Investor Behaviour and Stock Returns

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A DISSERTATION SUBMITTED TO THE FACULTY OF GRADUATE STUDIES IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

GRADUATE PROGRAM IN ECONOMICS

YORK UNIVERSITY

TORONTO, ONTARIO

February, 2022

Abstract

Both theoretical and empirical studies typically assume that agents are all rational thinkers in making decisions. Experimental evidence is, however, that human judgments are not always rational and people make systematic mental mistakes by using some intuitive simplifying rules and shortcuts, rather than strict logic to make choices. Judgment errors can lead to decisions that differ from those that would be made by rational agents. These shortcuts are also known as "behavioural heuristics" (Tversky and Kahneman (1974) and Stracca (2004), among others).

A number of recent papers provide empirical evidence that allowing for psychological biases in the agent's beliefs about the probabilities of future events is a powerful problem solving tool in a wide range of financial disciplines. It has been demonstrated by Boudoukh et al. (1998), Pritsker (2006), and Dowd (2013) that assigning to historical returns probability weights declining through the past yields more accurate estimates of the risk of loss on a specific portfolio of stocks. Departing from the assumption of rational expectations, Abel (2002) and Semenov (2009a) show that the consumption-based CAPM with pessimism, doubt, and the availability heuristic in the agent's beliefs can match the historical average equity premium and risk-free rate with plausible values of the relative risk aversion coefficient and the time discount factor.

This thesis contributes to the existing literature by exploring the influence of behavioural heuristics on the first four moments of the stock return distribution. It is comprised of three research papers.

The first paper "Investor Behaviour and the Predictability of Stock Returns" (coauthored with A. Semenov) examines the effect of three distinct pairs of mutually exclusive behavioural heuristics: (a) optimism/pessimism, (b) overconfidence/doubt, and (c) conservatism/availability on the mean of the stock return distribution.

The conventional rational investor approach to testing the predictability of stock returns by past returns relies on the assumption that returns are identically distributed through time and, hence, ignores heteroskedasticity in stock returns. We find empirical evidence that, assuming investor's rationality, one may substantially understate (overstate) the predictability of the next period stock return when the next period volatility of returns is higher (lower) than the historical volatility. The greater the deviation between the next period and historical volatilities, the greater the bias in the implied degree of predictability. The evidence is stronger for higher-frequency returns and smaller stocks. This paper won the Ben Graham Center for Value Investing Award for the best paper in

areas related to value investing such as asset pricing, market anomalies, and behavioural finance presented at the 26th Annual Conference of the Multinational Finance Society, 2019, Jerusalem, Israel.

The second paper "Behavioural Value-at-Risk" explores whether behavioural heuristics have power to explain the volatility of stock returns. This paper investigates whether allowing for behavioural heuristics makes it possible to more accurately estimate the portfolio Value-at-Risk (VaR), which is defined as an estimate of the maximum loss to be expected over a given time horizon that will not be exceeded with a given probability. This measure is widely used by security houses, investment banks, pension funds, and other financial institutions to assess the market risk of their asset portfolios. We find strong evidence that availability heuristic together with either optimism or overconfidence provides a more accurate forecast of the portfolio VaR compared with the conventional historical simulation and weighted historical simulation approaches.

In these two research papers, behavioural heuristics are accounted for through the subjective probabilities that an investor assigns to future stock returns. In contrast to these papers, the third paper "Higher-Order Return Moments under Irrational Behaviour" (coauthored with A. Semenov) uses a different approach to recognize the investor's irrationality. It incorporates different behavioural heuristics through various behavioural factors deemed to influence the third (skewness) and fourth (kurtosis) moments of the stock return distribution. We find strong empirical evidence that market overreaction, herding intensity, momentum on high volume stocks, and optimistic seasons are statistically significant in forecasting negative skewness. Excess kurtosis can be explained by market overreaction, herding intensity, and the disparity between winning and losing stocks.

This thesis is the first attempt in the asset pricing literature to investigate whether allowing for psychological biases helps more accurately explain the first four moments of the stock return distribution. The theoretical and empirical results of the thesis will be useful for researchers and practitioners working on efficient capital allocation and risk management.

Acknowledgements

Here is a small tribute to all those who supported magnificently in writing this thesis. First of all, I am profoundly grateful to my Supervisor Professor Andrei Semenov, for his invaluable supervision, tireless guidance, and stoic patience. His immense knowledge and experience in behavioural finance have encouraged me to pursue my academic specialization in this field. I have sincerely enjoyed working with him in a research environment that stimulated my passion for new insights and shaped my experiment techniques by resolving complex modeling issues and critiquing the results. I would also like to thank my Ph.D. committee members Professor Tsvetanka Karagyozova and Professor Alexey Kuznetsov, for their time and valuable suggestions on my research. I wish to acknowledge the support received from Regina Pinto, the administrative assistant, and Lisa Guidi, the graduate program assistant in the Department of Economics. Their kind help and advice made my academic journey smooth. In addition, I extend my gratitude to the Faculty of Graduate Studies for the financial support and the approval of my dissertation topic. Finally, my deepest appreciation belongs to my parents Md. Habibur Rahman and Parvin Khundker, and my husband Razin Mosharraf Ahmed. Without their incessant moral support and understanding in the past few years, it would have been impossible for me to complete this degree.

Contents

List of Figures

List of Tables

1 Investor Behaviour and the Predictability of Stock Returns

1.1 Introduction

The efficient market theory states that asset prices fully and correctly reflect all available information, so that any future price changes are determined entirely by future news. The weak form market efficiency asserts that future asset returns are not forecastable by past returns alone, i.e., follow a random walk. Extant empirical evidence, however, suggests that the returns on individual stocks are predictable to some degree. The results in Lo and MacKinlay (1988, 1990), Campbell et al. (1993), Abraham et al. (2002), Lewellen (2002), Chaudhuri and Wu (2003), Patro and Wu (2004), Kim and Shamsuddin (2008), and Kim et al. (2011) show that the predictability is stronger for the stocks with smaller capitalization and the returns at shorter intervals.

It is common to argue that the fine structure of stock markets and market frictions (such as non-synchronous trading and non-trading, for example) can explain the large body of evidence that stock returns are predictable by past returns. The findings in Barberis et al. (1998), Veronesi (1999), and Lewellen (2002) suggest that, apart from these perfectly rational factors, there might also be some irrational factors relevant to predicting stock returns.[1]

When testing the random walk model, it is conventional to assume that the historical distribution of stock returns is an adequate proxy for the next period return distribution. This assumption is indirectly built through weighting future stock returns by their objective probabilities of occurrence and, thus, assuming that investors are all rational thinkers. The assertion that the probability distribution of stock returns remains unchanged through time is implausible for stock prices over long time spans. When the next period return distribution differs from the historical distribution, this may influence the investor's beliefs about the probabilities of the next period returns on his investment. The resulting subjective probabilities may deviate substantially from the objective probabilities.

The well-documented empirical result is that stock returns are heteroskedastic over time. When the next period volatility of returns is higher than the historical volatility, increasing uncertainty about the next period return may lead the investor to assign lower probabilities to the returns that are close to the target return and higher probabilities to extreme returns.[2] In the psychological

[1] Barberis et al. (1998), Veronesi (1999), and Lewellen (2002) argue that different autocorrelation patterns across the return distribution are likely due to market participants' irrational behaviour and, more specifically, to the overreaction of investors to macroeconomic news if stocks are in a good state and the underreaction to macroeconomic news if stocks are in a bad state.

