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DOES MENTAL ACCOUNTING MATTER IN PORTFOLIO MANAGEMENT? A PROSPECT THEORY APPLICATION

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Abstract. Do the propositions of mental accounting matter in investors' portfolio management? In assisting the investors in their portfolio management, this study explores if the separation principle in mental accounting (MA) can be applied in their portfolio decision choices. It also examines if investors prefer an individual stock to the portfolio of stocks for investments. With the use of daily market prices data during a twenty-year time period for nine NSE Nifty sample stocks and their portfolio as well, this study applies the prospect theory (PT) decision references in the non-linear autoregressive distributive lag (NARDL) models. It also performs robustness checks with t-tests for differences between the coefficient magnitudes in the models. At PT implications with the variables for market premium, systematic beta and isolation effects, the separation principle of the MA theory matters in the portfolio management for stocks' returns and market return. Investors' psychological effect is found to contribute to their preferences amongst the sample stocks for their inclusion in the portfolio. Ingenious applications of the PT views on MA in portfolio management reveal the presence of synchronicity in terms of long-memory and short-memory effects on returns of the stocks and portfolio as well. Even if the generalizability of the stated findings is subject to its sample size, this empirical exploration with the Indian stocks market data shows original contribution in mental accounting and its use to explain the equity premium puzzle could enhance its applicative value.

1. Introduction

In behavioral finance, the mental accounting (MA) theory addresses problems of accounting mismatches like fungibility in balancing accounts by individuals and households. People create mental accounts for ex-post and ex-ante cost-benefit analysis, group expenditures into different categories like housing, food, entertainment etc, treat their different expenses at implicit or explicit budgetary constraints, and they balance them at some intervals. In explaining MA, Thaler (1980, 1985, 1999) used the prospect theory (PT) value function in Kahneman and Tversky (1979) and Tversky and Kahneman (1992) as well, where the value function is defined at gains and losses relative to their decision references while gains and losses have diminishing sensitivity and people show loss aversion behavior. The MA theory can explain the consumers' behaviors in advance purchase, considering sunk cost in current purchase, payment decoupling, consumption-based budgeting, self-control and gift-giving, etc. Can the separation principle in mental accounting be applied to portfolio decision choice? Should investors invest in individual stock of preference or portfolio of stocks? These queries are occasionally puzzling in investors' minds but least addressed in behavioral finance empirically.

The standard finance proposition in Markowitz (1952)'s portfolio theory suggests for investing in diversified portfolios while that in the capital assets pricing model (CAPM) of Sharpe (1964), Lintner (1965) and Mossin (1966) suggests for investing in the stocks which complement their

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returns at the rate of the excess risk premium (the market rate of return, Rm less the risk-free rate of return, Rf) for the beta of the stocks under an investor's decision choice. The propositions of Markowitz (1952) and the CAPM have an interconnection at the market rate of return Rm representing it as the return of a well-diversified portfolio. At the center of the two propositions, the standard finance researchers put their beliefs on the investors' rationality and view risks of investment from the expected utility perceptions. In contrast, the behavioral finance researchers put forward behavioral dimensions in the investors' decision-making. For example, investors' past memory about performances of the stocks or the stock market serves as decision references and influences their present decision choices (Nguyen, Prokopczuk, and Sibbertsen 2020 read with Han, Li, Ma, and Kennedy 2023). The researchers have also explored the hierarchy-need based portfolios (Majewski and Majewska 2022) or the investors' goal-based portfolio (Parker 2021; Özyörük 2022). The standard finance theories fail to address investors' time-tracking, time-dependent and goal-oriented decision choices while the behavioral finance theories and its experimental researches appear very eloquent (Broihanne, Merli, and Roger 2008; Silva, de Lacerda Moreira, and Bortolon 2023) even if there exists a dearth of empirical studies.

This study explores the stated research queries empirically with a sample of nine stocks listed in the NSE Nifty in India during the Pre-COVID-19 period. This effort is an extension of Barberis and Huang (2001) in the Indian context. Barberis and Huang (2001) have developed the theoretical model for the stock-level accounting and portfolio-level accounting and derived simulation results whereas we explore empirically. Its related studies include style investing in Barberis and Shleifer (2003) and Hossain (2018), where stocks in the same style are correlated in their price movements but stocks in different styles are uncorrelated. The proposition of style investing is somewhat in contrast to those in the modern portfolio theory and CAPM framework as well but the same is well tuned to the MA theory. We ingeniously show the presence of non-linear dynamic equilibrium effects at the prospects of gains and losses along with their short-run and long-run impacts at the stock-level accounting and portfolio-level accounting.

In the flow, we review the literature in Section 2. We discuss the concepts on prospect theory applications in mental accounting in Section 3, the empirical data and methodology in Section 4, and the empirical results and findings in Section 5. In Section 6, we demonstrate the originality, limitations and future research areas of the study and conclude it as well.

2. Literature Review

The mental accounting (MA) theory has received huge research interest from academics in the field of behavioral psychology since its early development in the nineties by Richard H. Thaler (Thaler 1985, 1999; read with Thaler 2008). In the experimental fields vis-à-vis empirical literature of financial economics viz., finance, economics and marketing, it has been happening just very recently primarily with the works of Barberis, Jin, and Wang (2021), Wang, Wu, and Zhong (2021), Barberis, Mukherjee, and Wang (2016), Mahapatra and Mishra (2020), Cheng, Yu, Wang, and Zheng (2023), and do Nascimento Junior, et al., (2021) as well. However, a clustered theoretical review of the same can be found in Kiky (2023) and Mundi and Vashisht (2024). Nonetheless, in the field of financial accounting, the views of researchers and academics on the propositions of the MA theory itself are in sharp contrasts to their standard accounting practices while the business practitioners and financial economists are yet to receive substantive explorations on their capital market implications empirically. . In addressing the aforementioned two puzzling queries of the investors in general, the mental accounting theory (hereinafter, MAT or "MA theory" interchangeably) of Thaler (1999) considers the prospect theory (PT) views of Kahneman and Tversky (1979) and Tversky and Kahneman (1992). The MA theory suggests that investors consider performances of their stocks and portfolios in different mental accounts and the PT proposition assists in using their different reference-dependent decision choices at the relevant issues of loss aversion and narrow framing (Thaler 1999, 202). In developing the MA theory, Thaler (1985) has viewed the process of mental accounting by individuals at their reference to consumer choices while in explaining investors' disposition effects with the loss-stocks, Shefrin and Thaler (1988) have incorporated self-control, mental accounting and framing-effects in the behavioral life-cycle theory of the households. Brendl, Markman, and Higgins (1998) and Cheema and Soman (2006) have viewed the same at active goal-oriented self-regulations or self-control by consumers where their gains and losses are weighted at their contributions to the active goals. Okada (2001) has viewed the mental accounting functions at assets' mental book values along with their mental depreciations in deriving the mental replacement costs of the durable assets.

The MA theory explains the sunk cost fallacy in the consumer behaviors (Soman, 2001) while the sunk cost gives some additional information about future profits (Baliga and Ely 2011). Baucells and Hwang (2017) and Tait and Miller Jr (2019) have showed that the MA theory uses consumers' adaptation to the reference price and this can explain their sunk-cost effects, payment depreciation, reluctance to trade, preference for prepayment and the flat-rate bias etc. A further extension of the MA theory can be observed in developing the collective mental accounting model for selection of the behavioral portfolios and sub-portfolios (Momen, Esfahanipour, and Seifi 2019). A preliminary answer can be found in the experimental study of Cheng, et al., (2023) such that under the conditions of a scarcity mindset, the consumers prefer to display hedonic consumption effects with their windfall gains significantly while at the absence of such scarcity mindset, the said effect becomes insignificant.

But how do investors simultaneously make their mental accounts for the risk-seeking behaviors at prospects of profits in the bull stocks and for risk-averse behaviors at prospects of losses in the bear stocks? Since at shifting of reference points, the relative values for gains and losses change, the said research proposition needs shifting of decision references on a real-time basis while keeping the alternative references active in mind. That is, the behavioral investors need to merge their decision choices for the prospect theory effects along with those for the mental accounting effects. The said mixed theoretical flavours of behavioral explanation for the MAT combined with that of the PT can be observed to explain the disposition effect in Shefrin and Statman (1985), rational momentum effect in Johnson (2002), and consumers' flexibility at attractive spending in Grinblatt and Han (2005), Cheema and Soman (2006) and Lim (2006). This theoretical mix explains the price-sensitive consumers' avoidance of online purchases even at the lowest prices in the e-commerce markets (Gupta and Kim 2010). The combined effects can also be applied to explain investors' financial risk tolerance at the presence of perceived uncertainties about the future cash flows or at their absence. Martin and Davari (2018) have found the presence of a negative relationship of the investors' perceived current debts with their financial risk tolerance but such negative relationship ceases to exist at the reverse situation. Fels (2020) has explored the implications of the stated combined effects in the case of over-insurance and has found that investors' over-insurances are caused by their wrong perceptions of mental accounts about the perceived future risks. With a comparative study for the pre-COVID-19 and during the COVID-19 time periods, Sinha and Agarwal (2021) have found some promising results for their proposed PT/MAT assimilation of the positive and negative effects of the decision references in the selection of individual stocks.

The related literature to the present research problem includes the studies explaining the standard finance anomaly of the equity premium puzzle – the investors demand large premiums for the equity stocks over the risk-free rate of return but insignificant returns for the stocks with higher idiosyncratic risks (Ang, Hodrick, Xing, and Zhang 2006; Barberis and Huang 2006; Gürtler and Hartmann 2007). The said equity premium puzzle can be explained by the MA theory (Barberis and Huang 2001). In this direction of research, there is an urgent need to explore Barberis and Huang (2001) empirically and to examine if the investors prefer stock-level accounting to portfolio-level accounting in their investment decision choices. In a remote exploration of the issue, Barberis and Huang (2008) have showed that highly skewed stocks' returns can be explained by investors' considerations of risky stocks as lotteries, and thereby, underestimating their high idiosyncratic risks. In a related exploration, Tudor (2012) found that individual stocks in the Romanian stock markets illustrate an inferior performance of investors' active portfolio management to that of their passive portfolio management.

The related empirical literature includes a few recent studies. Barberis, Mukherjee, and Wang (2016) have used a two-step process where investors form their mental representation about a stock with its distribution of past returns, evaluated its prospect theory value and predicted if the stock's prospect theory value is negatively autocorrelated such that the stocks with high prospect theory value will attract a demand pressure followed by its overvaluation in the market and resulting diminishing long-run returns. But this prediction is anomalous because once the investor considers the values of the same stock's returns in deriving its prospect theory value, the presence of its diminishing long run returns history itself makes it a low prospect theory value asset in the first place. Barberis, Jin, and Wang (2021), however, have incorporated parameters for the cumulative prospect theory (CPT) value of the gains and losses in modelling the prices of capital assets and found empirical supports in explaining many standard finance anomalies, but they have not included the influence of mental accounting as a factor. Gupta, Mishra, and Jacob (2022) find that the CPT valuation of historical returns of the equity mutual funds from the countries across Europe, Asia Pacific (but not from India) and North America influence capital flows in mutual funds while investors exhibit loss aversion and overweighting behaviors significantly. do Nascimento Jn., Klotzle, Brandão, and Pinto (2021) have examined the effects of narrow framing bias on stock returns in Brazil, China, Russia, Mexico and South Africa and have found asymmetric results. With the sample stocks listed in China, Wang, Wu, and Zhong (2021) find predictive power for investors' loss aversion, diminishing sensitivity to gains or losses and probability weighting as well.

None of the studies explored mental accounting perspectives in portfolio management and its possible links to the prospect theory aspects such that the investors treat their individual stock accounts and the portfolio accounts separately in deciding their preference for individual stocks to portfolios. Nonetheless, there is a need for attention on exploring the anomaly of the equity premium puzzle empirically within the context of the NSE or BSE listed stocks in India. This paper targets this specific niche research needs in the empirical literature and it addresses the same with the following theoretical proposition.

P0: *Investors' mental accounting matters at individual stocks' levels and portfolio level and both show presence of prospect theory references for short-run and long-run effects of market premium and systematic risk along with adjustments to their long-run relationships.*

3. Prospect Theory Applications in Mental Accounting

Before we move to formulate the empirical methodology and its testable hypothesis, let us briefly explain the relevant concepts on the prospect theory applications in mental accounting.

a) Narrow Framing of Isolation effects: Investors' framing of decision choices depends on the style of presentation, their preference for choice of contexts, treatments involved in data processing, and nature of display of the data and facts as well (Kahneman and Tversky 1986). Very often investors are framed with the historical results of the stocks in the market or the market indices and are depicted the expected consistency (inconsistency) over the time periods as if the stocks are invariant (variant) of time period only. This short of narrow framing involves data manipulation in terms of decision endogeneity and thereby, involving isolation effects where investors disregard commonalities in the alternatives (Kahneman and Tversky 1979) and consider that the past reference of decision variable influences the future performances. In the other words, there exist lagged effects consistently.

b) Change of decision references: Under the prospect theory perspectives (Kahneman and Tversky 1979; Tversky and Kahneman 1992), investors depict the certainty effects and risk-seeking effects as well while investors have weighting problems. They are risk-averse (risk-seeker) at the presence of low (high) probability of risk-levels because in decision coding, they overestimate (underestimate) the magnitudes of risk. Their risk perception can include references of systematic risk and market premium for stocks and portfolio. Nonetheless, a change in each decision reference would include consideration of their effects at different lags of these variables, that is, at their short-run and long-run effects as well.

c) Adaptive learning: The CPT proposition in Tversky and Kahneman (1992) advances the aspects of adaptive learning, where investors consider their competitive decision prospects as a bundle of positive and negative aspects for the prospect theory value function. That is, investors' PT values demonstrate an additive property but subject to the weighting problem. Thus, the adaptive learning proposition is embedded in the CPT and it advances the co-integrating relationship amongst the prospect theory values and decision weights. Interested readers can find links of investors' adaptive learning behaviors and reinforcement learning in Prashanth, Jie, Fu, Marcus, and Szepesvári (2016) as well.

d) Dynamic adjustments: Tversky and Kahneman (1992, 314) have demonstrated that for the same magnitude of probability weight, indifference curve of the non-positive prospects become more steeper than that of the non-negative prospects. This suggests for presence of non-linear property as demonstrated in the probability weighting function and so, referring towards dynamic adjustments in investors' decision choices at the different situations. That is, at times of reinforcement of the decision choices, investors' mental accounting involves dynamic adjustments towards their long-run targets. An elaborative theoretical study towards the dynamic prospect theory can be found in Tymula, et al., (2023).

e) Mental separation: The investors' decision choice for selection of particular stocks over a portfolio of stocks and vice-versa involves regret aversion. Investors can find benefits of trust from financial advisors (Cruciani and Cruciani 2017) or by means of mental accounts themselves since their mental accounting provides mental shortcuts towards structuring the alternatives and making preferences. Nonetheless, a plausible mental shortcut is comparing the parameter values at the stock level with those at portfolio level. Investors susceptible to mental losses also need mental separation besides taking advisor's assistances.

