
B (-1)	**0.065648** (0.035408) (0.0638)	**0.100028** (0.027982) (0.0004)	**0.066668** (0.029756) (0.0251)	**0.117569** (0.031929) (0.001)		**0.126165** (0.032293) (0.001)		**0.157040** (0.035239) (0.001)	**0.199163** (0.034822) (0.001)
C	0.000365 (0.000522) (0.4846)	0.000534 (0.000369) (0.1479)	0.000322 (0.000467) (0.491)	0.000215 (0.000543) (0.693)	**0.000826** (0.000415) (0.0468)	-0.000035 (0.000508) (0.9456)	0.000126 (0.000812) (0.8765)	0.000721 (0.000705) (0.3064)	-0.000785 (0.000824) (0.3409)

R^2 (Aj. R^2)	0.1122 (0.1107)	0.1441 (0.1413)	0.118 (0.115)	0.151 (0.149)	0.1068 (0.1047)	0.1347 (0.1325)	0.1545 (0.1531)	0.1446 (0.1424)	0.12003 (0.1185)
Reg. F-stat (Prob.)	**73.102** (0.001)	**53.10** (0.001)	**35.61** (0.001)	**88.18** (0.001)	**51.80** (0.001)	**59.92** (0.001)	**105** (0.001)	**65.08** (0.001)	**78.88** (0.001)
Durbin Watson Stat	**2.001**	**1.998**	**1.996**	**1.998**	**2.001**	**1.999**	**1.996**	**1.998**	**1.999**
HTBPG F-stat (Prob.)	**3.063** (0.001)	**3.93** (0.001)	**3.379** (0.001)	**2.978** (0.004)	0.898 (0.516)	**1.655** (0.094)	**4.919** (0.001)	1.319 (0.22)	**2.830** (0.0095)
BGSCLM F-stat (Prob.)	0.33 (0.565)	0.131 (0.717)	0.222 (0.637)	0.162 (0.687)	0.49 (0.699)	0.00413 (0.949)	0.450 (0.502)	0.304 (0.58)	0.0001 (0.99)
JB Norm (Prob.)	**1479** (0.001)	**561** (0.001)	**413** (0.001)	**1094** (0.001)	**1856** (0.001)	**632** (0.001)	**23457** (0.001)	**704** (0.001)	**607** (0.001)
F-Bound F-Stat	**230** (0.01)	**119** (0.01)	**106** (0.01)	**195** (0.01)	**146.54** (0.01)	**183.28** (0.01)	**186.78** (0.01)	**125** (0.01)	**206** (0.01)
ECT	**-0.630878** (0.001)	**-0.69743** (0.001)	**-0.787304** (0.001)	**-0.65269** (0.001)	**-0.743655** (0.001)	**-0.702727** (0.001)	**-0.627732** (0.001)	**-0.642031** (0.001)	**-0.632503** (0.001)

In Table 8, in contrast, the study finds long memory effects of endogenous return variables of the stocks' returns at their different lag variables. It documents the least lags to an extent of three lags for *GRAS* and *TISC*, four lags for *ICBK* and *SBI*, six lags for *ITC* and *RIL*, and eight lags for *HDBK* and nine lags for *HDFC*. These lags are significant with a mixed presence of positively and negatively significant coefficient values and these suggest for the presence of dynamic revisions in their impacts on the sample stocks' returns. Furthermore, it documents a presence of negatively significant coefficients for the risk-free rate of return with all the nine sample stocks. Nonetheless, it reports negatively (positively) significant coefficients for the systematic risk β (lag β) variables for all stocks except *ITC* and *SBI*. These observations also confirm dynamic revisions in their impacts on the sample stocks' returns. However, it finds the constant intercept significant only with *ITC*. These ARDL models have explanatory powers ranging within 0.1122 (0.1107) and 0.1545 (0.1531) in terms of R^2 (Adj. R^2) while these models have a good fit. It finds a significant presence of heteroskedasticity with GRAS, HDBK, HDFC, ICBK, RIL, and TISC while there is the absence of residual serial correlations across the stocks. The F-bound F-test statistics for the ARDL models confirm the presence of cointegration amongst the variables and there isa presence of significant speeds of adjustments in terms of ECT coefficients in these regression models. Therefore, it confirms mixed evidence on the model's coefficients with the adaptive data sets -some stocks have efficient statistics while some other lacks the same even if these all are unbiased estimates of the variable parameters. However, as it finds residual non-normality with the JB normality test across the stocks, the table casts some doubts about the power of the efficiency of the parameters' statistics.

