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Does Prospect Theory Non-Linearity Explain Mental Accounting? A Study at COVID-19

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Abstract

In examining how investors in the stock markets make many decisions in their minds at once, this study has empirically explored the proposition of possible assimilation of the prospect theory (PT) and the theory of mental accounting (MA) at the use of investors' multiple decisions references. In such pursuit, it has examined the non-linearity property in the PT value function and accordingly it has applied the same at the presence of positive and negative effects for investors' multiple decision references at once. Nonetheless, in the empirical literature of behavioral finance, it has ingeniously used the empirical methodology of the non-linear auto-regressive distributive/ dynamic lag (NARDL) model with the use of three separate data sets covering the pre-COVID-19 period from August 2019 to February 2020, that during COVID-19 period from March 2020 to September 2020 and that covering both altogether, that is, from August 2019 to September 2020. The observed results are all promising to put forth the proposed PT/MA assimilation proposition across the sample stocks over the different sample-data periods as well. The study finally identifies the applicative values of the proposed PT/MA assimilation.

Keywords: *Prospect Theory*, *Non-linear Value Function, Mental Accounting, Assimilation of PT/MA, NARDL Model, Behavioral Finance.*

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I. Introduction: At investment in stock markets, investors decide on the list of available stocks, their prices, historical return, risk, future growth prospects, etc. They feel love, greed, passion and hatred for them as well. They ponder upon - Will the stock be as loving in the future as it was in the past? They decide on their lucky days or months - When to buy or sell the stocks? Investors take all these decisions instantly. How do they make so many decisions at once?

Essentially, investors take many decisions in their minds – be it a case of buying or holding or selling a common good for day-to-day uses or at long-term financial investments or diversifying a portfolio, holding a losing stock or selling a gaining one, etc. In behavioral finance, these all are covered in Mental Accounting. It describes the policy of keeping accounts in the mind – what they record, classify and evaluate, how to do the same, and when to do as well, etc.? The people record, classify and evaluate available options psychologically. According to Thaler (1985; 1999), by applying mental accounting people psychologically record costs and benefits of different options for decision choices, identify them in separate accounts, categorize their choices from different decision frames, and evaluate them with their perceived gains and losses.

How do human minds operationalize so many decision issues simultaneously? In a simple package on decision guide, Thaler (1985) described this query with the framing effect of Tversky and Kahneman (1981), the theory of self-control of Thaler and Shefrin (1981) and the prospect theory of Kahneman and Tversky (1979). Given the budget constraints, people decide upon their mental accounts at their local situations rather than at global optimization while their perceived value functions define their gains and losses at references. Nonetheless, the value function is non-linear – concave at gains and convex at losses, and losses loom larger than equivalent gains. Thaler (1999) has showed that people decide on their choice brackets, violate the economic principle of fungibility and follow dynamic mental accounting where their mental accounts are evaluated frequently. That is, their mental accounts matter in decision choices like advance purchases, sunk costs, payment depreciation, payment decoupling, self-control and gift-giving, wealth accounting and income accounting and risky choices at given prior outcomes, etc.

In addressing the applicability of mental accounting to solve the equity premium puzzle in the stock markets, Thaler (1999) has argued that "… we need a combination of loss aversion and one-bet-at-a-time mental accounting" and hypothesized that investors show the prospect theory preferences as stipulated in the study of Tversky and Kahneman (1992) and they follow myopic loss aversion (Benartzi & Thaler, 1995). On such myopia, Thaler, Tversky, Kahneman and Schwartz (1997) (read with Thaler, 1999, p.200) have showed that investors are more (less) risk-averse – in the other words, less (more) risk-seeker, at positions in short (long)-horizon periods and prefer the bond (stock) markets for investments. But what role does the parameter "time" play in determining the investors' risk coefficients? Does time itself or its underlying uncertainty contribute "time" to become a risk factor?

The COVID-19 situation across the markets has paved an opportunity to explore the short-horizon impacts of time in aggravating impacts of myopic loss aversion. In examining it, this study seeks to explore the propositions of mental accounting theory with the reference to a few-months short window for COVID-19, the one-bet, and examine if non-linearity property i.e., loss-aversion in the prospect theory value function explains the mental accounting theory.

In organizing the flow, we firstly, review the literature on the exact problem statement briefly, then, we put forth the data and methodology of its empirical explorations, followed by that for the results and findings, and finally, the conclusion and policy implications.

II. Literature Review: At a presence of myopic loss-aversion and assimilation of prospect theory (PT) preferences with those of mental accounting (MA) ones, there are a few experimental studies, empirical studies and microstructure models. These studies put efforts to explain three standard finance puzzles viz., the equity premium puzzle, disposition effects and momentum effect.

On the pursuits of investors' loss-aversion and narrow framing, Barberis and Huang (2001) put forth two alternative MA platforms - individual stock-level accounting and portfolio-level accounting. They showed that at an individual (portfolio)-level, there is a high (moderate) presence of mean returns and volatilities along with a presence of less (high) correlated return series and that of predictable (unpredictable) risk-premiums over a cross-section of stocks. Their first two results are linked to the equity premium puzzle while the rest two have remained unaddressed. Barberis, Huang, and Santos (2001) also found support for the applicability of PT to the stock-level mental accounting. How do stocks' risk-premiums are predictable if their returns series are uncorrelated? What are the factors that contribute to such predictability? Resolving the rest two puzzles appears promising with the assimilation approach at hand.

Langer and Weber (2001) have experimentally showed that investors behave differently at exposure to overall evaluation from that to isolated evaluation. In the first one, they apply mental accounting in processing the non-linear pay-offs with the prospect theory value function and prefer portfolio choice to split it and in the second case, their myopic loss aversion makes individual stock's pay-offs more attractive and so splitting the portfolio into stocks. They have further argued that at exposure to overall (myopic) information, a long-horizon period is viewed at aggregation (isolation) of the series of separate decision frames over time. Investors' decision choices at overall (myopic) information exposure to the items in the income statements have serious implications on the decision choices of the management as well (Bonner, Clor-Proell & Koonce, 2014).

In addressing the puzzle of disposition effects, that is, selling the winner stocks but holding the loser ones, Lim (2006) has documented support for investors' myopic loss aversion effects in their mental accounting efforts and investors aggregate losses from the losing stocks on the same day but segregate gains from the winner stocks on different days. Shapira and Venezia (2001) have found disposition effects for both professional and individual investors in the Israeli stock market. In explaining the same with the PT preferences, Barberis and Xiong (2009) have revealed that an accrual-based accounting of the annual paper gains and losses over holding periods fails to explain the disposition effect while a realization-based accounting explains it.