4. Data and Methdology

In exploring the theoretical proposition P0 empirically, we needed sample firms which could represent itself as strong candidates for inclusion in the portfolio by the investors and thereby, satisfying the prospect theory certainty effect. Since we consider the Indian context, the NSE Nifty fifty index with its consistent presence provides a well-performed list of such stocks for consideration. We have considered a long time period of mostly 20 years' returns data. We tracked the daily prices of the NSE Nifty stocks over a data period 03.04.2000 to 14.01.2020 consistently and found nine sample stocks which persistently incorporated into the NSE Nifty index. We have included these stocks' price data up to 14.01.2020 but in deriving the stocks' annual returns data, we have used up to 14.01.2019 at the base period prices, exactly just one year earlier from the first news about COVID-19 on 15.01.2020 as reported in Japan. This assists us making our results free from the COVID-19 attention bias. Hence, our sample stocks included only nine stocks which are viz., Grasim India (GRAS), Housing Development Finance Corporation (HDFC), HDFC Bank (HDBK), ICICI Bank (ICBK), ITC Ltd (ITC), Reliance Industries Ltd (RELI), State Bank of India (SBI), Tata Motors (TAMO), and Tata Steel (TISC). Besides the nine stocks' returns data, we have used ten years' government bonds' yield rate of returns to proxy for the risk-free rate of return (Rf). The study uses the secondary data source of www.investing.com for the above two sets of returns data.

We derive their daily returns data in terms of percentage change in their closing market values – the closing price data for the individual stocks and the closing index figure for the NSE Nifty index. The portfolio return data is derived as the simple mean of the individual sample stocks' annual returns. Taking one year's historical returns data on a rolling year-to-year basis and using the NSE Nifty market returns as the reference for comparison, we derive the linear slope coefficients of the stocks and the portfolio, that is, the systematic risk beta of individual stocks as well as the portfolio. In deriving the linear slope coefficient of the NSE Nifty market's risk premium (i.e., market's returns over R¬f), it regresses the same as independent variable on individual stocks' risk premium and portfolio risk premium as dependent variables separately, that is, the stocks/portfolio's excess returns over Rf are used as dependent variable/s. Thus, in defining the portfolio risk measure, we use the empirical methodology of the adaptive dynamic decision choice reference and thereby, derive the portfolio beta from the basic input data of the daily portfolio returns and the market returns rather than using the Markowitz mean-variance methodology. Such application is intuitively simple and it appears appropriate in the terms of investors' dynamic switching of mental accounts amongst the sample stocks.

We have a large size of data series of daily data (6491, 6493, 6487, 6494, 6493, 6494, 6493, 6485 and 6492 for GRAS, HDBK, HDFC, ICBK, ITC, PORT, RELI, SBI, TAMO and TISC respectively and 6490 for portfolio). In exploring data characteristics, we firstly examine stationarity with the Augmented Dicky Fuller (ADF) test for possible unit-roots of the return variables and systematic risk beta variables. In Table 1, we show that individual stocks' returns, NSE Nifty market returns, risk-free rate of returns and the risk premiums both at the individual stocks' level and the portfolio level - all are of I(0) stationarity both at data level, at their 1st differences, and at with or without trend effects. Interestingly, the relevant beta coefficients for the individual stocks as well as the portfolio beta are not of I(0) stationary but of I(1) both with or without the trend effects. Since the data set covers a very long-time range of mostly twenty years, we also perform ADF break point tests. The relevant results are showed in Table 2 and it suggests that the return variables have no significant break points while the systematic risk - beta variables at individual stocks' level and at portfolio level have significant breakpoints at their I(0) data level at 1% level of significance but not at I(1) data level. An examination of the root cause of the non-stationarity of systematic risk beta variables at I(1) level may reveal if the same at stocks' level and portfolio level may have dynamic cointegrations with stocks' returns and portfolio returns respectively. The presence of such cointegration warrants considering the presence of a long-memory effect which is otherwise inexplicable in the linear capital asset pricing model (CAPM) framework for its instantaneous effect-based relationship.

Table 1. Statistics at ADF Unit Root Tests for the Variables

Variables	**ADF Test without Trend and Intercept**			**ADF Test with Trend and Intercept**		
	I(0)	**I(1)**	**I(2)**	**I(0)**	**I(1)**	**I(2)**
Dependent Variables (SR: Stock Return, PR: Portfolio Return)						
SRGRASIM	-40.96 (0.001)	-27.99 (0.001)	-30.22 (0.001)	-41.06 (0.001)	-27.99 (0.001)	-30.21 (0.001)
SRHDBK	-38.55 (0.001)	-26.62 (0.001)	-31.38 (0.001)	-38.77 (0.001)	-28.62 (0.001)	-31.37 (0.001)
SRHDFC	-42.04 (0.001)	-26.90 (0.001)	-31.11 (0.001)	-42.16 (0.001)	-26.89 (0.001)	-31.11 (0.001)
SRICBK	-39.42 (0.001)	-27.16 (0.001)	-30.86 (0.001)	-39.50 (0.001)	-27.15 (0.001)	-30.84 (0.001)
SRITC	-41.37 (0.001)	-32.43 (0.001)	-29.02 (0.001)	-41.48 (0.001)	-32.42 (0.001)	-29.02 (0.001)
SRRELI	-40.62 (0.001)	-31.48 (0.001)	-28.59 (0.001)	-40.72 (0.001)	-31.48 (0.001)	-28.59 (0.001)
SRSBI	-42.86 (0.001)	-26.48 (0.001)	-29.64 (0.001)	-39.39 (0.001)	-26.47 (0.001)	-29.64 (0.001)
SRTAMO	-8.97 (0.001)	-23.44 (0.001)	-31.52 (0.001)	-9.14 (0.001)	-23.44 (0.001)	-31.52 (0.001)
SRTISC	-39.04 (0.001)	-28.09 (0.001)	-31.84 (0.001)	-39.17 (0.001)	-28.09 (0.001)	-31.84 (0.001)
PRNIFTY	-27.57 (0.001)	-27.83 (0.001)	-30.54 (0.001)	-27.88 (0.001)	-27.82 (0.001)	-30.53 (0.001)
Independent Variables (SB: Stock Beta, PB: Portfolio Beta, MPR: Market Premium)						
SBGRASIM	-1.468 (0.133)	-44.04 (0.001)	-26.16 (0.001)	-1.68 (0.759)	-44.04 (0.001)	-26.16 (0.001)
SBHDBK	-1.436 (0.141)	-47.03 (0.001)	-25.63 (0.001)	-1.887 (0.661)	-47.04 (0.001)	-25.63 (0.001)
SBHDFC	-1.198 (0.212)	-42.18 (0.001)	-29.18 (0.001)	-1.86 (0.676)	-42.18 (0.001)	-29.18 (0.001)
SBICBK	-1.537 (0.117)	-41.63 (0.001)	-25.04 (0.001)	-1.58 (0.801)	-41.64 (0.001)	-25.04 (0.001)
SBITC	-1.62 (0.099)	-46.19 (0.001)	-25.11 (0.001)	-1.72 (0.743)	-46.19 (0.001)	-25.10 (0.001)
SBRELI	-1.408 (0.148)	-42.31 (0.001)	-25.62 (0.001)	-1.365 (0.871)	-42.32 (0.001)	-25.62 (0.001)
SBSBI	-1.430 (0.143)	-45.26 (0.001)	-28.99 (0.001)	-1.932 (0.637)	-45.26 (0.001)	-28.99 (0.001)
SBTAMO	-1.915 (0.053)	-27.14 (0.001)	-24.21 (0.001)	-2.104 (0.543)	-27.16 (0.001)	-24.21 (0.001)
SBTISC	-1.689 (0.087)	-23.94 (0.001)	-26.92 (0.001)	-1.849 (0.681)	-23.97 (0.001)	-26.92 (0.001)
PBNIFTY	-1.479 (0.130)	-42.76 (0.001)	-25.61 (0.001)	-1.393 (0.863)	-42.78 (0.001)	-25.59 (0.001)
MPNIFTY	-55.11 (0.001)	-30.94 (0.001)	-28.71 (0.001)	-55.17 (0.001)	-30.94 (0.001)	-28.70 (0.001)

TABLE 2. Test Statistics at ADF Breakpoint Unit Root Tests for the Variables

Variables	**Innovative Outlier Method**			**Additive Outlier Method**		
	I(0)	**I(1)**	**I(2)**	**I(0)**	**I(1)**	**I(2)**
Dependent Variables (SR: Stock Return, PR: Portfolio Return)						
SR_{GRASIM}	-56.995 (<0.01) [27-04-2001]	-118.11 (<0.01) [30-04-2001]	-166.41 (<0.01) [30-04-2001]	-57.001 (<0.01) [30-04-2001]	-118.13 (<0.01) [27-04-2001]	-166.43 (<0.01) [30-04-2001]
SR_{HDBK}	-58.978 (<0.01) [17-04-2001]	-118.62 (<0.01) [19-04-2001]	-165.85 (<0.01) [20-04-2001]	-59.39 (<0.01) [18-05-2009]	-118.64 (<0.01) [19-04-2001]	-165.87 (<0.01) [20-04-2001]
SR_{HDFC}	-56.07 (<0.01) [16-04-2001]	-114.23 (<0.01) [18-04-2001]	-162.24 (<0.01) [07-04-2001]	-56.43 (<0.01) [02-11-2008]	-114.25 (<0.01) [18-04-2001]	-162.29 (<0.01) [14-01-2019]
SR_{ICBK}	-51.87 (<0.01) [06-05-2001]	-111.89 (<0.01) [07-05-2001]	-161.11 (<0.01) [07-05-2001]	-52.03 (<0.01) [02-11-2008]	-111.91 (<0.01) [07-05-2001]	-161.14 (<0.01) [07-05-2001]
SR_{ITC}	-58.95 (<0.01) [05-04-2001]	-121.61 (<0.01) [16-04-2001]	-171.14 (<0.01) [11-04-2001]	-58.96 (<0.01) [05-04-2001]	-121.63 (<0.01) [16-04-2001]	-171.19 (<0.01) [06-04-2001]
SR_{RELI}	-54.84 (<0.01) [19-04-2001]	-117.29 (<0.01) [16-04-2001]	-169.41 (<0.01) [20-04-2001]	-54.85 (<0.01) [19-04-2001]	-117.31 (<0.01) [16-04-2001]	-169.43 (<0.01) [20-04-2001]
SR_{SBI}	-54.88 (<0.01) [05-05-2001]	-116.57 (<0.01) [20-04-2001]	-164.90 (<0.01) [20-04-2001]	-54.94 (<0.01) [14-01-2019]	-116.58 (<0.01) [20-04-2001]	-164.92 (<0.01) [20-04-2001]
SR_{TAMO}	-79.73 (<0.01) [10-04-2001]	-165.46 (<0.01) [06-04-2001]	-226.72 (<0.01) [02-05-2001]	-79.74 (<0.01) [09-04-2001]	-165.48 (<0.01) [05-04-2001]	-226.75 (<0.01) [02-05-2001]
SR_{TISC}	-55.49 (<0.01) [27-04-2001]	-120.01 (<0.01) [16-04-2001]	-170.36 (<0.01) [16-04-2001]	-55.50 (<0.01) [14-01-2019]	-120.02 (<0.01) [16-04-2001]	-170.38 (<0.01) [30-04-2001]
PR_{NIFTY}	-57.56 (<0.01) [27-04-2001]	-125.28 (<0.01) [30-04-2001]	-178.64 (<0.01) [30-04-2001]	-57.59 (<0.01) [29-04-2001]	-125.29 (<0.01) [30-04-2001]	-178.67 (<0.01) [30-04-2001]
Independent Variables (SB: Stock Beta, PB: Portfolio Beta, MPR: Market Premium)						
SB_{GRASIM}	-2.998 (0.687) [18-04-2002]	-65.87 (<0.01) [07-05-2001]	-128.86 (<0.01) [08-05-2001]	-2.997 (0.688) [15-04-2002]	-65.88 (<0.01) [07-05-2001]	-128.88 (<0.01) [08-05-2001]
SB_{HDBK}	-2.627 (0.859) [29-10-2014]	-65.70 (<0.01) [10-04-2001]	-130.22 (<0.01) [02-05-2001]	-3.104 (0.624) [14-04-2004]	-65.72 (<0.01) [10-04-2001]	-130.24 (<0.01) [02-05-2001]
SB_{HDFC}	-2.472 (<0.909) [29-10-2014]	-63.91 (<0.01) [06-04-2001]	-130.93 (<0.01) [10-04-2001]	-2.608 (0.866) [23-04-2004]	-63.89 (<0.01) [07-04-2001]	-130.87 (<0.01) [10-04-2001]
SB_{ICBK}	-2.811 (0.782) [12-09-2002]	-62.09 (<0.01) [04-05-2001]	-126.05 (<0.01) [04-05-2001]	-2.846 (0.765) [10-09-2002]	-62.09 (<0.01) [04-05-2001]	-126.07 (<0.01) [04-05-2001]
SB_{ITC}	-2.547 (0.889) [13-11-2003]	-63.56 (<0.01) [08-05-2001]	-127.65 (<0.01) [07-04-2001]	-2.547 (0.888) [11-11-2003]	-63.54 (<0.01) [02-05-2001]	-127.67 (<0.01) [07-04-2001]
SB_{RELI}	-3.487 (0.394) [21-10-2003]	-61.48 (<0.01) [19-04-2001]	-123.71 (<0.01) [19-04-2001]	-3.485 (<0.395) [18-10-2003]	-61.49 (<0.01) [19-04-2001]	-123.73 (<0.01) [19-04-2001]
SB_{SBI}	-2.844 (0.766) [24-02-2003]	-61.38 (<0.01) [16-04-2001]	-125.29 (<0.01) [09-05-2001]	-2.821 (0.777) [14-09-2002]	-61.39 (<0.01) [16-04-2001]	-125.31 (<0.01) [11-04-2001]
SB_{TAMO}	-4.369 (0.061) [22-06-2003]	-67.49 (<0.01) [17-04-2001]	-133.06 (<0.01) [17-04-2001]	-4.634 (0.029) [19-05-2003]	-67.50 (<0.01) [17-04-2001]	-133.08 (<0.01) [17-04-2001]
SB_{TISC}	-3.656 (0.304) [21-10-2003]	-65.49 (<0.01) [17-04-2001]	-130.50 (<0.01) [17-04-2001]	-3.544 (<0.363) [18-10-2003]	-65.51 (<0.01) [17-04-2001]	-130.53 (<0.01) [17-04-2001]
PB_{NIFTY}	-2.529 (0.895) [02-11-2003]	-63.49 (<0.01) [15-04-2001]	-127.79 (<0.01) [04-05-2001]	-2.528 (0.896) [30-10-2003]	-63.49 (<0.01) [15-04-2001]	-127.81 (<0.01) [04-05-2001]
MP_{NIFTY}	-55.85 (<0.01) [20-05-2009]	-113.27 (<0.01) [30-04-2001]	-159.76 (<0.01) [30-04-2001]	-55.51 (<0.01) [28-10-2008]	-113.29 (<0.01) [30-04-2001]	-159.78 (<0.01) [30-04-2001]

Empirical Models

The models used in the related empirical literature are dependent on their respective parameters, which covered the calculation of the prospect theory value of the stocks from stock prices data and not from their sample stock return data directly. The prospect theory value of the individual stocks, therefore, becomes biased based on the weights considered in those models themselves. Hence, to avoid this hurdle, we introduce our ingeniously developed empirical models that deal with stock prices themselves methodologically.Since the theoretical proposition stated in the mental accounting theory suggests exploring investors' choice dilemmas on their investment decisions between an individual stock and a portfolio of stocks, we put forth our empirical setup. Firstly, we start with the capital asset pricing model (CAPM) as augmented for portfolio theory in the model equations of Eq-1 and Eq-2. In Eq-1, the study evaluates individual stock returns (SR_{it}) with reference to the NSE Nifty's risk premium over the risk-free rate of return (MP_t) along with the respective stock's systematic risks beta (SB_{it}). In contrast, in Eq-2, it evaluates the portfolio returns (PR_t) with reference to the market's risk premium (MP_t) along with the portfolio beta (PB_t). Here, the investors are to choose whether to invest in an individual stock or a portfolio of stocks. Since the systematic risk beta variables, at both the stock level and portfolio level, are $I(1)$ in nature, their linear specifications as given in the following equations are not feasible to proceed methodologically.

