

## COVID-19 and CAPM: a tale of reference dependence with the pharma stocks' returns

**Paritosh Chandra SINHA**

Rabindra Mahavidyalaya, India  
paritoshchandrasinha@gmail.com

**Pooja AGARWAL**

Burdwan University, India  
poojaagarwal9413@gmail.com

**Abstract.** *Given the sustained attention to COVID-19, we explore if a reference dependent version of the CAPM has a good explanatory power. It views the CAPM with the prospect theory references - certainty effect, reflection effect and isolation effect. It firstly follows a linear prospect theory version of the CAPM, then, it extends that with the autoregressive distributed lag (ARDL) model, and finally, it augments them in the generalized autoregressive conditional heteroskedastic (GARCH-X) setup. It views the risk-free rate and market rate of returns as the certainty effect and reflection effect respectively while the lagged endogenous returns and the ARCH and GARCH effects as the isolation effects. With the NSE listed pharma-stocks' data during COVID-19, pre-COVID-19 and both periods together, the prospect theory references depict that investors can build up different implications of the CAPM. With certainty effect, the prospect theory version of CAPM has less explanatory power while with reflection effect, the same has good explanatory power with the sample stocks over the data sets but it does not explain the isolation effects at all. Investors may re-look into that the CAPM if calibrated with the prospect theory references at ARDL and GARCH-X augmentations, it provides better explanatory powers.*

**Keywords:** CAPM; the prospect theory; reference-dependence; behavioral finance; ARDL and GARCH-X augmentations.

**JEL Classification:** G130, G4, C580, G140.

## Introduction

Since January 2020, the breakout of COVID-19 pandemic has taken a lead in public discussion throughout the world. The most discussions are about the future of the pharmaceutical industry and its short-run prospects in the markets. Will the nations fall apart! Will there be a remedy for COVID-19? The managements' policy decisions in this industry and their progress in research and development are linked with the effects of these uncertainties. The same uncertainties are likely to be felt in the stock markets around the world. Investors in the NSE stock market in India have experienced the same uncertainties as well. For example, on 1 March 2020, at outset of COVID-19 but a fortnight period before the nation-wide lock-down in India, the NSE Nifty (BSE Sensex) has got down to its July 2016 (March 2017) index level of 8597 (29446).

In financial economics, these expectations can be viewed with both the informational and behavioral contexts. The informational (behavioral) context believes that the capital market will be efficient (noisy) and investors be rational (irrational). Interestingly, investors are not in a tight-jacket situation/s about their camps – whether informational context/s or behavioral context/s. They are free to swing at their wills or they may be forced by situations. That means, they can be rational at their buy/sell position/s and behavioral at the sell/buy position/s. In brief, there exists chaos, unordered noise in the stock-markets – informational, behavioral or both. Is this chaos systematic or unsystematic? Can this chaos be examined with the references to COVID-19?

In financial economics, a reference point describes situations involving subjective and/or objective decision makings. It projects preferential and/or substantive convictions of the decision maker (Wierzbicki, 1999). It demonstrates how investors' framing the decision choices at situations under uncertainty and risk (Tversky & Kahneman, 1981, 1986). Such thought processes are applied by Sharpe (1964), Lintner (1965), Mossin (1966), and Ross (1976) to develop the capital asset pricing models but from the perspective of expected utility theory along with their respective theoretical assumptions, and that in the prospect theory by Kahneman and Tversky (1979) from the perspective of the behavioral utility theory, and in the cumulative prospect theory by Tversky and Kahneman (1992) as well (Barberis, 2013; and Fama & French, 2004). If we consider the mean-variance view of perceiving risk at presence homogeneous investors as a special case of perceiving the risk, then both these thought processes seem to coincide each other such that at presence of heterogeneous investors, the perception of risk will have some more dimensions (Levy, Giorgi & Hens, 2011). In Ricciardi (2008), these dimensions may include one or more factors from its list of more than one hundred behavioral factors viz., investors' familiarity factor/s, search for information, worry, their perception about quality of stocks, their past financial losses, confidence level, attention, perceived control on their affects, seriousness, and reputations etc.

Both standard finance and behavioral finance fields are interrelated - their thought processes meet at their conceptualizations of reference points and differs at both perceiving risk and assessing the values. Levy, Giorgi and Hens (2011) have argued that the paradigm of the capital asset pricing model (CAPM) can be explained by that of the cumulative

prospect theory but not vice-versa. This study, however, seeks to explore if the prospect theory version of the CAPM can explain the stock markets' dynamics at three distinct viewpoints – pre- COVID-19, COVID-19, and taking the two together. We flow a brief literature review on the CAPM and prospect theory in Section 2, data and methodology in Section 3, results and findings in Section 4, and conclusion in Section 5.

## 2. Literature Review

The chaos in the financial markets is mostly explored with the information asymmetry (Cepoi, 2020; Lakhali, 2008), the chaotic market hypothesis (Kristoufek, 2012, Quang, 2005), and firms' strategic positioning at the market sentiments (Chang, 2020) etc. The unordered volatility or noise, a chaos, can be linked to stocks' liquidity shocks in the stock markets. Sinha (2019a) has showed that the noise has market microstructure component, and it relates to investors' adaptive behaviors in the markets. Sinha (2019b) has showed that the Indian stock markets are not immune to the political chaos. Investors also show attention mania caused by their attention impacts on the stock markets (Sinha, 2021). Bali, Peng, Shen, and Tang (2014) have showed that investors' inattention and illiquidity lead to under-reactions of stock markets.

Theoretically, in the single period CAPM, stocks' beta explains returns on the risky assets (Theobald, 1979; Black, 1993). To arrive at investor's current decision choices, the CAPM is empirically used with a reference to stocks' historical annual beta. With stocks' daily prices in the NSE CNX 500 market, Bajpai and Sharma (2015) have found support over 2004-13. With weekly data during 2010-14, Lee, Cheng and Chong (2016) also have found the reasonability of the model in the Kuala Lumpur Stock Exchange. On the model's empirical status-quo, the review studies of Fama and French (1996, 2004) have identified insufficiency of the CAPM in explaining stocks' expected returns. With monthly returns' data during the study period of 2000-2009, Coffie and Chukwulobelu (2012) have showed a low predictive power of the beta for the stocks in the Ghana Stock Exchange. With the BSE Sensex listed stocks during 2005-2008, Maji (2010) has identified that stocks' beta is not always stable, and it moves ups and downs at times of market crashes. With daily and monthly data during 1993-2004, Javid and Ahmed (2008) have found inability of the CAPM for the stocks listed in the Karachi Stock Exchange.

With the INR-USD exchange rates data, Khuntia and Pattanayak (2019) have identified that the time varying efficiency of the Indian Foreign Exchange Market is caused by the changes in exchange rate regime, financial turbulence, interventions by the major central banks etc. Such time varying behavior is also identified by Akhter and Yong (2019) in Dhaka Stock Exchange over 1995-2018. These show that markets' conditions perform as reference points in investors' decision choices. These dynamics lead to inconsistency in empirical applications of the CAPM with the real world at changing reference points.

We view investors' reactions to the stock markets from three distinct references: the pre-COVID-19 situation, COVID-19 situation, and taking both situations together. At sustained attention to information by investors on updates of COVID-19 status, highly informed investors may depict panicked behaviors while their uninformed counterparts may show

calmness at their trading positions (Herjanto, Amin, & Purington, 2021). The chaos in the market is so high that the investors may lose their perspectives to view or compare the markets. That is, at the uncertainties, the five-factor Capital Asset Pricing Model along with two additional factors viz., profitability and investments, in Fama and French (2015), even if promises the investors a better explanatory power than the single factor or three factor CAPM (read with Fama & French, 1996; 2004), but the same may lose its real-life relevance at COVID-19 like disruptions since the lack of details for the new two firm-specific variables in the modified CAPM models or that for the existing firm size and the book to market value ratio lead them towards the availability bias caused by the news of COVID-19 (Nemeth, 2020). The five-factor CAPM also involves spurious regression problems caused by the data properties like the weakly dependent process, near unit root process, structural breaks in the data due to 2008 -2012 financial recession, and the I(1) process (Liu & Wang, 2019).

In contrast, the behavioral finance theories have explicit add-ins to the limitations of the standard finance version of the CAPM. Here, investors' behavior is viewed with framing effect. In framing effect, people's choices are dependent on the description of options i.e., how it is framed (Tversky & Kahneman, 1981; 1986). For examples, the prospect theory of Kahneman and Tversky (1979) and the cumulative prospect theory of Tversky & Kahneman (1992) show investors' dichotomous attitudes at reference points – risk-averse at the gains and risk-seeking at the losses. Kahneman and Tversky (1979) have identified that investors show certainty effect, reflection effect, and isolation effect at decision choices. In certainty effect, people put more weights to the sure prospects for gains than to losses, and at reflection effect, they show an inverse decision choice at opposite scenarios. Isolation effect refers to the tendency of people to value information that is unique and different from the rest. Baucells and Villasis (2009) have also documented supports for the empirical validity of reflection effects. By analyzing the stocks listed in the NYSE, AMEX, and NASDAQ over 1962-2014, Wang, Yan and Yu (2017) have showed that investors' decisions are based on their reference points and there exists a positive (negative) risk-return relationship when investors face prior gains (Losses). With the stocks listed in the above three stock markets over the study period of 1963-2014, Barberis, Jin and Wang (2020) have showed that investors' narrow framing can explain the anomalies to the CAPM like maximum daily return, long-term and short-term reversals, idiosyncratic volatility etc.

Besides the systematic risk premium, in Fama & French (2015), stocks' unsystematic risk-premiums for the idiosyncratic risks are tried to be identified with the four firm-specific variables viz., the firm-size, book to market value, profitability, and investment. Can the proposition of the CAPM be viewed with the lenses of certainty effects, reflection effects, and isolation effects at investors' reference dependent decision choices? For example, a certainty effect can be felt at the presence of the risk-free rate of return,  $R_f$  while the reflection effect can be observed at the presence of the market rate of return,  $R_m$  and in the spirit of Qadan (2019), isolation effect can be recognized with the residual idiosyncratic risk of a stock.

Towards the said direction, there is an urgent research need to explore empirical validity of the prospect theory version of the CAPM. In addressing this gap, we explore the CAPM if relevant at investors' reference-dependent perspectives of prospect theory and examine it empirically with the pharma stocks listed in the National Stock Exchange in India.

### 3. Data and Methodology

We have used the daily prices of ten stocks listed in the National Stock Exchange (NSE) in India. It covers the relevant data for fourteen months viz. from 01-08-2019 to 30-09-2020, divided into three slabs: the pre-COVID-19 period of seven months from 01-08-2019 to 29-02-2020, and during the COVID-19 period from 01-03-2020 to 30-09-2020, and finally taking both slabs' data together. The sample stocks are listed in the National Stock Exchange (NSE) for more than 5 years' period. These stocks are Alkem Laboratories Ltd. (i.e., ALKE), Aurobindo Pharma Ltd. (i.e., ARBN), Biocon Ltd. (i.e., BION), Cadila Healthcare Ltd. (i.e., CADI), Cipla Ltd. (i.e., CIPL), Divis Laboratories Ltd. (i.e., DIVI), Lupin Ltd. (i.e., LUPN), Dr.Reddys Laboratories Ltd. (i.e., REDY), Sun Pharmaceuticals Industries Ltd. (i.e., SUN), and Torrent Pharmaceuticals Ltd. (i.e., TORP). To proxy for the risk-free rate of return ( $R_f$ ), we have used the ten years' Government bonds' yield data. It is used as the reference rate for the risk-free rate of return for investors in the stock markets. We have collected their secondary data from [www.investing.com](http://www.investing.com) and process them in Microsoft Excel. In deriving their return data, we use daily percentage change in the closing value of the stocks' price or market index.

#### Market Microstructure Models

Let us now understand the relationship between stocks' risk and return. Here, we consider the CAPM as the basic regression model. The individual stock's return ( $R_{it}$ ) performs as the explained dependent variable and stock's systematic risk - *beta* performs as the explanatory independent variable. On the assumption of markets' informational efficiency and presence of no-arbitrage opportunity in the markets, the model *beta* is the linear coefficient of the independent variable of the stock market's risk premium – the excess return of stock market's return ( $R_{mt}$ ) over the risk-free rate of market return ( $R_{ft}$ ). This beta based CAPM model theoretically assumes that the intercept is equivalent to be the risk-free interest rate ( $R_{ft}$ ) in the capital market.

$$R_{it} = R_f + \beta_{it}(R_{mt} - R_{ft})_{it} + \varepsilon \dots \dots \dots (CAPM - 1)$$

At presence of inefficiency in the capital markets, a variant of the above *CAPM-1* model is the Security Market Line (SML), where an individual stock's risk premium – the excess of stock's return over the risk-free rate of return (i.e.,  $R_{it} - R_{ft}$ ) is regressed with that of stock market's risk premium (i.e.,  $R_{mt} - R_{ft}$ ). In the SML framework, the risk-free rate of return is considered as the additional market variable, but it is adjusted over the two sides of the equation in the *CAPM-1*, and the intercept is derived as the *alpha* ( $\alpha$ ) of this SML-1 model. The magnitude of aggregate impact of *alpha* varies over the time periods under study and the specific stock in the empirical sample as well and the same is a derived one. Both the market microstructure models of *CAPM-1* and *SML-1* recognize stocks' market risk-

premium as the composite rather than conjoined decision reference for investors. Nonetheless, the CAPM fails to view the *alpha* as investors' decision reference point once we consider  $R_f$  as a variable with parametric distribution rather than a constant only.

$$(R_{it} - R_{ft})_{it} = \alpha_0 + \beta_{it}(R_{mt} - R_{ft})_{it} + \varepsilon \dots \dots \dots (SML - 1)$$

### Prospect Theory View

Since the capital market is not homogeneous across investors and the time periods,  $R_{ft}$  has its own dimension of variability. That is, methodologically, we cannot simply subtract  $R_{ft}$  from  $R_{it}$  and  $R_{mt}$  to derive the risk premium variables of  $(R_{it} - R_{ft})$  and  $(R_{mt} - R_{ft})$  for the stocks and the market respectively. In this study, therefore, we consider  $R_{ft}$  as a separate reference variable and derive the basic prospect theory version of the CAPM, the prospect theory model (PTM) as the third relationship in *PTM-1*. That is, while a stock's market risk premium performs as investors' single decision-reference point in both CAPM and SML, the variables  $R_{ft}$  and  $R_{mt}$  perform as the joint decision-reference points in the *PTM-1*. In the following pages, however, we include another dimension of investors' decision-reference – the isolation effect.

$$R_{it} = \alpha_0 + \alpha_1 R_{ft} + \beta_{it} R_{mt} + \varepsilon \dots \dots \dots (PTM - 1)$$

As discussed, the prospect theory offers three decision-references viz. certainty effect, reflection effect, and isolation effect. Here, the risk-free rate of return ( $R_{ft}$ ) in the market [viz., the governments' treasury bonds' yield rate of return] can as usual be assumed to have certainty effects on stocks' returns while the market's rate of return ( $R_{mt}$ ) can be assumed as to have the reflection effect, and the isolation effect can be interpreted as the third dimension along with  $R_{ft}$  and  $R_{mt}$ . For example, investors' past experiences at stock's short- or long-time lags, and/or his understandings about time-dependent dynamics of  $R_{ft}$  in the market, and/or that about the dynamics of  $R_{mt}$  etc. – these all can form a set of the third dimension of decision-references. We formally incorporate the said three features in the following autoregressive distributed lag (ARDL) model. We include these dimensions within the third dimension of investors' decision-reference.