On the persistency of the momentum effect, Grinblatt and Han (2005) have argued that over a time horizon, investors' price expectations at the forward and backward regions around a reference point – the point of inflection over the non-linear "*S* " shaped PT value function create a momentum of returns – a continued existence of spreads between the perceived fundamental value of a stock and its equilibrium price. They have showed that factors determining PT/MA assimilated lagged demand functions explain the stocks' aggregate returns. The framing of different regions around reference points in the non-linear value function can also be found justified in the "pull-to-center" effect in Gu and Zhang (2020) that refers to overorder (underorder) by the newsvendors at low (high)-profit situations irrespective of their optimal ordering quantities.

That is, at framing the decision issue in the process, PT links MA. Amongst the empirical studies, Barberis, Mukherjee, and Wang (2016) and Wen, Gong, Chao, and Chen (2014) have showed that investors make decision choices on the basis of their observations of the past profit (loss) while at times of their current loss (profit), investors demonstrate risk-seeking (risk-averse) attitudes. On evaluating risk and return, they do not always perceive that their high (low)-risk stocks will ensure the presence of high (low) returns (Mascareñas & Yan, 2017). Investors psychologically entangle (disentangle) loss-making (profit-making) stocks at losses (profits) across different stocks (Shams, Kordlouie, & Dezfuli, 2012). Amongst the recent studies, Tsai and Bui (2021) have explored such a proposition on the consumer's purchase intentions for the cruise travel products with the Word of Mouth (WOM) responses from the social media.

COVID-19 has made itself a reference point in investors' minds (Sinha & Agarwal, 2021). How do investors view gains and losses together in the stock markets and assimilate PT with MA? How do they frame assimilation in the presence of alternative references? The following section explores if PT and MA jointly can explain the stock markets dynamics from the pre-COVID and COVID viewpoints with the sample stocks in the pharmaceuticals industry those are also listed in the National Stock Exchange (NSE) in India.

Data and Methodology: At ontological reality, the present authors utilize the non-linear property in the PT value function along with the separate vis-à-vis overall accounting proposal in the MA. The PT value function as offered in Kahneman and Tversky (1979) is that of an *S*-shape, that is, it is concave (i.e., risk-averse) in the domain of gains and convex (i.e., risk-loving) in the domain of losses relative to a reference point. At decision choices, there are three prime effects: a certainty effect inferring investors' inclination to risk-neutral reference, a reflection effect for reflective adjustments as demanded by situations and an isolation effect suggesting some new dimension of decision choice. In certainty effect, nonetheless, investors are used to putting more weights on their sure prospects for the gains than those they weigh for the losses, and at the reflection effect, they tempt to show familiar (inverse) decision choice in similar (opposite) underpinnings of the decision scenarios. The isolation effect, an innovative aspect as offered in Kahneman and Tversky (1979), essentially suggests to proxy for investors' attitude to value that information which is somewhat unique but additive and different in its nature. The cumulative PT of Tversky and Kahneman (1992) specifies a two-part cubic or quadratic cumulative value function with different weighting functions for gains and losses. The weighing function shows the effects of investors' risk-averse (risk-seeking) towards their decision preferences for their feasible gains (losses) at the limits of its moderate or high probability. The MA helps in assimilating the decision issues at reference points.

***Sample and Data Period*:** The study covers a sample stock of 10 scripts those are already listed in the NSE (National Stock Exchange) in the pharmaceutical industry in India. The sample stocks have a track record of listing in the NSE for more than a period of five consecutive years. These stocks are representative to reflect the industry characteristics. These ten stock scripts are popularly known as the ALKE, ARBN, BION, CADI, CIPL, DIVI, LUPN, REDY, SUN and TORP. Their full names are respectively Alkem Laboratories Ltd., Aurobindo Pharma Ltd., Biocon Ltd., Cadila Healthcare Ltd., Cipla Ltd., Divis Laboratories Ltd., Lupin Ltd., Dr.Reddys Laboratories Ltd., Sun Pharmaceuticals Industries Ltd. and Torrent Pharmaceuticals Ltd.

The study covers the relevant full-length data for a period of fourteen months - from August 2019 to September 2020. This full-length data period is sub-divided into three data periods. The first data set covers the pre-COVID-19 period and it consists of seven months' data from August 2019 to February 2020. The second data set covers the COVID-19 data period where we deal with the period from March 2020 to September 2020. The third data set includes the both periods, that is, August 2019 to September 2020.

***Variables*:** On the relationship of stocks' returns with the different reference points, we use proxy measures for various independent variables. The sample stocks' daily return over the said periods is taken as the dependent variable. The ten-years Government bonds' yield data over the said periods is taken as the risk-free rate of return (R_f) and it depicts the PT certainty effect. The other daily time series variables - the gold return (*GR*), the USD-INR exchange rate return (*UI*), EURO-INR exchange rate return (*EI*) and NSE NIFTY index return (*NI*) during the same periods are taken as alternative references for market return variables. We have used www.investing.com to collect these data and each data set consists of 427 observations.

Regression Method: Since the theoretical proposition of the proposed PT/MT assimilation needs both long-run and short-run decision references, the representation of the nonlinear auto-regressive distributed lag (NARDL) model of (Shin, Yu, & Greenwood-Nimmo, 2014) is used to regress the stock's daily returns data with the independent variables. Essentially, before applying the NARDL methodology, the stationarity of each dataset is checked with the Augmented Dickey-Fuller (ADF) unit-root test and all the concerned daily return variables are found to be stationary at *I(0)*. To save space, the ADF unit-root test results are not reported in detail here but could be presented in the appendix on-demand from interested readers. The NARDL approach shows long-run and short-run effects of independent variables. It provides an error correction mechanism to understand the asymmetries in the long run and helps in understanding positive and negative fluctuations. The regression methodology is followed in the next sub-section.

Regression Model: If MA and PT are viewed jointly, the PT can help investors to frame reference points for their mental accounts in determining gains and losses and the MA can help to segregate those gains and losses into separate accounts and apply at decision issues. This study examines if investors in the stock market view the PT/MA perspectives.

Let us consider a long-run decision function R(·) in the equation *Eq-1*such that R_{it} is an *i*-th stock's return at time *t* is a dependent variable defined with the independent variables X_{it} for the

reference points. R_{ft}, the Govt. bond returns proxy for the risk-free return and it represents the certainty effect. EI_t, UI_t, GR_t and NI_t are the other market-returns reference points. The coefficients of these market returns will project their respective systematic risk factor being reflection effects and R_{ft-d}, R_{it-d}, and β_{it-d} being isolation effects respectively for past-memories of R_{it}, R_{ft} and β_{it} at their d time lags viz., r and s, explained latter. At such PT decision frame, it attracts dichotomy of risk averse and risk-seeking attitudes where investors psychologically examine the prospects at positive and negative values for decision inputs $X_{it}(p,n)$ with respect to certainty effect, reflection effects and isolation effects. Since a stock's past return R_{it-d} is already observed by the investors and kept in memory, R_{it-d} has its respective isolation effect at risk-seeking/risk-averse behavior, that is, $X_{it}()$. The proposed assimilation of PT/MA has the following functional form.