$$\mathrm{SR}_{it} = \alpha_{i0} + \alpha_{1i}\mathrm{MP}_t + \beta_{is}\mathrm{SB}_{it} + \tilde{r}_{it} \tag{Eq-1}$$

$$\mathrm{PR}_t = \alpha_{p0} + \alpha_{1p}\mathrm{MP}_t + \beta_p\mathrm{PB}_t + \tilde{r}_{pt} \tag{Eq-2}$$

Now, given the non-linear nature of the systematic risks, let us consider the prospect theory (PT) track of decision choices. The dynamics of investors' dilemmas of mental accounts at the individual stock level vis-à-vis the portfolio level can be traced with the "S"-shaped value function as proposed in the PT. This function suggests that investors are risk-averse in the profits zone and risk-seeking in the losses zone. That is, investors need to maintain the mental accounts for current profits and losses simultaneously for individual stocks and the portfolio as well. Besides, investors face the disposition effect of past returns in their memory, where they exhibit patience with loss-making stocks but feel tempted to sell gain-making stocks. To address these dynamics, we use the non-linear autoregressive distributed lag (NARDL) models in Eq-3 and Eq-4, where we transform the linear regression models (Eq-1 and Eq-2) for the individual stocks and their portfolio, respectively. Here, interested readers may refer to the studies of Pesaran, Shin, and Smith (2001) to gain familiarity with the linear ARDL models and the F-bound tests, and to Shin, Yu, and Greenwood-Nimmo (2014) for the non-linear ARDL, i.e., the NARDL models.

$$\mathrm{SR}_{it} = \alpha_{i0} + \sum_{r=1}^{R}\sum_{t=1}^{n}\alpha_{1ir}\mathrm{SR}_{it-r} + \sum_{s=1}^{S}\sum_{i=1}^{X,-X}\sum_{t=1}^{n}\beta_{is}X_{it-s} + \sum_{i=1}^{X,-X}\sum_{t=1}^{n}\beta_i X_{it} + \varepsilon_{it} \tag{Eq-3}$$

$$\mathrm{PR}_t = \alpha_{p0} + \sum_{r=1}^{R}\sum_{t=1}^{n}\alpha_{1pr}\mathrm{PR}_{t-r} + \sum_{s=1}^{S}\sum_{i=1}^{X,-X}\sum_{t=1}^{n}\beta_{is}X_{it-s} + \sum_{i=1}^{X,-X}\sum_{t=1}^{n}\beta_{pi} X_{it} + \varepsilon_{pt} \tag{Eq-4}$$

In the model Eq-3 (Eq-4), disposition effects can be observed for the respective endogenous lagged variables of SR_{it-r} (PR_{t-r}), while the independent variables—in the array of X_{it} for the market premium (MP_t) and stocks' beta (SB_{it}) or portfolio beta (PB_t) at the unrestricted dynamic references to their current values and lagged exposures—are expected to demonstrate the prospect theory (PT) effects of loss aversion behavior at the profit zone and risk-seeking behavior at losses. But which one will be the best choice for investors—an individual stock account or a portfolio account? This decision dilemma can be resolved with applications of the mental accounting theory (MAT) for individual stocks separately and by comparing it with the portfolio.

The said NARDL setup is unrestricted in its autoregressive regression nature, and long-run relationships of the dependent variables with those of explanatory variables are not taken into consideration. A theoretical backing of such a long-run relationship is that investors show adaptive learning attitudes to new information and revise their past references of decision choices (Sinha 2019 read with Camerer and Ho 1999, Sinha 2022). In a nutshell, the investors adjust their past decision choices. Their dilemma for individual stock accounts over portfolio accounts can be resolved if such adaptation to the long-run relationship is taken into account. We explore the same with the conditional long-run form (LRF) of the NARDL models in Eq-5 and Eq-6 for the individual stock level and portfolio level, respectively.

$$\begin{aligned}\Delta \mathrm{SR}_{it} = \alpha_{i0} &+ \sum_{r=1}^{R}\sum_{t=1}^{n}\alpha_{jr}\Delta\mathrm{SR}_{it-r} + \sum_{s=1}^{S}\sum_{i=1}^{X,-X}\sum_{t=1}^{n}\beta_{is}\Delta X_{it-s}\\ &+ \sum_{r=1}^{R}\sum_{t=1}^{n}\alpha_{kr}\mathrm{SR}_{it-r} + \sum_{s=0}^{S}\sum_{i=1}^{X,-X}\sum_{t=1}^{n}\beta_{iq}X_{it-s} + \xi_{it} \qquad \text{(Eq-5)}\end{aligned}$$

$$\begin{aligned}\Delta \mathrm{PR}_{t} = \alpha_{p0} &+ \sum_{r=1}^{R}\sum_{t=1}^{n}\alpha_{jpr}\Delta\mathrm{PR}_{t-r} + \sum_{s=1}^{S}\sum_{i=1}^{X,-X}\sum_{t=1}^{n}\beta_{is}\Delta X_{it-s}\\ &+ \sum_{r=1}^{R}\sum_{t=1}^{n}\alpha_{kr}\mathrm{PR}_{t-r} + \sum_{s=0}^{S}\sum_{i=1}^{X,-X}\sum_{t=1}^{n}\beta_{iq}X_{it-s} + \xi_{pt} \qquad \text{(Eq-6)}\end{aligned}$$

Now, if investors become successful in adapting to the long-run effects on their current investment decision choices and dynamically adjust to the same, they may do so either at the individual stock accounts or at the portfolio level. Such behavioral adaptation takes time, and investors show dynamic adjustments. That is, the evolution in investment choices can be resolved with the respective conditional error correction forms (ECF) of the NARDL models in Eq-7 and Eq-8, where the first difference of the endogenous return variable and explanatory variables also show their respective short-run effects. Further, Z_{t-1} is the cointegrating error correction factor at its first lag, and it reveals the adjustment speed. We explore the difference of their respective impacts at the individual stock level compared to the portfolio level as well.

$$\Delta \mathrm{SR}_{it} = \alpha_{i0} + \sum_{r=1}^{R}\sum_{t=1}^{n}\alpha_{jr}\Delta\mathrm{SR}_{it-r} + \sum_{s=1}^{S}\sum_{i=1}^{X,-X}\sum_{t=1}^{n}\beta_{is}\Delta X_{it-s} + \eta_i Z_{it-1} + \phi_{it} \qquad \text{(Eq-7)}$$

$$\Delta \mathrm{PR}_{t} = \alpha_{p0} + \sum_{r=1}^{R}\sum_{t=1}^{n}\alpha_{jpr}\Delta\mathrm{PR}_{t-r} + \sum_{s=1}^{S}\sum_{i=1}^{X,-X}\sum_{t=1}^{n}\beta_{is}\Delta X_{it-s} + \eta_p Z_{pt-1} + \phi_{pt} \qquad \text{(Eq-8)}$$

Therefore, in the respective NARDL models' specifications in Eq-3 and Eq-4, Eq-5 and Eq-6, and Eq-7 and Eq-8, the intercept coefficients are α_{i0} and α_{p0} for the individual stocks and the stocks' portfolio. In these respective regression equations, ε_{it} and ε_{pt}, ξ_{it} and ξ_{pt}, and ϕ_{it} and ϕ_{pt} are their respective residual error components. The dependent variables $\Delta\mathrm{SR}_{it}$ and $\Delta\mathrm{PR}_{it}$ in the sets of equations for Eq-5 and Eq-6 as well as Eq-7 and Eq-8 are at their first differences of the respective dependent variables of SR_{it} and PR_{it} as represented in the linear (non-linear ARDL, that is, NARDL) regression models Eq-1 (Eq-3) and Eq-2 (Eq-4). We use SR_{it} (SB_{it}) as the general notation for the individual stock returns (beta). We regress the individual sample stock returns data separately, while PR_t (PB_t) represents the portfolio returns (beta).

In the unrestricted NARDL models as demonstrated in the equations Eq-3 and Eq-4 respectively, the endogenous dependent variables SR_{it} and PR_t at the r lags show the past impacts on their present decision choices. The independent X_{it} variables at the s ($s \geq 0$) lags show the effects of long memory, while the same at the current time t shows the recency effects. In the conditional LRFs in the respective equations of Eq-5 and Eq-6, referred within the brackets, the independent variables SR_{it-r} and PR_{t-r} ($\Delta\mathrm{SR}_{it-r}$ and $\Delta\mathrm{PR}_{t-r}$) at their respective r lags represent the prospect theory long-memory (short-run) endogenous effects, while the array of independent X_{it} (ΔX_{it}) variables at the s lags represent the long-run (short-run) effects.However, in the ECFs of the NARDL models in the equations Eq-7 and Eq-8, $\Delta\mathrm{SR}_{it-r}$ and $\Delta\mathrm{PR}_{t-r}$ represent short-run endogenous effects, ΔX_{it-s} variables show the short-run effects of independent decision choices, and Z_{t-1} depicts the cointegrating speed of adjustments at its first lag towards their long-run relationships in the model equations Eq-5 and Eq-6, respectively.

Lag Selection: An empirical exploration in the NARDL setup needs a selection of appropriate lag lengths for the endogenous dependent variable and the explanatory independent variables as well. In EViews 10, at Var Estimation with the endogenous the individual stocks' (portfolio) return variable along with the other two independent variables, we identify that lag-selection criteria of "LR", "FPE", "AIC", "SC" and "HQ" suggest for using different lags. Since the AIC (SC) method is biased towards over (under)-specification of the lag variables, we follow the AIC method if that suggests for a lag length lower than twelve, and otherwise, we follow the SC method. Since EViews 10 set up for the NARDL has limitations for inclusion of a maximum number of explanatory variables, we allow a length of four lags for the independent explanatory variables at the automatic lag selection menu in it and allow the system to enhance the degree of explanatory power in terms of the Adj. R2 value in the regression model/s.

TABLE 3. VAR Lag Order Selection Criteria for the Regression Models

Endogenous Variables	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
$\mathbf{R_{PORT}}$	ND†	21st Lag	21st Lag	21st Lag	7th Lag	21st Lag
$\mathbf{R_{GRAS}}$	ND†	6th Lag	6th Lag	6th Lag	3rd Lag	6th Lag
$\mathbf{R_{HDBK}}$	ND†	20th Lag	20th Lag	20th Lag	4th Lag	4th Lag
$\mathbf{R_{HDFC}}$	ND†	14th Lag	11th Lag	11th Lag	3rd Lag	10th Lag
$\mathbf{R_{ICBK}}$	ND†	20th Lag	22nd Lag	22nd Lag	3rd Lag	3rd Lag
$\mathbf{R_{ITC}}$	ND†	9th Lag	6th Lag	6th Lag	3rd Lag	4th Lag
$\mathbf{R_{RELI}}$	ND†	29th Lag	29th Lag	29th Lag	3rd Lag	3rd Lag
$\mathbf{R_{SBI}}$	ND†	12th Lag	8th Lag	8th Lag	3rd Lag	3rd Lag
$\mathbf{R_{TAMO}}$	ND†	30th Lag	30th Lag	30th Lag	30th Lag	30th Lag
$\mathbf{R_{TISC}}$	ND†	16th Lag	16th Lag	16th Lag	3rd Lag	3rd Lag

†ND refers to Not Defined.

Empirical Hypotheses: Given the stated PT applications and empirical methodologies, we set the following empirical hypotheses. We empirically examine the sample stocks' systematic risk—beta (SB_{it}), and the NSE market premium (MP_t) in explaining their return (SR_{it}) both at the individual stocks' level and at their portfolio level separately. In exploring the said PT effects with the two unrestricted NARDL models in Eq-3 and Eq-4 as well, we set two null hypotheses $\mathbf{H_{01}}$ and $\mathbf{H_{02}}$ against the respective alternative hypotheses $\mathbf{H_{11}}$ and $\mathbf{H_{12}}$. In exploring the adaptive learning behaviors over short-run and long-run time periods, we identify the null hypothesis $\mathbf{H_{03}}$ against the alternative hypothesis $\mathbf{H_{13}}$ with the conditional LRFs of the NARDL models in Eq-5 and Eq-6 as well. We explore dynamic adjustment behaviors between the short-run and long-run references with the null hypothesis $\mathbf{H_{04}}$ against the alternative hypothesis $\mathbf{H_{14}}$ with use of conditional ECFs of the NARDL models in the equations Eq-7 and Eq-8 separately.

$\mathbf{H_{01}}$: In the respective unrestricted NARDL models, at the individual stocks' level vis-à-vis their portfolio level, the dependent variables viz., individual stocks' return (SR_{it}) and their portfolio return (PR_t) show no effect of their respective endogenous lagged dependent variables for SR_{it-r} and PR_{t-r} at their short-run or long-run presence.

$\mathbf{H_{11}}$: In the respective unrestricted NARDL models, at the individual stocks' level vis-à-vis their portfolio level, the dependent variables viz., individual stocks' returns (SR_{it}) and their portfolio return (PR_t) show significant effects of their respective endogenous lagged dependent variables for SR_{it-r} and PR_{t-r} at their short-run or long-run presence.

$\mathbf{H_{02}}$: In the respective unrestricted NARDL models, at the individual stocks' level vis-à-vis their portfolio level, the dependent variables viz., individual stocks' return (SR_{it}) and their portfolio return (PR_t) respectively show no effect of their respective systematic risk variables for SB_{it} and PB_t, and the market premium (MP_t) at their short-run or long-run presence.

$\mathbf{H_{12}}$: In the respective unrestricted NARDL models, at the individual stocks' level vis-à-vis their portfolio level, the dependent variables viz., individual stocks' return (SR_{it}) and their portfolio return (PR_t) respectively show significant effects of their respective systematic risk variables for SB_{it} and PB_t, and the market premium (MP_t) at their short-run or long-run presence.

$\mathbf{H_{03}}$: In the respective conditional LRFs of the NARDL models, at individual stocks' level vis-à-vis portfolio level, the dependent variables of individual stocks' return (SR_{it}) and their portfolio return (PR_t) respectively show no effect of the cointegrating relationship of adaptive learning in terms of the F-bound test and relevant coefficients of the variables at their respective short-run or long-run specifications are insignificant.

$\mathbf{H_{13}}$: In the respective conditional LRFs of the NARDL models, at individual stocks' level vis-à-vis portfolio level, the dependent variables of individual stocks' return (SR_{it}) and their portfolio return (PR_t) respectively show significant effects of the cointegrating relationship of adaptive learning in terms of the F-bound test and the relevant coefficients of the variables at their respective short-run or long-run specifications are statistically significant.

$\mathbf{H_{04}}$: In the respective conditional ECFs of the NARDL models, at individual stocks' level vis-à-vis portfolio level, the dependent variables of individual stocks' return (SR_{it}) and their portfolio return (PR_t) respectively show no effect of dynamic adjustments in terms of the coefficients of the error correction terms (ECTs) in the models.

$\mathbf{H_{14}}$: In the respective conditional ECFs of the NARDL models, at individual stocks' level vis-à-vis portfolio level, the dependent variables of individual stocks' return (SR_{it}) and their portfolio return (PR_t) respectively show statistically significant effects of dynamic adjustments in terms of the coefficients of the error correction terms (ECTs) in the models.

Robustness Tests: The above four research hypotheses explore the presence of the prospect theory effects, particularly the risk-seeking (averse) impacts at the losses (profits), empirically with negative and positive values of the explanatory variables in the NARDL models besides the long-run adaptation and dynamic adjustments. However, as already mentioned earlier, we need to examine the differences in the impacts of the investors' behavioral dynamism on their stock-specific mental accounting, if any, over the portfolio-specific mental accounting.