In econometrics, the ARDL model has three distinct versions of its form – the unconditional short-run form (*USRF*), the conditional long-run form (*CLRF*), and the conditional error correction form (*CECF*) and we formulate their respective models for the basic *PTM-1* in the following model equations of *ARDL-1*, *ARDL-2*, and *ARDL-3*.

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

$$\Delta R_{it} = \alpha_0 + \left[ \sum_{r=1}^r \sum_{t=1}^n \alpha_{jr} \Delta R_{it-r} + \sum_{s=1}^s \sum_{i=1}^R \sum_{t=1}^n \beta_{is} \Delta X_{it-s} + \sum_{r=1}^r \sum_{t=1}^n \alpha_{kr} R_{it-r} \right] + \sum_{s=0}^s \sum_{i=1}^R \sum_{t=1}^n \beta_{iq} X_{it-s} + \xi_t \dots \dots \dots (ARDL - 2)$$

$$\Delta R_{it} = \alpha_0 + \left[ \sum_{r=1}^r \sum_{t=1}^n \alpha_{jr} \Delta R_{it-r} + \sum_{s=1}^s \sum_{i=1}^R \sum_{t=1}^n \beta_{is} \Delta X_{it-s} + \eta Z_{t-1} \right] + \varphi_t \dots \dots \dots (ARDL - 3)$$

In the above three ARDL specifications,  $\alpha_0$  represents the intercept and  $\varepsilon_t, \zeta_t$ , and  $\varphi_t$  are the residual error terms. The regressand  $\Delta R_{it}$  is the 1st difference of the regressand  $R_{it}$ . We have used  $R_{it}$  as the general notation for the stocks' returns and we regress the sample stocks' returns data individually. The regressor  $\Delta X_{it}$  denotes the 1st difference of the regressor  $X_{it}$  and,  $X_{it}$  is the  $i$ -th data of the variables of  $R_j$ , and  $R_m$  in the array of decision reference,  $R$ .

In *ARDL-1*, the regressors within bracket are the endogenous variable at  $r$  lags, independent variables at  $s$  lags, and independent regressors at current time  $t$  as well. In *ARDL-2*, the regressors within bracket include the endogenous 1st difference variable at  $r$  lags, the 1st difference of the independent decision-reference 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 *ARDL-2*, the 1st difference variables represent short-run effects while the rest two show long-run effects. In *ARDL-3*, the 1st difference variables show short-run effects and the third one,  $Z_{t-1}$  is the cointegrating equation factor at 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 our sample data for the concerned variables in the models are of  $I(0)$  stationary in nature, we do 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, we firstly employ *ARDL-1* models for the sample stocks' data at their different episodic sub-periods separately, use their respective bound-tests in *ARDL-2* for the robustness checks (Pesaran, Shin, & Smith, 2001), and then, derive the magnitudes of their error correction (EC) effects in the *ARDL-3* models.

**Lag selection**

Even if an Augmented Dicky Fuller (ADF) test for the unit root of the variables show the  $I(0)$  stationarity of the data both at the level and 1st difference with or without trend effects, in examining the cointegration dynamics, we 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 two independent regressor variables, we have identified the optimal lag-length of the endogenous variable under different methods, and we have used the AIC method for most of the cases but the SQ method only if the AIC method suggests for use of more than 12 lags. With the explanatory variables' set, we have selected a length of 4 lags and choose a procedure of the automatic selection in EViews 10 system.

**Empirical hypotheses**

With the individual pharma stock's returns in the NSE market in India, we have the following four null hypotheses of  $H_{01}, H_{02}, H_{03}$  and  $H_{04}$  against their respective alternative

research hypotheses of  $H_{11}$ ,  $H_{12}$ , and  $H_{13}$  and  $H_{14}$  with the explanatory variables in the regression models of respectively *PTM-1*, *ARDL-1*, *ARDL-2*, and *ARDL-3*.

**$H_{01}$ :** *In the PTM-1 model, the sample stocks' return  $R_{it}$  has no relationship with the explanatory decision-reference variables in the array  $R$  for the NSE Nifty market rate of return,  $R_{mt}$  and the risk-free rate of return,  $R_{ft}$ .*

**$H_{11}$ :** *In the PTM-1 model, the sample stocks' return  $R_{it}$  has significant positive or negative impacts of the explanatory decision-reference variables in the array  $R$  for the NSE Nifty market rate of return,  $R_{mt}$  and the risk-free rate of return,  $R_{ft}$ .*

**$H_{02}$ :** *In the ARDL-1 model, the sample stocks' return  $R_{it}$  has no short-run impact of the explanatory decision-reference variables in the array  $R$  for the market rate of return,  $R_{mt}$  and the risk-free rate of return,  $R_{ft}$  and their lag variables as well.*

**$H_{12}$ :** *In the ARDL-1 model, the sample stocks' return  $R_{it}$  has significant short-run impacts of the explanatory decision-reference variables in the array  $R$  for the market rate of return,  $R_{mt}$  and the risk-free rate of return,  $R_{ft}$  and their lag variables as well.*

**$H_{03}$ :** *In the ARDL-2 model, the stocks' return  $R_{it}$  has no long-run relationship with the explanatory decision-reference variables in the array  $R$  for the NSE Nifty market rate of return,  $R_{mt}$  and the risk-free rate of return,  $R_{ft}$  and their lag variables as well.*

**$H_{13}$ :** *In the ARDL-2 model, the stocks' return  $R_{it}$  has significant long-run relationship with the explanatory decision-reference variables in the array  $R$  for the NSE Nifty market rate of return,  $R_{mt}$  and the risk-free rate of return,  $R_{ft}$  and their lag variables as well.*

**$H_{04}$ :** *In the ARDL-3 model, the stocks' return  $R_{it}$  has insignificant error-correction effect with the explanatory decision-reference variables in the array  $R$  for the NSE Nifty market rate of return,  $R_{mt}$  and the risk-free rate of return,  $R_{ft}$  and their lag variables as well.*

**$H_{04}$ :** *In the ARDL-3 model, the stocks' return  $R_{it}$  has significant magnitudes for the error-correction term with the explanatory decision-reference variables in the array  $R$  for the NSE Nifty market rate of return,  $R_{mt}$  and the risk-free rate of return,  $R_{ft}$  and their lag variables as well.*

### Robustness Check

As proposed in Qadan (2019), the stocks' idiosyncratic risk can be identified as the residual component in the five-factor CAPM model in Fama and French (2015). In other words, the investors' isolation effect can be crept into the market microstructure model by means of their behavioral and psychological biases. For example, investors' fads and fashion to a specific stock can contribute to certain patterns in the prices. Hence, besides the earlier mentioned cases for the third dimension, there may be presence of stock-specific heteroscedasticity effects in the above ARDL models suggesting for a presence of stock specific residual noise effect and returns' variance effect. On the robustness of the results for the said hypotheses, the study performs the GARCH-X augmentation for the *ARDL-1* model in following *GARCH(p,q)* model for the stated ten sample firms over three different sample study periods separately. Hence, this test explores the following null hypothesis  $H_{05}$  against the relevant alternative research hypothesis  $H_{15}$ .



$$R_{it} = \alpha_0 + \left[ \sum_{r=1}^r \sum_{t=1}^n \alpha_{1r} R_{it-r} + \sum_{s=1}^s \sum_{i=1}^R \sum_{t=1}^n \beta_{is} X_{it-s} + \sum_{i=1}^R \sum_{t=1}^n \beta_i X_{it} \right] + u_{0p} \varepsilon_{t-p}^2 + v_{0q} \sigma_{R_{it-q}}^2 \dots \dots \dots (GARCHp, q)$$

**H<sub>05</sub>:** In the *GARCH-X(p,q)* augmentation of the *ARDL-1* model at the lag-orders of *p* and *q*, the squares of returns' residuals (viz.,  $\varepsilon_{it-p}^2$ ) and the variances of returns (viz.,  $\sigma_{R_{it-q}}^2$ ) have no effects on the sample stocks' returns over the different sample study periods.

**H<sub>15</sub>:** In the *GARCH-X(p,q)* augmentation of the *ARDL-1* model at the lag-orders of *p* and *q*, the squares of returns' residuals  $\varepsilon_{it-p}^2$  and the variances of returns  $\sigma_{R_{it-q}}^2$  have significant effects on the sample stocks' returns over the different sample study periods.

#### 4. Results and Findings

In Table 1, Table 2, and Table 3, we firstly document the results for the *PTM-1* model - a derived one from the linear CAPM framework for the periods of pre-COVID-19, COVID-19, and taking both data together. Then in Table 4, Table 5, and Table 6, we put forth our results of the *PTM-1* model in the ARDL framework for the sample stocks over the said three data sets. Here, we incorporate the observations of the unconditional ARDL models in details, the results on the F-bound F-test of Pesaran, Shin, & Smith (2001) in the conditional long-run form of the ARDL models, and magnitudes of the error correction factor in the conditional error correction form of these ARDL models. Finally, in Table 7, Table 8, and Table 9, we articulate the results for the *GARCH-X(p,q)* augmentation of the unconditional ARDL models for the said three cases of the sample data. We report these results in the stated sequence of the tables.

##### Results on prospect theory version of CAPM

The prospect theory, in Kahneman and Tversky (1979), views investors' framing decision choice with references of certainty effect, reflection effect, and isolation effect. A certainty effect is framed as the reference of investment opportunities at sure gains or sure losses. The risk-free rate of return ( $R_{ft}$ ) in the form of yields in governments' treasury bonds can proxy for certainty effect to sure gains in investors' decision choice. The present rate of inflation can proxy for certainty effect of sure losses. Again, investors compare the stocks' returns ( $R_{it}$ ) and/or performances vis-à-vis the market's returns ( $R_{mt}$ ) and/or performances and are also eager to know a reflection of the market on the stocks - that is, how much the investors for a particular stock are aligned with the investors in the overall stock market. Nonetheless, a framing caused by isolation effect can be represented by investors' arbitrage opportunity at his/her access of new information or a biased personal opinion or a stock-specific unsystematic risk component etc. That is, in the CAPM,  $R_{ft}$  can show the certainty effect while  $R_{mt}$  can show the reflection effect and the presence of *alpha* can depict the isolation effect component in the CAPM.

**Table 1.** Results on the Linear PTM-1 of the CAPM during the Pre-COVID-19 Data Period

Stocks	Variables	Coefficient	Std. Error	t-Statistic	Prob.	R <sup>2</sup> (Adj. R <sup>2</sup> )	F-stat (prob.)	DW	HTBPG (prob.)	BGSCLM (prob.)	JB_Norm (prob.)	CUSUM Test #
ALKE	$R_m$	0.218585	0.089794	2.434294	0.0158	0.098193 (0.089604)	11.432 (0.001)	1.629	0.6546 (0.521)	7.1326 (0.008)	11.1036 (0.0039)	Stable (Stable*)
	$R_f$	0.551447	0.13067	4.220155	0.001							
	$C$	0.004111	0.001055	3.895932	0.0001							
ARBN	$R_m$	1.730396	0.157173	11.00949	0.001	0.366808 (0.360777)	60.826 (0.001)	1.517	1.707 (0.184)	12.423 (0.001)	1283 (0.001)	Stable (Unstable)
	$R_f$	-0.040088	0.22872	-0.17527	0.861							
	$C$	0.000035	0.001847	0.019018	0.9848							
BION	$R_m$	0.592253	0.104239	5.681663	0.001	0.134926 (0.126687)	16.377 (0.001)	1.655	0.5296 (0.589)	6.23 (0.0134)	11.349 (0.0034)	Stable (Unstable)
	$R_f$	0.142539	0.151691	0.939666	0.3485							
	$C$	0.003486	0.001225	2.846226	0.0049							
CADI	$R_m$	0.695674	0.076587	9.083476	0.001	0.287744 (0.280961)	42.419 (0.001)	1.691	0.954 (0.387)	4.912 (0.0277)	27.172 (0.001)	Stable (Stable)
	$R_f$	-0.1248	0.11145	-1.1198	0.2641							
	$C$	0.001391	0.0009	1.546031	0.1236							
CIPL	$R_m$	0.798977	0.078596	10.16558	0.001	0.330147 (0.323768)	51.751 (0.001)	1422	3.482 (0.0325)	18.938 (0.001)	8.735 (0.0127)	Stable (Unstable)
	$R_f$	0.005684	0.114375	0.049696	0.9604							
	$C$	-0.00139	0.000924	-1.5073	0.1332							
DIVI	$R_m$	0.618599	0.075189	8.227229	0.001	0.256035 (0.24895)	36.136 (0.001)	1.698	0.0356 (0.965)	4.833 (0.029)	590 (0.001)	Stable (Unstable)
	$R_f$	0.274128	0.109416	2.505365	0.013							
	$C$	0.002235	0.000884	2.529802	0.0121							
LUPN	$R_m$	0.804155	0.062658	12.83406	0.001	0.472911 (0.467891)	94.207 (0.001)	1.606	2.150 (0.119)	8.479 (0.004)	7.84 (0.001)	Stable (Stable)
	$R_f$	-0.39135	0.091181	-4.29201	0.001							
	$C$	-0.00039	0.000736	-0.52508	0.6001							
REDY	$R_m$	0.775576	0.064825	11.96419	0.001	0.410436 (0.404822)	73.098 (0.001)	1.319	0.2179 (0.804)	26.811 (0.001)	16.86 (0.001)	Stable (Stable)
	$R_f$	0.214957	0.094334	2.278683	0.0237							
	$C$	0.000203	0.000762	0.266182	0.7904							
SUN	$R_m$	1.109299	0.066109	16.77975	0.001	0.578127 (0.57411)	143.89 (0.001)	1.685	1.524 (0.2203)	5.118 (0.0247)	61.98 (0.001)	Stable (Unstable)
	$R_f$	-0.1678	0.096203	-1.74426	0.0826							
	$C$	-0.0007	0.000777	-0.8987	0.3698							
TORP	$R_m$	0.415645	0.090319	4.601991	0.001	0.09444 (0.0858)	10.95 (0.001)	1.631	2.028 (0.124)	7.353 (0.0073)	12.25 (0.002)	Stable (Stable)
	$R_f$	-0.08465	0.131433	-0.64408	0.5202							
	$C$	0.002045	0.001061	1.927374	0.0553							