$$R_{it} = R\left(X: R_{ft}, \beta_{it}, UI_t, EI_t, GR_t, NI_t, R_{ft-d}, \beta_{it-d}, UI_{t-d}, EL_{t-d}, GR_{t-d}, PI_{t-d}, R_{it-d} \middle| X(n) < 0, X(p) > 0, X() = R_{it-d}\right) \dots (Eq-1)$$

In theorizing the said PT/MA assimilation, investors' decision choice is set forth in a joint function of reference points, reflection effect and isolation effect along with possible dichotomy effects in the unrestricted non-linear autoregressive distributed lag, NARDL model in the equation *Eq-2* where coefficient α_0 is the time invariant effect, and β_{is}-s and β_i-s represent the respective effects at gains and losses. The equation *Eq-4* represents the conditional long-run error correction form (ECF) of the equation *Eq-3* which is the conditional long-run form of the equation *Eq-2*. The coefficient η in *Eq-4* represents the long-run speed of adjustment and the variable Z_{it-1} is the lagged error correction term (ECT). The ECT shows the combine effect of all the long-run variables mentioned in second brackets in *Eq-3*.

$$R_{it} = C_0 + [\sum_{r=1}^{r}\sum_{t=1}^{n} C_{1r}\, R_{it-r} + \sum_{s=1}^{s}\sum_{i=1}^{+P,-P}\sum_{t=1}^{n} \beta_{is} X_{it-s} + \sum_{i=1}^{+P,-P}\sum_{t=1}^{n} \beta_i X_{it}] + \varepsilon_t \dots\dots\dots (Eq-2)$$

$$\Delta R_{it} = C_0 + [\sum_{r=1}^{r}\sum_{t=1}^{n} C_{jr}\, \Delta R_{it-r} + \sum_{s=1}^{s}\sum_{i=1}^{+P,-P}\sum_{t=1}^{n} \beta_{is} \Delta X_{it-s} + \sum_{r=1}^{r}\sum_{t=1}^{n} C_{kr}\, R_{it-r} + \sum_{s=0}^{s}\sum_{i=1}^{+P,-P}\sum_{t=1}^{n} \beta_{iq} X_{it-s}] + \xi_t \dots\dots\dots (Eq-3)$$

$$\Delta R_{it} = C_0 + [\sum_{r=1}^{r}\sum_{t=1}^{n} C_{jr}\, \Delta R_{it-r} + \sum_{s=1}^{s}\sum_{i=1}^{+P,-P}\sum_{t=1}^{n} \beta_{is} \Delta X_{it-s} + \eta Z_{t-1}] + \varphi_t \dots\dots\dots\dots (Eq-4)$$

Lag Selection: In using any auto-regressive model, appropriate lag selection serves a greater role in identifying the influences and their extents in terms of magnitudes of the variable coefficients. We have, therefore, examined the lengths of appropriate lag for the concerned variables in the respective regression models. In doing do, we apply the procedure of Variance Estimation with the relevant dependent variable viz., the stock's return variable and the set of independent variables under the different information criteria viz., AIC, SC, etc. However, we have used the AIC method for determining the optimum lag lengths (r) for its lagged-endogenous terms in the model. We have selected a default length of (s =) 4 lags for the independent variables but opted "automatic selection" in EViews 10 system.

Hypothesis: As mentioned in the proposed assimilation of PT/MA, we formulate the following null H_{01} and alternative H_{11} hypothesis.

H_{01}: The coefficients of positive effect and negative effect of the variables in the NARDL models show presence of the PT/MA effects at the non-linear value function.

H_{11}: The coefficients of positive effect and negative effect of the variables in the NARDL models show absence of the PT/MA effects at the non-linear value function.

Results & Findings: In this section, we report the results and findings in Table 1-3. These tables show coefficients in the Equation *Eq-2*, its regression summery statistics, the results on the BPG heteroskedasticity (HTBPG) tests, the BG serial correlation LM (BGSCLM) tests, the Jarque-Bera Histogram Normality (J-B Norm.) tests along with the F-bound F-test statistics for the conditional NARDL long-run model in *Eq-3*, and the coefficients of the speed of adjustments in the conditional error correction form (*ECF*) of the long-run NARDL model in *Eq-4*. Besides, the results on the persistency of the model specification are reported briefly for the Ramsey RESET Test and the both the CUSUM tests and CUSUM of Squares Test of the recursive residuals.

Pre-COVID-19 Observations: The results in Table 1 depict that coefficients of the independent risk-free rate of return variable at its positive and negative effects $R_{fit,p}$ and $R_{fit,n}$ are different at the current time and at the different time lags as well. Such difference in magnitudes of the coefficients between relevant positive and negative effects over the current time and time-lags can also be observed for coefficients of the variables suggesting for the reference market returns - NSE Nifty (NI_{tp}, NI_{tn}), gold returns ($GR_{t,p}$, $GR_{t,n}$), EURO-INR exchange rate return ($EI_{t,p}$, $EI_{t,n}$), USD-INR exchange rate return ($UI_{t,p}$, $UI_{t,n}$). The magnitudes of all explanatory variables are not reported in details here to save space. In brief, the magnitudes and their directions of effects are different across the sample stocks but these are consistent with the non-linear PT value function of the investors. The results also confirm the presence of stock-specific different weights for gains and losses across the references.

For example, the sample stocks viz., ALKE and BION have significant negative effect for NI_{it} variable while the rest sample stocks have different significant coefficients for their respective positive and negative effects. Besides, the effects of the gold market as a decision reference are observed for the sample stocks viz., ARBN, CADI and REDY only. Investors in the sample stocks viz., LUPN and TROP (CADI, CIPL and REDY) have used EURO-INR (USD-INR) exchange return i.e., *EI* (*UI*) as their decision references. The proportions of these negative and positive effects are not exactly equal to 2. In the other words, the weights for gains in the PT value functions is not strictly twice of that for losses. That is, investors demonstrate dynamic risk-seeking or risk-averseness to an equivalent loss and gain. Similar observations can be found for the positive and negative effects of NI_{it} at its time lags. These results are contrary to a static PT view in Kahneman and Tversky (1979) but consistent with Tversky and Kahneman (1992).

The summery statistics show that the models have explanatory powers ranging 17.13% (12.98%) and 58.75% (57.76%) in terms of R^2 (Adj. R^2). The DW statistics are mostly about 2.00 suggesting absence of residual auto-correlations and the BGSCLM confirms the same. Our HTBPG test finds presence of heteroskedasticity for six stocks except ALKE, ARBN, CIPL and SUN. Therefore, the predictive power of the NARDL models for those six stocks remains under

further cross-checks. The J-B normality test for the regression residuals suggests for presence of non-normal residual distribution as well. This limits real-life applicative value of the unrestricted NARDL model for appraisal of the investment proposals during the pre-COVID-19 periods. The relevant F-value of the F-Bound F-tests suggests that the conditional long-run form of the NARDL models (*Eq-3*) is methodologically stable where there is presence of long-run and short-run effects of the concerned variables across positive and negative regions. Besides the long-run form, the magnitudes of the speed of adjustments (η) in the ECF suggests that investors always seek for adjustments to their perceived long-run equilibrium. Their speeds of adjustments vary across the stocks from -0.72284 (in the case of REDY) to -0.91853 (in the case of SUN).