In doing so, we statistically test the differences between the intercept vis-à-vis the slope of the specific variables in the equations of the NARDL models at Eq-3 over the same at Eq-4, Eq-5 over those at Eq-6, and Eq-7 over Eq-8 as well. However, in determining the relevant test statistics for a difference in the respective pairs of coefficients, we find the statistical calculator for the t-test at `https://www.danielsoper.com/statcalc/formulas.aspx?id=103` very helpful. The methodology of the same is depicted in equation Eq-9 at a degree of freedom (df) in Eq-10. Readers may find an important critique of this procedure in Andrade and Estévez-Pérez (2014).

$$t = \frac{b_{\mathrm{sl}} - b_{\mathrm{pl}}}{\sqrt{s_{\mathrm{sl}}^2 + s_{\mathrm{pl}}^2}} \tag{Eq-9}$$

$$df = n_{\mathrm{sl}} + n_{\mathrm{pl}} - 4 \tag{Eq-10}$$

Here, b_{sl} and b_{pl} respectively are the coefficients of explanatory variables at the individual stock level and portfolio level in the NARDL models. These are separately applied for their intercept coefficients and the slope coefficients. s_{sl}^2 and s_{pl}^2 are their respective standard error measures, and n_{sl} and n_{pl} are their respective sample sizes. df is the degree of freedom of the t-test statistic. Since we have a large sample size ranging from 6485 to 6495 with $n_{\mathrm{sl}} \approx n_{\mathrm{pl}}$ for the sample stocks and their portfolio as well, the stated t-test statistics are assumed to follow the normal distribution in our investigation.

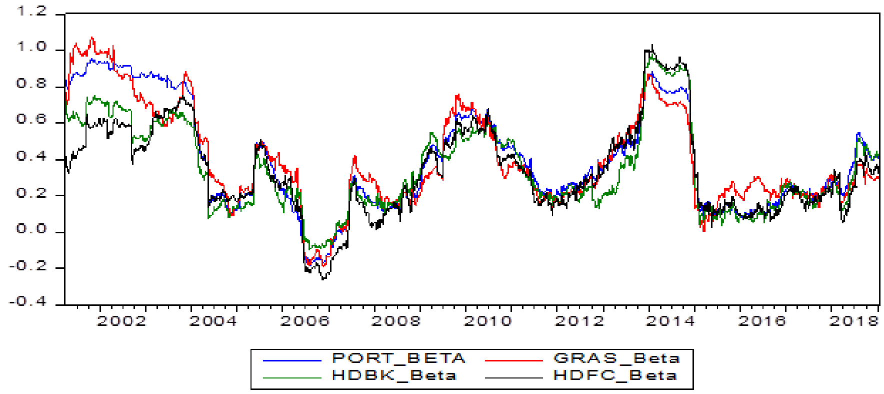

FIGURE 1. Beta variables of GRAS, HDFC, HDBK and the Portfolio of Nine Stocks

Now, in exploring investors' behavioral preferences bias, if any, towards the individual stocks over their stocks' portfolio or towards the portfolio of stocks over the individual stocks, we have the following fifth null hypothesis $\mathbf{H_{05}}$ against the alternative hypothesis $\mathbf{H_{15}}$.

$\mathbf{H_{05}}$: In the respective NARDL models, investors show no difference in terms of the impacts of the respective NARDL model-specified variables on the relevant dependent variables at their stock-level mental accounting over the same at the portfolio-level mental accounting.

$\mathbf{H_{15}}$: In the respective NARDL models, investors show a statistically significant difference in terms of the impacts of the respective NARDL model-specified variables on the relevant dependent variables at their stock-level mental accounting over that at the portfolio-level mental accounting.

5. Results and Findings

As mentioned in the literature review, there has been a little study on the prospect theory applications in mental accounting and so, a direct comparison of the present findings with the existing literature cannot be offered here. We try to make an overall alignment of our observations originally. Thus, on how mental accounting matters in portfolio choices, we firstly, come up with a general outlook on the returns data of the sample stocks and portfolio, followed by the adaptive outlook with the prospect theory view in portfolio management along with the aspects of dynamic adjustment. Finally, we perform a robustness analysis.

General Outlook: In Figure 1-3, we find unusual instances of negative values for the stocks' betas and portfolio beta around June, 2006 to December, 2006. This shows inverse relationship between the stock's /portfolio's risk premium and the NSE Nifty market's risk premium. Since the NSE Nifty comprises fifty stocks and we consider only nine stocks, such observations infer more appealing applicability of mental accounting. Further, a general depiction of all the stocks and portfolio betas shows that these are below unity in their magnitudes over most of the data period, that is, the investments are less risky ones in comparison to the market. Besides, Figure 1 shows that the portfolio beta (`PORT_BETA`) has remained subdued next to `GRAS_Beta` most frequently till 2010 and `HDFC_Beta` from 2013 to 2014. Figure 2 depicts that `PORT_Beta` remained subdued to `ICBK_Beta` mostly till 2014. Figure 3 finds that the script `PORT_BETA` lags behind `TISC_Beta`, `TAMO_Beta` and `SBI_Beta`. That is, the portfolio beta has passed more than half of the study period as being subdued to a majority of the sample stocks, and these suggest that the portfolio beta is mostly disappointing as compared to the stocks. This impression can be justified with the presence of its unimpressive returns moderately around 5% specifically since 2009 as well (please see Appendix). Given the said narrative of investors' lost importance on the Markowitz portfolio theory, let us look into how prospect theory view on mental accounting matters in portfolio management.

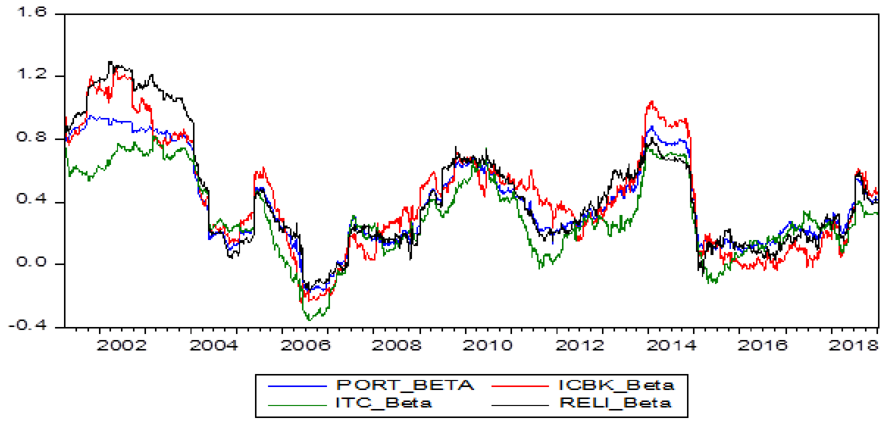

FIGURE 2. Beta variables of ITC, ICBK, RELI and the Portfolio of Nine Stocks

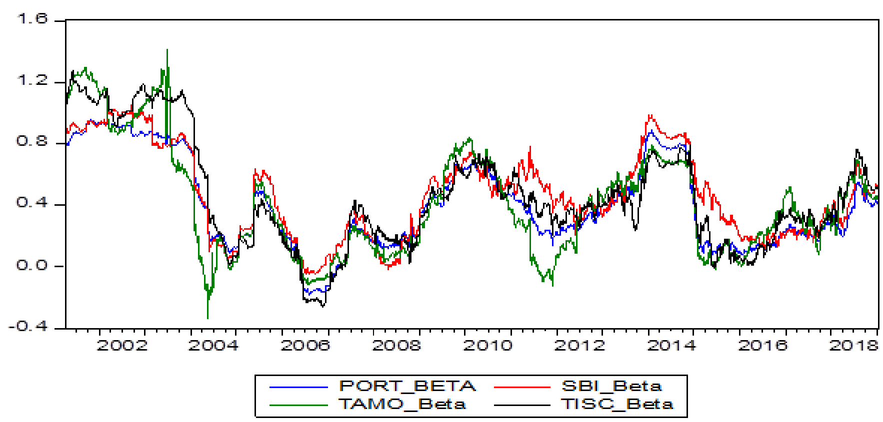

FIGURE 3. Beta variables of TAMO, SBI, TISC and the Portfolio of Nine Stocks

With the unrestricted NARDL models, Table 4 demonstrates that the returns of sample stocks and portfolio as well involve different effects of lagged endogenous returns. There are significant effects over a length of seven lags for the portfolio returns, a length of six lags for `GRAS`, that of four lags for `HDBK`, `ITC` and `SBI`, that of three lags for `ICBK`, `RELI` and `TISC`, and a presence of twelve lags for `TAMO`. These lagged dependences of the returns data suggest for the presence of long memory effects and thereby, put forth for the use of prospect theory aspects like lagged isolation effects. It shows a homogeneous lag effect across the first three lags of the stocks vis-à-vis portfolio returns along with the effects at the sixth and seven lag as well. It also shows that portfolio returns are heightened by homogeneous lag effects of isolation but neutralized by heterogeneous lag effects of isolation as well.

Table 4 also shows significant impacts of the respective market premium variables on the stocks' returns and portfolio returns. The short-run positive values of the market premium variable appear positively significant for five stocks viz., GRAS, HDBK, RELI, SBI and TISC only while other four stocks' returns and portfolio returns remain unresponsive. In contrast, the short-run negative values of the market premium variable depict significantly positive impacts for all except two stocks viz., HDFC and ITC. These suggest for differentiative accounting of positive and negative market premium. Nonetheless, there is a presence of significantly positive lagged-effect of positive and negative market premiums as well and their respective coefficients differ across the lags. The lag effects of positive market premiums are also different from those of the negative market premiums.

Besides, Table 4 also shows the effects of positive and negative values of the systematic beta variables on stocks' returns and market returns. The short-run positive values of systematic beta have a negatively significant impact on the portfolio returns and five sample stocks' returns viz. GRAS, HDBK, ICBK, RELI and TISC as well but the effect is insignificant for two stocks viz., HDFC and SBI while the same is positively significant for TAMO. The short-run negative values of the systematic beta variables have negatively significant impacts on stocks' returns (except ICBK) and market returns and interestingly, magnitudes of the coefficients are mostly twice or more than those for the short-run positive values of the variables. These observations confirm the non-linear effects of the PT value function in portfolio management. Even if the coefficients are negative, the quotients for risk-seeking at negative values of systematic risk are twice or more than those for risk-averseness at its positive values. That is, investors are more mentally affected by the negative systematic risk effects than its positive risk effects. However, there are effects of investors' mental readjustments in terms of effects of positive and negative values of the systematic risk variable at the other higher lags. These observations are supportive for the non-linear prospect theory view of portfolio management.

The summary statistics in Table 4 also show the persistency of results in terms of the values of R2 and Adjusted R2 statistics i.e., the degree of determination or explanatory power, the regression F-statistics, DW-statistics, BPG heteroskedasticity test statistics and the CUSUM tests of residuals. The JB normality test results suggest for the presence of non-normal residuals and the CUSUM of the squared residuals suggests for insufficiency in terms of stability of the parameter statistics with the unrestricted NARDL models and these raise some discomfort.

TABLE 4. Stocks' Returns and Portfolio Returns with the Unrestricted NARDL Model

Variables	**PR (7,4)**	**GRAS (6,2)**	**HDBK (4,3)**	**HDFC (10,2)**	**ICBK (3,2)**	**ITC (4,3)**	**RELI (3,2)**	**SBI (4,3)**	**TAMO (12,4)**	**TISC (3,4)**
$R_t(-1)$	0.2871 (0.0123) (0.001)	0.3210 (0.0123) (0.001)	0.3084 (0.0125) (0.001)	0.3305 (0.0124) (0.001)	0.3922 (0.0124) (0.001)	0.2846 (0.0124) (0.001)	0.3463 (0.0123) (0.001)	0.3312 (0.0124) (0.001)	0.0084 (0.0124) (0.496)	0.3242 (0.0124) (0.001)
$R_t(-2)$	0.1345 (0.0131) (0.001)	0.0601 (0.0130) (0.001)	0.0314 (0.0131) (0.0166)	0.0342 (0.0132) (0.0099)	0.0536 (0.0136) (0.001)	0.0783 (0.0131) (0.001)	0.0790 (0.0133) (0.001)	0.0567 (0.0133) (0.001)	0.1748 (0.0124) (0.001)	0.0924 (0.0133) (0.001)
$R_t(-3)$	-0.1184 (0.0131) (0.001)	-0.0762 (0.0130) (0.001)	-0.0574 (0.0129) (0.001)	-0.0786 (0.0132) (0.001)	-0.0839 (0.0126) (0.001)	-0.0632 (0.0130) (0.001)	-0.1102 (0.0126) (0.001)	-0.0541 (0.0132) (0.001)	-0.1117 (0.0125) (0.001)	-0.0800 (0.0126) (0.001)
$R_t(-4)$	-0.0013 (0.0129) (0.923)	-0.0078 (0.0129) (0.545)	-0.0543 (0.0124) (0.001)	-0.0299 (0.0131) (0.0227)	- - -	-0.0334 (0.0125) (0.0078)	- - -	-0.0337 (0.0125) (0.0072)	0.0555 (0.0125) (0.001)	- - -
$R_t(-5)$	0.0033 (0.0129) (0.799)	0.0149 (0.0129) (0.248)	- - -	-0.0177 (0.0131) (0.177)	- - -	- - -	- - -	- - -	0.1070 (0.0124) (0.001)	- - -
$R_t(-6)$	0.0599 (0.0127) (0.001)	0.0328 (0.0122) (0.0072)	- - -	-0.0017 (0.0131) (0.895)	- - -	- - -	- - -	- - -	0.1234 (0.0123) (0.001)	- - -
$R_t(-7)$	-0.0489 (0.0122) (0.0001)	- - -	-0.0552 (0.0130) (0.001)	- - -	- - -	- - -	- - -	- - -	-0.1401 (0.0124) (0.001)	- - -
$R_t(-8)$	- - -	- - -	-0.0068 (0.0130) (0.6024)	- - -	- - -	- - -	- - -	- - -	0.0932 (0.0123) (0.001)	- - -
$R_t(-9)$	- - -	- - -	-0.0281 (0.0130) (0.031)	- - -	- - -	- - -	- - -	- - -	-0.0373 (0.0123) (0.001)	- - -
$R_t(-10)$	- - -	- - -	-0.0300 (0.0123) (0.0152)	- - -	- - -	- - -	- - -	- - -	-0.0401 (0.0122) (0.0062)	- - -
$R_t(-11)$	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	0.0773 (0.0119) (0.001)	- - -
$R_t(-12)$	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	-0.1260 (0.0119) (0.001)	- - -

Note: In the upper part of the table, values in each cell are the coefficients (standard errors) (Sign. level) and in the lower part, values in each cell are the test statistics (Sign. level). Source: Author's own computation. Stable* indicates marginally stable. Bold figures indicate their importance in reporting the results and findings.

Besides, with the above unrestricted model, Table 4A shows significant impacts of the respective market premium variables on the stocks' returns and portfolio returns. The short-run positive values of the market premium variable appear positively significant for five stocks viz., GRAS, HDBK, RELI, SBI and TISC only while other four stocks' returns and portfolio returns remain unresponsive. In contrast, the short-run negative values of the market premium variable depict significantly positive impacts for all except two stocks viz., HDFC and ITC. These suggest for differentiative accounting of positive and negative market premium. Nonetheless, there is a presence of significantly positive lagged-effect of positive and negative market premiums as well and their respective coefficients differ across the lags. The lag effects of positive market premiums are also different from those of the negative market premiums.