[2] Kahneman and Tversky (1979) claim that agents derive utility from deviations of outcomes from a reference point, rather than absolute outcomes. This behavioural heuristic is referred to as anchoring. Under anchoring, investors fixate on a target (anchor) asset return (for example, an economic forecast or historical average return) and tend to base their judgments on the comparison of the return on an investment with this target return. There is a substantial literature, including Tversky and Kahneman (1974), Kermer et al. (2006), Erev et al. (2008), Englich and Soder (2009), Bergman et al. (2010), McGraw et al. (2010), Furnham and Boo (2011), DeLisle et al. (2017), and Mukherjee et al. (2017), dealing with

literature this phenomenon is known as doubt. By contrast, when the next period volatility is lower than its historical counterpart, this may make the investor more confident that the next period return will be close to the target return, leading him to assign higher probabilities to the returns that are closer to the target return and lower probabilities to the returns that are further from the target return. This behavioural heuristic is called overconfidence.[3,4] When testing the predictive ability of past returns, it may also be claimed that the most recent returns are the most relevant for the next period distribution. This is the availability heuristic.[5] The availability heuristic refers to the phenomenon that human judgments are limited by the most recent available information. The availability effect is observed when investors assign higher probabilities to more recent asset returns and lower probabilities to the returns further in the past. In contrast to the availability heuristic, conservatism occurs when investors assign less weight to more recent asset returns and more weight to the returns that happened long ago.

A number of recent papers provide empirical evidence that allowing for psychological biases in the agent's beliefs about the probabilities of future events is a powerful problem solving tool in a wide range of financial disciplines. It has been demonstrated by Boudoukh et al. (1998), Pritsker (2006), and Dowd (2013) that assigning to historical returns probability weights declining through the past yields more accurate estimates of the risk of loss on a specific portfolio of stocks. Departing from the assumption of rational expectations, Abel (2002) and Semenov (2009a) show that the consumption-based CAPM with pessimism, doubt, and the availability heuristic in the agent's beliefs can match the historical average equity premium and risk-free rate with plausible values of the relative risk aversion coefficient and the time discount factor.

Our study contributes to this literature by exploring the implications of behavioural heuristics for the ability of past returns to predict future returns on individual stocks.

Despite the progress made in using behavioural heuristics to solve various problems documented in the finance literature, it is still an issue how to incorporate behavioural heuristics into the investor's subjective probabilities, especially when two or more heuristics are used by the investor simultaneously. To address this issue, we propose an approach to compute subjective probabilities

anchoring.

[3]As shown in Tversky and Kahneman (1974), investors typically judge the upper and lower bounds of the confidence interval for the value of a stock market index (such as the value of the Dow-Jones average) on a particular day to be too close to the expected value, which results in the subjective probability distribution that is too tight compared with the historical distribution of the index.

[4]Overconfidence and doubt are analysed in Harvey (1997), Hall et al. (2007), Larrick et al. (2007), Herweg and Müller (2016), and Kramer and Liao (2016).

[5]See Tversky and Kahneman (1973, 1974), Taylor (1982), Boudoukh et al. (1998), Morewedge et al. (2005), Pritsker (2006), Morewedge and Todorov (2012), and Dowd (2013) for the availability heuristic.

of future asset returns in the presence of one or more behavioural heuristics.

We argue that for each behavioural heuristic there is typically an opposite (and, thus, mutually exclusive) heuristic. The examples of mutually exclusive heuristics are optimism/pessimism, overconfidence/doubt, availability/conservatism, etc. Each of such pairs of heuristics may be regarded as a complement of rationality. The heuristics that belong to distinct pairs of mutually exclusive heuristics may combine.[6] We show that the subjective probability that the investor assigns to an asset return may be presented as a convex combination of the objective probability of the return and the subjective probabilities of the return conditional on the combinations of behavioural heuristics that belong to distinct pairs of mutually exclusive heuristics. The respective weights are the objective probability that the investor is rational and the objective probabilities of the conditioning combinations of heuristics. In the absence of behavioural heuristics, the subjective probability coincides with the objective probability, as in the standard theory. This approach produces the estimates of the probabilities of future asset returns that do not so heavily rely on the historical data and better reflect the next period market conditions.

In addition to developing the approach to computing the subjective probabilities under one or more behavioural heuristics, an important contribution of our paper is that it investigates empirically whether behavioural heuristics influence the inferences about the predictability of stock returns by past returns alone. In our empirical investigation, we focus on the impact of overconfidence/doubt and the availability heuristic on the predictability of the returns on individual stocks.

To determine whether the investor is overconfident or doubtful about the next period return on a particular stock, for each stock we estimate a conditional volatility model and compare the forecasted next period conditional volatility from this model with the stock's historical volatility.[7] When the next period conditional volatility of returns is lower than the historical volatility, the investor is overconfident in his judgments about the next period return on this stock. When the next period conditional volatility for the stock is higher than its historical counterpart, the investor exhibits doubt about the next period stock return.

For each stock, we then estimate the subjective probabilities that the investor assigns to different

[6] For instance, the investor may be overconfident about the future asset return and, at the same time, use the availability heuristic.

[7] The traditional rational investor approach implicitly relies on the assumption that the distribution of stock returns does not change through time and, hence, completely ignores volatility changes. Our approach is somewhat similar to the volatility-weighted historical simulation technique for computing the portfolio Value-at-Risk that consists in using a conditional volatility model (for example, a GARCH model) to forecast the next period volatility of returns and then weighting historical returns by the ratio of the estimated next period conditional volatility to the historical volatility (Hull and White (1998) and Dowd (2013)). The idea of both the approach proposed in this paper and the volatility-weighted historical simulation approach is to produce estimates that do not so heavily rely on the historical data and better reflect the next period market conditions.

historical returns when using overconfidence/doubt and the availability heuristic jointly. As such, we consider the subjective probabilities at which the implied standard deviation of the stock return matches the next period conditional standard deviation from the conditional volatility model for this stock.

Next, for each stock we employ the weighted linear quantile regression technique to estimate the autocorrelation coefficients for the returns weighted by the previous-step estimates of the subjective probabilities. Using the quantile regression estimates of the coefficients of autocorrelation, for each stock and each quantile of the return distribution we test the random walk hypothesis using the conventional Lo and MacKinlay (1988) variance ratio statistic. For each quantile, we then compute the percentage of stocks for which the random walk model is rejected statistically. This percentage is regarded as a measure of the predictability of individual stock returns in a considered quantile. We contrast these results with the results under the conventional assumption that the investor is rational and, hence, weights stock returns by their objective probabilities.

The rest of the paper is organized as follows. Section 1.2 first explains the approach to computing the subjective probabilities of asset returns when the investor uses one or more behavioural heuristics. Then, it describes the estimation and testing procedure. Section 1.3 exploits daily and monthly data on NYSE, Nasdaq, and AMEX-traded common stocks from December 31, 2009, to December 31, 2018, to test the predictability of individual stock returns under overconfidence/doubt and the availability heuristic. Section 1.4 concludes.