Table 9: T-Statistics for equality of coefficients with the CAPM for the different data sets

H$_0$: Equality of parameter values for the intercept of the regression model*									
Alternative Hypothesis	GRAS	HDBK	HDFC	ICBK	ITC	RIL	SBI	TAMO	TISC
$C_{0S} \neq C_{0U}$	**3.3770**	**3.3321**	**3.0877**	**3.8997**	0.4115	**3.6904**	**3.2394**	**3.6585**	**5.0073**
$C_{0S} \neq C_{0A}$	0.8895	1.0222	**1.7091**	0.6878	-0.5708	**2.4379**	1.4392	-0.4308	**3.3051**
$C_{0S} \neq C_{0F}$	-0.9141	-0.7091	-0.9174	-0.5567	0.0980	-1.4181	-0.9899	-0.3938	**-2.2885**
$C_{0U} \neq C_{0A}$	**-3.2923**	**-3.2324**	**-2.9408**	**-3.8537**	-0.4936	**-3.3780**	**-2.9862**	**-4.1089**	**-4.4992**
$C_{0U} \neq C_{0F}$	**3.2990**	**3.2656**	**3.0138**	**3.8657**	0.4260	**3.5345**	**3.1137**	**3.7025**	**4.7396**
$C_{0A} \neq C_{0F}$	-0.0552	-0.4430	-1.0367	-0.1964	0.6112	-1.4176	-0.7168	**1.6029**	**-1.6409**
H$_0$: Equality of parameter values for the coefficient of the risk free rate of return (R_f) in the regression models*									
Alternative Hypothesis	GRAS	HDBK	HDFC	ICBK	ITC	RIL	SBI	TAMO	TISC
$R_{fS} \neq R_{fU}$	-0.8570	1.1420	-0.0439	0.9097	-0.1344	1.1953	0.4375	0.1143	0.7748
$R_{fS} \neq R_{fA}$	-1.1042	0.1638	0.1014	-0.7034	-0.3514	**-2.9245**	-0.0251	-0.2417	0.6165
$R_{fS} \neq R_{fF}$	1.2202	-0.2673	0.3602	0.2170	0.1603	0.9008	0.1395	0.1013	-0.0982
$R_{fU} \neq R_{fA}$	0.2345	-1.1386	0.0994	-1.2891	-0.1382	**-2.7564**	-0.4616	-0.6266	-0.4727
$R_{fU} \neq R_{fF}$	-0.2286	1.0990	0.1340	1.0587	-0.0308	**1.7035**	0.5514	0.3472	0.7676
$R_{fA} \neq R_{fF}$	-0.0277	0.1350	-0.5918	0.6601	0.2798	2.7635	-0.1180	0.2963	-0.6657
H$_0$: Equality of parameter values for the coefficient of the systematic risk, *Beta* (β) in the regression models*									
Alternative Hypothesis	GRAS	HDBK	HDFC	ICBK	ITC	RIL	SBI	TAMO	TISC
$\beta_S \neq \beta_U$	**-3.3787**	**-3.5688**	**-3.5475**	**-4.1092**	-0.2125	**-4.1270**	**-3.4410**	**-3.9701**	**-5.2455**
$\beta_S \neq \beta_A$	0.1833	-1.3934	-1.3054	-0.3318	0.9909	**-1.7299**	-1.0249	**2.8074**	**-2.0458**
$\beta_S \neq \beta_F$	0.3676	1.0268	0.9490	0.5480	-0.3597	1.1428	0.7758	-0.4371	1.5170
$\beta_U \neq \beta_A$	**3.3885**	**3.4339**	**3.4567**	**4.0903**	0.3139	**3.9853**	**3.2966**	**4.6274**	**5.0208**
$\beta_U \neq \beta_F$	**-3.3626**	**-3.4715**	**-3.4838**	**-4.0833**	-0.2444	**-4.0605**	**-3.3676**	**-4.1200**	**-5.1448**
$\beta_A \neq \beta_F$	-0.5595	0.5175	0.4886	-0.1676	-0.7854	0.9284	0.4690	-3.6277	1.0826

* *Note: Sample Size (N): N_S = 2722, N_U = 296, N_A = 3480, N_F = 6497* where $_S$ refers to stable data sets, $_U$ to unstable data sets, $_A$ to adaptive data sets, and $_F$ for full-length data sets.