COVID-19 Observations: Table 2 demonstrates that the coefficients of variable R_{ft} at its positive and negative effects i.e., $R_{fit,p}$ and $R_{fit,n}$ also different at time t and at its time-lags. Such difference in magnitudes is also prevailed for returns of the respective reference market viz., the NSE Nifty return, the gold returns and the two variables proxying for the exchange-rate return.

Table 2 shows that the sample stocks have significant positive and negative effects for the *NI* variable at its current time and at one period time-lag while the coefficient is significant at two periods time-lag for CADI, LUPN and SUN. It also shows effects of the gold market as a decision reference for ALKE, ARBN and CIPL at current time and for ALKE at 1st and 2nd period lag. The investors in the sample stocks - ALKE, ARBN and CADI (ALKE, ARBN, CIPL, REDY and SUN) have used *EI* (*UI*) as their decision references at current time and at time-lags as well. These results suggest that amongst the sample stocks, investors have changed their decision frames and choice references during the COVID-19 periods. But, interestingly, the weights for gains in the stated PT value functions are not approaching to be double at losses than that for gains even at COVID-19 risk-frames. That is, investors' dynamic adjustments sustain at losses and gains.

The explanatory powers range within 41.35% (35.519%) and 79.65% (78.31%) in terms of the magnitudes of R^2 (Adj. R^2). The DW statistics mostly at about 2.00 suggest for absence of residual auto-correlations. The predictability of the model Eq-2 is confirmed by the observations of absence of serial correlation across the stocks except ALKE while the same is restricted with the presence of heteroskedasticity for the stocks except ARBN, BION and DIVI.

However, on applicability and predictive power of the respective NARDL model at *Eq-2* during COVID-19, the results demand further examination since the regression residuals across the stocks confirm non-normality of regression residuals. The statistics of the F-Bound F-tests confirm our handiness with the conditional long-run form of NARDL models in *Eq-3* and the same is methodologically sound at presence of long-run and short-run effects for decision issues. The speed of adjustments (η) in the ECF also confirms adjustments to investors' long-run equilibrium where the speeds of adjustments vary across the stocks from -0.54369 (at the sample stock TROP) to -0.8851 (at stock ARBN).

Pulled Observations: On the pulled data period, Table 3 also depicts that the coefficients of risk-free return R_{ft} at its positive and negative effects ($R_{fit,p}$ and $R_{fit,n}$) are different at time t and lags.

Such difference in magnitudes is also observed for the markets' returns references like the NSE Nifty return, gold return and the two exchange-rates' returns.

The table further shows that the sample stocks have positive and negative effects for the *NI* variable at current *t* time and one period lag as well while coefficients are significant at two periods lag for BION and LUPN. Besides, the effects of the gold market return are present for ARBN and TROP at *t* time and for TROP at 1st time-lag as well. The sample stocks viz., ALKE, ARBN, CADI and TROP have effects of the *EI* as investors' decision reference while the sample stocks of ARBN along with those scripts of BION, CADI, CIPL, REDY, SUN and TROP as well demonstrate effects at *t* time while CADI (ARBN and BION) shows the same at one (two) period lag. That is, investors consider the decision references even at an aggregate time-scale consideration and such framing of decision issue and the choice of market references become different. Therefore, in brief, the PT decision weights for the gains and losses follow a dynamic path of adjustment rather than achieving PT proportions only.

The summery statistics of Eq-2 for R^2 (Adj. R^2) values ranging within 23.01% (21.469%) and 72.52% (71.86%) and DW statistics mostly at 2.00 support for satisfactory observations about the model *Eq-2*. Besides, the presence of residual serial correlation for CADI and CIPL and that of heteroskedasticity for all stocks except BION definitely derogates the predictability of the model *Eq-2*. The respective magnitudes of the F-Bound F-test statistics ventilates the applicative value of the conditional LRF of NARDL models in *Eq-3.* That is, investors decide about a frame for two-front choices - short-run equilibrium and long-run equilibrium where they adjust towards the latter one at an adjustment speed from -0.56403 (at LUPN) to -0.85463 (at BION).

Stability Analysis: We perform the Ramsey RESET test for persistency of the unrestricted version of the NARDL model *Eq-2*. Here, we find that the magnitudes of the relevant t-test statistics and F-test statistics are insignificant at four instances out of ten sample stocks under considerations, and this suggests for a good model specification during the pre-COVID-19 data period. With the rest six cases, the Ramsey RESET test suggests for the use of an advance GARCH set-up with the data. The both CUSUM test of residuals and that of squared residuals mostly suggest for model stability with the data sets during the pre-COVID-19 time periods (please see Table 1). During the COVID-19 periods, in Table 2, the earlier status of stability with the sample stocks shows updates in terms of their magnitudes and level of significance as well. The CUSUM test of residuals shows coefficient stability for all sample stocks while the CUSUM test statistics of the squared residuals show stability for four cases. Besides, with the pull data set, in Table 3, the said update in terms of the Ramsey RESET test statics are further observed showing a presence of five stocks those are sufficiently specified in the NARDL models. The models are mostly stable at presence of positive and negative effects where investors track these effects at their market references.

Conclusion: Investors consider many decision references simultaneously. At decision making, they consider positive and negative effects of the decision issues for all available references. In determining the decision values, such assimilation of the PT aspects along with the MA aptitudes is not a rare phenomenon rather investors are well adapted in doing so. Perhaps, the upgradation of the human intellect over its long evolution across the time has contributed an enumerable mental capacity to process such complex and non-linear accounting in their minds. The present study has

originally contributed to the literature in this direction. It confirms feasibility of assimilation of the PT/MA empirically with a small sample of NSE listed stocks out of the Indian stock market at the references of COVID-19 phenomena – during the pre-COVID periods, the COVID periods and including the both. We substantiate the presence of the proposed assimilation in all the cases.

Essentially, the human adaptation comes across new information vis-à-vis noises at mental accounting and their evolutions carry the traces of such noises in the process. That is why, we find the mixed evidences for the models' persistency and stability along with their odds. Nonetheless, the presence of significant coefficients in the Ramsey RESET test suggests us to consider volatility clustering in the future studies and this could be explained by the momentum effects as mentioned in the theoretical development. The present study has remained its scope limited in explaining the aspects of PT/MA assimilations and avoided bringing in the momentum effects in explaining the observations here. Since the present study is limited within the NARDL model, it has avoided the said route theoretical argument. The future researchers can advance the same by augmenting the NARDL model within the GARCH framework.