**Source:** Authors' own findings; # Status (Status) status refers to status of CUSUM test for residuals (squared residuals) at 5% level of significance; \* is for marginal status.

Now, with the results in Table 1, Table 2, and Table 3, we document the empirical findings at the prospect theory view of the CAPM respectively for Pre-COVID-19 period, during COVID-19 period, and taking them together.

In Table 1, we find that the coefficients of the intercept term i.e., the *alpha* component are significant only for ALKE, and BION (DIVI and TORP) at 0.1% (5%) level of significance and the same is insignificant for the rest six stocks. The table also shows that the coefficients of the risk-free rate of return i.e., the certainty effects are significant for ALKE and LUPN (DIVI and REDY) at 0.1% (5%) level of significance only while the coefficients remain insignificant with the other stocks. Interestingly, the table shows that the coefficients of the NSE market's returns i.e., the reflection effects are significant for all stocks at 0.1% level of significance while ALKE is significant at 1.6% level. The model shows a broader range of explanatory power (viz., from 8.58% to 57.411%, in the terms of the Adj.  $R^2$ -value), good-fit of their respective models (with presence of significant F-values at the range of 10.95 and 143.89) and residual homoscedasticity at 1% level of significance. The said explanatory power has less degree of precision in terms of their respective magnitudes of the Durbin Watson statistics (i.e., ranging from 1.319 to 1.689), and a sustained presence of residuals' serial correlation and non-normality at 1% level of significance. In general, given the nature of stability of the regression model for the stocks with the Pre-COVID-19 sample data, the prospect theory view of the CAPM finds good explanatory power for the reflection effect only while the other two effects are irregular and stock-specific as well.

In Table 2, our observations on reflection effects are mostly similar to those mentioned for Table 1 while certainty effects for SUN, ARBN and CIPL are significant respectively at 0.1%, 1% 2.5%, and 10% levels of significance but the isolation effect i.e., *alpha* component with CIPL only. Interestingly, we find an enhancement both in the magnitudes of Adj.  $R^2$  (within a range of 17.901% and 72.7012%) and F-statistics (to the range of 24.221 and 284.63) and these confirm the presence of huge attention of investors to the sample stocks during these COVID-19 sample period. Nonetheless, the table shows a presence of significant residual heteroscedasticity for the stocks, viz., ALKE, DIVI, and SUN respectively at 11.50%, 4%, and 1.75% levels of significance while the rest at 0.1% level of significance. Such general presence of heteroscedasticity across the pharma stocks hints for presence of isolation effects other than the *alpha* component for the sample stocks during the COVID-19 period. This presumption is confirmed with the presence of significant residual non-normality (read with the relevant DW statistics and the JB Normality test statistics as well) coupled with the instability at the CUSUM test of square of the residuals where we find most of the stocks unstable strictly at 5% level of significance. In brief, at investors' high alertness for COVID-19 information, the sample stocks show investors' reflection framing effect and the prospect theory model of the CAPM becomes inefficient to locate the certainty effects and isolation effects as well. That is, at times of information exigency in the capital markets, the CAPM fails to substantially incorporate all three aspects of the prospect theory within it.

**Table 2.** Results on the Linear PTM-1 of the CAPM Model during the COVID-19 Data Period

Stocks	Variables	Coefficient	Std. Error	t-Statistic	Prob.	R <sup>2</sup> (Adj. R <sup>2</sup> )	F-stat (prob.)	DW	HTBPG (prob.)	BGSCLM (prob.)	JB_Norm (prob.)	CUSUM Test #
ALKE	$R_m$	0.509207	0.073235	6.95306	0.001	0.186714 (0.17901)	24.221 (0.001)	1.479	2.209 (0.112)	15.239 (0.001)	311 (0.001)	Stable (Unstable)
	$R_f$	-0.14892	0.163196	-0.9125	0.3625							
	$C$	-0.0012	0.001702	-0.70516	0.4815							
ARBN	$R_m$	1.273133	0.086557	14.70859	0.001	0.507464 (0.5028)	108.69 (0.001)	1.265	5.634 (0.004)	34.851 (0.001)	258 (0.001)	Stable (Unstable)
	$R_f$	-0.44334	0.192883	-2.29847	0.0225							
	$C$	-0.00214	0.002011	-1.06208	0.2894							
BION	$R_m$	0.90024	0.056147	16.03373	0.001	0.549227 (0.54496)	128.54 (0.001)	1.521	6.327 (0.002)	12.573 (0.001)	55.74 (0.001)	Stable (Stable*)
	$R_f$	-0.16536	0.125117	-1.32161	0.1877							
	$C$	-0.0001	0.001305	-0.07838	0.9376							
CADI	$R_m$	0.99105	0.070405	14.07646	0.001	0.484345 (0.47946)	99.09 (0.001)	1.024	15.239 (0.001)	65.033 (0.001)	645.4 (0.001)	Stable (Unstable)
	$R_f$	-0.15972	0.156889	-1.01803	0.3098							
	$C$	0.000713	0.001636	0.43561	0.6636							
CIPL	$R_m$	1.224643	0.056344	21.73512	0.001	0.697602 (0.69474)	243.38 (0.001)	1.294	6.053 (0.003)	31.32 (0.001)	171.19 (0.001)	Stable (Unstable)
	$R_f$	0.236872	0.125556	1.886585	0.0606							
	$C$	0.002913	0.001309	2.22475	0.0272							
DIVI	$R_m$	0.938361	0.049782	18.8495	0.001	0.628031 (0.62451)	178.126 (0.001)	1.257	3.331 (0.038)	33.54 (0.001)	15.13 (0.001)	Stable (Stable*)
	$R_f$	-0.07384	0.110933	-0.66564	0.5064							
	$C$	-0.00076	0.001157	-0.65248	0.5148							
LUPN	$R_m$	1.089167	0.071778	15.17419	0.001	0.56159 (0.557435)	135.14 (0.001)	1.044	30.05 (0.001)	65.58 (0.001)	31.73 (0.001)	Stable (Unstable)
	$R_f$	0.797549	0.159948	4.986295	0.001							
	$C$	0.000822	0.001668	0.493077	0.6225							
REDY	$R_m$	0.881906	0.054974	16.04224	0.001	0.560193 (0.556024)	134.38 (0.001)	1.176	30.395 (0.001)	43.22 (0.001)	56.16 (0.001)	Stable (Unstable)
	$R_f$	-0.58263	0.122503	-4.75605	0.001							
	$C$	0.000479	0.001278	0.375208	0.7079							
SUN	$R_m$	1.072512	0.045925	23.35357	0.001	0.729575 (0.727012)	284.63 (0.001)	1.354	4.1624 (0.0169)	24.90 (0.001)	10.66 (0.001)	Stable (Stable*)
	$R_f$	0.290676	0.102339	2.840331	0.0049							
	$C$	-0.0000934	0.001067	-0.08747	0.9304							
TORP	$R_m$	0.778992	0.068319	11.40226	0.001	0.385613 (0.37979)	66.22 (0.001)	1.069	9.217 (0.001)	57.70 (0.001)	45.48 (0.001)	Stable (Unstable)
	$R_f$	0.085335	0.152241	0.560522	0.5757							
	$C$	-0.00096	0.001588	-0.60371	0.5467							

Source: Authors' own findings; # Status (Status) status refers to status of CUSUM test for residuals (squared residuals) at 5% level of significance; \* is for marginal status.

**Table 3. Results on the Linear PTM-1 of the CAPM Model during the Full-Length Data Period**

Stocks	Variables	Coefficient	Std. Error	t-Statistic	Prob.	R <sup>2</sup> (Adj. R <sup>2</sup> )	F-stat (prob.)	DW	HTBPG (prob.)	BGSCLM (prob.)	JB_Norm (prob.)	CUSUM Test #
ALKE	$R_m$	0.414314	0.054856	7.552762	0.001	0.123439 (0.119305)	29.85 (0.001)	1.466	4.878 (0.008)	32.623 (0.001)	514.96 (0.001)	Stable (Unstable)
	$R_f$	0.140587	0.109219	1.2872	0.1987							
	$C$	0.001768	0.001013	1.74576	0.0816							
ARBN	$R_m$	1.352398	0.074101	18.25081	0.001	0.441094 (0.438458)	167.313 (0.001)	1.365	1.208 (0.299)	48.84 (0.001)	1649 (0.001)	Stable (Unstable)
	$R_f$	-0.30492	0.147536	-2.06677	0.0394							
	$C$	-0.00128	0.001368	-0.93683	0.3494							
BION	$R_m$	0.815524	0.04877	16.72189	0.001	0.397586 (0.394744)	139.92 (0.001)	1.562	3.450 (0.0326)	21.054 (0.001)	58.28 (0.001)	Stable (Stable)
	$R_f$	-0.02902	0.097102	-0.29884	0.7652							
	$C$	0.001959	0.0009	2.175616	0.0301							
CADI	$R_m$	0.926035	0.050185	18.45259	0.001	0.445561 (0.442945)	170.37 (0.001)	1.199	21.365 (0.001)	80.99 (0.001)	2197 (0.001)	Stable (Unstable)
	$R_f$	-0.13256	0.099918	-1.32664	0.1853							
	$C$	0.001253	0.000927	1.351995	0.1771							
CIPL	$R_m$	1.158535	0.044217	26.20129	0.001	0.621331 (0.619545)	347.86 (0.001)	1.266	13.34 (0.001)	67.95 (0.001)	347.35 (0.001)	Unstable (Unstable)
	$R_f$	0.161929	0.088036	1.839348	0.0666							
	$C$	0.000965	0.000816	1.181863	0.2379							
DIVI	$R_m$	0.85317	0.039865	21.40147	0.001	0.521368 (0.51911)	230.93 (0.001)	1.416	1.869 (0.156)	39.614 (0.001)	131.05 (0.001)	Stable (Stable*)
	$R_f$	0.078028	0.079372	0.983065	0.3261							
	$C$	0.001012	0.000736	1.375105	0.1698							
LUPN	$R_m$	1.054093	0.050929	20.69744	0.001	0.513481 (0.511187)	223.75 (0.001)	1.033	51.703 (0.001)	132.95 (0.001)	380.53 (.001)	Stable (Unstable)
	$R_f$	0.34743	0.1014	3.426329	0.0007							
	$C$	0.000272	0.00094	0.289406	0.7724							
REDY	$R_m$	0.848249	0.040906	20.73656	0.001	0.506725 (0.504398)	217.78 (0.001)	1.145	56.77 (0.001)	94.64 (0.001)	248.74 (0.001)	Stable (Unstable)
	$R_f$	-0.26857	0.081445	-3.29752	0.0011							
	$C$	0.000484	0.000755	0.641068	0.5218							
SUN	$R_m$	1.090131	0.035773	30.47329	0.001	0.688525 (0.687056)	468.63 (0.001)	1.426	11.203 (0.001)	37.92 (0.001)	52.31 (0.001)	Stable (Stable*)
	$R_f$	0.110516	0.071225	1.551644	0.1215							
	$C$	-0.00047	0.00066	-0.71261	0.4765							
TORP	$R_m$	0.692933	0.051723	13.39692	0.001	0.298521 (0.295212)	90.22 (0.001)	1.238	15.95 (0.001)	71.59 (0.001)	119.47 (0.001)	Stable (Unstable)
	$R_f$	0.038051	0.102982	0.369494	0.7119							
	$C$	0.000793	0.000955	0.83056	0.4067							

Source: Authors' own findings; # Status (Status) status refers to status of CUSUM test for residuals (squared residuals) at 5% level of significance; \* is for marginal status.