1.2 Behavioural Heuristics and the Subjective Probabilities of Asset Returns

1.2.1 The Subjective Probabilities of Asset Returns

Let R denote rationality and X the return on an asset. Assume that the investor can use heuristic A. Since events R and A are mutually exclusive, by the law of total probability,

$$\begin{aligned} P\left(X = r_s\right) = P\left(X = r_s \cap R\right) + P\left(X = r_s \cap A\right) = P\left(X = r_s | R\right) P\left(R\right) + P\left(X = r_s | A\right) P\left(A\right) \\ = P\left(X = r_s | R\right) P\left(R\right) + P\left(X = r_s | A\right) \left[1 - P\left(R\right)\right], \end{aligned} \tag{1.1}$$

i.e., the investor's subjective probability that the asset return X equals r_s ($s = 1, ..., S$), $P\left(X = r_s\right)$, is a convex combination of the objective probability of $X = r_s$, $P\left(X = r_s | R\right)$, and the subjective probability of $X = r_s$ conditional on that the investor uses heuristic A, $P(X = r_s|A)$, weighted by the probability of the investor's rationality, $P(R)$, and the probability of heuristic A, $P(A) = 1 - P(R)$, respectively.

When there are H heuristics A_h ($h = 1, ..., H$),

$$P(X = r_s) = P(X = r_s \cap R) + P\left(X = r_s \cap \left(\cup_{h=1}^{H} A_h\right)\right)$$
$$= P(X = r_s \cap R) + \sum_{h=1}^{H} P(X = r_s \cap A_h) - \sum_{1 \le h_1 < h_2 \le H} P(X = r_s \cap (A_{h_1} \cap A_{h_2}))$$
$$+ \sum_{1 \le h_1 < h_2 < h_3 \le H} P(X = r_s \cap (A_{h_1} \cap A_{h_2} \cap A_{h_3})) + (-1)^{H-1} P\left(X = r_s \cap \left(\cap_{j=1}^{H} A_{h_j}\right)\right)$$
$$= P(X = r_s \cap R) + \sum_{j=1}^{H} (-1)^{j-1} \sum_{1 \le h_1 < ... < h_j \le H} P(X = r_s \cap (\cap_{n=1}^{j} A_{h_n}))$$
$$= P(X = r_s|R) P(R) + \sum_{j=1}^{H} (-1)^{j-1} \sum_{1 \le h_1 < ... < h_j \le H} P(X = r_s| \cap_{n=1}^{j} A_{h_n}) P(\cap_{n=1}^{j} A_{h_n}) \quad (1.2)$$

If heuristics A_h are all mutually exclusive, then $\cap_{n=1}^{j} A_{h_n} = \varnothing$ for all $j > 1$ and, therefore, equation (1.2) reduces to

$$P(X = r_s) = P(X = r_s \cap R) + \sum_{h=1}^{H} P(X = r_s \cap A_h)$$
$$= P(X = r_s|R) P(R) + \sum_{h=1}^{H} P(X = r_s|A_h) P(A_h), \quad (1.3)$$

where $\sum_{h=1}^{H} P(A_h) = 1 - P(R)$.

For each heuristic, there is typically an opposite (and, thus, mutually exclusive) heuristic. The examples of mutually exclusive heuristics are: overconfidence/doubt, availability/conservatism, etc. Let A_1 and A_2 be two mutually exclusive heuristics. Because R, A_1, and A_2 are all mutually exclusive,

$$P(X = r_s) = P(X = r_s \cap R) + P(X = r_s \cap A_1) + P(X = r_s \cap A_2)$$
$$= P(X = r_s|R) P(R) + P(X = r_s|A_1) P(A_1) + P(X = r_s|A_2) P(A_2)$$
$$= P(X = r_s|R) P(R) + P(X = r_s|A_1) P(A_1) + P(X = r_s|A_2) [1 - P(R) - P(A_1)] \quad (1.4)$$

Two or more pairs of mutually exclusive heuristics may combine. Assume that there are N pairs of mutually exclusive heuristics and denote these heuristics by A_h^n, with $n = 1, ..., N$ and $h = 1, 2$

for each n. Although the heuristics in each pair are mutually exclusive, each heuristic in one pair is not necessarily mutually exclusive with the heuristics in other pairs.[8]

Therefore,

$$\begin{aligned} P\left(X=r_s\right) &= P\left(X=r_s \cap R\right) + \sum_{h_1,\dots,h_N=1,2} P(X=r_s \cap (\cap_{n=1}^{N} A_{h_n}^{n})) \\ &= P\left(X=r_s|R\right)P\left(R\right) + \sum_{h_1,\dots,h_N=1,2} P(X=r_s|(\cap_{n=1}^{N} A_{h_n}^{n}))P(\cap_{n=1}^{N} A_{h_n}^{n}) \end{aligned} \quad (1.5)$$

Since $A_h^n \cap R = \varnothing$ for all $h = 1, 2$ and $n = 1, \dots, N$ and $A_1^n \cap A_2^n = \varnothing$ for all $n = 1, \dots, N$, the subjective probability $P\left(X=r_s\right)$ is a convex combination of the objective probability of $X = r_s$, $P\left(X=r_s|R\right)$, and the subjective probabilities of $X = r_s$ conditional on that the investor uses N heuristics $A_{h_n}^n$ ($n = 1, \dots, N$) (that belong to different pairs of mutually exclusive heuristics) simultaneously. The respective weights are the probabilities that the investor is rational and that heuristics $A_{h_n}^n$ ($n = 1, \dots, N$) are used jointly.

Under the conventional assumption of rationality, $P(\cap_{n=1}^{N} A_{h_n}^{n})$ are all 0 and $P\left(R\right) = 1$, so that the probability of any return equals its objective probability,

$$P\left(X=r_s\right) = P\left(X=r_s|R\right), \quad (1.6)$$

as typically supposed in the asset pricing literature.

It is common in empirical applications to assume that the historical distribution of asset returns can serve as an adequate proxy for the next period return distribution. Suppose that at time $t-1$ the investor observes the most recent T realizations of the asset returns. This provides the investor with T scenarios ($s = 1, \dots, T$) for what might happen at time t. The rational investor weights different historical returns (scenarios) by their objective probabilities of occurrence. Therefore, under rational expectations, each scenario s is equally likely to occur, i.e., $P\left(X=r_s|R\right) = 1/T$ for all $s = 1, \dots, T$.

Apart from the objective probability $P\left(X=r_s|R\right)$, computing the subjective probability of the asset return in equation (1.5) also requires knowledge of the conditional probabilities $P(X = r_s|(\cap_{n=1}^{N} A_{h_n}^{n}))$ ($h_1, \dots, h_N = 1, 2$).

When using a behavioural heuristic, the investor ranks the observed historical asset returns according to some decision criterion and then assigns to each return the subjective probability that

[8] For example, the investor can weight heavier larger returns (i.e., can be optimistic about the next period asset return) and, at the same time, can overestimate the likelihood of the most recent returns on the asset (i.e., can use the availability heuristic).

depends on the rank $d = 1, ..., T$ of the return. Investors sort the returns based on the ranks[9] that decrease as the value of d increases. The subjective probability assigned to the returns by the investor decreases as the rank of the returns decreases.