This research has many applicative values to the investors, market practitioners, academics, researchers, and the government as well. For example, the investors may be got accustomed about their own PT/MA aspects and take decisions accordingly. Essentially, investors who have attention exposure to the exchange-rate fluctuations should have different portfolios from others who have attention exposure to the gold rate in the bullion market. At times of launching new or innovative products like E-Bikes, Solar-electricity panel, etc., the market practitioners can apply mixed tools for their product promotions, and thereby, can penetrate both on-sought and un-sought customers. The researchers and academics with the economics background are exposed differently from those with commerce backgrounds and persons in these camps have different underpinnings of viewing the ontology of the economic reality around us and collaborative researches can explore the reality at much more logically than that at separate exploration. Finally, the government agencies like the Reserve Bank of India (RBI) or the management of the nationals banks or insurances agencies can use the PT/MA tools for trapping the long-term and short-term investors in the primary as well as secondary capital markets, and thereby, maintaining a dynamic equilibrium in the markets.

Table 1: Results on the NARDL Model during the sample's data period of Pre-COVID-19

Regression Model	$R_{it} = C_0 + [\sum_{r=1}^{r}\sum_{t=1}^{n} C_{1r}\, R_{it-r} + \sum_{s=1}^{s}\sum_{i=1}^{P}\sum_{t=1}^{n} \beta_{is} X_{it-s} + \sum_{i=1}^{P}\sum_{t=1}^{n} \beta_i X_{it}] + \varepsilon_t$									
t	**ALKE**	**ARBN**	**BION**	**CADI**	**CIPL**	**DIVI**	**LUPN**	**REDY**	**SUN**	**TORP**
R_{it} (-1)	**0.126967**^^ (0.068985)	**0.193034*** (0.061235)	**0.153971**^^ (0.06841)	**0.141078**^^ (0.059709)	**0.253014**** (0.067984)	**0.112353**^^ (0.065294)	**0.170289**^ (0.06775)	**0.277156**** (0.062597)	**0.081469**^^ (0.047095)	**0.145208**^ (0.064916)
R_{it} (-2)	0.107073 (0.067759)									
R_{fit} p	**0.525535**** (0.154482)	-0.31701 (0.24629)	0.10307 (0.157765)	**-0.80342**** (0.183674)	-0.1114 (0.129145)	0.124715 (0.17186)	**-0.4066**** (0.100295)	**0.24625**^ (0.106859)	**-0.19999**^ (0.100839)	-0.06766 (0.142826)
R_{fit} n	**0.40962*** (0.140528)	0.186671 (0.227188)	0.18329 (0.155522)	**0.381184**^ (0.174921)	**0.33867*** (0.170984)	**0.30346**^ (0.121798)	**-0.3213**** (0.098463)	0.119215 (0.101689)	**-0.1766**^^ (0.100037)	-0.09437 (0.141015)
R_{fit} p (-1)				**0.966279**** (0.227181)		**0.303171**^^ (0.178393)				
R_{fit} n (-1)				**-0.75232**** (0.221059)	**-0.41264**^ (0.190159)					

R_{fit} p (-2)				**-0.35218^** (0.17082)						
R_{fit} n (-2)				**0.44715*** (0.173875)						
EI_t p							-0.11447 (0.255078)	0.284238 (0.360581)		**-1.20147*** (0.382433)
EI_t n							**0.638792^** (0.269724)	-0.20249 (0.319071)		-0.40263 (0.482817)
EI_t p (-1)							0.381541 (0.25203)	**-0.77852^** (0.3709)		
EI_t n (-1)							**-0.4559^^** (0.258662)			**-0.92511*** (0.359184)
GR_t p	0.16773 (0.110778)	**0.520949^^** (0.282212)		**0.248771*** (0.092534)		0.06174 (0.091196)		**-0.26447^** (0.105571)		
GR_t n	0.145938 (0.109746)	**-0.89344**** (0.269931)		0.127854 (0.090508)		0.111069 (0.093261)		-0.14337 (0.090728)		
GR_t p (-1)		**-0.46229^^** (0.276659)						0.171097 (0.116465)		
GR_t n (-1)		**0.668632^** (0.294379)								
NI_t p	0.091662 (0.098851)	**1.624749**** (0.204614)	0.282632 (0.181098)	**0.637168**** (0.084187)	**0.867343**** (0.134737)	**0.743018**** (0.123502)	**0.918566**** (0.111316)	**0.917764**** (0.102477)	**1.094026**** (0.075233)	**0.374707**** (0.099506)
NI_t n	**0.169977^^** (0.093323)	**2.123628**** (0.235649)	**0.825718**** (0.161569)	**0.645068**** (0.079585)	**0.665618**** (0.126395)	**0.498608**** (0.089199)	**0.821905**** (0.100328)	**0.574121**** (0.077388)	**1.079639**** (0.069031)	**0.380286**** (0.092526)
NI_t p (-1)			**0.330327^^** (0.182197)		**-0.42659*** (0.144516)	**-0.27806^** (0.133566)	**-0.31204^** (0.125386)	**-0.58756**** (0.144844)		
NI_t n (-1)		**-0.5868^** (0.285014)	-0.26706 (0.169752)		-0.21167 (0.133545)		**-0.23575^** (0.110806)			
NI_t p (-2)								0.152226 (0.105361)		
UI_t p	-0.30634 (0.299741)			**0.768601^** (0.35235)	-0.45151 (0.288463)			-0.43359 (0.425451)		**1.211479*** (0.453463)
UI_t n	-0.2567 (0.280828)			**-1.76231**** (0.411913)	0.11635 (0.371819)			0.405003 (0.382371)		**1.3785*** (0.484487)
UI_t p (-1)				**-0.96274*** (0.376511)				**1.038963^** (0.44988)		
UI_t n (-1)				**1.314235*** (0.385332)	**-0.68017^^** (0.394699)					
C	0.000435 (0.004897)	**-0.01328^^** (0.006835)	0.001401 (0.004393)	**-0.01983**** (0.004539)	**-0.01104^** (0.004578)	**-0.00785^** (0.003238)	**-0.00867^** (0.004202)	-0.00436 (0.004413)	**-0.01564**** (0.002701)	-0.00493 (0.006027)
R^2 (Aj. R^2)	0.171321 (0.129887)	0.459058 (0.432011)	0.192022 (0.164161)	0.448131 (0.405461)	0.432807 (0.401455)	0.30052 (0.2692)	0.532266 (0.506411)	0.534629 (0.496049)	0.587571 (0.57756)	0.208576 (0.169005)
Reg. F-stat	**4.1348****	**16.97252****	**6.892069****	**10.50219****	**13.80462****	**9.595161****	**20.58686****	**13.85769****	**58.69589****	**5.270919****
DW Statistics	1.99827	1.944132	2.017242	2.009558	2.048446	1.961212	2.062071	1.97702	1.842227	1.955076
HTBPG F-stat	**1.774514^^**	**2.241752^**	1.598425	1.44385	**2.796182***	1.312168	1.135675	0.892443	**1.969164^^**	1.336408
BGSCLM F-stat	0.003886	0.571977	0.724399	0.177658	1.337295	0.423068	1.49589	0.039993	2.413486	0.630021
JB Norm (Prob.)	**8.58^**	**577.18****	**17.92****	**5.38^^**	**10.85****	**582.50****	**84.23****	**17.55****	**76.99****	**12.30***
F-value of F-Bound Test	8.303783 (2.62)	22.86427 (3.17)	25.84635 (3.60)	23.05367 (2.62)	15.57854 (3.17)	24.98563 (3.17)	19.67993 (3.17)	12.37576 (2.41)	85.21276 (3.60)	18.56299 (2.62)
η	**-0.76596**** (0.08223)	**-0.806966**** (0.05865)	**-0.846029**** (0.067116)	**-0.85892**** (0.055301)	**-0.74698**** (0.065765)	**-0.88765**** (0.061719)	**-0.82971**** (0.064992)	**-0.72284**** (0.057694)	**-0.91853**** (0.040138)	**-0.85479**** (0.061373)
Ramsey RESET: t-stat (F-Stat)	**3.909**** **(15.285)****	**2.908 *** **(8.4601)***	1.1188 (1.25187)	**2.061 ^** **(4.2459) ^**	0.0261 (0.00068)	**1.69123*** **(2.8604) ***	0.445578 (0.20773)	**1.7399^^** **(3.02759)^^**	1.05013 (1.102768)	**1.7637 ^^** **(3.111) ^^**
CUSUM Test of Residual Stability	**Stability ^**	**Stability ^**	**Stability ^**	**Stability ^**	**Stability ^**	**Stability ^**	**Stability ^**	**Stability ^**	**Stability ^**	**Stability ^**
CUSUM Test for Squared Residual	**Marginally Stable ^**	**Unstable ^**	**Marginally Stable ^**	**Stable ^**	**Marginally Stable ^**	**Marginally Stable ^**	**Stable ^**	**Stable ^**	**Marginally Stable ^**	**Stable ^**
** 0.1 % significance level; * 1% significance level; ^ 5% significance level; ^^ 10% significance level.										