Let us have a closure look into the results in Table 3 for the aggregate data – taking the two segments of study period together. This table shows that the reflection effects across the stocks are as usual significant, but they differ in magnitudes from their segmented magnitudes as depicted in Table 1 and Table 2. To our great surprise, we identify that the pre-COVID presence of *alpha* component sustains with only two stocks – ALKE and BION respectively at 8.5% and 3.5% level of significance while a list of five stocks – ARBN, CIPL and SUN (LUPN and REDY) respectively show sustained certainty effects at 4%, 7%, and 12.5% level (0.1% level) of significance during COVID-19 and at aggregate as well. These observations confirm that both certainty effect and isolation effect are stock-specific effects rather than general effects as hypothesized in the CAPM while the reflection effect is more general in nature. Moreover, we find moderate figures for the magnitudes of Adj.  $R^2$  in the models across the stocks ranging within 11.9305% and 68.7056%, and enhanced F-statistics value ranging within 29.85 and 486.63 each significant at 0.1% level of significance. The aggregate data shows significant heteroscedasticity problem for all stocks at 0.1% level of significance except ARBN at 30% level, BION at 4% level, and DIVI at 16% level. In regression, the sample stocks' return-residuals show significant serial correlations and presence of non-normality both at 0.01% level of significance while only BION have predictive stability at 5% level of significance in the terms of CUSUM test of square of the residuals. Hence, we find stock-specific general (selective) empirical evidence for reflection effect (isolation and certainty effects) even with the aggregate data.

In brief, the above three tables show that the prospect theory model can eloquently interpret investors' decision parameters differently from those as in the CAPM. The notion of risk-free rate of return is a dynamic decision reference to investors rather than a static one. Without incorporating the presence of information contents into the market microstructure model, the *alpha* component can be explained as the stock-specific isolation effect as we have proposed in the prospect theory view of the CAPM. Since there might be different components for isolation effects, the coefficients in models are unbiased but not the efficient ones. Hence, we report the ARDL augmentation of the CAPM in the following towards building an efficient empirical framework for the prospect theory view of the CAPM.

#### ARDL augmentation of prospect theory view

As mentioned in the earlier, investors' experience at short- or long-time horizons with a specific-stock, their understandings about the dynamics of the risk-free rate of return in the market, and that about the dynamics of the market's rate of return etc. constitute the matrix of third dimension of decision-references. By assuming investors be rational and the markets efficient, feasibility of such behavioral and/or psychological dimensions or decision matrix are theoretically ignored in the systematic risk-based framework of the CAPM. Based on the feasibility of the unbiased estimates for the stated prospect theory view of the CAPM, this study now brings into the issues of returns' endogeneity with the autoregressive lag distributed (ARDL) model.

**Table 4.** Results on the ARDL Augmentation of the PTM-1 Model during the Pre-COVID-19 Data Period

Variables / Parameters	ALKE	ARBN	BION	CADI	CIPL	DIVI	LUPN	REDY	SUN	TORP
$R_{it-1}$	0.163438 (0.067257) (0.016)	0.240636 (0.067982) (0.001)	0.167393 (0.064867) (0.0106)	0.143069 (0.061207) (0.0204)	0.290178 (0.066233) (0.001)	0.164107 (0.068025) (0.0167)	0.167977 (0.069041) (0.0159)	0.33749 (0.065251) (0.001)	0.149437 (0.068199) (0.0296)	0.187221 (0.065688) (0.0048)
$R_{it-2}$	0.118457 (0.066963) (0.0784)						0.158237 (0.069511) (0.0239)			
$R_{it-3}$							0.046012 (0.069695) (0.5099)			
$R_{it-4}$							-0.23069 (0.067193) (0.001)			
$R_{mt}$	0.180178 (0.088255) (0.0425)	1.792861 (0.170272) (0.001)	0.563426 (0.103756) (0.001)	0.668089 (0.081457) (0.001)	0.803772 (0.083355) (0.001)	0.62815 (0.083017) (0.001)	0.854062 (0.068322) (0.001)	0.790466 (0.067737) (0.001)	1.117673 (0.072759) (0.001)	0.374547 (0.090501) (0.001)
$R_{mt-1}$		-0.513822 (0.215223) (0.0179)			-0.331773 (0.098373) (0.001)	-0.185936 (0.098617) (0.0608)	-0.27484 (0.092732) (0.0034)	-0.332257 (0.083564) (0.001)	-0.148874 (0.108327) (0.1708)	
$R_{mt-2}$						0.13001 (0.09177) (0.1581)	-0.18452 (0.095082) (0.0537)			
$R_{mt-3}$						-0.153183 (0.086994) (0.0798)	0.048969 (0.096888) (0.6138)			
$R_{mt-4}$							0.209419 (0.090665) (0.0219)			
$R_{it}$	0.438381 (0.132363) (0.0011)	-0.019898 (0.224692) (0.9295)	0.105181 (0.151192) (0.4874)	-0.155723 (0.123235) (0.2078)	0.141817 (0.120792) (0.2417)	0.246967 (0.1105) (0.0265)	-0.28249 (0.091524) (0.0023)	0.167502 (0.090223) (0.0648)	-0.176282 (0.095951) (0.0676)	-0.081992 (0.129853) (0.5285)
$R_{it-1}$				0.128277 (0.134032) (0.3397)	-0.24961 (0.120622) (0.0398)					
$R_{it-2}$				-0.069792 (0.133048) (0.6005)						
$R_{it-3}$				0.265472 (0.122596) (0.0315)						

Variables / Parameters	ALKE	ARBN	BION	CADI	CIPL	DIVI	LUPN	REDY	SUN	TORP
<i>C</i>	0.003103 (0.001093) (0.005)	0.000139 (0.001809) (0.939)	0.002927 (0.001236) (0.0188)	0.00119 (0.0009) (0.1875)	-0.000953 (0.000887) (0.284)	0.001973 (0.000896) (0.0287)	-0.00046 (0.000713) (0.5192)	0.000142 (0.00072) (0.8435)	-0.000648 (0.000774) (0.4033)	0.001651 (0.001057) (0.1197)
R <sup>2</sup> (Aj. R <sup>2</sup> )	0.143719 (0.127092)	0.40071 (0.389129)	0.159982 (0.147866)	0.32659 (0.306687)	0.399541 (0.384967)	0.288076 (0.267034)	0.541065 (0.517886)	0.479756 (0.469703)	0.590581 (0.58267)	0.128365 (0.115794)
Reg. F-stat (Prob.)	8.643804 (0.001)	34.60216 (0.001)	13.20458 (0.001)	16.40851 (0.001)	27.41416 (0.001)	13.69048 (0.001)	23.34336 (0.001)	47.7225 (0.001)	74.6487 (0.001)	10.21069 (0.001)
Durbin Watson Stat	2.0175	2.0125	1.992	1.985	2.079	1.9784	2.041	2.022	1.974	1.984
HTBPG F- stat (Prob.)	0.4703 (0.7558)	1.755 (0.139)	1.339 (0.263)	0.670914 (0.6733)	1.0636 (0.3817)	0.694072 (0.6547)	1.310475 (0.2269)	0.317251 (0.8662)	1.410663 (0.2316)	1.213103 (0.306)
BGSCLM F- stat (Prob.)	0.271 (0.6034)	0.3069 (0.5802)	0.0776 (0.7809)	0.000043 (0.9948)	3.947097 (0.0483)	0.245534 (0.6208)	0.987667 (0.3215)	0.315157 (0.5751)	0.540856 (0.4629)	0.105358 (0.7458)
JB Norm (Prob.)	15.75 (0.001)	1001.83 (0.001)	16.83 (0.001)	23.71 (0.01)	12.473 (0.002)	789.7 (0.001)	106.89 (0.001)	31.514 (0.001)	95.97 (0.001)	16.73 (0.001)
CUSUM Test for residuals	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)
CUSUM Test for sq. of residuals	Stable (0.05)	Unstable (0.05)	Stable* (0.05)	Stable (0.05)	Stable* (0.05)	Unstable (0.05)	Stable (0.05)	Stable* (0.05)	Unstable (0.05)	Stable (0.05)
Results on the Error Correction Model for the ARDL Augmented <i>PTM-T</i> Model										
F-Bound F- stat (Table value at $\alpha =$ 0.01)	19.03289 (4.358)	31.19858 (4.358)	45.96364 (4.358)	53.03931 (4.358)	29.25209 (4.358)	38.36944 (4.358)	17.85997 (4.358)	25.97725 (4.358)	39.76414 (4.358)	39.50605 (4.358)
Magnitude of ECT (Prob.)	-0.718105 (0.001)	-0.759364 (0.001)	-0.832607 (0.001)	-0.856931 (0.001)	-0.709822 (0.001)	-0.835893 (0.001)	-0.858463 (0.001)	-0.66251 (0.001)	-0.850563 (0.001)	-0.812779 (0.001)

**Source:** Authors' own findings; # Status (Status) status refers to status of CUSUM test for residuals (squared residuals) at 5% level of significance; \* is marginal status.



**Table 5.** Results on the ARDL Augmentation of the PTM-1 Model during the COVID-19 Data Period

Variables / Parameters	ALKE	ARBN	BION	CADI	CIPL	DIVI	LUPN	REDY	SUN	TORP
$R_{it-1}$	0.284515 (0.059784) (0.001)	0.380896 (0.065531) (0.001)	0.204014 (0.069354) (0.004)	0.495082 (0.057713) (0.001)	0.36958 (0.065963) (0.01)	0.350741 (0.066089) (0.001)	0.488221 (0.059718) (0.001)	0.422355 (0.060364) (0.001)	0.335253 (0.065017) (0.001)	0.468832 (0.061971) (0.001)
$R_{it-2}$		0.123974 (0.045003) (0.006)	0.19958 (0.068629) (0.004)			0.070725 (0.040606) (0.083)				
$R_{it-3}$			-0.07611 (0.047357) (0.1096)							
$R_{it-4}$			-0.08266 (0.046264) (0.076)							
$R_{mt}$	0.476997 (0.070942) (0.001)	1.428135 (0.083964) (0.001)	0.899198 (0.057327) (0.001)	1.04353 (0.064437) (0.001)	1.129446 (0.056964) (0.001)	0.977536 (0.049032) (0.001)	0.967917 (0.066359) (0.001)	0.882059 (0.052283) (0.001)	1.066871 (0.045941) (0.001)	0.752513 (0.063956) (0.001)
$R_{mt-1}$		-0.710113 (0.121347) (0.001)	-0.19358 (0.086669) (0.0266)	-0.37328 (0.086822) (0.001)	-0.35421 (0.094731) (0.001)	-0.366168 (0.079556) (0.001)	-0.458733 (0.090711) (0.001)	-0.291072 (0.075249) (0.001)	-0.37306 (0.083913) (0.001)	-0.299572 (0.078861) (0.001)
$R_{mt-2}$			-0.19212 (0.08422) (0.0236)	-0.07932 (0.064669) (0.2214)			0.131947 (0.065224) (0.0444)	-0.12344 (0.051769) (0.018)	-0.09156 (0.044718) (0.0419)	
$R_{mt-3}$				-0.01001 (0.063376) (0.8746)						
$R_{mt-4}$				-0.23044 (0.060883) (0.001)						
$R_{it}$	-0.202579 (0.156012) (0.1956)	-0.070676 (0.18202) (0.6982)	-0.172404 (0.121677) (0.1581)	-0.24773 (0.138712) (0.0756)	0.158486 (0.118382) (0.1821)	-0.029642 (0.103835) (0.7756)	0.454494 (0.144505) (0.002)	-0.428191 (0.113061) (0.001)	0.103683 (0.102332) (0.3122)	-0.060569 (0.136932) (0.6587)
$R_{it-1}$				-0.11056 (0.145297) (0.4476)					0.242474 (0.10398) (0.0207)	
$R_{it-2}$				0.059827 (0.14607) (0.6826)						
$R_{it-3}$				0.338738 (0.142122) (0.0181)						

Variables / Parameters	ALKE	ARBN	BION	CADI	CIPL	DIVI	LUPN	REDY	SUN	TORP
<i>C</i>	-0.001561 (0.001632) (0.340)	-0.001579 (0.001876) (0.4009)	0.000861 (0.001305) (0.5098)	0.001481 (0.001435) (0.3032)	0.00185 (0.001257) (0.1425)	-0.000927 (0.001115) (0.4063)	-0.000018 (0.001496) (0.9906)	0.000591 (0.001193) (0.621)	0.000549 (0.001028) (0.5938)	-0.000767 (0.001442) (0.5953)
R <sup>2</sup> (Aj. R <sup>2</sup> )	0.267282 (0.256764)	0.605926 (0.596361)	0.597051 (0.581013)	0.672153 (0.655679)	0.736074 (0.730998)	0.68413 (0.676464)	0.677844 (0.670025)	0.6468 (0.63821)	0.771661 (0.764978)	0.521556 (0.512356)
Reg. F-stat (Prob.)	25.4131 (0.001)	63.34893 (0.001)	37.22774 (0.001)	40.79913 (0.001)	145.0246 (0.001)	89.23352 (0.001)	86.6885 (0.001)	75.44 (0.001)	115.4648 (0.001)	56.68575 (0.001)
Durbin Watson Stat	1.997	1.927	1.991	1.8879	1.988	2.0328	1.862	1.958	1.997	2.048
HTBPG F- stat (Prob.)	2.252346 (0.0833)	2.038295 (0.0747)	1.507665 (0.1563)	2.57502 (0.006)	9.872773 (0.001)	0.84329 (0.5204)	7.715094 (0.001)	9.959 (0.001)	2.382964 (0.0301)	2.440839 (0.048)
BGSCLM F- stat (Prob.)	0.00219 (0.9627)	1.172954 (0.2801)	0.040557 (0.8406)	1.219048 (0.2709)	0.02526 (0.8739)	0.709531 (0.4006)	2.915215 (0.0893)	0.2481 (0.619)	0.005529 (0.9408)	0.772548 (0.3804)
JB Norm (Prob.)	272.89 (0.001)	461.4 (0.001)	139.58 (0.001)	634.98 (0.001)	136.61 (0.001)	20.25 (0.001)	130.03 (0.001)	30.589 (0.001)	9.446 (0.009)	29.63 (0.001)
CUSUM Test for residuals	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)
CUSUM Test for sq. of residuals	Unstable (0.05)	Unstable (0.05)	Stable* (0.05)	Unstable (0.05)	Unstable (0.05)	Stable (0.05)	Stable* (0.05)	Unstable (0.05)	Stable (0.05)	Unstable (0.05)
Results on the Error Correction Model for the ARDL Augmented <i>PTM-1</i> Model										
F-Bound F- stat (Table value at $\alpha =$ 0.01)	43.81127 (4.358)	14.25022 (4.358)	15.42842 (4.358)	19.57932 (4.358)	23.27522 (4.358)	19.30204 (4.358)	18.51519 (4.358)	23.86318 (4.358)	26.62122 (4.358)	18.99444 (4.358)
Magnitude of ECT (Prob.)	-0.715485 (0.001)	-0.49513 (0.01)	-0.755171 (0.001)	-0.504918 (0.001)	-0.63042 (0.001)	-0.578534 (0.001)	-0.511779 (0.001)	-0.577645 (0.001)	-0.664747 (0.001)	-0.531168 (0.001)

**Source:** Authors' own findings; # Status (Status) status refers to status of CUSUM test for residuals (squared residuals) at 5% level of significance; \* is marginal status.