Table 4A. Stocks' Returns and Portfolio Returns with the Unrestricted NARDL Model

Variables	**PR (7,4)**	**GRAS (6,2)**	**HDBK (4,3)**	**HDFC (10,2)**	**ICBK (3,2)**	**ITC (4,3)**	**RELI (3,2)**	**SBI (4,3)**	**TAMO (12,4)**	**TISC (3,4)**
$MP_t(p)$	0.0215 (0.0196) (0.2729)	0.0615 (0.0221) (0.0054)	0.0520 (0.0213) (0.0145)	-0.0161 (0.0249) (0.5167)	0.0250 (0.0290) (0.3892)	0.0208 (0.0209) (0.3193)	0.0705 (0.0235) (0.001)	0.0768 (0.0259) (0.003)	-0.0041 (0.0759) (0.9569)	0.0780 (0.0304) (0.0103)
$MP_t(-1,p)$	0.1855 (0.0197) (0.001)	0.1264 (0.0223) (0.001)	0.1264 (0.0235) (0.001)	0.1444 (0.0317) (0.001)	0.2297 (0.0314) (0.001)	0.0780 (0.0287) (0.0066)	0.1695 (0.0256) (0.001)	0.1750 (0.0354) (0.001)	0.2464 (0.0972) (0.0113)	0.1602 (0.0415) (0.0001)
$MP_t(-2,p)$	- - -	- - -	0.0614 (0.0251) (0.0145)	- - -	0.0454 (0.0230) (0.0479)	- - -	0.0140 (0.0333) (0.6738)	0.1355 (0.0766) (0.077)	0.0602 (0.0336) (0.0732)	- - -
$MP_t(-3,p)$	- - -	- - -	- - -	- - -	0.0404 (0.0256) (0.1147)	- - -	- - -	- - -	- - -	- - -
$MP_t(n)$	0.059915 (0.020073) (0.0028)	0.054956 (0.022907) (0.0165)	0.063851 (0.021931) (0.0036)	0.023256 (0.025445) (0.3608)	0.104349 (0.029669) (0.001)	0.020649 (0.021535) (0.3377)	0.1176 (0.024256) (0.001)	0.131793 (0.026669) (0.001)	0.184065 (0.078475) (0.019)	0.058724 (0.031341) (0.061)
$MP_t(-1,n)$	0.147146 (0.020137) (0.001)	0.132987 (0.022816) (0.001)	0.072088 (0.028172) (0.0105)	0.166172 (0.02811) (0.001)	0.082197 (0.038489) (0.0328)	0.097134 (0.029948) (0.0012)	0.07909 (0.031168) (0.0112)	0.113078 (0.036992) (0.0022)	0.194354 (0.086666) (0.025)	0.17987 (0.043334) (0.001)
$MP_t(-2,n)$	- - -	- - -	0.074443 (0.027201) (0.0062)	- - -	0.068235 (0.029949) (0.0227)	-0.01647 (0.027931) (0.5554)	0.043117 (0.024177) (0.0746)	0.061347 (0.029614) (0.0383)	- - -	0.058769 (0.040155) (0.1434)
$MP_t(-3,n)$	- - -	- - -	-0.032095 (0.01988) (0.1065)	- - -	0.042919 (0.021406) (0.045)	- - -	- - -	- - -	- - -	-0.072291 (0.038186) (0.0584)
$MP_t(-4,n)$	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	0.073219 (0.028176) (0.0094)	- - -

Note: In the upper part of the table, values in each cell are the coefficients (standard errors) (Sign. level) and in the lower part, values in each cell are the test statistics (Sign. level). Source: Author's own computation. Stable* indicates marginally stable. Bold figures indicate their importance in reporting the results and findings.

The summary statistics in Table 4C also show the persistency of results in terms of the values of R2 and Adjusted R2 statistics i.e., the degree of determination or explanatory power, the regression F-statistics, DW-statistics, BPG heteroskedasticity test statistics and the CUSUM tests of residuals. The JB normality test results suggest for the presence of non-normal residuals and the CUSUM of the squared residuals suggests for insufficiency in terms of stability of the parameter statistics with the unrestricted NARDL models and these raise some discomfort.

Table 4B. Stocks' Returns and Portfolio Returns with the Unrestricted NARDL Model

Variables	**PR (7,4)**	**GRAS (6,2)**	**HDBK (4,3)**	**HDFC (10,2)**	**ICBK (3,2)**	**ITC (4,3)**	**RELI (3,2)**	**SBI (4,3)**	**TAMO (12,4)**	**TISC (3,4)**

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Variables	PR (7,4)	GRAS (6,2)	HDBK (4,3)	HDFC (10,2)	ICBK (3,2)	ITC (4,3)	RELI (3,2)	SBI (4,3)	TAMO (12,4)	TISC (3,4)
$\beta_t(p)$	-0.171851 (0.049095) (0.005)	-0.107 (0.040472) (0.0082)	-0.084189 (0.044599) (0.0591)	-0.00077 (0.001021) (0.4507)	-0.08502 (0.050151) (0.0901)	0.000273 (0.000844) (0.7465)	-0.128907 (0.041007) (0.0017)	-0.000096 (0.000951) (0.9193)	1.201585 (0.096015) (0.001)	-0.115263 (0.050172) (0.0216)
$\beta_t(-1,p)$	0.280078 (0.080357) (0.005)	0.106978 (0.040463) (0.0082)	0.084396 (0.044592) (0.0585)	0.086297 (0.050163) (0.0854)	0.128545 (0.040991) (0.0017)	-0.375595 (0.154424) (0.015)	0.115807 (0.050153) (0.021)	- - -	- - -	- - -
$\beta_t(-2,p)$	-0.107364 (0.048962) (0.0284)	- - -	- - -	- - -	- - -	- - -	- - -	- - -	-0.916366 (0.154844) (0.001)	- - -
$\beta_t(-3,p)$	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	-0.114569 (0.154672) (0.4589)	- - -
$\beta_t(-4,p)$	- - -	- - -	- - -	- - -	- - -	- - -	- - -	- - -	0.212593 (0.097399) (0.0291)	- - -
$\beta_t(n)$	-0.353894 (0.048074) (0.001)	-0.482581 (0.047334) (0.001)	-0.53919 (0.040747) (0.001)	-0.220981 (0.043052) (0.001)	0.001122 (0.000928) (0.2266)	-0.218202 (0.044682) (0.001)	-0.318851 (0.047733) (0.001)	-0.224634 (0.045822) (0.001)	-0.718547 (0.0967) (0.001)	-0.243728 (0.050577) (0.001)
$\beta_t(-1,n)$	0.414821 (0.077388) (0.001)	0.722826 (0.075461) (0.001)	0.743639 (0.062748) (0.001)	0.319184 (0.067588) (0.001)	0.31656 (0.071012) (0.001)	0.470991 (0.076647) (0.001)	0.373595 (0.072374) (0.001)	-0.30361 (0.154422) (0.0493)	0.384275 (0.080848) (0.001)	- - -
$\beta_t(-2,n)$	0.023436 (0.076064) (0.758)	-0.240313 (0.046787) (0.001)	-0.20392 (0.040757) (0.001)	-0.098416 (0.043203) (0.0228)	-0.098074 (0.044775) (0.0285)	-0.151827 (0.047065) (0.0013)	-0.149038 (0.046006) (0.0012)	1.589598 (0.155575) (0.001)	-0.13982 (0.049722) (0.0049)	- - -
$\beta_t(-3,n)$	-0.211124 (0.075021) (0.0049)	- - -	- - -	- - -	- - -	- - -	- - -	- - -	-0.948373 (0.156152) (0.001)	- - -
$\beta_t(-4,n)$	0.127731 (0.046801) (0.0064)	- - -	- - -	- - -	- - -	- - -	- - -	- - -	0.387574 (0.098798) (0.001)	- - -
C	0.0000896 (0.000638) (0.8882)	-0.000544 (0.000621) (0.3807)	-0.000887 (0.000666) (0.183)	0.000147 (0.000683) (0.8292)	0.0000087 (0.000815) (0.9915)	-0.00072 (0.000656) (0.2722)	-0.00121 (0.0007) (0.0839)	-0.00069 (0.000791) (0.3832)	-0.000624 (0.002328) (0.7887)	-0.000818 (0.000974) (0.4012)

Note: In the upper part of the table, values in each cell are the coefficients (standard errors) (Sign. level) and in the lower part, values in each cell are the test statistics (Sign. level). Source: Author's own computation. Stable* indicates marginally stable. Bold figures indicate their importance in reporting the results and findings.

Table 4C. Summary Statistics for the Unrestricted NARDL Model Setup

Statistic	PR (7,4)	GRAS (6,2)	HDBK (4,3)	HDFC (10,2)	ICBK (3,2)	ITC (4,3)	RELI (3,2)	SBI (4,3)	TAMO (12,4)	TISC (3,4)
R2 (Adj. R2)	0.162993 (0.160535)	0.152513 (0.15055)	0.136363 (0.134363)	0.14915 (0.14665)	0.1901 (0.1887)	0.11128 (0.10922)	0.175142 (0.173487)	0.164142 (0.162206)	0.2241 (0.2209)	0.15863 (0.15655)
Reg. F-stat (Prob.)	66.31 (0.001)	77.68 (0.001)	68.18 (0.001)	59.67 (0.001)	138.28 (0.001)	54.06 (0.001)	105.84 (0.001)	84.80 (0.001)	69.08 (0.001)	76.29 (0.001)
Durbin Watson Stat	2.001	2.0013	1.99	1.997	2.0021	2.001	2.007	1.9974	2.017	2.0023
HT-BPG F-stat (Prob.)	14.10 (0.001)	46.74 (0.001)	115.30 (0.001)	35.74 (0.001)	60.42 (0.001)	22.36 (0.001)	49.45 (0.001)	20.69 (0.001)	34.84 (0.001)	56.53 (0.001)
BG-SC-LM F-stat (Prob.)	0.9667 (0.3804)	0.6452 (0.5246)	0.6516 (0.5212)	1.8368 (0.1594)	1.651 (0.192)	0.7149 (0.4893)	2.594 (0.0748)	0.0649 (0.9371)	42.65 (0.001)	3.1849 (0.0414)
JB Norm (Prob.)	270688 (0.001)	6689 (0.001)	23097 (0.001)	9928 (0.001)	12182 (0.001)	4902 (0.001)	13731 (0.001)	18736 (0.001)	43128359 (0.001)	3768 (0.001)
CUSUM of RESID (RESID2)	Stable (Unstable)	Stable (Unstable)	Stable (Unstable)	Stable (Unstable)	Stable (Unstable)	Stable (Unstable)	Stable (Unstable)	Stable (Stable*)	Unstable (Unstable)	Stable (Stable*)

Note: Values in each cell are the coefficients (standard errors) (Sign. level) or test statistics (Sign. level). Source: Author's computation. Stable* indicates marginally stable. Bold figures highlight significant results.

Adaptive Outlook at Dynamic Adjustments. The insufficiency of the results in above tables viz., Table 4, 4A, 4B, and 4C are logically analysed with the results for the conditional NARDL model in Table 5, 5A, 5B, and 5C along with the same for the error correction forms (ECFs) in Table 6, 6A, 6B, and 6C respectively. Here, rather than observing the coefficients of mixed nature in Table 4 for the endogenous lag return variables in the unconditional NARDL model, with the results in Table 5, we find a presence of the long-run negative effect of the endogenous lag-return variable at the first lag for all sample stocks as well as the portfolio. That is, the conditional long-run form of the model sufficiently corrects the noise captured by the effects of different higher order lags in the unconditional version of the NARDL model.

TABLE 5. Stocks' Returns and Portfolio Returns with the Conditional Long-Run NARDL Model

Variables	PR (7,4)	GRAS (6,2)	HDBK (4,3)	HDFC (10,2)	ICBK (3,2)	ITC (4,3)	RELI (3,2)	SBI (4,3)	TAMO (12,4)	TISC (3,4)
C	0.0000896 (0.000638) (0.8882)	-0.0005 (0.000621) (0.3807)	-0.0008 (0.000666) (0.183)	0.000147 (0.000683) (0.8292)	0.0000087 (0.000815) (0.9915)	-0.00072 (0.000656) (0.2722)	-0.00121 (0.0007) (0.0839)	-0.00069 (0.000791) (0.3832)	- 0.000624 (0.002328) (0.7887)	- 0.000818 (0.000974) (0.4012)
$R_t(-1)$	- 0.683605 (0.022485) (0.001)	- 0.655196 (0.021528) (0.001)	-0.77179 (0.019444) (0.001)	- 0.883379 (0.029573) (0.001)	- 0.638051 (0.015508) (0.001)	- 0.733689 (0.019082) (0.001)	-0.68492 (0.016068) (0.001)	- 0.699886 (0.018405) (0.001)	- 0.815384 (0.031164) (0.001)	- 0.663488 (0.016325) (0.001)
$MP_t(-1,p)$	0.207073 (0.016199) (0.001)	0.187907 (0.017993) (0.001)	0.178412 (0.019121) (0.001)	0.189637 (0.021523) (0.001)	0.254723 (0.025328) (0.001)	0.144249 (0.02034) (0.001)	0.240069 (0.020614) (0.001)	0.306221 (0.025613) (0.001)	0.37775 (0.066031) (0.001)	0.298364 (0.030613) (0.001)
$MP_t(-1,n)$	0.207061 (0.016202) (0.001)	0.187943 (0.017996) (0.001)	0.178288 (0.01912) (0.001)	0.189428 (0.021522) (0.001)	0.254781 (0.025329) (0.001)	0.144232 (0.020341) (0.001)	0.239807 (0.020614) (0.001)	0.306218 (0.025615) (0.001)	0.378419 (0.066035) (0.001)	0.29829 (0.030615) (0.001)
$\beta_t(p)$			-0.00077 (0.001021) (0.4507)		0.000273 (0.000844) (0.7465)		- 0.000096 (0.000951) (0.9193)			
$\beta_t(-1,p)$	0.000864 (0.000749) (0.249)	- 0.0000221 (0.000936) (0.9812)	0.000207 (0.000941) (0.8256)		0.001277 (0.000931) (0.1699)		- 0.000363 (0.000755) (0.6308)		0.007648 (0.002605) (0.0033)	0.000544 (0.000957) (0.5697)
$\beta_t(n)$				0.001122 (0.000928) (0.2266)						
$\beta_t(-1,n)$	0.00097 (0.000799) (0.2247)	- 0.0000675 (0.000964) (0.9442)	0.000529 (0.000924) (0.5672)	- 0.000213 (0.001014) (0.8334)		0.000284 (0.000868) (0.7438)	0.000312 (0.000817) (0.7024)	- 0.000076 (0.000994) (0.9385)	0.006643 (0.00235) (0.0047)	0.000727 (0.001031) (0.4805)
$\Delta R_t(-1)$	- 0.029247 (0.021734) (0.1784)	- 0.023805 (0.020417) (0.2437)	0.080234 (0.017602) (0.001)	0.213842 (0.027736) (0.001)	0.030294 (0.014722) (0.0397)	0.018252 (0.01735) (0.2928)	0.031209 (0.015054) (0.0382)	0.031113 (0.016948) (0.0664)	- 0.176192 (0.029907) (0.001)	- 0.012353 (0.015259) (0.4182)
$\Delta R_t(-2)$	0.105296 (0.020286) (0.001)	0.036319 (0.018653) (0.0516)	0.111654 (0.015293) (0.001)	0.248011 (0.025989) (0.001)	0.083875 (0.012601) (0.001)	0.09657 (0.015343) (0.001)	0.110198 (0.012583) (0.001)	0.087769 (0.014987) (0.001)	- 0.001363 (0.028276) (0.9615)	0.079998 (0.012621) (0.001)
$\Delta R_t(-3)$	- 0.013056 (0.018399) (0.478)	-0.03989 (0.016521) (0.0158)	0.054262 (0.012388) (0.001)	0.169374 (0.024213) (0.001)		0.033364 (0.012543) (0.0078)		0.033701 (0.012546) (0.0072)	- 0.113026 (0.026907) (0.001)	
$\Delta R_t(-4)$	- 0.014306 (0.016574) (0.3881)	- 0.047706 (0.014749) (0.0012)		0.139469 (0.022454) (0.001)				- 0.057513 (0.026009) (0.0271)		
$\Delta R_t(-5)$	- 0.011018 (0.014996) (0.4625)	- 0.032809 (0.012204) (0.0072)		0.121798 (0.020652) (0.001)				0.049524 (0.024839) (0.0462)		
$\Delta R_t(-6)$	0.04886 (0.012237) (0.0001)			0.120071 (0.018699) (0.001)				0.172943 (0.024191) (0.001)		
$\Delta R_t(-7)$				0.064822 (0.016701) (0.001)				0.032833 (0.023106) (0.1554)		
$\Delta R_t(-8)$				0.058045 (0.014802) (0.001)				0.126062 (0.021272) (0.001)		
$\Delta R_t(-9)$				0.029975 (0.01234) (0.0152)				0.088757 (0.018727) (0.001)		
$\Delta R_t(-10)$								0.048628 (0.01648) (0.0032)		
$\Delta R_t(-11)$								0.125968 (0.011906) (0.001)		