As in Boudoukh et al. (1998) and Christoffersen (2011), assume the following function for the subjective probability of the historical return r_t $(t = 1, ..., T)$ evaluated under heuristic A:

$$P(X = r_t|A) = \frac{\theta^{d-1}(1-\theta)}{1-\theta^T}, \tag{1.7}$$

where d is the rank of r_t and $0 < \theta < 1$ is the rate of decay. The closer to 1 the value of θ, the slower the decrease in $P(X = r_t|A)$ as d increases. $lim_{\theta \to 1} P(X = r_t|A) = 1/T$, i.e., the probability of the return under the assumption of the investor's rationality.

Suppose that the investor uses N heuristics (i.e., decision criteria) A_h $(h = 1, ..., N)$ simultaneously. As in Kahneman and Tversky (1979), assume also that the investor evaluates asset returns based on their deviations from the target return a_t, $\widetilde{r}_t = r_t - a_t$.[10] Let g_{th} denote the value corresponding to scenario r_t when the scenario is assessed by the investor in terms of the decision criterion A_h. For each A_h, g_{th} is a particular function of $\widetilde{r}_t$. The g_{th} concept is quite general and covers a variety of cases. For doubt and overconfidence, g_{th} is the absolute deviation of the asset return r_t from the target return a_t, i.e., $g_{th} = |\widetilde{r}_t|$. In the case of the availability heuristic and conservatism, $g_{th} = t$.

For each scenario r_t, we can compute its performance value as

$$v_{th} = \frac{g_{th} - g_h^{min}}{g_h^{max} - g_h^{min}} \tag{1.8}$$

if, under A_h, a higher probability is assigned to the scenario with a greater value of g_{th}, and as

$$v_{th} = \frac{g_h^{max} - g_{th}}{g_h^{max} - g_h^{min}} \tag{1.9}$$

if, according to the decision criterion A_h, the scenario with a smaller value of g_{th} has a higher probability of occurrence. Here, g_h^{min} and g_h^{max} are, respectively, the smallest and largest (across the scenarios r_t $(t = 1, ..., T)$) values of g_{th}.

The performance value v_{th} is bounded in the sense that $v_{th} = 0$ for the scenario with the lowest

[9] For instance, the optimistic investor assigns the highest rank ($d = 1$) to the largest asset return and the lowest rank ($d = T$) to the smallest return on the asset. Under the availability heuristic, $d = 1$ for the most recent return and the value of d increases for the returns further in the past, etc.

[10] We suppose that the target return is invariant to behavioural heuristics and may change over time.

probability and $v_{th} = 1$ for the scenario to which the investor assigns the highest probability of occurrence. For all other scenarios, $0 < v_{th} < 1$. Since $0 \leqslant v_{th} \leqslant 1$ for all t and h, this enables us to express in the same units the performance values of different scenarios for all A_h. When the decision criteria are used jointly, the total performance value of scenario r_t may be computed as

$$V_t = \sum_{h=1}^{N} w_h v_{th}, \tag{1.10}$$

where w_h is the relative weight of importance of criterion A_h.[11]

The total performance values of different scenarios, V_t ($t = 1, ..., T$), may be ranked from 1 to T, with rank $d = 1$ assigned to scenario r_t with the highest value of V_t and rank $d = T$ assigned to r_t with the lowest total importance V_t.

By analogy with the case of a single behavioural heuristic,[12] the subjective probability of each scenario r_t ($t = 1, ..., T$), conditional on that the investor uses N heuristics simultaneously, in equation (1.5) may then be computed as

$$P\left(X = r_t | \cap_{h=1}^{N} A_h\right) = \frac{\theta^{d-1}(1-\theta)}{1-\theta^T}, \tag{1.11}$$

where d is the rank of the total performance value of r_t, V_t.

1.2.2 The Estimation and Testing Procedure

Assume that the returns lagged up to K periods can influence the next period stock return. Define r_{it} as the time $t = 1, ..., T$ continuously compounded return on stock $i = 1, ..., I$. When testing the ability of past returns to predict future stock returns, it is conventional in the empirical asset pricing literature to estimate the linear autoregressive model of order K, $AR(K)$:

$$r_{it} = \mathbf{x}_{it}'\beta_i + \eta_{it}, \tag{1.12}$$

where $\mathbf{x}_{it} = (1, r_{i,t-1}, ..., r_{i,t-K})'$, $\beta_i = (\mu_i, \rho_i(1), ..., \rho_i(K))'$, and η_{it} is the error term.

Conditional on the information available to the investor at time $t-1$, $\Omega_{i,t-1} = \{r_{i,t-1}, ..., r_{i,t-K}\}$, the expected return is

$$E[r_{it}|\Omega_{i,t-1}] = \mathbf{x}_{it}'\beta_i \tag{1.13}$$

[11] Fishburn (1967) and Triantaphyllou (2000).

[12] See equation (1.7).

The weighted least squares (WLS) estimate of the vector of factor sensitivities β_i in equation (1.12) is

$$\widehat{\beta}_i = arg\ \underset{\beta_i}{min} \sum_{t=1}^{T} w_{it}\eta_{it}^2 = (\mathbf{X}_i'\mathbf{W}_i\mathbf{X}_i)^{-1}\mathbf{X}_i'\mathbf{W}_i\mathbf{r}_i, \tag{1.14}$$

where $\mathbf{r}_i$ is the $(T \times 1)$ vector of stock returns, $\mathbf{X}_i$ is the $(T \times K + 1)$ regressor matrix, and $\mathbf{W}_i$ is the $(T \times T)$ diagonal matrix of weights w_{it}.[13]

The method of least squares implicitly relies on the assumption that the effect of lagged returns on future stock returns is homogeneous across different parts of the return distribution. This somewhat "averages" the influence of past returns on future returns. If the loadings of stock returns on lagged returns vary across quantiles of the return distribution, then using the WLS estimation approach for inference would lead to model misspecification.

In contrast to the WLS regression technique, the quantile regression methodology allows for different sensitivity of various quantiles of the return distribution to lagged returns and, therefore, provides a distributional perspective on the effect of lagged returns on the next period stock return r_{it}. Quantile regression estimates each quantile τ of the distribution of r_{it}, $Q^{\tau}(r_{it})$, as a linear function of $\mathbf{x}_{it} = (1, r_{i,t-1}, ..., r_{i,t-K})'$:[14]

$$Q^{\tau}(r_{it}) = \mathbf{x}_{it}'\beta_i^{\tau} + \varepsilon_{it} \tag{1.15}$$

This is the quantile autoregressive model of order K, $QAR(K)$. The vector of parameters $\beta_i^{\tau} = (\mu_i^{\tau}, \rho_i^{\tau}(1), ..., \rho_i^{\tau}(K))'$ in this model is allowed to be τ-dependent, while it is restricted to be constant for all quantiles in model (1.12).