**Table 6.** Results on the ARDL Augmentation of the PTM-1 Model during the Full-Length Data Period

Variables / Parameters	ALKE	ARBN	BION	CADI	CIPL	DIVI	LUPN	REDY	SUN	TORP
$R_{it-1}$	0.275788 (0.044081) (0.001)	0.318123 (0.047233) (0.001)	0.179361 (0.048271) (0.001)	0.390256 (0.043549) (0.001)	0.380752 (0.045843) (0.001)	0.297711 (0.046597) (0.001)	0.503971 (0.04831) (0.001)	0.425448 (0.04846) (0.001)	0.294876 (0.046571) (0.001)	0.382191 (0.045291) (0.001)
$R_{it-2}$		0.07176 (0.035174) (0.042)	0.163832 (0.048323) (0.001)				0.037699 (0.053797) (0.484)	0.020768 (0.051059) (0.6844)		
$R_{it-3}$			-0.06411 (0.038245) (0.095)				-0.12947 (0.050772) (0.011)	-0.074553 (0.033804) (0.028)		
$R_{it-4}$			-0.08568 (0.037711) (0.0236)				-0.01211 (0.037791) (0.749)			
$R_{it-5}$							0.06447 (0.037714) (0.088)			
$R_{it-6}$							0.073563 (0.037563) (0.051)			
$R_{it-7}$							-0.15396 (0.034285) (0.001)			
$R_{mt}$	0.383396 (0.052842) (0.001)	1.476899 (0.075102) (0.001)	0.830042 (0.050234) (0.001)	0.943227 (0.048663) (0.001)	1.08238 (0.044745) (0.001)	0.890333 (0.040748) (0.001)	0.956292 (0.047355) (0.001)	0.849086 (0.039632) (0.001)	1.096848 (0.036621) (0.001)	0.6703 (0.051094) (0.001)
$R_{mt-1}$		-0.625558 (0.100292) (0.001)	-0.16044 (0.066596) (0.0164)	-0.274884 (0.064189) (0.001)	-0.371026 (0.066729) (0.001)	-0.308728 (0.057756) (0.001)	-0.48824 (0.065174) (0.001)	-0.309311 (0.058332) (0.001)	-0.31653 (0.0634) (0.001)	-0.221858 (0.059642) (0.0002)
$R_{mt-2}$			-0.14076 (0.064603) (0.299)	-0.033649 (0.050991) (0.5097)			0.083687 (0.069563) (0.229)	-0.090084 (0.056927) (0.1143)	-0.07917 (0.036494) (0.0306)	
$R_{mt-3}$				0.042529 (0.050445) (0.3997)			0.162794 (0.066449) (0.015)			

Variables / Parameters	ALKE	ARBN	BION	CADI	CIPL	DIVI	LUPN	REDY	SUN	TORP
$R_{mt-4}$				-0.227265 (0.048397) (0.001)						
$R_{it}$	0.065853 (0.105532) (0.533)	-0.111366 (0.141517) (0.4318)	0.022705 (0.101157) (0.8225)	-0.136217 (0.096598) (0.1593)	0.180662 (0.088253) (0.0413)	0.084955 (0.076248) (0.2658)	0.207511 (0.087796) (0.0186)	-0.192861 (0.074416) (0.0099)	-0.02427 (0.073838) (0.743)	-0.029369 (0.096169) (0.7602)
$R_{it-1}$			-0.05856 (0.10748) (0.5861)	-0.013388 (0.10276) (0.8964)	-0.155703 (0.088668) (0.0798)				0.182967 (0.073632) (0.0133)	
$R_{it-2}$			0.046117 (0.10657) (0.6654)	-0.00144 (0.102692) (0.9888)						
$R_{it-3}$			0.196772 (0.106539) (0.0655)	0.347367 (0.097299) (0.001)						
$R_{it-4}$			-0.32829 (0.100638) (0.001)							
$C$	0.00108 (0.000979) (0.2704)	-0.000839 (0.0013) (0.5187)	0.001725 (0.00089) (0.0532)	0.001078 (0.000843) (0.2016)	0.000642 (0.000764) (0.4012)	0.000751 (0.000711) (0.2914)	-0.00014 (0.000816) (0.863)	0.000571 (0.000693) (0.4103)	-0.00016 (0.000635) (0.8023)	0.000448 (0.000892) (0.6157)
$R^2$ (Aj. $R^2$ )	0.197266 (0.19156)	0.510273 (0.504429)	0.470529 (0.455032)	0.576382 (0.5661)	0.676256 (0.672402)	0.56446 (0.560322)	0.665153 (0.65528)	0.606987 (0.600374)	0.723303 (0.719332)	0.400737 (0.395044)
Reg. F-stat (Prob.)	34.56785 (0.001)	87.31567 (0.001)	30.36315 (0.001)	56.05733 (0.001)	175.4641 (0.001)	136.404 (0.001)	67.3733 (0.001)	91.78408 (0.001)	182.1133 (0.001)	70.3825 (0.001)
Durbin Watson Stat	2.012	1.987	2.0034	1.9756	2.0533	2.021	1.925	1.983	2.0191	2.0338
HTBPG F- stat (Prob.)	3.163779 (0.0244)	1.645883 (0.1467)	1.413314 (0.1565)	4.880011 (0.001)	12.44818 (0.001)	1.189099 (0.3149)	7.691089 (0.001)	12.153 (0.001)	3.310046 (0.0034)	4.464703 (0.002)
BGSCLM F- stat (Prob.)	0.108443 (0.7421)	0.171619 (0.6789)	0.185508 (0.6669)	0.23555 (0.6277)	2.308762 (0.1294)	0.595803 (0.4406)	2.488747 (0.1154)	0.522433 (0.4702)	0.500665 (0.4796)	1.053825 (0.305)
JB Norm (Prob.)	482.85 (0.001)	1623 (0.001)	124.18 (0.001)	1133 (0.001)	221.65 (0.001)	186.69 (0.001)	512.65 (0.001)	144.13 (0.001)	69.219 (0.001)	70.91 (0.001)

Variables / Parameters	ALKE	ARBN	BION	CADI	CIPL	DIVI	LUPN	REDY	SUN	TORP
CUSUM Test for residuals	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)	Stable (0.05)
CUSUM Test for sq. of residuals	Unstable (0.05)	Unstable (0.05)	Stable (0.05)	Unstable (0.05)	Stable* (0.05)	Stable (0.05)	Unstable (0.05)	Stable* (0.05)	Stable* (0.05)	Stable* (0.05)
<b>Results on the Error Correction Model for the ARDL Augmented <i>PTM-1</i> Model</b>										
F-Bound F-stat (Table value at $\alpha = 0.01$ )	76.21134 (4.358)	35.68326 (4.358)	31.80534 (4.358)	49.93508 (4.358)	46.38048 (4.358)	42.63587 (4.358)	23.95963 (4.358)	33.1161 (4.358)	57.67847 (4.358)	46.96279 (4.358)
Magnitude of ECT (Prob.)	-0.724212 (0.001)	-0.610117 (0.001)	-0.806587 (0.001)	-0.609744 (0.001)	-0.619248 (0.001)	-0.665897 (0.001)	-0.615839 (0.001)	-0.628338 (0.001)	-0.705124 (0.001)	-0.617809 (0.001)

**Source:** Authors' own findings; # Status (Status) status refers to status of CUSUM test for residuals (squared residuals) at 5% level of significance; \* is for marginal status.

Even if the presence of returns' endogeneity effects on investors' present decision choices can be theoretically examined by presence of endowment effects, we limit our scope of exploration to isolation effect only and we hypothesize that investors' stock-specific and market-oriented long-memory vis-à-vis short-memory effects are different. We document our results on the ARDL augmentation of the prospect theory view of the CAPM in the following. We portray the results in Table 4, Table 5, and Table 6 respectively for the Pre-COVID-19 period, during COVID-19 period, and the aggregate data as well.

In Table 4 for the Pre-COVID-19 period, we document that the stock-specific isolation effects for ARBN, BION, CADI, CIPL, DIVI, REDY, SUN and TORP are significant at 3% level of significance up to their first lags while for ALKE and LUPN, the effects have presence of higher order significant lag impacts. Besides, stocks viz., ARBN, CIPL, DIVI, LUPN, REDY, and SUN have presence of higher order NSE Nifty market-oriented isolation impacts. Nonetheless, we also report the presence of bond-market oriented isolation effects for CADI and CIPL as well. Further, the table confirms that the magnitudes of isolation effects in the terms of the *alpha* component across the stocks are now somewhat different from that observed in the prospect theory view of the CAPM earlier in Table 1. These observations confirm that isolation effect is of matrix in nature. On the brief statistics of the ARDL models here, we find that the regression models for the stocks in general have very good explanatory powers, they have significant F-statistics values, satisfactory Durbin Watson statistics values, the absence of residual heteroscedasticity serial correlations at 0.01 level of significance. At 5% level of significance, all stocks are stable at CUSUM tests of residuals while their CUSUM tests of squares of residuals are stable for ALKE, CADI, LUPN, and TROP, the same are marginally stable for BION, CIPL, and REDY but unstable for ARBN, DIVI, and SUN. Apart from the above, the long-run ARDL form and F-bound tests also confirm their long-run cointegration relationships at 1% level of significance. Furthermore, we find presence of significant (at 0.1% level) coefficients for the error correction terms in the error correction forms of the respective ARDL models. However, we find non-normality of the residual error components for the ARDL models. In brief, we document that the ARDL augmentation of the prospect theory view of CAPM during pre-COVID-19 has greater degree of stability and efficiency in explaining the stocks' returns with the certainty effects, reflection effects, and isolation effects than those at the simple prospect theory model of the CAPM only.

With the ARDL model for COVID-19 sample period, in Table 5, the study finds somewhat different observations from those observed for pre-COVID-19 sample period. Here, we report that all stocks have significant short-memory isolation effect at 0.1% level of significance at the 1st day's lag while ARBN (DIVI) has the same at 1% (10%) level of significance at the 2nd day's lag and BION has the same effects at the 3rd and 4th days lag respectively at 11% and 8% levels of significance. Besides the presence of significant reflection effect across the stocks at 0.1% level of significance, we find stock-specific short-memory isolation effects with the lags of market returns viz., with the 1st lag for all stocks at 3% level of significance, with the 2nd lag for BION, LUPIN, REDY and SUN, and with the 4th lag for CADI at 0.1% level of significance. Nonetheless, we find presence of certainty effect with LUPN and REDY at 0.2% level of significance while there are

bond-market return specific short-run isolation effect respectively with SUN and CADI at the 2nd lag and 4th lag at 1% level of significance. It is interesting to observed that none of the stocks, those have showed significant intercept figures representing the *alpha* component in Table 1, are now have become insignificant and these suggest that arbitrage opportunity is neither a market-specific factor nor a stock-specific factor. The arbitrage opportunity that is contributing to isolation effect can be located at investors' short-memory effects. Furthermore, the regression models for the sample stocks have good-fits and explanatory powers with reference to their respective values for the DW statistics, F-statistics, and Adj.  $R^2$  values. We also find a presence of homoscedasticity with the stocks' returns except of four stocks viz., CADI, CIPL, LUPN, and REDY all at 1% level of significance. The models with the respective stocks are stable at CUSUM test of residuals at 5% level of significance while with only two stocks viz., DIVI and SUN, the respective models are stable at CUSUM test of squares of residuals at 5% level while BION and LUPN are marginally stable, and the rest stocks are unstable. At diagnosis for the presence of such model instability can be attributed to presence of residual non-normality (read with the JB normality test statistics) and heteroscedasticity problem as well. We confirm presence of significant long run cointegrations and document significant magnitudes for the error correction (EC) terms in the ARDL models.

Now, we investigate results for the augmented ARDL model for the prospect theory view of the CAPM with the full-length sample period in Table 6. It shows presence of investors' short-memory isolation effects significant at 0.1% level of significance at one day lag for all stocks and besides this, ARBN has an additional isolation effect at the 2nd day's lag, BION has at the 2nd, 3rd, and 4th day's lags, LUPN has at 3rd, 5th, 6th, and 7th day's lags as well. The higher order lags with BION (LUPN) shows the presence of continued isolation effect at the combined study period but linked to the COVID-19 (pre-COVID-19) sample period as well. The market-specific reflection effects are also live there with the full-length study period across the stocks and robustly significant as well while the relevant isolation effects are visible at the 1st lag for all stocks (except ALKE), at the 2nd lag with SUN, at the 3rd lag with LUPN, and at the 4th lag with CADI. Furthermore, we find limited presence of certainty effect with CIPL, LUPN, and REDY significant at 5%, 2%, and 1% levels of significance respectively. Bond market-specific isolation effects are also observable with BION at its 3rd and 4th lags, that with CADI at the 3rd lag, and with CIPL (SUN) at 8% level of significance (1.5% level of significance). Nonetheless, we report of the *alpha* component with BION only at 6% level of significance. On the validity of these results, we find robust explanatory power of the model ranging from 19.156% to 71.933% in the terms of Adj.  $R^2$  value, significant F-statistics value for the regression models, and absence of serial correlations for returns' residuals. However, at residual diagnosis of the results, we find that the residuals are as usual non-normal for all stocks and there exist heteroscedasticity with ALKE, CADI, CIPL, LUPN, REDY, SUN and TORP while ARBN, BION, and DIVI stands residual homoscedasticity. Apart from the above, the regression models for the stocks are all stable at CUSUM test of residuals while BION and DIVI qualify CUSUM test of squares of residuals modestly, CIPL, REDY, SUN, and TROP manages the same marginally but ALKE, ARBN, and CADI show their instability. Therefore, besides the presence of limited certainty effects and general reflection effects,

significant long-run cointegrations, and significant error correction terms as well, we acknowledge the possibility of a presence of yet-not-revealed isolation effects.