The utility of the sufficiency criteria on the applications of the conditional model can further be supported by the absence of static influence in terms of significant coefficient of systematic beta in the long-run level equation (hereinafter also refer LRLE), please read with Table 5C, but at presence of significant short-run dynamics of the same. To emphasize it further, in the LRLE depicted in Table 5C, we also find the said absence of long-run conditional effects of systematic beta for the sample stocks (except TAMO) and the portfolio across the respective positive and negative values of systematic beta while in the conditional long-run error correction regression (please refer to Table 5B) there is a presence of positive long-run impacts at the 1st lag of the systematic risk variable across its positive and negative values along with the presence of mixed coefficients for its short-run dynamic effects at the different lag orders. These suggest for the presence of investors' long-memory effects in their decision choices. We also portray (please read with Table 5) positively significant coefficients values for the short-run endogenous return variable at its first lag for a limited number of sample stocks viz., HDBK, HDFC, ICBK, RELI and SBI while at the 2nd lag, the same is observed for all stocks (except TAMO) and the portfolio as well. These suggest for synchronicity in the application of mental accounting to portfolio management.

TABLE 5A. Coefficient Results for the Market Premium Variable in the Conditional Long-Run NARDL Model Setup for Stocks' Returns and Portfolio Returns

Variables	PR (7,4)	GRAS (6,2)	HDBK (4,3)	HDFC (10,2)	ICBK (3,2)	ITC (4,3)	RELI (3,2)	SBI (4,3)	TAMO (12,4)	TISC (3,4)
$\Delta MP_t(p)$	0.021545 (0.019649) (0.2729)	0.061499 (0.022092) (0.0054)	0.052013 (0.021261) (0.0145)	-0.016141 (0.024891) (0.5167)	0.024981 (0.029007) (0.3892)	0.020813 (0.020895) (0.3193)	0.070549 (0.023541) (0.0027)	0.076828 (0.025858) (0.003)	-0.004108 (0.07594) (0.9569)	0.077953 (0.030372) (0.0103)
$\Delta MP_t(-1,p)$			-0.061404 (0.025104) (0.0145)		-0.045418 (0.022954) (0.0479)		-0.054389 (0.026366) (0.0392)	-0.1355 (0.076608) (0.077)	-0.060232 (0.033617) (0.0732)	
$\Delta MP_t(-2,p)$							-0.040363 (0.025586) (0.1147)			
$\Delta MP_t(n)$	0.059915 (0.020073) (0.0028)	0.054956 (0.022907) (0.0165)	0.063851 (0.021931) (0.0036)	0.023256 (0.025445) (0.3608)	0.104349 (0.029669) (0.0004)	0.020649 (0.021535) (0.3377)	0.1176 (0.024256) (0.001)	0.131793 (0.026669) (0.001)	0.184065 (0.078475) (0.019)	0.058724 (0.031341) (0.061)
$\Delta MP_t(-1,n)$			-0.042348 (0.022426) (0.059)		-0.068235 (0.029949) (0.0227)	-0.026449 (0.021868) (0.2265)	-0.043117 (0.024177) (0.0746)	-0.061347 (0.029614) (0.0383)		-0.059696 (0.031764) (0.0602)
$\Delta MP_t(-2,n)$			0.032095 (0.01988) (0.1065)		-0.042919 (0.021406) (0.045)			-0.000928 (0.031566) (0.9766)		
$\Delta MP_t(-3,n)$							-0.073219 (0.028176) (0.0094)			

TABLE 5B. Coefficient Results for the Systematic Beta Variable in the Conditional Long-Run NARDL Model Setup for Stocks' Returns and Portfolio Returns

Variables	PR (7,4)	GRAS (6,2)	HDBK (4,3)	HDFC (10,2)	ICBK (3,2)	ITC (4,3)	RELI (3,2)	SBI (4,3)	TAMO (12,4)	TISC (3,4)
$\Delta\beta_t(p)$	-0.171851 (0.049095) (0.0005)	-0.107 (0.040472) (0.0082)	-0.084189 (0.044599) (0.0591)		-0.08502 (0.050151) (0.0901)		-0.128907 (0.041007) (0.0017)		1.201585 (0.096015) (0.001)	-0.115263 (0.050172) (0.0216)
$\Delta\beta_t(-1,p)$	0.107364 (0.048962) (0.0284)								0.818342 (0.099496) (0.001)	
$\Delta\beta_t(-2,p)$									-0.098024 (0.099975) (0.3269)	
$\Delta\beta_t(-3,p)$									-0.212593 (0.097399) (0.0291)	
$\Delta\beta_t(n)$	-0.353894 (0.048074) (0.001)	-0.482581 (0.047334) (0.001)	-0.53919 (0.040747) (0.001)	-0.220981 (0.043052) (0.0001)		-0.218202 (0.044682) (0.001)	-0.318851 (0.047733) (0.001)	-0.224634 (0.045822) (0.001)	-0.718547 (0.0967) (0.001)	-0.243728 (0.050577) (0.001)
$\Delta\beta_t(-1,n)$	0.059957 (0.049406) (0.225)	0.240313 (0.046787) (0.001)	0.20392 (0.040757) (0.001)	0.098416 (0.043203) (0.0228)		0.098074 (0.044775) (0.0285)	0.151827 (0.047065) (0.0013)	0.149038 (0.046006) (0.0012)	-1.0288 (0.099776) (0.001)	0.13982 (0.049722) (0.0049)
$\Delta\beta_t(-2,n)$	0.083393 (0.04833) (0.0845)								0.560798 (0.100437) (0.001)	
$\Delta\beta_t(-3,n)$	-0.127731 (0.046801) (0.0064)								-0.387574 (0.098798) (0.001)	

If we just dive a little more into Table 5A, the variables for positive and negative values of market premium inferring about long-run effects in the LRLE show the presence of positively significant coefficients for the sample stocks and portfolio as well. In contrast, the dynamic short-run proxy variables for the positive and negative values of the market premium in the conditional long-run error correction regression model respectively show positively significant coefficients at their current period for most of the sample stocks and portfolio as well but they show negatively significant coefficients for a few sample stocks only at their one or higher period lags. These confirm the presence of static long-run effects but mixed dynamic short-run effects for the market premium variable. These observations also put forth the synchronicity proposition in the application of mental accounting to portfolio management.

TABLE 5C. Statistics of Long Run Level Equation with the Conditional Long-Run NARDL Model Setup

Variables	PR (7,4)	GRAS (6,2)	HDBK (4,3)	HDFC (10,2)	ICBK (3,2)	ITC (4,3)	RELI (3,2)	SBI (4,3)	TAMO (12,4)	TISC (3,4)
$MP_t(p)$	0.302914 (0.023539) (0.001)	0.286795 (0.027327) (0.001)	0.231167 (0.02385) (0.001)	0.214673 (0.024221) (0.001)	0.39922 (0.03852) (0.001)	0.196608 (0.02723) (0.001)	0.350507 (0.02899) (0.001)	0.437529 (0.034657) (0.001)	0.463279 (0.080406) (0.0002)	0.44969 (0.044372) (0.001)
$MP_t(n)$	0.302896 (0.023543) (0.001)	0.28685 (0.027331) (0.001)	0.231006 (0.02385) (0.001)	0.214436 (0.024221) (0.001)	0.399311 (0.038521) (0.001)	0.196584 (0.027233) (0.001)	0.350124 (0.028994) (0.001)	0.437525 (0.03466) (0.001)	0.464099 (0.080403) (0.0002)	0.449579 (0.044376) (0.001)
$\beta(p)$	0.001263 (0.001095) (0.2488)	-0.0000337 (0.001429) (0.9812)	0.000269 (0.00122) (0.8256)	-0.000872 (0.001156) (0.4507)	0.002002 (0.001458) (0.1696)	0.000372 (0.00115) (0.7465)	-0.00053 (0.001102) (0.6308)	-0.000138 (0.001359) (0.9193)	0.009379 (0.003168) (0.0031)	0.00082 (0.001443) (0.5696)
$\beta(n)$	0.001419 (0.001168) (0.2244)	-0.000103 (0.001471) (0.94442)	0.000685 (0.001198) (0.5672)	-0.000242 (0.001148) (0.8334)	0.001758 (0.001453) (0.2263)	0.000386 (0.001182) (0.7438)	0.000456 (0.001193) (0.7024)	-0.00011 (0.001421) (0.9385)	0.008147 (0.002862) (0.0044)	0.001096 (0.001553) (0.4804)
C^*	0.000131 (0.000932) (0.8882)	-0.000831 (0.000949) (0.3814)	-0.001149 (0.000862) (0.1827)	0.000167 (0.000773) (0.8291)	0.0000136 (0.001277) (0.9915)	-0.000982 (0.000894) (0.2722)	-0.001767 (0.001021) (0.0836)	-0.000985 (0.001129) (0.3831)	-0.000765 (0.002857) (0.7889)	-0.001233 (0.001468) (0.4009)

In Table 6 along with Table 6A, Table 6B and Table 6C, we report the results on the conditional error correction form (ECF) of the NARDL model. It shows the extents of an overall long-run speed of adjustment for individual stock returns as well as the portfolio returns besides the factor-specific short-run adjustments (please refer to Table 6, Table 6A and Table 6B). The factor-specific short-run effects are the same as reported in the above for the conditional long-run form of the NARDL model. In Table 6B, we also find that there is significant presence of moderately high speeds of adjustment to their long-run targets and their magnitudes range within -63.80% and -88.33% for the stocks. These adjustment speeds suggest for the presence of adaptability in investors' long-run dynamic adjustments. The table further shows that the adjustment speed for the portfolio returns is 68.36% which interestingly, falls short of the magnitude of the simple average of sample stocks' adjustment speeds. This infers for presence of conservative outlooks at investor's synchronised mental adaptability across sample stocks' speed of adjustments over the long-range sample time period from 03.04.2000 to 14.01.2019.

TABLE 6. Stocks' Returns and Portfolio Returns with the Conditional ECF of NARDL Model Setup

Variables	PR (7,4)	GRAS (6,2)	HDBK (4,3)	HDFC (10,2)	ICBK (3,2)	ITC (4,3)	RELI (3,2)	SBI (4,3)	TAMO (12,4)	TISC (4,1)
$\Delta R_t(-1)$	-0.029247 (0.021416) (0.1721)	-0.023805 (0.020207) (0.2388)	0.080234 (0.017542) (0.001)	0.213842 (0.027533) (0.001)	0.030294 (0.014695) (0.0393)	0.018252 (0.017333) (0.2924)	0.031209 (0.015033) (0.0379)	0.031113 (0.016932) (0.0662)	-0.176192 (0.029548) (0.001)	-0.012353 (0.015223) (0.4171)
$\Delta R_t(-2)$	0.105296 (0.0199) (0.001)	0.036319 (0.018449) (0.049)	0.111654 (0.015255) (0.001)	0.248011 (0.025729) (0.001)	0.083875 (0.01259) (0.001)	0.09657 (0.015335) (0.001)	0.110198 (0.012573) (0.001)	0.087769 (0.014978) (0.001)	-0.001363 (0.027817) (0.9609)	0.079998 (0.012613) (0.001)
$\Delta R_t(-3)$	-0.013056 (0.017808) (0.4635)	-0.03989 (0.016284) (0.0143)	0.054262 (0.012378) (0.001)	0.169374 (0.023868) (0.001)		0.033364 (0.012533) (0.0078)		0.033701 (0.01254) (0.0072)	-0.113026 (0.026368) (0.001)	
$\Delta R_t(-4)$	-0.014306 (0.01595) (0.3698)	-0.047706 (0.014526) (0.001)		0.139469 (0.02199) (0.001)					-0.057513 (0.025383) (0.0235)	
$\Delta R_t(-5)$	-0.011018 (0.014412) (0.4446)	-0.032809 (0.012043) (0.0065)		0.121798 (0.020175) (0.001)					0.049524 (0.024169) (0.0405)	
$\Delta R_t(-6)$	0.04886 (0.012004) (0.001)			0.120071 (0.018342) (0.001)					0.172943 (0.023583) (0.001)	
$\Delta R_t(-7)$				0.064822 (0.016474) (0.0001)					0.032833 (0.022585) (0.1461)	
$\Delta R_t(-8)$				0.058045 (0.01467) (0.001)					0.126062 (0.020905) (0.001)	
$\Delta R_t(-9)$				0.029975 (0.01229) (0.0148)					0.088757 (0.018503) (0.001)	
$\Delta R_t(-10)$									0.048628 (0.016361) (0.003)	
$\Delta R_t(-11)$									0.125968 (0.011868) (0.001)	

Table 6A. Coefficient Results for the Market Premium Variable in the Conditional ECF of NARDL Model Setup for Stocks' Returns and Portfolio Returns

Variables	PR (7,4)	GRAS (6,2)	HDBK (4,3)	HDFC (10,2)	ICBK (3,2)	ITC (4,3)	RELI (3,2)	SBI (4,3)	TAMO (12,4)	TISC (4,1)
$\Delta MP_t(p)$	0.021545 (0.017081) (0.2072)	0.061499 (0.018895) (0.0011)	0.052013 (0.019568) (0.0079)	- 0.016141 (0.020811) (0.438)	0.024981 (0.025883) (0.3345)	0.020813 (0.018994) (0.2732)	0.070549 (0.021396) (0.001)	0.076828 (0.023369) (0.001)	- 0.004108 (0.064198) (0.949)	0.077953 (0.028067) (0.0055)
$\Delta MP_t(-1,p)$				- 0.061404 (0.022811) (0.0071)		- 0.045418 (0.020393) (0.026)		- 0.054389 (0.023602) (0.0212)	-0.1355 (0.069416) (0.051)	- 0.060232 (0.029761) (0.043)
$\Delta MP_t(-2,p)$								- 0.040363 (0.023312) (0.0834)		
$\Delta MP_t(n)$	0.059915 (0.017402) (0.001)	0.054956 (0.019651) (0.0052)	0.063851 (0.018677) (0.0006)	0.023256 (0.023183) (0.3158)	0.104349 (0.024794) (0.001)	0.020649 (0.019578) (0.2916)	0.1176 (0.020614) (0.001)	0.131793 (0.024512) (0.001)	0.184065 (0.071946) (0.0105)	0.058724 (0.028704) (0.0408)
$\Delta MP_t(-1,n)$			- 0.042348 (0.019872) (0.0331)		- 0.068235 (0.026744) (0.0108)	- 0.026449 (0.019421) (0.1733)	- 0.043117 (0.021756) (0.0475)	- 0.061347 (0.026254) (0.0195)		- 0.059696 (0.028325) (0.0351)
$\Delta MP_t(-2,n)$			0.032095 (0.018398) (0.0811)			- 0.042919 (0.019342) (0.0265)				- 0.000928 (0.028167) (0.9737)
$\Delta MP_t(-3,n)$										- 0.073219 (0.026387) (0.0055)