Whereas the WLS method estimates the conditional mean (1.13), quantile regression estimates the conditional quantiles of r_{it}. Conditional on $\Omega_{i,t-1}$, the τth quantile of the distribution of r_{it} is

$$Q^{\tau}(r_{it}|\Omega_{i,t-1}) = \mathbf{x}_{it}'\beta_i^{\tau} \tag{1.16}$$

The weighted quantile regression (WQR) estimate of the vector of factor loadings β_i^{τ} in model (1.15) is obtained as

$$\widehat{\beta}_i^{\tau} = arg\ \underset{\beta_i^{\tau}}{min} \sum_{t=1}^{T} w_{it}(\tau \mathbf{1}_{\{\varepsilon_{it} \geq 0\}} + (1-\tau)\,\mathbf{1}_{\{\varepsilon_{it} < 0\}})\,|\varepsilon_{it}|\,, \tag{1.17}$$

[13] The ordinary least squares (OLS) estimate of β_i is a special case of (1.14), where all time-series observations are equally weighted, i.e., $w_{it} = 1/T$ for all $t = 1, ..., T$.

[14] Koenker and Xiao (2006).

where $\mathbf{1}_{\{\cdot\}}$ is the indicator function and $\varepsilon_{it} = Q^{\tau}(r_{it}) - \mathbf{x}_{it}'\beta_i^{\tau}$.[15]

In our framework, w_{it} in (1.14) and (1.17) is the probability of r_{it}, $w_{it} = P(X = r_{it})$, defined in (1.5). As argued in Section 1.2.1, $w_{it} = P(X = r_{it})$ depends on the underlying assumptions about the investor's behaviour. We consider three different cases. The first case is where the investor is rational ($P(R) = 1$), as typically assumed in the literature. Then, we consider two cases where the investor is not rational ($P(R) = 0$) and uses different sets of behavioural heuristics. The first set of heuristics includes anchoring and overconfidence/doubt about the next period stock return. The second set consists of anchoring, overconfidence/doubt, and the availability heuristic.

First, we assume that the investor is rational ($P(R) = 1$) and call the corresponding model the Rational Model. This is our benchmark model. In this special case, $w_{it} = P(X = r_{it}|R) = 1/T$ for all $t = 1, ..., T$ and, hence, the investor weights stock returns by their objective probabilities of occurrence, as claimed by the theory.

Under the assumption of the investor's irrationality ($P(R) = 0$), we first examine the case where the investor uses anchoring and is overconfident/doubtful about the next period stock return. This is the Behavioural Model 1. To capture anchoring in forming the investor's beliefs about the probabilities of the next period stock returns, we assume that the investor evaluates stock returns based on their deviations from the historical average stock return, i.e., the target return $a_{it} = \overline{r}_i = T^{-1}\sum_{t=1}^{T} r_{it}$.

When the investor is overconfident or doubtful (heuristics A_1 and A_2, respectively) about the next period stock return, the subjective probability of r_{it} is[16]

$$P(X = r_{it}) = P(X = r_{it}|A_1)\,P(A_1) + P(X = r_{it}|A_2)\,[1 - P(A_1)]\,, \tag{1.18}$$

where $P(X = r_{it}|A_1)$ and $P(X = r_{it}|A_2)$ are as shown in (1.7). For the sake of simplicity, here and henceforth, we assume that the decay rate θ in (1.7) is identical across heuristics.

To determine whether the investor is overconfident or doubtful about the next period return on a given stock, we compare the next period conditional volatility from the GARCH(1,1) model for this stock with the stock's historical volatility. If the next period conditional volatility is lower than the historical volatility, then we assume that the investor is overconfident about the next period stock return ($P(A_1) = 1$ and $P(A_2) = 0$) and suppose that the investor exhibits doubt ($P(A_1) = 0$ and $P(A_2) = 1$) if the next period conditional volatility is higher than its historical counterpart.[17]

[15] Koenker and Bassett (1978) and Wooldridge (2010).

[16] There is a single pair of mutually exclusive heuristics.

[17] When the next period volatility of stock returns is lower than the historical volatility, the investor may expect that

In this setting, the only unknown parameter in the equation for the subjective probability (1.18) is the decay rate θ in the conditional probabilities $P(X = r_{it}|A_1)$ and $P(X = r_{it}|A_2)$. For each stock, we consider the values of θ decreasing from 0.9999 with decrements of 0.0001 and estimate θ as the value of this parameter at which the standard deviation of the stock returns weighted by the subjective probabilities computed at a particular θ matches the next period conditional standard deviation from the GARCH(1,1) model for the stock. We denote this estimate of θ by $\theta^1$and the subjective probabilities, computed at θ^1, by w_{it}^1.[18]

Then, we assume that, in addition to anchoring and overconfidence/doubt, the investor also uses the availability heuristic. This is the Behavioural Model 2. As in the Behavioural Model 1, in order to accommodate anchoring, we let the target return be equal the historical average stock return ($a_{it} = \overline{r}_i$). We denote overconfidence and doubt by, respectively, A_1^1 and A_2^1, and the availability heuristic by A_1^2 (with conservatism being A_2^2 and $P(A_2^2) = 0$). As before, we suppose that the investor is overconfident ($P(A_1^1 \cap A_1^2) = 1$, $P(R) = P(A_1^1 \cap A_2^2) = P(A_2^1 \cap A_1^2) = P(A_2^1 \cap A_2^2) = 0$) or doubtful ($P(A_2^1 \cap A_1^2) = 1$, $P(R) = P(A_2^1 \cap A_2^2) = P(A_1^1 \cap A_1^2) = P(A_1^1 \cap A_2^2) = 0$) about the next period stock return depending on whether the next period conditional volatility is, respectively, lower or higher than the historical volatility.

When there are two pairs of mutually exclusive heuristics $\{A_1^1, A_2^1\}$ and $\{A_1^2, A_2^2\}$, $P(R) = 0$, and $P(A_2^2) = 0$ (and, thus, $P(A_1^1 \cap A_2^2) = P(A_2^1 \cap A_2^2) = 0$), equation (1.5) becomes

$$P(X = r_{it}) = P\left(X = r_{it}|A_1^1 \cap A_1^2\right) P\left(A_1^1 \cap A_1^2\right) + P\left(X = r_{it}|A_2^1 \cap A_1^2\right) \left[P\left(A_1^2\right) - P\left(A_1^1 \cap A_1^2\right)\right], \tag{1.19}$$

where the conditional probabilities $P(X = r_{it}|A_1^1 \cap A_1^2)$ and $P(X = r_{it}|A_2^1 \cap A_1^2)$ are computed as shown in Section 1.2.1.[19] We assume that the decay rate θ is identical across heuristics and the relative weight of importance w equals 0.5 for all heuristics.

Similarly to the Behavioural Model 1, for each stock we estimate θ as the value of this parameter at which the standard deviation of the stock returns matches the next period conditional standard

in the next period the price of the stock will not fluctuate dramatically and, hence, large (positive or negative) returns are less likely than in the past. By contrast, when the volatility increases, the investor may suppose that in the next period large changes in the stock price are more likely to occur than would be expected based on historical data.

[18]The closer to the historical standard deviation the next period conditional standard deviation, the closer to 1 the value of θ^1 and, hence, the closer to the objective probabilities $1/T$ the subjective probabilities w_{it}^1. When the next period conditional standard deviation equals the historical standard deviation (and, therefore, the historical distribution may be regarded as an adequate proxy for the next period return distribution), the subjective probabilities of returns coincide with their objective probabilities, i.e., $w_{it}^1 = 1/T$ for all $t = 1, ..., T$.