Robustness Checks: In Table 9, with the DSML regression model the study has tried to compare the difference of the coefficient statistics if they differ significantly for the constant intercept *C*, risk-free rate of return R_f and systematic risk β as well over the four periods of data sets – full-length, stable, unstable and adaptive data periods. In comparing any two coefficients out of the said four data sets, for any parameter statistics viz., *C*, R_f and β, it develops six combinations and these are reported in the table accordingly. The study compares the same and examines them critically one after another in the following.

It shows that with the DSML model, the constant intercept at stable (unstable) data period is different from that at unstable (adaptive) data period for all stocks except the case of *ITC*.A similar observation is also found in comparing the constant intercept between unstable and full-length data sets as well. Nonetheless, at the said comparison for stable and adaptive (full-length) data sets, it identifies a significant difference with *HDFC*, *RIL* and *TISC* (*TISC*) only while that between adaptive and full-length data sets, it finds significant differences for *TAMO* and *TISC* only. These confirm that the DSML model estimates can help us in differentiating the constant impacts across the stocks even if the model has the least explanatory powers, as mentioned earlier, but with unbiased parameter estimates. Investors can explore the presence of arbitrage opportunities across the stocks and over the different data periods as well.

With reference to the parameter estimates for the risk-free rate of return R_f, it finds that the statistics differ between stable and adaptive data period, unstable and adaptive period, and unstable and full-length data period for the case of RIL only. In the other instances across the stocks, it finds no comparative difference in the magnitudes of R_f. These limited but critical observations suggest that R_f has some sort of generalized impact across the stocks and these substantiate the proposition in the CAPM in the standard finance literature. Besides the said generalized impacts, it shows some additional information with RIL, and investors can identify the underlying reason for the impacts of the government bond market on the stock's return for RIL. Therefore, the present DSML model has some information advantage over the linear two-factor CAPM setup.

Apart from the above observations, with the coefficients of systematic risk β, it finds mostly similar observations to those it is found for the constant intercepts earlier. The table shows that in the sample stocks except for *ITC*, the coefficients of β are comparatively different for the stable data period from that at unstable data period, that for unstable data period from adaptive data period as well as full-length data period. Besides the above, it can be found that the said coefficients are significantly different between stable and adaptive data periods for the three stocks viz., RIL, TAMO and

TISC. These results confirm the relevance of systematic risk even in the DSML model as proposed in the study.

Table 10: T-Statistics for equality of coefficients with the ARDL for the different data sets