Table 2: Results on the NARDL Model during the sample's data period of COVID-19

T	ALKE	ARBN	BION	CADI	CIPL	DIVI	LUPN	REDY	SUN	TORP

R_{it} (-1)	**0.286618**** (0.065551)	**0.292444**** (0.071529)	**0.19545*** (0.069288)	**0.480202**** (0.065595)	**0.356021**** (0.067873)	**0.340712**** (0.066615)	**0.527803**** (0.066439)	**0.410964**** (0.065418)	**0.231021**** (0.067945)	**0.456301**** (0.062905)
R_{it} (-2)	**-0.09891^^** (0.06072)	**0.141568*** (0.046915)	**0.155526*** (0.05899)	-0.01019 (0.05881)		**0.075877^^** (0.041045)	-0.03246 (0.063317)	**-0.07989^^** (0.046968)		
R_{it} (-3)		-0.02259 (0.048648)	**-0.09987^** (0.047882)	-0.01566 (0.049095)			-0.06736 (0.052447)	**-0.08957^** (0.04395)		
R_{it} (-4)		**-0.08889^^** (0.048152)	**-0.10031^** (0.04742)	**-0.12561*** (0.045923)			0.01431 (0.052675)			
R_{it} (-5)		**-0.09531^** (0.046415)					0.067845 (0.052132)			
R_{it} (-6)		-0.01225 (0.046971)					0.069144 (0.0518)			
R_{it} (-7)		0.044704 (0.046037)					**-0.19926**** (0.047296)			
R_{it} (-8)		**-0.14476*** (0.047705)								
R_{fit} p	-0.1363 (0.172703)	0.035578 (0.217484)	**-0.2058^^** (0.125647)	**-0.22707^^** (0.137892)	0.063553 (0.147239)	-0.00984 (0.108426)	**0.633313*** (0.199436)	**-0.42281**** (0.121348)	0.010032 (0.131253)	0.239757 (0.192167)
R_{fit} n	**-0.27795^^** (0.17161)	0.09761 (0.200766)	-0.13356 (0.124577)	**-0.40358*** (0.13648)	**0.455353^** (0.184085)	-0.06965 (0.107673)	**0.384391^** (0.169585)	**-0.50355**** (0.120778)	**0.323953*** (0.114069)	-0.24025 (0.155934)
R_{fit} p (-1)							**-0.37495^^** (0.207888)		**0.420494*** (0.160568)	**-0.43867^** (0.19912)
R_{fit} n (-1)					**-0.39035^** (0.198936)					
R_{fit} p (-2)									-0.19717 (0.126296)	
EI_t p	**2.013899**** (0.540448)	-0.09008 (0.623469)		0.501929 (0.332563)	-0.3661 (0.274914)					
EI_t n	-0.42336 (0.399339)	**1.468299**** (0.43994)		**-0.41868^^** (0.250263)	-0.19307 (0.258318)					
EI_t p (-1)	**-1.34028*** (0.506233)	**1.746639*** (0.6337)		-0.17595 (0.40901)						
EI_t n (-1)	**0.735426^^** (0.38013)									
EI_t p (-2)				**-0.9224*** (0.315591)						
GR_t p	**-0.63797**** (0.175479)	**-0.55964**** (0.153816)			0.120345 (0.093292)					
GR_t n	**0.345353^^** (0.188279)	**-0.39265*** (0.140335)			**0.156826^^** (0.092809)					
GR_t p (-1)	**0.648959*** (0.2042)									
GR_t n (-1)	**-0.98388**** (0.206106)									
GR_t n (-2)	**0.619571**** (0.16315)									
NR_t p	**0.500728**** (0.091051)	**1.42456**** (0.133086)	**0.918854**** (0.086773)	**1.136596**** (0.096321)	**1.116332**** (0.087399)	**1.014092**** (0.071907)	**0.948132**** (0.099756)	**1.011473**** (0.078853)	**1.02203**** (0.066593)	**0.742792**** (0.094066)
NR_t n	**0.361447**** (0.113545)	**1.336629**** (0.131309)	**0.809477**** (0.079171)	**1.070872**** (0.091521)	**1.217656**** (0.08722)	**0.966035**** (0.068276)	**1.017411**** (0.094991)	**0.899877**** (0.078239)	**0.999972**** (0.064823)	**0.825741**** (0.091391)
NR_t p (-1)		**-0.6596**** (0.172015)	-0.11293 (0.128429)	**-0.41278**** (0.118936)	**-0.24993^** (0.116167)	**-0.37869**** (0.090395)	**-0.57347**** (0.135918)	**-0.40235**** (0.083729)	**-0.23565^** (0.102623)	**-0.24702^** (0.097563)
NR_t n (-1)	**0.221078^^** (0.127669)	**-0.67669**** (0.157059)	**-0.26173^** (0.110405)	-0.13695 (0.152329)	**-0.42991**** (0.118761)	**-0.30532*** (0.100766)	**-0.46588**** (0.123919)	**-0.30035*** (0.111082)	**-0.31643*** (0.100625)	**-0.31493*** (0.114865)
NR_t p (-2)			**-0.22619^** (0.094865)				**0.250039^** (0.107598)		**-0.1209^** (0.058489)	
NR_t n (-2)				-0.18354 (0.126567)						
UI_t p	-0.75193 (0.637922)	0.725982 (0.815908)			**1.443309*** (0.52126)		-0.38331 (0.354395)	**1.011292*** (0.353155)	**-1.1665**** (0.310913)	
UI_t n	**0.895874^^** (0.485208)	**-2.26777**** (0.690405)			**-0.20579^^** (0.460424)		-0.30487 (0.343287)	**1.17428**** (0.296508)	-0.39458 (0.306001)	