Table 6B. Coefficient Results for the Systematic Beta Variable in the Conditional ECF of NARDL Model Setup for Stocks' Returns and Portfolio Returns

Variables	PR (7,4)	GRAS (6,2)	HDBK (4,3)	HDFC (10,2)	ICBK (3,2)	ITC (4,3)	RELI (3,2)	SBI (4,3)	TAMO (12,4)	TISC (4,1)
$\Delta\beta_t(p)$	- 0.171851 (0.048165) (0.0004)	-0.107 (0.038839) (0.0059)	- 0.084189 (0.043229) (0.0515)		-0.08502 (0.04796) (0.0763)		- 0.128907 (0.039599) (0.001)		1.201585 (0.095291) (0.001)	- 0.115263 (0.04852) (0.0175)
$\Delta\beta_t(-1,p)$	0.107364 (0.048025) (0.0254)								0.818342 (0.098893) (0.001)	
$\Delta\beta_t(-2,p)$									- 0.098024 (0.099292) (0.3236)	
$\Delta\beta_t(-3,p)$									- 0.212593 (0.096508) (0.0276)	
$\Delta\beta_t(n)$	- 0.353894 (0.047367) (0.001)	- 0.482581 (0.046089) (0.001)	-0.53919 (0.040099) (0.001)	- 0.220981 (0.042362) (0.001)		- 0.218202 (0.044099) (0.001)	- 0.318851 (0.04664) (0.001)	- 0.224634 (0.041591) (0.0031)	- 0.718547 (0.095778) (0.001)	- 0.243728 (0.049362) (0.001)
$\Delta\beta_t(-1,n)$	0.059957 (0.048908) (0.2203)	0.240313 (0.045952) (0.001)	0.20392 (0.040363) (0.001)	0.098416 (0.042536) (0.0207)		0.098074 (0.044103) (0.0262)	0.151827 (0.046478) (0.0011)	0.149038 (0.045499) (0.0011)	-1.0288 (0.099138) (0.001)	0.13982 (0.049377) (0.0046)
$\Delta\beta_t(-2,n)$	0.083393 (0.04808) (0.0829)								0.560798 (0.099619) (0.001)	
$\Delta\beta_t(-3,n)$	- 0.127731 (0.046091) (0.0056)								- 0.387574 (0.097951) (0.001)	
ECT*	- 0.683605 (0.021993) (0.001)	- 0.655196 (0.021222) (0.001)	-0.77179 (0.019418) (0.001)	- 0.883379 (0.029302) (0.001)	- 0.638051 (0.015484) (0.001)	- 0.733689 (0.019067) (0.001)	-0.68492 (0.016061) (0.001)	- 0.664137 (0.023113) (0.001)	- 0.815384 (0.030859) (0.001)	- 0.663488 (0.016306) (0.001)

The summery statistics of the ECFs of the NARDL models (please refer to Table 6C) show a presence of 37.92% explanatory power in explaining the portfolio returns while those of the sample stocks remain within 30.80 - 60.66. The coefficients of the ECF models have persistency in terms of an absence of the BPG serial correlations tests except TAMO. The Durbin-Watson (DW) test-statistics are mostly within 1.997 and 2.0023 and these statistics confirm absence of auto correlations for the sample stocks and the portfolio as well. The CUSUM test of regression residuals also confirm stability of ECFs of NARDL models. The results in Table 5 and Table 6, both read along with their other related tables, depict the presence of long-run relationships in terms of the significant test statistics of the F-Bound F-statistics as depicted in Table 6C respectively for the conditional long-run forms of the NARDL models and the ECFs as well. The presence of instability in terms of the CUSUM test of the residuals-squares, that of residual non-normality in terms of JB Normality tests and heteroskedasticity in terms of BPG test statistics cast limited generalizability about the aforementioned observations.

Table 6C. Summary Statistics for the Conditional ECF of the NARDL Model Setup

Variables	PR (7,4)	GRAS (6,2)	HDBK (4,3)	HDFC (10,2)	ICBK (3,2)	ITC (4,3)	RELI (3,2)	SBI (4,3)	TAMO (12,4)	TISC (4,1)
R^2(Adj. R^2)	0.380585 (0.379246)	0.359699 (0.358711)	0.380687 (0.379732)	0.3480 (0.3466)	0.3089 (0.3083)	0.3628 (0.3618)	0.3424 (0.3416)	0.340129 (0.339111)	0.6079 (0.6066)	0.3449 (0.3438)
Durbin Watson Stat	2.001	2.00128	1.999	1.997	2.0021	2.0004	2.007	1.9977	2.017	2.0023
HT-BPG F-stat (Prob.)	14.10338 (0.001)	46.7416 (0.001)	81.983 (0.001)	35.739 (0.001)	60.419 (0.001)	23.36 (0.001)	49.448 (0.001)	20.691 (0.001)	34.8356 (0.001)	56.527 (0.001)
BG-SC-LM F-stat (Prob.)	0.96674 (0.3804)	0.645244 (0.5246)	0.6516 (0.5212)	1.837 (0.1594)	1.651 (0.192)	0.7149 (0.4893)	2.594 (0.0748)	0.0649 (0.9371)	42.657 (0.001)	3.1849 (0.0414)
JB Norm (Prob.)	270688 (0.001)	6689.43 (0.001)	23097 (0.001)	9929 (0.001)	12182 (0.001)	4902 (0.001)	12168 (0.001)	18736 (0.001)	43158359 (0.001)	3786 (0.001)
F-bound F-stat	160.904 (0.01)	158.7433 (0.01)	263.09 (0.01)	151.36 (0.01)	282.77 (0.01)	246.59 (0.01)	302.86 (0.01)	241.08 (0.001)	11627 (0.01)	275.75 (0.01)
CUSUM-RESID (CUSUM-SQ-RESID)	Stable (Unstable)	Stable (Unstable)	Stable (Unstable)	Stable (Unstable)	Stable (Unstable)	Stable (Unstable)	Stable (Unstable)	Stable (Stable*)	Unstable (Unstable)	Stable (Stable*)

Note: Stable (Unstable) suggests respective residual stability (instability) at 5% level of significance while Stable* suggests marginally stable. In the upper part of the table, values in each cell are the coefficients (standard errors) (Sign. level), and in the lower part, values in each cell are the test statistics (Sign. level). Source: Author's own computation. ECT represents the error correction terms in the respective error correction models. Bold figures indicate their importance in reporting the results and findings.

Robustness Checks. On robustness of prospect theory (PT) implications on mental accounting in portfolio management, we perform the t-test of difference for coefficient magnitudes as found in the different NARDL regression models for the portfolio returns if these differ from those for sample stocks' returns. We perform the tests across the variables representing positive and negative values of the variables and report the same in Table 7 for unrestricted NARDL models, those in Table 8 for the conditional long-run forms and in Table 9 for their ECFs.

Table 7 shows that the coefficient of the endogenous return of the portfolio return at its 1st lag is significantly higher (lower) than that of GRAS, HDFC, ICBK, RELI, SBI and TISC (TAMO) while the relevant coefficient at the 2nd lag is significantly lower (higher) from that of GRAS, HDBK, HDFC, ITC, RELI, SBI and TISC (TAMO). Nonetheless, the coefficient of the portfolio return at its 3rd endogenous lag is significantly higher (lower) than that of GRAS, HDBK, HDFC, ITC, SBI and TISC (ICBK). These observations suggest that a pattern could be found in terms of endogenous effects and investors can use such endogeneity as their decision references in the construction of a mental portfolio at the synchronization of the sample stocks' lag effects. There is evidence of other higher-order lagged endogeneity effect/s at 4th, 5th and 6th lag for the sample stocks of GRAS, HDBK, HDFC, ITC and TAMO as well.

Table 7. T-Statistics for Equality of Coefficients with the Unrestricted NARDL Models

Hypothesis	GRAS	HDBK	HDFC	ICBK	ITC	RELI	SBI	TAMO	TISC
H0: Equality of the lagged endogenous return parameter values									
$SR_{t-1,i} \neq PR_{t-1}$	1.945	1.216	2.478	16.51	-0.148	3.395	2.522	-15.983	2.120
$SR_{t-2,i} \neq PR_{t-2}$	-4.027	-5.562	-5.38	-1.517	-3.038	-2.969	-4.174	2.234	-2.263
$SR_{t-3,i} \neq PR_{t-3}$	2.279	3.306	2.131	-8.357	2.979	0.448	3.447	0.369	2.106
$SR_{t-4,i} \neq PR_{t-4}$	-0.359	-2.961	-1.556		-1.783			3.162	
$SR_{t-5,i} \neq PR_{t-5}$	0.636		-1.141					5.795	
$SR_{t-6,i} \neq PR_{t-6}$	1.944		-3.379					3.588	
$SR_{t-7,i} \neq PR_{t-7}$			-0.357					-5.241	
H0: Equality of the risk free rate of return parameter values									
$MP(p)_i \neq MP(p)_P$	1.351	1.053	-1.189	0.098	-0.026	1.598	1.702	-0.327	1.559
$MP(-1,p)_i \neq MP(-1,p)_P$	-1.989	-1.926	-1.102	1.194	-3.088	-0.495	-0.259	0.614	-0.552
$MP(n)_i \neq MP(n)_P$	-0.163	0.132	-1.131	1.240	-1.334	1.832	2.154	1.533	-0.032
$MP(-1,n)_i \neq MP(-1,n)_P$	-0.465	-2.168	0.550	-1.495	-1.386	-1.834	-0.809	0.531	0.685
H0: Equality of parameter values for the coefficient of the systematic risk									
$\beta(t,p)_i \neq \beta(t,p)_P$	1.019	1.322	3.484	3.678	3.505	0.671	3.498	12.736	0.8067
$\beta(-1,p)_i \neq \beta(-1,p)_P$	-1.924	-2.129		-3.471		-1.679		-3.767	-1.734
$\beta(-2,p)_i \neq \beta(-2,p)_P$								-4.982	

(Continued)

Hypothesis	GRAS	HDBK	HDFC	ICBK	ITC	RELI	SBI	TAMO	TISC
$\beta(t,n)_i \neq \beta(t,n)_P$	-1.907	-2.940	2.060	7.361	2.068	0.517	1.946	-3.377	1.579
$\beta(-1,n)_i \neq \beta(-1,n)_P$	2.849	3.301	-0.931		-0.936	0.516	-0.389	-4.159	-0.273
$\beta(-2,n)_i \neq \beta(-2,n)_P$	-2.954	-2.635	-1.393		-1.377	-1.959	-1.940	9.044	-1.797
$\beta(-3,n)_i \neq \beta(-3,n)_P$								-4.256	
$\beta(-4,n)_i \neq \beta(-4,n)_P$								2.377	
H0: Equality of the intercept parameter values									
$C_0,i \neq C_{0,P}$	-0.712	-1.097	0.064	-0.078	-0.885	-1.372	-0.767	-0.296	-0.779

On performing the t-test for difference of coefficient magnitudes of the conditional LRF of the NARDL model, in Table 8, intercept coefficients of the relevant NARDL models show no difference between coefficients for sample stocks and portfolio return. Investors' conditional decision on portfolio management has least fixed effects in terms of mental accounting portfolio choices. There exists a combined endogeneity effect at the 1st lag for sample stocks where ICBK (HDBK, HDFC, ITC and TAMO) has a positive (negative) contribution at endogeneity effect in portfolio return. Besides, the positive and negative values of lagged market premium variables have significantly negative (positive) contributions towards the portfolio return for ITC (SBI, TAMO and TISC) as well while with positive and negative values of systematic beta variables, we can find presence of positive contribution only for TAMO. These reveal that using prospect theory references like endogeneity effects, long-run market premium and long-run systematic beta, decision criteria for portfolio selection/rejection could be developed towards identifying the sample stocks to be included or excluded in portfolio management under mental accounting. This observation also finds robust support concerning the short-run endogeneity effects for the sample stocks except for TISC only. Interestingly, on the short-run effects of positive and negative values of the market premium variable, the above-stated contributory effects are visible only for RELI and SBI while on that of the systematic beta variable, contributory effects are in abundance except for TISC and RELI. There exists a psychological thrust on investors' decision choices that put emphasis either on short-run or long-run mental accounting and this has roles towards gains or losses from their individual portfolio choices

Table 8. T-Statistics for Equality of Coefficients with the Conditional LRF of NARDL Models

Hypothesis	GRAS	HDBK	HDFC	ICBK	ITC	RELI	SBI	TAMO	TISC
H0: Equality of the intercept parameter values for the individual stocks and the portfolio									
$C_{0,i} \neq C_{0,P}$	-0.712	-1.097	0.064	-0.078	-0.885	-1.372	-0.767	-0.296	-0.779
H0: Equality of the combined endogenous return parameter values									
$R^*_{t-1,i} \neq R^*_{t-1,P}$	0.913	-2.833	-6.418	1.668	-1.698	-0.048	-0.560	-3.429	0.724
H0: Equality of the effects of long run systematic risk parameter values									
$MP_{t-1,p,i} \neq MP_{t-1,p,P}$	-0.792	-1.144	-0.647	1.585	-2.416	1.259	3.272	2.510	2.636
$MP_{t-1,n,i} \neq MP_{t-1,n,P}$	-0.789	-1.148	-0.655	1.587	-2.416	1.249	3.272	2.520	2.634
H0: Equality of the effects of long run systematic risk parameter values									
$\beta_{t-1,p,i} \neq \beta_{t-1,p,P}$	-0.739	-0.546	-1.291	0.346	-0.524	-1.154	-0.794	2.503	-0.263
$\beta_{t-1,n,i} \neq \beta_{t-1,n,P}$	-0.828	-0.361	-0.916	0.124	-0.582	-0.576	-0.821	2.286	-0.186
H0: Equality of the effects of dynamic short run endogenous return parameter values									
$\Delta R_{t-1,i} \neq \Delta R_{t-1,P}$	0.183	3.915	6.899	2.268	1.708	2.287	2.190	-3.975	0.636
$\Delta R_{t-2,i} \neq \Delta R_{t-2,P}$	-2.503	0.250	4.329	-0.897	-0.343	0.205	-0.695	-3.065	-1.059
$\Delta R_{t-3,i} \neq \Delta R_{t-3,P}$	-1.085	3.035	5.999		2.086		2.099	-3.067	
$\Delta R_{t-4,i} \neq \Delta R_{t-4,P}$	-1.505		5.509					-1.401	
$\Delta R_{t-5,i} \neq \Delta R_{t-5,P}$	-1.127		5.204					2.087	
$\Delta R_{t-6,i} \neq \Delta R_{t-6,P}$			3.187					4.577	
H0: Equality of the effects of short run Market Premium parameter values									
$\Delta MP_{t,p,i} \neq \Delta MP_{t,p,P}$	1.351	1.053	-1.188	0.098	-0.026	1.598	1.702	-0.327	1.559
$\Delta MP_{t,n,i} \neq \Delta MP_{t,n,P}$	-0.163	0.132	-1.131	1.241	-1.334	1.832	2.154	1.533	-0.032

(Continued)

Hypothesis	GRAS	HDBK	HDFC	ICBK	ITC	RELI	SBI	TAMO	TISC
H0: Equality of parameter values for the coefficient of the short-run systematic risk									
$\Delta\beta_{t,p,i} \neq \Delta\beta_{t,p,P}$	1.019	1.322		1.237		0.671		12.736	0.806
$\Delta\beta_{t-1,p,i} \neq \beta_{t-1,p,P}$								6.412	
$\Delta\beta_{t,n,i} \neq \Delta\beta_{t,n,P}$	-1.907	-2.940	2.059		2.068	0.517	1.946	-3.377	1.579
$\Delta\beta_{t-1,n,i} \neq \Delta\beta_{t-1,n,P}$	2.651	2.248	0.586		0.572	1.346	1.319	-9.779	1.139
$\Delta\beta_{t-2,n,i} \neq \Delta\beta_{t-2,n,P}$								4.283	
$\Delta\beta_{t-3,n,i} \neq \Delta\beta_{t-3,n,P}$								-2.377	

In Table 9, we find ingenious findings with the conditional ECF of the NARDL models. The coefficient of the speed of adjustment for the portfolio return is found to be significantly lower (higher) than that for the sample stocks for HDBK, HDFC, ITC and TAMO (ICBK only). That is, the combined long-run effect of the decision references for these sample stocks has prospect theory decision impetus in portfolio choices. Intuitively speaking, a slow(quick)-paced investor finds it adaptive to choose a sample stock having lesser (higher) long-run speed of adjustments and thereby, he can control the speed of adjustments of the portfolio over psychological holding periods of investment. This matter of mental accounting can further be validated with the results for differences of the coefficients for the dynamic reference variables in the ECF models where the results for the short-run endogeneity effects, market premium variable and systematic beta show the scopes of investors' dynamic adaptation.