H_0: Equality of parameter values for the intercept of the regression model*									
Alternative	GRAS	HDBK	HDFC	ICBK	ITC	RIL	SBI	TAMO	TISC
$C_{OS} \neq C_{OU}$	**2.2379**	**2.3701**	**2.2317**	**2.5222**	0.2088	**2.5108**	**2.1348**	**3.0071**	**3.3414**
$C_{OS} \neq C_{OA}$	**2.5160**	0.7965	1.3884	0.5188	-0.5946	1.5843	1.0017	-0.0866	-1.5637
$C_{OS} \neq C_{OF}$	-0.5524	-0.5705	-0.7004	-0.4152	0.2045	-0.8952	-0.6791	-0.3931	-1.5541
$C_{OU} \neq C_{OA}$	**-2.1891**	**-2.2935**	**-2.1090**	**-2.4873**	-0.2896	**-2.3065**	**-2.0604**	**-2.8940**	**-2.9931**
$C_{OU} \neq C_{OF}$	**-2.1917**	**-2.3166**	**-2.1737**	**-2.4967**	-0.2351	**-2.4127**	**-2.0490**	**-3.7037**	**2.1909**
$C_{OA} \neq C_{OF}$	-0.0121	-0.3172	-0.8999	-0.1554	0.5135	-0.9527	-0.5059	**-11.1207**	-1.2114
H_0: Equality of parameter values for the coefficient of the risk-free rate of return (R_f) in the regression models*									
Alternative Hypothesis	GRAS	HDBK	HDFC	ICBK	ITC	RIL	SBI	TAMO	TISC
$R_{fS} \neq R_{fU}$	-1.4880	0.4043	0.6697	0.7209	-0.3291	1.1183	-0.0945	-0.0993	1.1023
$R_{fS} \neq R_{fA}$	-0.7898	0.0030	0.2269	-0.6947	0.1766	**-2.6873**	0.2190	-0.3128	0.5361
$R_{fS} \neq R_{fF}$	1.1599	-0.3778	-0.1708	0.0907	0.0488	0.8215	0.2299	0.0143	-0.2244
$R_{fU} \neq R_{fA}$	1.0877	-0.4351	-0.5767	-1.0938	0.4858	**-2.5785**	0.2332	-0.3393	-0.8477
$R_{fU} \neq R_{fF}$	0.9549	-0.2157	-0.6231	-0.7997	0.3379	-1.5912	-0.0292	0.1411	-1.0517
$R_{fA} \neq R_{fF}$	-0.3616	0.5194	-0.0873	0.7757	-0.2969	**2.5411**	-0.5208	0.6446	-0.4224
H_0: Equality of parameter values for the coefficient of the systematic risk, Beta (β) in the regression models*									
Alternative Hypothesis	GRAS	HDBK	HDFC	ICBK	ITC	RIL	SBI	TAMO	TISC
$\beta_S \neq \beta_U$	1.3601	-0.0797	**-3.9223**	**-2.6281**	0.8350	**-7.9953**	1.4253	**3.9062**	**-2.6018**
$\beta_S \neq \beta_A$	**-6.9050**	**-7.7160**	**-4.7088**	**3.6586**	**-4.3607**	**-4.2767**	**-4.4790**	**5.6128**	**2.3257**
$\beta_S \neq \beta_F$	**4.1426**	**4.0643**	**-5.1263**	0.5254	**2.6308**	**3.4078**	**2.0331**	**-1.6967**	**2.3072**
$\beta_U \neq \beta_A$	**-2.7366**	**-1.6587**	**2.9229**	**4.4855**	**-1.9091**	**4.7030**	**-2.2884**	**5.4538**	**2.3168**
$\beta_U \neq \beta_F$	**-2.1354**	-0.8333	**3.0871**	**2.6083**	-1.5678	**7.0190**	**-1.8808**	**-2.6616**	**-3.1649**
$\beta_A \neq \beta_F$	**3.9711**	**5.1509**	1.0451	-3.6777	**2.4778**	1.3972	**3.5644**	**-6.5402**	-0.8672

* *Note: Sample Size (N):* $N_S = 2722$, $N_U = 296$, $N_A = 3480$, $N_F = 6497$ where $_S$ refers to stable data sets, $_U$ to unstable data sets, $_A$ to adaptive data sets, and $_F$ for full-length data sets.

With the ARDL model, in Table 10, the study has also examined difference of the coefficient statistics for the constant intercepts *C*, risk-free rate of return R_f and systematic risk β as well over the four periods of data sets. Regarding constant intercepts, the table shows mostly similar findings as it is also reported with the DSML model for comparisons between stable and unstable data sets, unstable and adaptive data sets, and unstable and full-length data sets as well. The present table, however, differs for *GRAS* (*TAMO*) where the intercept coefficient differs between stable and adaptive (adaptive and full-length) data sets only. That is the observations with the ARDL model some information advantage over the DSML model. Concerning the risk-free rate of return, here the study avoids any repetition of the same results, and keeping them apart, it identifies the presence of significant difference for adaptive and full-length data sets instead of unstable and full-length data sets as it is observed for *RIL* in the DSML model earlier. These results confirm that the ADRL model has some additional information over the DSML model.

Besides the above, about the systematic risk variable, the study finds a completely different depiction with the ARDL model from that as observed in the DSML model earlier. Here, it finds a significant difference in the magnitudes of the said coefficient across the stocks for both stable and unstable data periods from the adaptive data period. The coefficient significantly differs for all stocks except *ICBK* (*HDBK* and *ITC*) for stable (unstable) data period from the full-length data period. Nonetheless, it finds significant coefficient differences for HDFC, ICBK, RIL, TAMO and TISC (GRAS, HDBK, ITC and TAMO) for stable to unstable (adaptive to full-length) data period. These findings illustrate that the present ARDL model has some different interpretations about the impacts of systematic risk across the stocks. Investors should look into the difference in coefficient estimates before making up minds to choose stocks for investment.

In a nutshell, besides the instances of similar and dissimilar effects for the two models' coefficients, the study traces the presence of reference-market dependence at the coefficients for the constant intercept, risk-free rate of return and the systematic risk factor across the stocks over the data sets.