[19]In the special case of a single pair of mutually exclusive heuristics, this equation simplifies to (1.18). To see this, denote A_1^1 by A_1 and A_2^1 by A_2. Because $A_h^1 \cap A_{h'}^2 = A_h^1$ for $h, h' = 1, 2$, equation (1.19) reduces to (1.18).

deviation from the GARCH(1,1) model and denote the subjective probabilities w_{it} computed at this value of θ, θ^2, by w_{it}^2.

After computing the probabilities w_{it} for each of the three models (the Rational Model, the Behavioural Model 1, and the Behavioural Model 2),[20] we assume that the stock returns lagged up to five periods influence the next period stock return and, for each of these three models, perform the following analysis.

We estimate the $QAR(5)$ model with $\tau = 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95$ for each stock under scrutiny and denote by $\rho_i^{\tau*}(k)$ ($k = 1, ..., 5$) the WQR estimates of the associated autocorrelation coefficients. For each stock and each quantile τ of the stock return distribution, we test the null hypothesis of random walk. To test whether the returns in the τth quantile obey the random walk model, we use the heteroskedasticity-consistent version of the Lo and MacKinlay (1988) q-period variance ratio statistic

$$VR_i^{\tau}(q) = 1 + \sum_{k=1}^{q-1} 2\left(1 - k/q\right)\rho_i^{\tau*}(k) \overset{a}{\sim} \mathcal{N}\left(1, \frac{\vartheta_i(q)}{T}\right) \tag{1.20}$$

Because the number of lags $K = 5$, we compute $VR_i^{\tau}(q)$ with aggregation values $q = 2, ..., 6$. If stock returns follow a random walk, then the returns are serially uncorrelated at all leads and lags, implying that $VR_i^{\tau}(q)$ is statistically indistinguishable from 1 for any aggregation value q. We use the multiple variance ratio test of Chow and Denning (1993) to test the joint null hypothesis H_0: $VR_i^{\tau}(q) = 1$ for all q against the alternative H_1: $VR_i^{\tau}(q) \neq 1$ for at least one q.

The Chow and Denning (1993) test depends on the corresponding standardized test statistic[21]

$$\phi_i^{\tau}(q) = \frac{\sqrt{T}\left(VR_i^{\tau}(q) - 1\right)}{\sqrt{\vartheta_i(q)}} \overset{a}{\sim} \mathcal{N}(0, 1) \tag{1.21}$$

For each stock at τth quantile, $\phi_i^{\tau}(q)$ is estimated for the corresponding $VR_i^{\tau}(q)$ with aggregation values $q = 2, ..., 6$. For a set of m variance ratios, the Chow and Denning (1993) test statistic is defined as

$$MV_i^{\tau} = max\left(\left|\phi_i^{\tau}(q_1)\right|, ..., \left|\phi_i^{\tau}(q_m)\right|\right), \tag{1.22}$$

We find the maximum of the absolute value of $\phi_i^{\tau}(q)$ across all q for a given stock i at τth quantile.

[20] For the Rational Model $w_{it} = 1/T$, for the Behavioural Model 1 $w_{it} = w_{it}^1$, and for the Behavioural Model 2 $w_{it} = w_{it}^2$.

[21] The $\phi_i^{\tau}(q)$ depends on the variance of $VR_i^{\tau}(q)$, which is obtained from $\vartheta_i(q) = \sum_{k=1}^{q-1} 4\left(1 - k/q\right)^2 \delta_i(k)$, and $\delta_i(k) = \frac{\sum_{t=k+1}^{T}\left[(r_{it}-\mu_i)^2 (r_{i,t-k}-\mu_i)^2\right]}{\left[\sum_{t=1}^{T}(r_{it}-\mu_i)^2\right]^2}$.

To control the overall test size, we use the upper α point of the Studentized Maximum Modulus (SMM) distribution with m and T degrees of freedom, $SMM(\alpha; m; T)$.[22] When T is large, the critical value of the test may be computed as the $[1 - (\alpha^*/2)]$th percentile of the standard normal distribution, where $\alpha^* = 1 - (1 - \alpha)^{1/m}$. For $\alpha = 0.05$ and $m = 5$, the $SMM(\alpha; m; T)$ critical value is 2.569. The random walk hypothesis is rejected at the 5% significance level for the returns on stock i in the τth quantile if the MV_i^τ statistic is greater than 2.569.

For each quantile τ, we then compute the percentage of stocks for which the random walk model for the returns in this quantile is rejected at the 5% level of significance. The higher this percentage, the greater the extent to which the stock returns in the considered quantile can be predicted by past returns alone.

Since it is conventional in the literature to test the predictability of mean stock returns, for each of the three models (the Rational Model, the Behavioural Model 1, and the Behavioural Model 2) we contrast the results for the quantiles of the return distribution with the results for the mean return. When testing the predictability of the mean returns on individual stocks, we use the $AR(5)$ model to estimate the autocorrelation coefficients. Apart from the autoregressive model, the procedure that we employ to determine the proportion of stocks, for which the random walk hypothesis is rejected at the 5% level of significance for the mean return, is identical to the described above procedure for the quantiles of the return distribution.

1.3 Empirical Investigation

1.3.1 Description of the Data

The tests are based on daily and monthly data. The sample period is from December 31, 2009, to December 31, 2018. Our sample of stocks consists of all NYSE, Nasdaq, and AMEX-traded common stocks (i.e., the stocks having CRSP share code 10 or 11). The historical closing (adjusted for dividends and stock splits) prices of the stocks are from CRSP.

To explore whether the testing results are sensitive to the firm size, we consider three groups of size-sorted stocks. A stock is defined as small-, mid-, or large-cap when its end-of-sample-period market value falls into, respectively, the lowest, central, or highest market capitalization quintile of all stocks in the sample. This reduces the likelihood of migration of equities from one size group to another during the sample period.

[22] Chow and Denning (1993).

Table 1.1 contains some sample statistics for the daily and monthly continuously compounded returns on individual stocks. The statistics are shown for a range of quantiles ($\tau = 0.05$, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95) of the return distribution.

[Table 1.1]

Table 1.2 shows the cross-sectional average estimates of the autocorrelation coefficients $\rho^{\tau}(k)$ ($k = 1, ..., 5$) for different τ. These estimates are contrasted with the estimates of the autocorrelation coefficients for the mean return.

[Table 1.2]

Regardless of the size of stocks and the data frequency, the first-order autocorrelation coefficient $\rho^{\tau}(1)$ is typically larger in absolute value on average compared to the autocorrelation coefficients of order two to five for all quantiles. For the small-cap stocks, the cross-sectional average $\rho^{\tau}(1)$ is negative for the returns in all quantiles at both the daily and monthly frequencies. At the daily frequency, the average $\rho^{\tau}(1)$ increases from lower to upper quantiles, while at the monthly frequency the average $\rho^{\tau}(1)$ is close to zero for all quantiles with slightly lower values for the central quantiles of the return distribution. The daily returns on the mid-cap stocks in lower quantiles exhibit weak negative dependence on past returns on average. This negative dependence becomes stronger for upper quantiles. At the monthly frequency, lower quantiles are marked by weak positive first-order autocorrelation, while upper quantiles exhibit negative dependence on past returns. For the large-cap stocks, at both the daily and monthly frequencies the cross-sectional average $\rho^{\tau}(1)$ is significantly positive for lower quantiles and then, like for the mid-cap stocks, decreases and becomes significantly negative for the returns in upper quantiles.[23]

Figure 1 displays the average and the 0.025 and 0.975 quantiles of the cross-sectional distribution of $\rho^{\tau}(1)$ for different τ.