At the kernel, with the ARDL augmentation procedures, we document an array of stock-specific isolation effects that contribute to the presence of heteroscedasticity - it can be linked to investors' long- vs short-memory effects related to the specific stocks, the stock market itself, and the bond-market as well. In brief, the observations are supportive to the presence of an open and dynamic market microstructure equilibrium. However, in the following, we explore the extents of such dynamicity of the ARDL models with their GARCH-X extensions.

### Results on GARCH(p,q) augmentation of prospect theory

In the GARCH-X augmentation, we augment the earlier ARDL models for the stocks with both their residuals' square and variances of the dependent return variables at certain lags. This methodology assists us in identifying the effects of the models' heterogeneity impacts if caused by either by models' noise factor (exogeneity issue) or the returns noise factor (endogeneity issue) or by both. Such exogeneity and endogeneity issues could influence investors' decision choice in the terms of isolation effects. Nonetheless, such isolation effects are otherwise mixed with the certainty effects and reflection effects.

Let us consider the results of the GARCH-X augmentation with the pre-COVID-19 data sets for our sample stocks in Table 7. Here, we find that the GARCH-X augmentation has refined the coefficient estimates from those observed in Table 4. We document some robust revisions in their magnitudes and levels of significance for the stocks. Remarkably, we find ten instances of prominent change in status from significant to insignificant (from insignificant to significant) for ALKE at reflection effect and with REDY (ARBN and BION) at certainty effect. Nonetheless, we find some other revisions viz., at the 1st lag of certainty effect i.e.,  $R_{t-1}$  for CADI and CIPL, and with the *alpha* component in the model for ARBN, CADI, CIPL, and TORP. That is, it is intuitive to find that investors' isolation effects influence their propensities to certainty effects and reflection effects as well. In examining the nature and magnitudes of such propensities, we document that at GARCH-X augmentation, the sample stocks show fixed residual impacts for all stocks (except two stocks – DIVI and TORP) while their squares of the residuals respectively at their 1st and 2nd lags mostly have positively and negatively significant coefficients at 1% level of significance. Beside the above, we depict evidence of positively significant variance effect of the dependent variable at the 1st lag across the sample stocks (except of BION and CADI) while CIPL shows a negatively significant coefficient value for them. In brief, with GARCH-X augmentation, we demonstrate the presence of both exogeneity and endogeneity and explain the same in the terms of the dimension of isolation effect in the prospect theory view of the CAPM.



**Table 7.** Results on the GARCH-X Augmentation of the PTM-1 Model during the Pre-COVID-19 Data

Variables / Parameters	ALKE	ARBN	BION	CADI	CIPL	DIVI	LUPN	REDY	SUN	TORP
$R_{it-1}$	0.117259 (0.052699) (0.0261)	0.275244 (0.080778) (0.001)	0.10886 (0.070633) (0.1233)	0.152421 (0.061608) (0.0134)	0.222876 (0.061995) (0.001)	0.122562 (0.062696) (0.0506)	0.240366 (0.082468) (0.0036)	0.261434 (0.061335) (0.001)	0.154386 (0.058242) (0.008)	0.215239 (0.073511) (0.0034)
$R_{it-2}$	0.042653 (0.015727) (0.0067)						0.116711 (0.069743) (0.0942)			
$R_{it-3}$							-0.01756 (0.0657) (0.7893)			
$R_{it-4}$							-0.19386 (0.060366) (0.0013)			
$R_{mt}$	0.062336 (0.066924) (0.3516)	1.246205 (0.075088) (0.001)	0.514795 (0.093472) (0.001)	0.769383 (0.069609) (0.001)	0.794231 (0.055581) (0.001)	0.549423 (0.049098) (0.001)	0.808519 (0.064635) (0.001)	0.712893 (0.04837) (0.001)	1.096123 (0.065232) (0.001)	0.463545 (0.082439) (0.001)
$R_{mt-1}$		-0.467275 (0.175276) (0.008)			-0.25524 (0.073779) (0.001)	-0.121594 (0.071554) (0.0893)	-0.27985 (0.09846) (0.0045)	-0.189209 (0.071204) (0.008)	-0.16944 (0.108394) (0.118)	
$R_{mt-2}$						0.076164 (0.060095) (0.205)	-0.14916 (0.08276) (0.0715)			
$R_{mt-3}$						-0.144278 (0.063325) (0.0227)	0.090178 (0.098507) (0.36)			
$R_{mt-4}$							0.153559 (0.085221) (0.0716)			
$R_{it}$	0.507223 (0.105394) (0.001)	0.257739 (0.122428) (0.0353)	-0.282223 (0.088184) (0.0014)	-0.022703 (0.104929) (0.8287)	0.059108 (0.122911) (0.6306)	0.241716 (0.092528) (0.009)	-0.35056 (0.094741) (0.0002)	-0.050711 (0.072806) (0.4861)	-0.18311 (0.064898) (0.005)	-0.15715 (0.126952) (0.2158)
$R_{it-1}$				0.264258 (0.130417) (0.0427)	-0.085404 (0.110806) (0.4409)					

Variables / Parameters	ALKE	ARBN	BION	CADI	CIPL	DIVI	LUPN	REDY	SUN	TORP
$R_{\beta_2}$				-0.02437 (0.116795) (0.8347)						
$R_{\beta_3}$				0.331248 (0.110239) (0.0027)						
$C$	0.00161 (0.000767) (0.0359)	0.001283 (0.0000893) (0.001)	0.002614 (0.001034) (0.0115)	0.001807 (0.000763) (0.0178)	-0.001112 (0.000515) (0.0307)	0.001443 (0.000624) (0.0208)	-0.00088 (0.000635) (0.1679)	-0.000233 (0.000603) (0.6993)	-0.00017 (0.000807) (0.8307)	0.002338 (0.000919) (0.011)
<b>Variance Equation</b>										
$C$	0.000086 (0.0000291) (0.0032)	0.0000338 (0.0000102) (0.001)	0.000113 (0.0000414) (0.006)	0.0000852 (0.0000272) (0.0017)	0.000118 (0.0000232) (0.001)	0.0000001 (0.000001) (0.9351)	0.0000126 (0.000007) (0.0491)	0.0000041 (0.000001) (0.001)	0.0000578 (0.00003) (0.0491)	0.000014 (0.00001) (0.1396)
$ARCH(-1)$	0.608484 (0.16765) (0.0003)	1.718401 (0.275918) (0.001)	0.481438 (0.169939) (0.005)	0.469276 (0.160286) (0.0034)	0.38088 (0.150072) (0.0111)	0.129391 (0.068534) (0.059)	0.375092 (0.117349) (0.0014)	0.224358 (0.116021) (0.0531)	0.101532 (0.051037) (0.0467)	0.429255 (0.1426) (0.0026)
$ARCH(-2)$	-0.3713 (0.098525) (0.001)	-1.236535 (0.168046) (0.001)			0.441142 (0.08265) (0.001)	-0.163628 (0.073299) (0.0256)	-0.304319 (0.105105) (0.004)	-0.300701 (0.120755) (0.0128)	-0.107101 (0.046044) (0.02)	-0.304996 (0.13722) (0.0262)
$GARCH(-1)$	0.41734 (0.204277) (0.0411)	0.759253 (0.073945) (0.001)	0.244527 (0.15978) (0.1259)	0.099225 (0.154672) (0.5212)	-0.513676 (0.165022) (0.0019)	1.045837 (0.013009) (0.001)	0.785383 (0.106294) (0.001)	1.047125 (0.012782) (0.001)	0.524699 (0.251018) (0.0366)	0.83659 (0.092806) (0.01)
$R^2$ (Aj. $R^2$ )	0.10962 (0.092331)	0.360323 (0.347962)	0.126002 (0.113396)	0.302368 (0.281749)	0.391027 (0.376246)	0.279848 (0.258562)	0.532172 (0.508544)	0.454608 (0.444069)	0.589383 (0.581449)	0.119172 (0.106468)
Durbin Watson Stat	1.871443	2.055	1.824	1.942715	1.926851	1.885396	2.178205	1.81796	1.982316	2.035421
ARCH LM F-stat (Prob.)	0.600669 (0.4392)	0.233059 (0.6298)	0.35063 (0.5544)	0.194843 (0.6594)	0.04838 (0.8261)	0.035928 (0.8498)	0.113136 (0.7369)	0.336073 (0.5627)	2.743036 (0.0992)	0.244812 (0.6213)
JB Norm (Prob.)	13.57 (0.0011)	2184 (0.001)	29.27 (0.001)	5.2412 (0.0728)	6.523 (0.0383)	30.86 (0.001)	31.608 (0.001)	4.386 (0.001)	79.25 (0.001)	19.81 (0.001)

**Source:** Authors' own findings; # Status (Status) status refers to status of CUSUM test for residuals (squared residuals) at 5% level of significance; \* is marginal status.

In Table 8, with the GARCH-X models for the sample firms' data for COVID-19 study period, we now corroborate our earlier findings with reference to Table 5 for their respective ARDL models. As mentioned in the preceding paragraph, here also we find mostly thirteen instances of robust revisions both in the magnitudes and levels of significance for coefficients with the ARDL model for the sample stocks. In brief, we document robust revisions at certainty effects for CADI, REDY, and SUN but at reflection effect for ALKE while the same at isolation effects are related to stock-specific (bond market-specific) long- vs short-memory effect for ALKE, ARBN, BION, and REDY (CADI only). We further show that investors' long- vs. short-memory reflection effects are also visible with LUPN and REDY. Nonetheless, with the variance equation we find positively significant constant drifts contributed by the ARDL regression residuals for the sample stocks, and positively significant coefficient values with the variances of the residuals as well as stocks' returns at their 1st lags. That is, the GARCH-X augmentation of the ARDL models showcases the extents of effects of exogeneity and endogeneity during the COVID-19 period and it postulates the same with reference to the isolation effect in the prospect theory view of the CAPM.

Finally, in Table 9, in terms of magnitudes of coefficients and their levels of significance with the combined data, we reveal nineteen instances of revisions in the GARCH-X augmentation from those we have showed in Table 6 with the ARDL models. For example, we can find significant revisions in the coefficients at certainty effects for the stocks viz., ALKE, CIPL, REDY, and SUN. Besides, we detect revisions in the magnitudes and status of significance of the coefficients at the stock-specific long-memory vs. short-memory effects for the stocks viz., ARBN, BION, LUPN, and REDY at their different lag specifications. Enthusiastically, we can identify investors' excitements at recognizing the revisions in the market-specific long-memory vs. short-memory effects for the sample stocks viz., BION, CADI, LUPN, REDY, and SUN as well. Nonetheless, we can locate a revision in the *alpha* component of the model for CADI. These all instances in a nutshell authenticate the hypothesis that the present GARCH-X augmentation of the ARDL models for the sample stocks even with the combined study period has advancement in explaining the prospect theory view of the CAPM empirically. In tune to our earlier observations, we again discover serious presence of exogeneity and endogeneity with the combine study period for the sample firms. All stocks (except REDY and SUN) show presence of fixed residual drifts robustly significant at 0.1% level of significance. All of these stocks' returns – except those of TORP, experience positively significant residuals' variance effects at the 1st lag, the stocks viz., ARBN, CADI, CIPL, REDY and SUN document presence of negatively significant residuals' variance effects at their 2nd lag, and only CADI (TORP) shows positively (negatively) significant residuals' variance impact at the 2nd lag (3rd lag). Besides, we demonstrate mostly positively significant effects of the returns' variances at the respective stocks' 1st lags for most of the stocks but with CADI, we find negatively significant impact. At the 2nd lags for ARBN, CADI, and SUN, we also show positively significant variance effects while with TORP, we demonstrate a negatively significant impact. We have a presence of negatively significant variance effect even at the 3rd lag for TORP. These results are supportive to the varied nature of isolation effects as hypothesized in the prospect theory view of the CAPM.