UI_t p (-1)	**1.198614^** (0.610048)	**-1.92539*** (0.713092)			**-0.72148^^** (0.38942)			**-0.85002^** (0.426695)		
UI_t n (-1)		1.041872 (0.711443)			**0.915871** (0.478378)				**-0.97437** (0.392112)	
UI_t p (-2)								**0.845861*** (0.324392)		
C	-0.01647 (0.01182)	-0.015 (0.014911)	**-0.02416**** (0.005365)	**-0.03237**** (0.007189)	**-0.03125**** (0.008369)	**-0.02719**** (0.004927)	**-0.02516**** (0.007256)	**-0.01182^** (0.006016)	**-0.03346**** (0.005501)	**-0.02369**** (0.006262)
R^2 (Aj. R^2)	0.413532 (0.355192)	0.686928 (0.647364)	0.607918 (0.586136)	0.697843 (0.674481)	0.764177 (0.744827)	0.687383 (0.675063)	0.721802 (0.696779)	0.689205 (0.668696)	0.796538 (0.783112)	0.535674 (0.517376)
Reg. F-stat (Prob.)	**7.088328****	**17.36243****	**27.90879****	**29.87009****	**39.49315****	**55.79449****	**28.84544****	**33.60448****	**59.32628****	**29.27412****
D.W. Statistics	2.102031	2.012967	2.020335	1.967641	2.044952	2.029483	2.068006	2.055491	1.986054	2.041241
HTBPG F-stat	**3.624936****	1.065606	1.478768	**4.757244****	**5.512248****	1.233973	**5.474794**	**6.969406****	**2.7257****	**4.043288****
BGSCLM F-stat	**3.383202^^**	0.079207	0.818646	0.00027	0.648444	0.585407	1.007062	0.753256	0.016555	0.661815
JB Norm (Prob.)	**73.14266****	**1321.714****	**124.0567****	**307.6893****	**90.30246****	**19.40260****	**44.55451****	**14.56127****	**16.0224****	**21.03362****
F-value of F-Bound Test (sign.)	10.34985 (2.41)	7.34356 (2.41)	14.99924 (3.60)	11.45586 (3.17)	8.88376 (2.41)	13.16218 (3.60)	7.6026 (3.17)	13.82075 (3.17)	16.66669 (3.17)	13.31173 (3.60)
η	**-0.8123**** (0.070876)	**-0.8851**** (0.091558)	**-0.8492**** (0.088407)	**-0.67125**** (0.068886)	**-0.64398**** (0.06068)	**-0.58341**** (0.064856)	**-0.61998**** (0.078065)	**-0.75849**** (0.070886)	**-0.76898**** (0.065443)	**-0.54369**** (0.060101)
Ramsey RESET Test	**2.05747 ^ (4.23319)^**	0.930214 (0.86299)	0.027252 (0.000743)	**4.41328 ** (19.477) ****	**3.6589** (13.388)****	0.16199 (0.26241)	**2.05054^ (4.2047)^**	**6.8804 ** (47.3345)****	0.21461 (0.046057)	**2.8618 * (8.18985)***
CUSUM Test of Residual **Stability**	**Stability ^**	**Stability ^**	**Stability ^**	**Stability ^**	**Stability ^**	**Stability ^**	**Stability ^**	**Stability ^**	**Stability ^**	**Stability ^**
CUSUM Test for Squared Residual	**Marginal Stability ^**	**Unstable ^**	**Marginal Stability ^**	**Marginal Stability ^**	**Unstable ^**	**Stability ^**	**Marginal Stability ^**	**Marginal Stability ^**	**Stability ^**	**Unstable ^**

** 0.1 % significance level; * 1% significance level; ^ 5% significance level; ^^ 10% significance level.

Table 3: Results on the NARDL Model with the full-length sample data period

Variables / Parameters	ALKE	ARBN	BION	CADI	CIPL	DIVI	LUPN	REDY	SUN	TORP
R_{it} (-1)	**0.235959**** (0.045995)	**0.269672**** (0.047558)	**0.18236**** (0.048872)	**0.368514**** (0.047982)	**0.378617**** (0.046134)	**0.291426**** (0.04683)	**0.514183**** (0.048391)	**0.434593**** (0.046452)	**0.282307**** (0.046937).	**0.358901**** (0.046125)
R_{it} (-2)		**0.0771^** (0.035693)	**0.136924*** (0.045151)	-0.0278 (0.03822)			-0.00065 (0.051311)	-0.04179 (0.036114)		
R_{it} (-3)			**-0.0744^^** (0.038969)	-0.02779 (0.03921)			-0.04832 (0.038166)	**-0.07434^** (0.033781)		
R_{it} (-4)			**-0.09944*** (0.038434)	**-0.12064**** (0.036263)			-0.01315 (0.038337)			
R_{it} (-5)							**0.064084^^** (0.03815)			
R_{it} (-6)							**0.068271^^** (0.037947)			
R_{it} (-7)							**-0.14844**** (0.03461)			
R_{fit} p	0.118538 (0.108684)	-0.00332 (0.147838)	-0.01547 (0.098554)	**-0.15937*** (0.093831)	0.016971 (0.097116)	0.102336 (0.078225)	**0.33192*** (0.12902)	**-0.20511** (0.076638)	-0.08142 (0.099985)	0.158272 (0.142267)
R_{fit} n	0.095618 (0.106895)	-0.12947 (0.143158)	-0.02399 (0.095718)	**-0.14924^^** (0.091908)	**0.384512*** (0.125442)	0.077228 (0.076555)	0.13537 (0.096875)	**-0.18974^** (0.075012)	0.102105 (0.076019)	-0.1478 (0.107851)
R_{fit} p (-1)							**-0.22136^^** (0.132355)		**0.19057^^** (0.102656)	**-0.27291^^** (0.145646)
R_{fit} n (-1)					**-0.34742^** (0.139668)					
EI_t p	**0.707127*** (0.261147)	-0.53798 (0.490455)		**0.62517^** (0.316147)						**-0.40038^^** (0.232393)
EI_t n	0.218116 (0.192833)	**0.974457*** (0.341409)		**-0.53682^** (0.21603)						**-0.48167^** (0.223155)
EI_t p (-1)	0.158571 (0.328983)	0.157056 (0.601502)		-0.47778 (0.352229)						
EI_t p (-2)	**-0.60416^** (0.249139)	**1.051933^** (0.461554)		**-0.69546*** (0.223267)						