Table 9. T-Statistics for equality of coefficients with the Conditional ECF of the NARDL models

H0: Equality of the intercept parameter values for the individual stocks and the portfolio									
Alternative Hypothesis	**GRAS**	**HDBK**	**HDFC**	**ICBK**	**ITC**	**RELI**	**SBI**	**TAMO**	**TISC**
$\Delta Rt(-1)_i \neq \Delta Rt(-1)_P$	0.185	3.955	6.969	2.292	1.724	2.311	2.211	-4.027	0.643
$\Delta Rt(-2)_i \neq \Delta Rt(-2)_P$	-2.542	0.254	4.388	-0.909	-0.347	0.208	-0.704	-3.118	-1.074
$\Delta Rt(-3)_i \neq \Delta Rt(-3)_P$	-1.112	3.104	6.126		2.132		2.147	-3.142	
$\Delta Rt(-4)_i \neq \Delta Rt(-4)_P$	-1.548		5.661					-1.441	
$\Delta Rt(-5)_i \neq \Delta Rt(-5)_P$	-1.160		5.357					2.151	
$\Delta Rt(-6)_i \neq \Delta Rt(-6)_P$		3.249						4.689	
H0: Equality of the effects of short run Market Premium parameter values									
$\Delta MPt(p)_i \neq \Delta MPt(p)_P$	1.569	1.173	-1.399	0.111	-0.029	1.789	1.909	-0.386	1.717
$\Delta MPt(n)_i \neq \Delta MPt(n)_P$	-0.189	0.154	-1.265	1.467	-1.499	2.138	2.391	1.677	-0.036
H0: Equality of parameter values for the coefficient of the short-run systematic risk									
$\Delta\beta_t(p)_i \neq \Delta\beta_t(p)_P$	1.048	1.355				0.689		12.863	0.828
$\Delta\beta_t(-1,p)_i \neq \beta_t(-1,p)_P$								6.467	
$\Delta\beta_t(n)_i \neq \Delta\beta_t(n)_P$	-1.947	-2.986	2.092	1.277	2.097	0.527	1.977	-5.444	1.610
$\Delta\beta_t(-1,n)_i \neq \Delta\beta_t(-1,n)_P$	2.688	2.270	0.593		0.579	1.362	1.334	-15.741	1.149
$\Delta\beta_t(-2,n)_i \neq \Delta\beta_t(-2,n)_P$								7.021	
$\Delta\beta_t(-3,n)_i \neq \Delta\beta_t(-3,n)_P$								-3.987	
H0: Equality of parameter values for the coefficient of the short-run systematic risk									
$ECT_{t-1,i} \neq ECT_{t-1,P}$	0.9295	-3.006	-5.452	1.694	-1.721	-0.048	-0.568	-3.478	0.735

Originality of Results. The study offers a step forward of the PT applications in the MA theory. It explores the PT non-linearity in the decision choices for MA. With the NARDL model, this study does not explore prospect theory values of the stocks'/portfolio's prices rather with the returns data, it examines the narrow framing of isolation effect, change in decision references, adaptive learning, dynamic adjustments, and mental separation as well. Its theoretical appeals and empirical delimitations differ from those of Barberis, et al., (2016), Barberis, et al., (2021), and Gupta, et al., (2022). On the PT effects, the readers may find the empirical findings being aligned with those in do Nascimento Jn., et al., (2021), and Wang, et al., (2021) such that the former study have found the effects of narrow framing and cross-country asymmetry with a market equilibrium model for emerging markets in Brazil, China, Russia, Mexico and South

Africa while we find within country asymmetry but with the NARDL model for Indian stock market data. Nonetheless, unlike Wang, Wu, and Zhong (2021) that explore portfolio analysis for the prospect theory effects of regulatory reforms during the pre-reform period and post-reform period in the Chinese stock markets, we find supports for loss aversion and diminishing sensitivity to positive or negative prospects with different coefficient values supporting the PT applications in mental accounting in investors' portfolio decision choices.

Financial Applications of Results. Let us highlight some prospective financial applications of the study. The corporate finance practitioners viz., the mutual fund managers in the mutual fund industry or the stock brokers in the stock markets may find the study very much helpful in their real-life decision choices. With use of asymmetric variance in the NARDL model, the study shows the coefficients for the positive values of returns as well as the negative values of returns with the stocks' annual returns data. The finance practitioners can apply the said methodology and find the effects of their decision choices at trading losses vis-à-vis trading profits for a particular stock or a mutual fund, and thereby avoiding selection bias in their fund management. Nonetheless, the speed of adjustment in the empirical models for each stock or the portfolio of stocks suggests for possible revisions the stock broker's long run dynamism and finding some sustainable trading strategy, thereby, postponing the sale of the winer stocks and holding the loss stocks, that is, avoiding the winer-stock bias. Since the study has used sample stocks' lagged return data as an endogenous variable and the stock's beta as the market's proxy for the stock, the finance managers can find whether their stocks are appealing to the investors or not. Besides, the study can be used by the market regulators in examining the effects of the capital market reforms on the behavioral biases in terms of returns.

6. Conclusion

The empirical literature on mental accounting and prospect theory as well has not expanded at a faster pace than that of their theoretical developments until the contemporary initiatives just very recently. In mental accounting, perhaps, the researchers have suffered from the prospect theory isolation effects! Exploring the separation principle of mental accounting if the same could be applied in portfolio management and if investors' preferences for individual stocks vis-à-vis a portfolio – if the both do matter at all, this empirical study contributes to this vital research gap with ingenious findings.

The study finds that the separation principle in mental accounting matters in portfolio management. There exist implications of the prospect theory references in terms of effects of market premium and systematic beta and that of isolation effects in terms of long-memory and short-memory endogeneity effects of the stocks and portfolio's return variables. We find the utility of synchronicity in the application of mental accounting in portfolio management where the adaptive outlook suggests for the presence of dynamic adjustments of the long-memory and short-memory effects for the decision references and isolation effects as well. The robustness tests also confirm that mental accounting matters to the investors in identifying their individual choices of stocks that are at their psychological thrusts in their decision choices and these contribute to setting up their specific preference criteria amongst the sample stocks for their possible inclusion into the portfolio.

Theoretical implications of this study can be identified in explaining the equity premium puzzle in standard finance. It goes as follows. Investors' adaptive mental accounting is linked to their psychological adjustment speeds where speeds of adjustment vary amongst the sample stocks and portfolios. Given the presence of multiple decision references and short-memory vis-à-vis long-memory effects, investors, in general, suffer indecisiveness decision myopia and they fail to adjust perfectly in their portfolio management. Investors avoid mental accounting at the portfolio level and the magnitude of speed of adjustment has mostly become less for the portfolio than that for the sample stocks. Their failed mental accounting, in brief, leads them to yield a lesser market premium for the portfolio than that to the stocks in the portfolio.

There are a few limitations of the study. Firstly, on portfolio construction, it considers only nine stocks and has used equal weights for them. Future researchers may use a large sample size along with differentiated weights for them and identify the effects on the portfolio returns in terms of their contributions to the speed of adjustments. Secondly, the data period is too long and it covers at least three different macroeconomic scenarios of stable, unstable and adaptive stock markets. Thirdly, the disruptive period of COVID-19 has remained out of the ambit of this study. In considering these into portfolio management, the future researchers can approach along with a data breakup over the stable, unstable, adaptive and disruptive market scenarios and thereby, they can utilise NARDL models and explore investors' episodic journey through the adaptive mental accounting aspects. In doing so, the empirical methodology of GARCH-X augmentations can be applied where the GARCH effects ventilate effects of noise in adaptive mental accounting in portfolio management.

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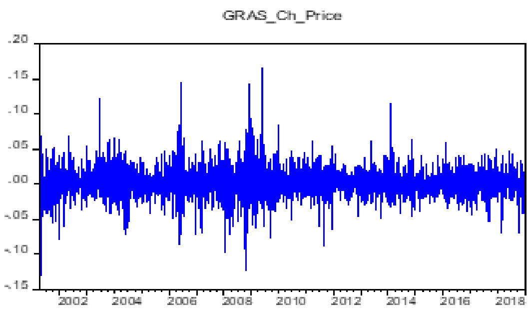
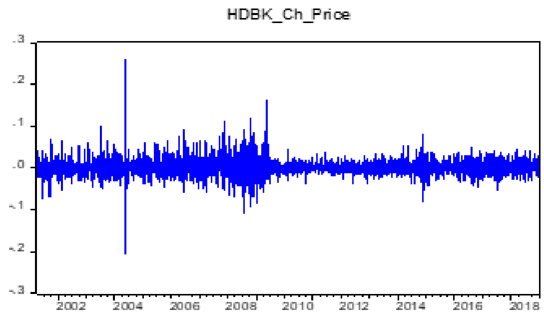
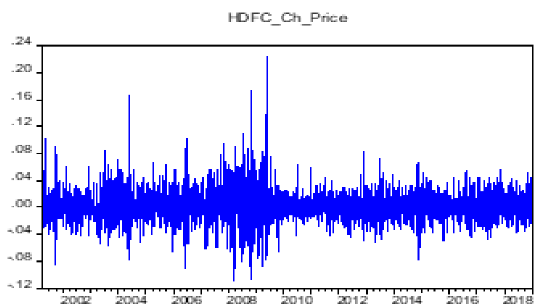
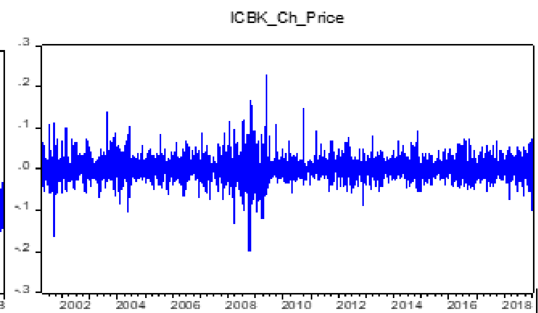
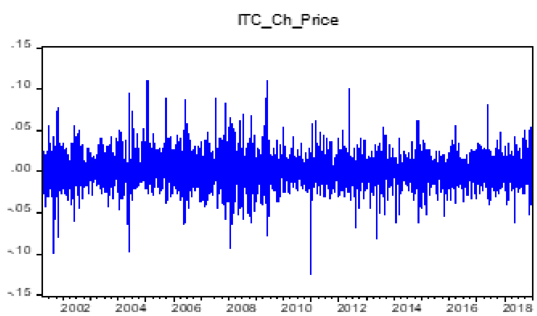
Appendix A. Figures for the Returns Data Series of the Sample Stocks and Portfolio

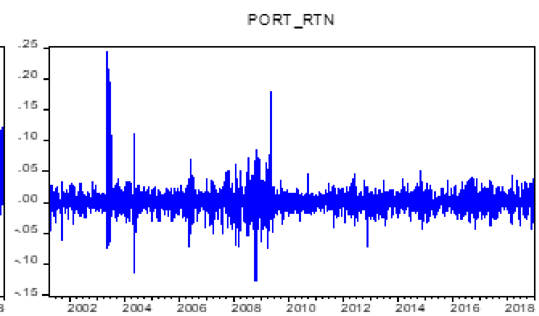


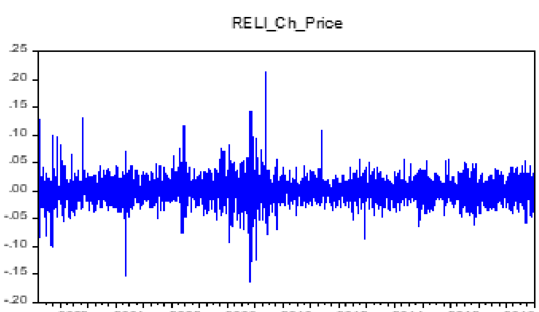


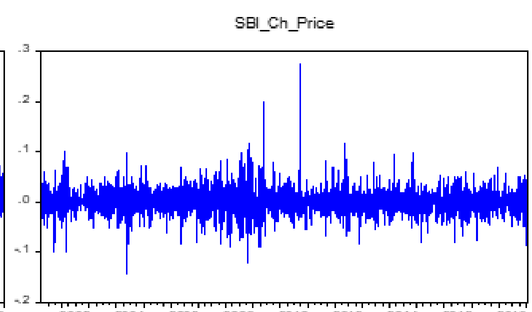


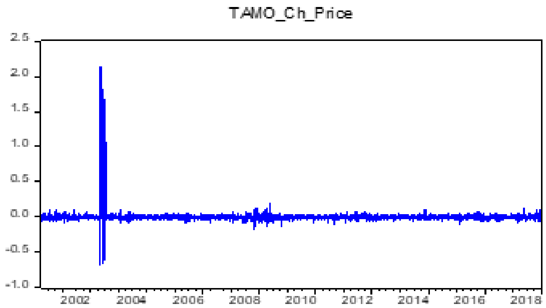


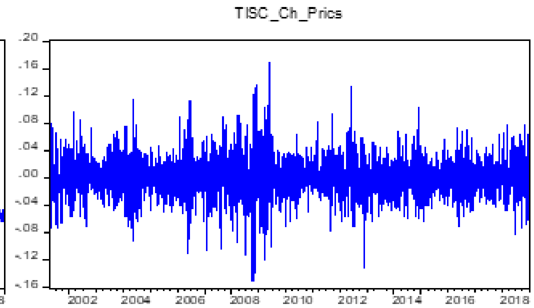









TAMO_Ch_Price
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
-1.0
2002
2004
2006
2008
2010
2012
2014
2016
2018


TISC_Ch_Prics
.20
.16
.12
.08
.04
.00
-.04
-.08
-.12
-.16
2002
2004
2006
2008
2010
2012
2014
2016
2018