**Table 8.** Results on the GARCH-X Augmentation of the PTM-1 Model during the COVID-19 Data

Variables / Parameters	ALKE	ARBN	BION	CADI	CIPL	DIVI	LUPN	REDY	SUN	TORP
$R_{it-1}$	0.117001 (0.076819) (0.1277)	0.253209 (0.069397) (0.001)	0.207803 (0.080445) (0.0098)	0.347264 (0.075737) (0.001)	0.311288 (0.060723) (0.001)	0.242008 (0.072995) (0.001)	0.350125 (0.065947) (0.001)	0.026163 (0.078453) (0.7388)	0.289124 (0.069741) (0.001)	0.381303 (0.072183) (0.001)
$R_{it-2}$		-0.00142 (0.05677) (0.98)	0.238742 (0.07695) (0.0019)			0.074268 (0.045674) (0.1039)				
$R_{it-3}$			-0.0502 (0.057443) (0.3822)							
$R_{it-4}$			-0.07999 (0.047743) (0.0938)							
$R_{mt}$	0.638862 (0.046082) (0.1277)	1.161824 (0.060629) (0.001)	0.92471 (0.065325) (0.001)	0.954584 (0.044579) (0.001)	1.189533 (0.039183) (0.001)	0.965203 (0.041858) (0.001)	0.976618 (0.061153) (0.001)	0.86575 (0.035653) (0.001)	1.07609 (0.03077) (0.001)	0.743462 (0.051252) (0.001)
$R_{mt-1}$		-0.35836 (0.108949) (0.001)	-0.23868 (0.094239) (0.0113)	-0.26887 (0.086944) (0.002)	-0.41633 (0.09002) (0.001)	-0.28232 (0.08631) (0.001)	-0.31586 (0.080915) (0.001)	-0.04326 (0.083852) (0.6059)	-0.32662 (0.078672) (0.001)	-0.25879 (0.081515) (0.0015)
$R_{mt-2}$			-0.23216 (0.102298) (0.0232)	0.010456 (0.066418) (0.8749)			0.065823 (0.055856) (0.2386)	-0.05126 (0.05606) (0.3606)	-0.06885 (0.035794) (0.001)	
$R_{mt-3}$				0.0000767 (0.058708) (0.999)						
$R_{mt-4}$				-0.01617 (0.049145) (0.7422)						
$R_{it}$	-0.08216 (0.129633) (0.1277)	0.068618 (0.137414) (0.6175)	-0.17807 (0.121975) (0.1443)	0.062651 (0.099078) (0.5272)	0.014497 (0.094717) (0.878)	0.063063 (0.095371) (0.5085)	0.284674 (0.114739) (0.0131)	-0.09843 (0.091145) (0.2802)	0.125475 (0.049178) (0.0107)	-0.01552 (0.149751) (0.9175)
$R_{it-1}$				0.020304 (0.111503) (0.8555)					0.139407 (0.04928) (0.0047)	

Variables / Parameters	ALKE	ARBN	BION	CADI	CIPL	DIVI	LUPN	REDY	SUN	TORP
$R_{\beta_2}$				-0.0116 (0.147715) (0.9375)						
$R_{\beta_3}$				0.064909 (0.123483) (0.5991)						
$C$	-0.00069 (0.001209) (0.1277)	-0.00137 (0.001383) (0.3235)	0.001167 (0.001554) (0.4527)	-0.00063 (0.000884) (0.4762)	0.000655 (0.001018) (0.519)	-0.00141 (0.000942) (0.1347)	-0.00041 (0.001329) (0.7589)	0.000000302 (0.000934) (0.9997)	0.0000699 (0.000971) (0.9426)	-0.00041 (0.001266) (0.7464)
<b>Variance Equation</b>										
$C$	0.000107 (0.0000371) (0.0041)	0.00001 (0.0000035) (0.0617)	0.000051 (0.00003) (0.0474)	0.000052 (0.00002) (0.009)	0.0000071 (0.000004) (0.0804)	0.0000499 (0.0000311) (0.1089)	0.0000511 (0.0000153) (0.001)	0.000119 (0.0000266) (0.001)	0.000167 (0.0000254) (0.001)	0.0000358 (0.00002) (0.0503)
$ARCH(-1)$	0.532763 (0.180756) (0.0032)	0.124144 (0.038213) (0.0012)	0.122414 (0.067387) (0.0693)	0.51978 (0.115018) (0.001)	0.125412 (0.032713) (0.001)	0.231922 (0.102562) (0.0237)	0.227683 (0.101862) (0.0254)	0.58713 (0.220746) (0.0078)	0.413138 (0.158222) (0.009)	0.135138 (0.065041) (0.0377)
$ARCH(-2)$								0.269117 (0.038241) (0.001)		
$GARCH(-1)$	0.349996 (0.137402) (0.0109)	0.87208 (0.024143) (0.001)	0.714922 (0.111571) (0.001)	0.374651 (0.12333) (0.0024)	0.849339 (0.02802) (0.001)	0.571053 (0.168601) (0.0007)	0.646689 (0.088388) (0.001)	-0.183453 (0.131482) (0.1629)	0.260275 (0.107486) (0.0155)	0.777664 (0.09472) (0.001)
$R^2$ (Aj. $R^2$ )	0.220775 (0.20959)	0.555942 (0.545164)	0.594175 (0.578023)	0.61185 (0.592345)	0.72225 (0.716909)	0.677739 (0.669917)	0.660034 (0.651782)	0.533706 (0.522388)	0.769314 (0.762562)	0.516261 (0.506958)
Durbin Watson Stat	1.707647	1.794745	1.996726	1.541	1.872792	1.799937	1.556769	1.126012	1.907408	1.854059
ARCH LM F-stat (Prob.)	0.087419 (0.7678)	0.462359 (0.4973)	0.170361 (0.6802)	0.343143 (0.5587)	0.410349 (0.5225)	0.018646 (0.8915)	0.053156 (0.8179)	0.015743 (0.9003)	0.354452 (0.5522)	0.007571 (0.9307)
JB Norm (Prob.)	87.81 (0.001)	74.754 (0.001)	189.47 (0.001)	30.871 (0.001)	30.724 (0.001)	16.86 (0.001)	306.27 (0.001)	83.78 (0.001)	22.801 (0.001)	67.33 (0.001)

Source: Authors' own findings; # Status (Status) status refers to status of CUSUM test for residuals (squared residuals) at 5% level of significance; \* is for marginal status.

**Table 9.** Results on the GARCH-X Augmentation of the PTM-1 Model during the Full-Length Data

Variables / Parameters	ALKE	ARBN	BION	CADI	CIPL	DIVI	LUPN	REDY	SUN	TORP
$R_{it-1}$	0.188848 (0.053977) (0.0005)	0.212718 (0.07319) (0.0037)	0.243997 (0.05687) (0.001)	0.223089 (0.052231) (0.001)	0.307159 (0.04571) (0.001)	0.192376 (0.055317) (0.001)	0.306268 (0.06722) (0.001)	0.241987 (0.054383) (0.001)	0.248082 (0.05441) (0.001)	0.384741 (0.03954) (0.001)
$R_{it-2}$		-0.00444 (0.04195) (0.9157)	0.141425 (0.051534) (0.006)				0.153979 (0.08096) (0.0572)	-0.04609 (0.051917) (0.3747)		
$R_{it-3}$			-0.05774 (0.043219) (0.182)				-0.10699 (0.07159) (0.135)	-0.05363 (0.034244) (0.1173)		
$R_{it-4}$			-0.05731 (0.037078) (0.122)				-0.04985 (0.04307) (0.2471)			
$R_{it-5}$							-0.02841 (0.0494) (0.5652)			
$R_{it-6}$							0.002722 (0.04519) (0.952)			
$R_{it-7}$							-0.0634 (0.02869) (0.0271)			
$R_{mt}$	0.483822 (0.030232) (0.001)	1.271733 (0.07469) (0.001)	0.849651 (0.051008) (0.001)	0.905266 (0.030854) (0.001)	1.026796 (0.02821) (0.001)	0.808013 (0.027607) (0.001)	0.882104 (0.04185) (0.001)	0.833307 (0.026749) (0.001)	1.059892 (0.02559) (0.001)	0.635241 (0.03415) (0.001)
$R_{mt-1}$		-0.2898 (0.12284) (0.0183)	-0.22632 (0.06758) (0.001)	-0.19037 (0.05956) (0.0014)	-0.39032 (0.05601) (0.001)	-0.22213 (0.057545) (0.001)	-0.29088 (0.07003) (0.001)	-0.20982 (0.059392) (0.001)	-0.26815 (0.06745) (0.001)	-0.27302 (0.04009) (0.001)
$R_{mt-2}$			-0.12836 (0.067586) (0.0575)	-0.02811 (0.052171) (0.59)			-0.1223 (0.07591) (0.1072)	0.006613 (0.062263) (0.9154)	-0.04203 (0.03174) (0.1854)	
$R_{mt-3}$				-0.02025 (0.046531) (0.6634)			0.179361 (0.06288) (0.0043)			

Variables / Parameters	ALKE	ARBN	BION	CADI	CIPL	DIVI	LUPN	REDY	SUN	TORP
$R_{mt-4}$				-0.05574 (0.036026) (0.1218)						
$R_{it}$	0.350949 (0.070355) (0.001)	0.08375 (0.13239) (0.527)	0.0000221 (0.092432) (0.998)	0.093872 (0.06654) (0.1583)	0.029357 (0.07703) (0.7031)	0.034132 (0.069443) (0.6231)	-0.18936 (0.06078) (0.002)	0.044512 (0.057892) (0.442)	-0.04102 (0.05659) (0.4685)	-0.04124 (0.06869) (0.5482)
$R_{it-1}$			-0.0327 (0.100493) (0.7449)	0.079891 (0.076759) (0.298)	-0.05627 (0.08337) (0.4997)				0.122419 (0.08033) (0.1275)	
$R_{it-2}$			0.001065 (0.118641) (0.9928)	0.072702 (0.092415) (0.4315)						
$R_{it-3}$			0.154658 (0.120048) (0.1976)	0.186934 (0.072861) (0.0103)						
$R_{it-4}$			-0.28907 (0.109444) (0.0083)							
$C$	0.000876 (0.000734) (0.2322)	-0.00067 (0.00118) (0.5675)	0.001609 (0.000888) (0.0699)	0.001069 (0.00052) (0.0398)	-0.00021 (0.00059) (0.7155)	0.000358 (0.000545) (0.5113)	-0.00058 (0.00063) (0.34)	0.000483 (0.00057) (0.3973)	-0.00011 (0.00058) (0.8486)	0.000899 (0.0007) (0.2017)
<b>Variance Equation</b>										
$C$	0.000103 (0.000025) (0.001)	0.000035 (0.00001) (0.001)	0.000277 (0.000064) (0.001)	0.000113 (0.00004) (0.001)	0.000011 (0.00001) (0.0123)	0.000141 (0.000023) (0.001)	0.0000192 (0.00001) (0.001)	0.00000485 (0.0000033) (0.1446)	0.0000134 (0.00001) (0.1542)	0.0000146 (0.00001) (0.001)
$ARCH (-1)$	0.430225 (0.116151) (0.001)	0.316868 (0.08803) (0.001)	0.179576 (0.079164) (0.0233)	0.527973 (0.097616) (0.001)	0.378708 (0.12173) (0.002)	0.465312 (0.099898) (0.001)	0.272714 (0.06449) (0.001)	0.441081 (0.114882) (0.001)	0.33392 (0.10724) (0.0018)	0.196308 (0.08334) (0.185)
$ARCH (-2)$		-0.214172 (0.09233) (0.0204)		0.351649 (0.133526) (0.0084)	-0.28137 (0.12113) (0.0202)			-0.392568 (0.113415) (0.001)	-0.260215 (0.10039) (0.0095)	-0.02964 (0.13925) (0.8314)
$ARCH (-3)$										-0.2832 (0.12438) (0.0228)

Variables / Parameters	ALKE	ARBN	BION	CADI	CIPL	DIVI	LUPN	REDY	SUN	TORP
										0.268966 (0.0491) (0.001)
<i>GARCH (-1)</i>	0.341156 (0.341156) (0.0036)	0.576811 (0.13849) (0.001)	0.125658 (0.227953) (0.5815)	-0.51135 (0.18701) (0.0062)	0.855695 (0.04119) (0.001)	-0.055078 (0.114296) (0.6299)	0.672524 (0.04501) (0.001)	0.928542 (0.044276) (0.001)	0.623703 (0.20989) (0.003)	1.609605 (0.10254) (0.001)
<i>GARCH (-2)</i>		0.279039 (0.10846) (0.0101)		0.266112 (0.09396) (0.0046)					0.21939 (0.13782) (0.114)	-1.04711 (0.14593) (0.001)
<i>GARCH (-3)</i>										0.256517 (0.07751) (0.001)
R <sup>2</sup> (Aj. R <sup>2</sup> )	0.171531 (0.165642)	0.482101 (0.475921)	0.466628 (0.451017)	0.529945 (0.518536)	0.659994 (0.655946)	0.553152 (0.548907)	0.594955 (0.583013)	0.567922 (0.560651)	0.720452 (0.71644)	0.397576 (0.39185)
Durbin Watson Stat	1.846008	1.803645	2.128019	1.60432	1.823123	1.793839	1.448734	1.554754	1.916603	2.03182
ARCH LM F-stat (Prob.)	0.312694 (0.5763)	0.003692 (0.9516)	0.057919 (0.8099)	0.068539 (0.7936)	0.161608 (0.6879)	0.307069 (0.5798)	0.218635 (0.6403)	0.261522 (0.6093)	0.108136 (0.7424)	0.059896 (0.8068)
JB Norm (Prob.)	87.43 (0.001)	5781 (0.001)	224.5 (0.001)	27.31 (0.001)	80.41 (0.001)	346.84 (0.001)	579.8 (0.001)	122.21 (0.001)	192.93 (.001)	159.32 (0.001)

Source: Authors' own findings; # Status (Status) status refers to status of CUSUM test for residuals (squared residuals) at 5% level of significance; \* is marginal status.



## Discussion

We have theoretically viewed the CAPM with the reference-dependence aspects of the prospect theory and formalized the same firstly in the prospect theory model (*PTM-1*), then we extend the same with the autoregressive heteroskedastic distributed lag (ARDL) model, and finally we locate their effects in the generalized autoregressive conditional heteroskedastic (GARCH-X) models. We explore the same with three sets of empirical data for ten stocks listed in the NSE stock market. Nonetheless, we have found impressive observations to empirically support of the prospect theory propositions from all three counters of our explorations.

In a bird's eye view, we assimilate the observations here. With the *PTM-1*, we have showed that stocks' returns generally recognize investors' reflection effects (that is, the NSE Nifty market rate of return) as the central decision-reference criteria across the ten sample stocks while the presence of isolation effects (the *alpha* component) and certainty effects (the risk-free rate of return) are of selective in nature. Besides, the explorations in the *PTM-1* models bring unbiased estimated with the sample firms but those are not efficient ones.