GR_t p		**-0.25732**^ (0.107022)	0.082298 (0.072908)							0.083938 (0.084414)
GR_t n		**-0.24963**^ (0.108463)	0.090114 (0.073877)							**0.245002**^ (0.102114)
GR_t n (-1)										**-0.15952**^ (0.113261)
NR_t p	**0.31938**** (0.077017)	**1.52359**** (0.114091)	**0.804482**** (0.076123)	**0.97499**** (0.073617)	**1.102319**** (0.067399)	**0.911891**** (0.058457)	**0.918403**** (0.071135)	**0.915575**** (0.057581)	**1.082861**** (0.053041)	**0.637924**** (0.077848)
NR_t n	**0.480281**** (0.061128)	**1.492466**** (0.109377)	**0.801402**** (0.074458)	**0.899033**** (0.074268)	**1.065019**** (0.065467)	**0.883077**** (0.057118)	**0.973052**** (0.067959)	**0.835744**** (0.057216)	**1.052258**** (0.053323)	**0.720956**** (0.077126)
NR_t p (-1)	**0.133298**^^ (0.081922)	**-0.53003**** (0.133285)	0.017883 (0.106938)	**-0.23966*** (0.077981)	**-0.37826**** (0.082659)	**-0.31726**** (0.069618)	**-0.46831**** (0.102872)	**-0.3752**** (0.061591)	**-0.33786**** (0.072027)	**-0.16421**^ (0.078536)
NR_t n (-1)		**-0.55816**** (0.129667)	**-0.28774*** (0.090738)	-0.14613 (0.093713)	**-0.34188**** (0.084135)	**-0.27539**** (0.07279)	**-0.51859**** (0.103744)	**-0.29883**** (0.074759)	**-0.30134**** (0.074919)	-0.22343 (0.087113)
NR_t p (-2)			**-0.29153**** (0.083478)				**0.142469**^^ (0.080319)			
NR_t n (-2)							0.125556 (0.08497)			
UI_t p		0.595939 (0.615384)	-0.32762 (0.281457)	-0.26342 (0.393385)	**0.420699**^^ (0.246275)			**0.573602**** (0.178446)	**-0.44104*** (0.166308)	**0.580019**^^ (0.313674)
UI_t n		**-1.44584*** (0.468879)	-0.21747 (0.314361)	**0.570435**^^ (0.307299)	-0.17185 (0.275766)			**0.556267**** (0.165245)	**-0.44939*** (0.153494)	**0.647705**^ (0.297881)
UI_t p (-1)		-0.4362 (0.7357)		**0.932956**^ (0.392295)						
UI_t n (-1)			**0.699288**^^ (0.403572)		-0.01609 (0.344563)					
UI_t p (-2)		**-1.67447*** (0.565823)								
UI_t n (-2)			**-0.74368**^ (0.311348)		0.568919 (0.25724)					
C	-0.00797 (0.005663)	-0.00128 (0.007806)	-0.00012 (0.00537)	**-0.01792**** (0.005311)	**-0.0114**^ (0.004552)	**-0.00875**** (0.002699)	-0.00479 (0.003305)	**-0.00795**^ (0.003746)	**-0.01104*** (0.003489)	**-0.01152**^ (0.005294)
R^2 (Aj. R^2)	0.230111 (0.211469)	0.546551 (0.526397)	0.474068 (0.451992)	0.585893 (0.568511)	0.685449 (0.676265)	0.567294 (0.56003)	0.663585 (0.650228)	0.616781 (0.60655)	0.725223 (0.718586)	0.425295 (0.404218)
Reg. F-stat (Prob.)	**12.34407****	**27.11965****	**21.47418****	**33.70638****	**74.63545****	**78.1004****	**49.68271****	**60.28223****	**109.2678****	**20.17795****
DW Statistics	2.021	2.009	2.013	2.05581	2.074223	2.022879	1.953503	2.015862	2.031004	2.012514
HTBPG F-stat	**3.434603****	**1.764482**^	1.25714	**8.419635****	**9.578595****	**3.07254***	**8.258328****	**14.31842****	**5.856832****	**3.325582****
BGSCLM F-stat	0.305574	0.07662	0.795008	**3.618635**^^	**3.679067**^^	0.631979	0.221208	0.312804	1.167386	0.245472
JB Norm (Prob.)	**371.0537****	**1544.076****	**116.3390****	**720.1504****	**209.7161****	**175.9312****	**428.2380****	**101.6336****	**86.69870****	**82.80607****
F-value of F-Bound Test (sign.)	38.02392 (3.17)	14.66499 (2.41)	15.63758 (2.62)	21.24846 (2.62)	24.28638 (3.17)	38.40325 (3.60)	15.02925 (3.60)	22.20015 (3.17)	29.55806 (3.17)	16.82458 (2.41)
η	**-0.7641**** (0.043440)	**-0.6532**** (0.048586)	**-0.85463**** (0.067596)	**-0.80772**** (0.054805)	**-0.62138**** (0.044204)	**-0.70857**** (0.046402)	**-0.56403**** (0.05903)	**-0.68153**** (0.050712)	**-0.71769**** (0.046282)	**-0.6411**** (0.044525)
Ramsey RESET Test	0.8244 (0.67964)	0.819028 (0.670807)	0.636904 (0.405647)	**6.2609 ** (39.199) ****	**4.88173 ** (23.8313)****	0.58129 (0.33790)	**3.9940 ** (15.9521)****	**7.05124 ** (49.7199)****	0.698817 (0.488345)	**4.03649 ** (16.2932)****
CUSUM Test of Residual **Stability**	**Stability** ^	**Stability** ^	**Stability** ^	**Stability** ^	**Stability** ^	**Stability** ^	**Stability** ^	**Stability** ^	**Stability** ^	**Stability** ^
CUSUM Test for Squared Residual	**Unstable** ^	**Marginal Stability** ^	**Stability** ^	**Unstable** ^	**Marginal Stability** ^	**Stability** ^	**Unstable** ^	**Unstable** ^	**Marginal Stability** ^	**Marginally Unstable** ^
** 0.1 % significance level; * 1% significance level; ^ 5% significance level; ^^ 10% significance level.										

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