[Figure 1]

Negative first-order autocorrelation may be caused by overreaction of stock prices to new information, while positive first-order autocorrelation may be explained by underreaction (or delayed reaction) of stock prices. The reported estimates of $\rho^{\tau}(1)$ provide evidence of overreaction of the

[23] This finding is in line with the result in Baur et al. (2012) who document that the cross-sectional average first-order autocorrelations for the central quantiles of the returns on the stocks comprised in the Dow Jones Stoxx 600 index are all close to zero, while they are significantly positive for lower quantiles and negative for upper quantiles. They find this result robust to different (daily, weekly, and monthly) data frequencies.

prices of the small-cap stocks to both bad (when $r_{i,t-1} < 0$) and good (when $r_{i,t-1} > 0$) news. Overreaction is stronger at the daily frequency. For the mid- and large-cap stocks, there is evidence of overreaction to bad news. For both these groups of equities, this evidence is stronger at the monthly frequency.

1.3.2 Empirical Results

To explore whether overconfidence/doubt, induced by changing volatility of stock returns, strengthens or weakens the predictive power of lagged returns, for each group of size-sorted stocks we report the results for the subset of stocks for which the next period conditional volatility is lower than the historical volatility (i.e., the set of stocks with decreasing volatility of returns) and the subset of stocks for which the next period conditional volatility is higher than the historical counterpart (i.e., the set of stocks with increasing volatility of returns). As argued in Section 1.2.2, the investor is overconfident about the next period returns on the stocks in the first subset and is doubtful about the next period returns on the stocks that belong to the second subset of equities. For each of these two subsets of stocks, we contrast the results under overconfidence/doubt with the results under the conventional assumption of rationality when the next period return volatility equals the historical volatility and, hence, there is no either overconfidence or doubt about the next period stock return.

Then, we add the availability heuristic to overconfidence/doubt and examine whether allowing for this behavioural heuristic influences the ability of past returns to forecast the next period stock return.

To investigate whether the influence of behavioural heuristics on the predictability of individual stock returns varies across return frequencies, we perform our analysis for the daily and monthly stock returns.

The Daily Returns

Table 1.3 reports the testing results for the daily returns.

[Table 1.3]

The Rational Model. Consistent with earlier results in the empirical literature, we find that, under the assumption of rationality, the random walk model for the mean return is rejected more often for smaller stocks than for larger stocks.

Regardless of the size of stocks, the evidence of predictability is weak for the returns in the central quantiles of the return distribution and gets stronger for the returns further from the middle of the distribution. This finding is also in line with the existing empirical evidence.[24] Like for the mean return, for all quantiles of the return distribution the percentage of stocks, for which the random walk model is rejected, decreases when the market value of stocks increases, except for the upper quantiles for which the percentage of stocks with predictable returns increases as larger stocks are considered.

These findings are robust to whether the next period conditional volatility of stock returns is lower or higher than the historical volatility.

The Behavioural Model 1. Regardless of the size of stocks with increasing volatility, doubt substantially increases, compared with the case of the investor's rationality, the predictability of the mean return as well as the returns in all quantiles. The greater increase in the percentage of stocks with predictable returns is found for the returns in the central quantiles of the distribution. Similarly to the case of rationality, the percentage of stocks, for which the random walk hypothesis is rejected statistically for the mean return, decreases as the size of equities increases. The same pattern holds for the returns in the left tail and the middle of the return distribution. Under doubt, the returns in the right tail of the distribution become more predictable for larger stocks.

In square brackets immediately below the row with the estimates for the behavioural model, Table 1.3 displays the differential between the percentage of stocks with predictable returns for this model and the model with the rational investor. Rows "d^+" and "d^-" report the percentage of stocks for which the heuristics, respectively, raise and lower the return predictability.

The picture is opposite for the stocks with decreasing volatility of returns. Irrespectively of the market value of these stocks, allowing for the investor's overconfidence makes substantially lower, than under rationality, the predictability of the mean return as well as the returns in all quantiles. The decrease in the percentage of stocks with predictable returns is greater for smaller equities and for the returns in the central quantiles of the distribution. Like under rationality, the percentage of stocks with predictable mean returns decreases as larger stocks are considered. For all quantiles, the percentage of stocks, for which the random walk model is rejected, also decreases when the market value of equities increases.

Figure 2 plots the percentage of equities with increasing and decreasing volatilities for which the random walk model is rejected statistically.

[24]See Barberis et al. (1998), Veronesi (1999), and Lewellen (2002), among others.

[Figure 2]

These findings suggest that the degree of predictability of the next period stock return by past returns substantially depends on whether the next period conditional volatility of returns is lower or higher than the historical volatility. More specifically, the lower the next period conditional volatility relative to the historical volatility, the greater the effect of overconfidence on forming the investor's beliefs about the next period return and, thus, the lower the degree to which stock returns are predictable by past returns alone. By contrast, if the next period conditional volatility is higher than the historical volatility, then doubt about the next period return increases the predictive power of past returns.

This may be explained as follows. The rational investor assigns to historical returns the objective probabilities of occurrence and, therefore, implicitly assumes that the next period return volatility equals the historical volatility. When the next period volatility of returns is higher than the historical volatility, increasing uncertainty about the next period return leads the investor to assign higher (than objective) probabilities to the returns that are further from the historical average return. Figure 1 shows that extreme quantiles of the return distribution typically have the first-order autocorrelation coefficients that are much larger in absolute value than the first-order autocorrelation coefficients for the returns in the central quantiles. Since the variance ratio statistic is the weighted sum of the autocorrelation coefficients with the weights declining linearly with the lag, assigning higher probabilities to large positive and negative returns yields larger absolute values of the standardized test statistics $\phi_i^{\tau}(q)$.[25] This leads to that the random walk model is rejected more often than when the investor weights historical returns by the objective probabilities.

When the next period volatility is lower than its historical counterpart, the investor is more confident that the realized next period return will be close to its historical average and, therefore, assigns higher probabilities to the returns that are closer to the historical average return. Because the returns in the central quantiles exhibit weaker first-order autocorrelation, this reduces the standardized test statistics $\phi_i^{\tau}(q)$. Consequently, the variance ratio test rejects the random walk hypothesis less often than when the investor is rational.[26]

[25]As shown in Table 1.2, for the returns in all quantiles the autocorrelation coefficients of order two to five are much smaller in magnitude than the first-order autocorrelation and, therefore, have only marginal effect on the value of the variance ratio test statistic.

[26]The closer to zero the next period conditional volatility, the lower the uncertainty about the next period return. In the extreme case where the next period distribution is degenerated, the next period return is not random and, thus, is not correlated with any variable in the investor's information set, including lagged stock returns.