Discussions: In the spirit of Lo (2004, 2005), the stock markets' information efficiency is to be judged about the conditions so provided by the outstanding business environment and the economic ecology as well. From that general perspective, it is intuitive that investors in the stock markets move through the periods of stable, unstable and adaptive market conditions. It expects a robust but differentiating presence of the variable impacts and constant intercepts as well for both the different sub-periods and the full-length data period.

The observations in the study are supportive of the above theoretical expectation. With the ARDL framework, it has found the presence of long-run endogeneity effects of stocks' past returns on their current returns across the stocks and the endogeneity cannot be apprehended otherwise in the DSML model. Therefore, the present ARDL augmentation of the dynamic CAPM model as envisaged in the study with the DSML setup has overarching effects in terms of cointegration relationships amongst the variables and the magnitudes of the speeds of adjustments across the stocks. The extents of the explanatory powers of the ARDL models across the stocks and over the sample data periods evidence the said overarching effects as well.

Since the study observes the presence of residual non-normality (in terms of JB normality tests) in the three sub-periods and full-length data period as well, a generalization of the findings with the proposition of the adaptive market hypothesis (AMH) is somewhat likely to be limited to the present contexts only. Amongst the prime findings, with both the DSML and ARDL model setups, the study in general documents negative impacts of the government bond market, (that is, the risk-free rate of return) on the stocks' returns across the evolutions of the stock market conditions viz., the stable, unstable and adaptive stock markets but the same evolution comes along with provisions for dynamic revisions at its lag periods only for the full-length data. These observations are supportive of the direct empirical validity of the AMH but with the presence of a limited number of stocks viz., *HDBK* and *HDFC* (read with Table 2).

Apart from the above results, the stocks' systematic risk has limited, of one instance, of positively significant effect in the DSML model at both the stable and adaptive data periods while the same has significantly positive impacts at eight cases of instances in general. The study has mixed results for the same with the full-length data period. It is evident that the latter data set provides the effect of the mixed data and should not be used for generalization. In brief, the information derived from the DSML model is of limited use with the unstable data sets only and this has little utility at the other two data sets while the same at full-length data period becomes noisy. The limitations of the said fractured observations can be overcome with the use of the ARDL model. Here, across the three sub-periods' data sets, the study finds that the systematic risk variable demonstrates dynamic revisions in terms of its current impacts and past impacts, and these findings are compatible with the propositions of the adaptive market hypothesis. Nonetheless, the overall impacts with the full-length data sets also corroborate the proposition of dynamic adaptation to the market conditions and the market ecology as well. Such adaptation could also be further validated with the vivid presence of differences in the coefficients in the systematic risk variable across the stocks and over the data sets as well (read with Table 10).

Nonetheless, at both the DSML and ARDL models, the study has demonstrated the presence of positive (negative) arbitrate opportunity for some selective sample stocks within the stable and adaptive (unstable) data periods while with the full-length data periods, it finds subsistence of only positive arbitrage benefits for some selective sample stocks. The investors can use both the models to extrapolate the exact extents of such stock-specific arbitrage opportunities. The aforementioned presence of stock-specific arbitrage opportunity, however, is contradictory to the proposition of the efficient market hypothesis but the same could be well accommodated within the propositions of the adaptive market hypothesis (AMH) since the AMH recommends for the conditional presence of arbitrage opportunity only.

Conclusion: The study has offered some original findings in favour of the AMH. As per the findings of the study, an ARDL augmentation of the known variables in the CAPM setup can provide better explanatory powers than that what it can be found otherwise with the DSML setup even if the coefficients in the both DSML and ARDL models lack complete persistency. It has also ingeniously applied a direct methodology of reference-dependence. That is, the study calibrates the DSML to the dynamic reference-dependence perspectives of behavioral finance.

At the practical use of the present study, the mutual fund managers can identify effects of investors' reference-dependence at the different market situations along with their overall market impacts and can assist investors in showing the extents of such reference dependencies. one of the limitations of the study is that the present empirical study lacks the presence of complete efficiency of the variable coefficients – they are not the best and efficient estimators but unbiased and linear ones, and hence, investors should be cautious on their predictive powers as observed in the models. Any replication of the empirical models is subject to the presence of non-normality of residual returns in the models. However, the present study could be extended in the GARCH-X framework and the stocks' idiosyncratic effects on their returns can be identified along with the aforementioned reference-dependencies. Nonetheless, an empirical extension of the present model with the use of non-linear setups can make some break-through towards the applicative value of the prospect theory and such development is under process.

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