We have examined the causes of such inefficiency in modeling the prospect theory view with the applications of the ARDL augmentations and further with the GARCH-X augmentation. Such methodological augmentation of the *PTM-1* makes us enable to examine the isolation effects at the different lags of the individual stocks' returns. Again, such methodology assists in identifying the components of isolation effects those are otherwise clubbed within the certainty effects and reflection effects as well and represent the long-memory vs. short-memory impacts. Therefore, we have found that vivid presence of the isolation effects for LUPN, DIVI, and CADI with the pre-COVID-19 data sets, and the same for most of the sample stocks with the COVID-19 study period. Our observations with the combined study period further substantiate the picture of heterogenised presence of the isolation effects across the sample stocks. However, the autoregressive dynamic models in the form of ARDL models have this limitation that these can identify individual stock-specific isolation effects in the form of the lag effect, but these do not capture the generalized ones and hence, these models do not show the general noise effects i.e., the public noise impacts in the markets and with the sample stocks as well. But these have the advantages of identifying the stock-specific noise impacts at long-memory vs. shorty-memory effects as the isolation effects. We have also empirically found satisfactory results with the models for the sample stocks with the three data sets of pre-COVID-19, during COVID-19, and taking the two altogether as well.

Therefore, with the GARCH-X extensions for the sample stocks across the study periods, we have innovatively overcome limitations of ARDL models with two advanced methodological augmentations in the form of the isolation effects – the general noise effects and stocks' variance effects. We have revealed that investors' long- vs. short-memory effects for these two effects vary across the sample stocks and study periods as well. However, we find some general pattern of such effects viz., the presence of positive impacts at the respective 1st lags of both the variances – the residuals' variances and stocks' return

variances, with the sample stocks for pre-COVID and COVID-19 study periods, and the combined data sets as well.

## 5. Conclusion

In financial economics, the CAPM has received the most attentions amongst the various assets pricing models from both empirical practitioners and academicians. They have found empirical validity vis-à-vis criticisms for and against the explanatory powers of the model. Very recently, researchers accommodate the limitations of the model at its classical version/s along with the modern time-varying adaptive market hypothesis. They propose for recognizing and adapting to the macro-economic impacts and changes in political or environmental or governmental regimes besides the relevant market/s of the financial assets (viz., stocks) under study by a researcher. But this adaptive hypothesis becomes inapplicable if investors' behavioral aspects as proposed in the prospect theory are kept aside. This present study has fulfilled this research need and it has found statistically significant empirical supports for the prospect theory view of CAPM with references to certainty effects, reflection effects, and isolation effects and with their augmentations in the ARDL as well as GARCH-X frameworks.

The study empirically explores the proposed prospect theory view with a sample pharma stocks over the slabs of pre-COVID-19 period, at present COVID-19 period, and incorporating both altogether as well. Hence, the results have substantive real-life applicative value to the mutual fund investors, and the same can be used to identify and cross-check the magnitudes of investors' reference-dependencies for certainty effects, reflection effects, and isolation effects with sample stocks in the pharma industry. We have showed the extents and their impacts of such reference dependencies subject to the different sample study periods.

The study has showed that the static and one-period single-beta classical CAPM view can be calibrated to the dynamic reference-dependence perspectives of prospect theory of Kahneman & Tversky (1979) in behavioral finance and the prospective investors may find the need to relook into the perspective of behavioral implications and applicative values at times of financial decision choices. Such calibrations can be further excelled by means of inclusion of an  $n$  number of firm-specific factors along with the lagged effects and thereby, they can recognize the active dimensions of the isolation effects. Therefore, the future research can re-examine the limitations of Fama and French (2015), specifically – its higher explanatory powers if these are caused by the AR processes as identified in Liu and Wang (2019), and thereby, explore if the five-factor CAPM model can be augmented in the prospect theory view as offered in this study.

However, the present empirical study has used a limited span of study period and only ten sample stocks, and any generalization of our observations is subject to inclusion of a larger sample size of stocks along with a larger study period. Towards a generalization, the future research can put forth industry specific vis-à-vis cross-industry empirical explorations and thereby, can compare if there are industry-specific isolation effects as well. At times of privatization of the government shares in the banking, mining, and telecommunication

industries, an indirect policy implication of the present research for the governments is to consider the behavioral impacts of isolation effects on the stock markets. For example, the post-COVID-19 low aspiration level and sustained presence of fear in the general investors can induce dampened mood and thereby, cause the negative isolation effects on the stocks' market returns. A policy implication for the corporates is not to attempt an initial public offer of equity (debt) issue in the capital market if there is an adverse isolation effect in the equity (debt) capital markets. Further, institutional investors may identify isolation effects and thereby can get hedging positions in the markets. For example, keeping an eye on the people's renewed aspiration towards the gold and gold-made ornaments during the post-COVID-19, the "prospect theory" investors may consider the Gold ETFs as hedging opportunity against any fall in their returns in the stock markets.

The prospect theory views gains and losses differently in terms of the decision weights and value function as well. This study can further be extended to explore the cumulative prospect theory view as proposed in Tversky and Kahneman (1992) and towards that direction, a use of non-linear autoregressive distributed lag (NARDL) model is under active consideration of the authors. Future researchers may also explore this direction of research as well.

### Acknowledgements

The author will be grateful to anonymous referee/s of the conference for his useful suggestions towards improving the quality of the paper.

### Declaration of Conflict of Interest

*The author declares that there is no actual or potential conflict of interest to this research, its authorship, and possible forthcoming publication of this research article in this Journal.*

### Funding

The author has neither received any fund from any government, non-government, profit-making or not-for profit organization nor the study is sponsored by any such agency at all.

---

### References

- Akhter, T. and Yong, O., 2019. Adaptive market hypothesis and momentum effect: Evidence from Dhaka Stock Exchange. *Cogent Economics & Finance*, 7(1), 1650441.
- Bajpai, S. and Sharma, A.K., 2015. An Empirical Testing of Capital Asset Pricing Model in India. *Procedia - Social and Behavioral Sciences*, 189, pp. 259-265. doi:10.1016/j.sbspro.2015.03.22
- Bali, Peng, Shen and Tang, 2014. Liquidity Shocks and Stock Market Reactions, *The Review of Financial Studies*, 27 (5), pp. 1434-1485, <<https://doi.org/10.1093/rfs/hht074>>

- Barberis, N.C., 2013. Thirty Years of Prospect Theory in Economics: A Review and Assessment. *Journal of Economic Perspectives*, 27(1), pp. 173-196. doi:10.1257/jep.27.1.173
- Barberis, N., Jin, L.J. and Wang, B., 2020. Prospect Theory and Stock Market Anomalies. *10th Miami Behavioral Finance Conference*, Available at SSRN: <<https://ssrn.com/abstract=3477463>> or <<http://dx.doi.org/10.2139/ssrn.3477463>>
- Baucells, M., and Villasís, A., 2009. Stability of risk preferences and the reflection effect of prospect theory. *Theory and Decision*, 68(1-2), pp. 193-211. doi:10.1007/s11238-009-9153-3
- Black, F., 1993. Beta and Return. *The Journal of Portfolio Management*, 20(1), pp. 8-18. doi:10.3905/jpm.1993.409462.
- Cepoi, C.-O., 2020. Asymmetric dependence between stock market returns and news during COVID19 financial turmoil. *Finance Research Letters*, 101658. doi:10.1016/j.frl.2020.101658
- Chang, M.C., 2020. Market sentiment, marketable transactions, and returns. *The European Journal of Finance*, pp. 1-26. doi:10.1080/1351847x.2020.1792961
- Coffie, W. and Chukwulobelu, O., 2012. The Application of Capital Asset Pricing Model (CAPM) to Individual Securities on Ghana Stock Exchange. *Finance and Development in Africa*, 12B, pp. 121-147. doi:10.1108/s1479-3563(2012)000012b010
- Fama, E.F. and French, K.R., 1996. The CAPM is Wanted, Dead or Alive. *The Journal of Finance*, 51(5), pp. 1947-1958. doi:10.2307/2329545
- Fama, E.F. and French, K.R., 2004. The Capital Asset Pricing Model: Theory and Evidence. *Journal of Economic Perspectives*, 18(3), pp. 25-46. doi:10.1257/0895330042162430
- Fama, E.F. and French, K.R., 2015. *A five-factor asset pricing model*. *Journal of Financial Economics*, 116(1), pp. 1-22. doi:10.1016/j.jfineco.2014.10.010
- Herjanto, H., Amin, M. and Purington, E.F., 2021. Panic buying: The effect of thinking style and situational ambiguity. *Journal of Retailing and Consumer Services*, 60, 102455.
- Javid, A.Y. and Ahmad, E., 2008. The Conditional Capital Asset Pricing Model: Evidence From Karachi Stock Exchange; *Pakistan Institute of Development Economics Islamabad*; PIDE Working Papers No. 2008:48; available at: <<http://www.pide.org.pk/pdf/Working%20Paper/WorkingPaper-48.pdf>>
- Kahneman, D. and Tversky, A., 1979. Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), pp. 263-291. DOI: 10.2307/1914185
- Tversky, A. and Kahneman, D., 1992. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty*, 5(4), pp. 297-323. DOI: 10.1007/BF00122574
- Khuntia, S. and Pattanayak, J.K., 2019. Evolving Efficiency of Exchange Rate Movement: An Evidence from Indian Foreign Exchange Market. *Global Business Review*, 097215091985699. doi:10.1177/0972150919856996
- Kristoufek, L., 2012. Fractal Markets Hypothesis and the Global Financial Crisis: Scaling, Investment Horizons and Liquidity. *Advances in Complex Systems*, 15(6), 1250065. doi:10.1142/s0219525912500658
- Lakhal, F., 2008. Stock market liquidity and information asymmetry around voluntary earnings disclosures. *International Journal of Managerial Finance*, 4(1), pp. 60-75. doi:10.1108/17439130810837384

- Lee, H.S., Cheng, F.F. and Chong, S.C., 2016. Markowitz Portfolio Theory and Capital Asset Pricing Model for Kuala Lumpur Stock Exchange: A Case Revisited. *International Journal of Economics and Financial Issues*, 6(S3), pp. 59-65.
- Levy, H., De Giorgi, E.G. and Hens, T., 2011. Two Paradigms and Nobel Prizes in Economics: a Contradiction or Coexistence? *European Financial Management*, 18(2), pp. 163-182. doi:10.1111/j.1468-036x.2011.00617.x
- Lintner, J., 1965. Security prices, risk, and maximal gains from diversification. *The Journal of Finance*, 20(4), pp. 587-615. doi:10.1111/j.1540-6261.1965.tb02930.x
- Liu, H.Y. and Wang, C.S., 2019. A New Perspective on the Fama–French Five-factor Model. In *Advances in Pacific Basin Business, Economics and Finance*. Emerald Publishing Limited. DOI :10.1108/S2514-465020190000007005
- Maji, K., 2010. Validity of Capital Asset Pricing Model & Stability of Systematic Risk (Beta): An Empirical Study on Indian Stock Market. *SSRN Electronic Journal*. doi:10.2139/ssrn.1708463
- Mossin, J., 1966. Equilibrium in a Capital Asset Market. *Econometrica*, 34(4), pp. 768-783. doi:10.2307/1910098
- Nemeth, J., 2020. News: The Information Overload of the COVID-19 Zeitgeist. *Emergency Medicine News*, 42(8B), pp. 10-1097.
- Pesaran, M.H., Shin, Y. and Smith, R.J., 2001. Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), pp. 289-326. DOI: 10.1002/jae.616
- Qadan, M., 2019. Risk appetite, idiosyncratic volatility and expected returns. *International Review of Financial Analysis*, 65, 101372. doi:10.1016/j.irfa.2019.101372
- Quang, T.V., 2005. The Fractal Market Analysis and Its Application on Czech Conditions [Fraktální analýza trhu a její aplikace na českých podmínkách], *Acta Oeconomica Pragensia, University of Economics, Prague*, vol. 2005(1), pp. 101-111.
- Ricciardi, V., 2008. *The Psychology of Risk: The Behavioral Finance Perspective. Handbook of Finance*. doi:10.1002/9780470404324.hof002010
- Ross, S.A., 1976. The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, 13(3), pp. 341-360. doi:10.1016/0022-0531(76)90046-6
- Sharpe, W.F., 1964. Capital asset prices: a theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3), pp. 425-442. doi:10.1111/j.1540-6261.1964.tb02865.x
- Sinha, P.C., 2021. Noise of Investors' Attention Mania in the Twenty-first-Century Indian Stock Markets: ARDL and Augmented GARCH-X Models. *Global Business Review*, First Published (Online) on January 28, 2021; <<https://doi.org/10.1177/0972150920982507>>
- Sinha, P.C., 2019a. Market Microstructure Noise, Intraday Stock Market Returns and Adaptive Learning: Indian Evidence. *Colombo Business Journal*, 10(2), pp. 25-47. doi:10.4038/cbj.v10i2.50.
- Sinha, P.C., 2019b. Does Popularity of Political Leaders Matter in the Indian Stock Markets? A Comparative Study of Four Lok Sabha Elections from 2004 to 2019. *Ramanujan International journal of Business and Research*, 4(1), pp. 37-78. <<https://doi.org/10.51245/rijbr.v4i1.2019.162>>
- Theobald, M., 1979. Capital Asset Pricing: Theory, Empirics and Implications for Portfolio Management. *Managerial Finance*, 5(1), pp. 57-64. doi:10.1108/eb01343

- Tversky, A. and Kahneman, D., 1981. The framing of decisions and the psychology of choice. *Science*, 211(4481), pp. 453-458.
- Tversky, A. and Kahneman, D., 1986. The behavioral foundations of economic theory. *The Journal of business*, 59(4), pp. 251-278.
- Wang, H., Yan, J. and Yu, J., 2017. Reference-dependent preferences and the risk–return trade-off. *Journal of Financial Economics*, 123(2), pp. 395-414.
- Wierzbicki, A.P., 1999. Reference Point Approaches. In *Multicriteria Decision Making* (pp. 237-275). Springer, Boston, MA doi:10.1007/978-1-4615-5025-9\_9