The Behavioural Model 2. When the availability heuristic is added to overconfidence/doubt, the percentage of stocks, for which the random walk model is rejected, increases for the mean return as well as for the returns in all quantiles. This finding is robust to the size of stocks and to whether the next day conditional volatility of returns is lower or higher than the historical volatility (i.e., whether the investor is overconfident or doubtful about the next day stock return).

With this uniform increase in the degree of predictability, for the stocks with decreasing volatility of returns the percentage of equities with predictable returns remains, however, lower than under the conventional assumption of rationality for all quantiles of the return distribution and for the mean return. In contrast to these stocks, for the equities with increasing volatility of returns the percentage of stocks, for which the random walk model is rejected statistically, is higher than under the assumption of rationality for all quantiles of the distribution as well as for the mean return. This pattern is robust with respect to the size of stocks.

Under the availability heuristic, the investor assigns higher probabilities to the most recent returns. Depending on how far from the historical average these returns are, this may lower or increase the investor's estimate of the historical volatility of returns compared with the estimate based on the objective probabilities of returns. If overestimating the likelihood of more recent returns lowers the historical volatility, since this does not affect the estimate of the next period volatility, it increases the ratio of the next period volatility to the historical volatility compared with the case of no availability heuristic. This is equivalent to when the next period return volatility increases relative to the historical volatility and no availability heuristic is used and, hence, increases the predictability of returns. If assigning higher probabilities to the most recent returns increases the estimated historical volatility of returns, this lowers the ratio of the next period volatility to the historical volatility and, thus, lowers the predictability of stock returns. From this, we may conclude that the availability heuristic lowers (increases) the predictability of returns when it increases (lowers) the estimate of the historical volatility of returns.

For most stocks in our sample, assigning higher probabilities to the most recent returns decreases the estimate of the historical volatility. This may explain why the availability heuristic increases, on average, the degree of predictability of stock returns irrespectively of the size of stocks.

The Monthly Returns

Table 1.4 shows the testing results for the monthly returns on individual stocks.

[Table 1.4]

The Rational Model. It is documented in the empirical asset pricing literature that, under rationality, the coefficients of autocorrelation in the monthly stock returns are typically smaller in magnitude and statistically less significant than the autocorrelation coefficients computed for the daily returns. Consequently, the random walk model is rejected less often for the monthly returns than for the daily returns.

Consistent with this result, we also find that for the monthly returns in all quantiles the evidence against the random walk hypothesis is weaker than for the daily returns. Like for the daily returns, the lowest percentage of stocks with predictable monthly returns is found for the returns in the middle of the return distribution. The effect of lagged returns on the next month return is stronger for the returns further from the center of the distribution. These findings are robust to the size of stocks as well as to whether the next month volatility of stock returns is lower or higher than the historical volatility.

The Behavioural Model 1. Taking into account overconfidence about the returns on the stocks with decreasing return volatility decreases the predictability of the monthly returns in all quantiles. By contrast, allowing for the investor's doubt about the returns on the stocks with increasing volatility of returns strengthens the evidence against the random walk hypothesis for the monthly returns in all quantiles. These findings are robust to the size of stocks and are similar to the results for the daily returns. Figure 3 shows the percentage of stocks with decreasing and increasing return volatilities for which the random walk hypothesis is rejected.

[Figure 3]

The Behavioural Model 2. For this model, the results for the monthly returns are also similar to the results for the daily returns. Regardless of whether the next month conditional volatility of returns is lower or higher than the historical volatility, adding the availability heuristic to overconfidence/doubt slightly increases the percentage of equities with predictable returns irrespectively of the quantile of the return distribution. For the stocks with decreasing volatility, the percentage of equities, for which the random walk model is rejected, remains lower than under the assumption of rationality for all quantiles. The findings are robust to the size of stocks.

1.4 Concluding Remarks

The traditional tests of the predictability of stock returns by past returns rely on the assumption that the next period distribution of returns is identical to the historical distribution and, hence, ignore the time-series heteroskedasticity in stock returns. We argue that when the next period return volatility differs from the historical volatility, this may induce overconfidence/doubt about future stock returns and, hence, may influence the investor's beliefs about the probabilities of future returns on his investment. The implied subjective probabilities of the next period returns may deviate substantially from the objective probabilities.

We find strong empirical evidence that, when the next period volatility of returns is lower than the historical volatility, overconfidence about the next period return lowers (compared with when the investor is rational) the predictability of stock returns. By contrast, when the next period volatility is higher than the historical volatility, doubt increases the predictive power of past returns.

In contrast to overconfidence and doubt that deal with the next period volatility of returns, overestimating the likelihood of more recent returns influences the ratio between the next period volatility and the historical volatility through the investor's estimate of the historical volatility of returns. When assigning higher probabilities to the most recent returns increases (lowers) the estimate of the historical volatility, this is equivalent to a decrease (increase) in the next period volatility relative to the historical volatility in the absence of the availability heuristic and, thus, lowers (increases) the predictability of future stock returns.

These findings imply that, when the next period return volatility deviates from the historical volatility, assigning objective rather than subjective probabilities to stock returns may substantially understate or overstate the ability of past returns to predict future stock returns. The greater the deviation, the greater the bias in the estimated degree of the return predictability. This bias is greater at higher frequencies and when smaller stocks are considered.

Table 1.1: Stock Returns

The cross-sectional mean, median, and standard deviation of the summary statistics for the time-series distributions of the daily and monthly continuously compounded returns (in percent) on individual stocks. τ is the quantile of the return distribution. The sample period is from December 31, 2009, to December 31, 2018. The sample of stocks consists of all NYSE, Nasdaq, and AMEX-traded common stocks. A stock is defined as small-, mid-, or large-cap when its end-of-sample-period market value falls into, respectively, the lowest, central, or highest market capitalization quintile of all stocks in the sample.

Statistic	Summary statistics for the time-series distribution										
					τ						
	Min	Max	Mean	SDev	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Small-Cap Stocks											
Daily Returns											
Mean	-40.69	48.24	-0.01	4.58	-6.00	-4.18	-1.60	-0.01	1.44	4.16	6.17
Median	-29.57	34.53	0.01	3.75	-5.32	-3.63	-1.54	0.00	1.46	3.64	5.49
SDev	48.16	55.66	0.09	6.71	8.47	8.27	0.67	0.06	0.49	8.24	8.45
Monthly Returns											
Mean	-55.51	63.70	-0.19	16.52	-26.78	-17.83	-8.28	-0.66	6.94	17.01	24.92
Median	-44.44	51.60	0.21	14.53	-22.37	-15.91	-7.63	-0.25	6.65	15.95	22.42
SDev	54.91	61.22	1.90	14.04	32.63	11.44	4.34	1.58	2.43	9.80	20.64
Mid-Cap Stocks											
Daily Returns											
Mean	-27.14	24.16	0.04	2.78	-3.91	-2.71	-1.21	0.03	1.28	2.77	3.98
Median	-21.75	19.95	0.04	2.59	-3.74	-2.57	-1.14	0.03	1.23	2.64	3.79
SDev	21.80	16.26	0.05	0.89	1.07	0.76	0.36	0.04	0.32	0.74	1.11
Monthly Returns											
Mean	-39.81	39.95	0.84	11.74	-18.24	-12.77	-5.68	0.89	7.28	13.64	18.31
Median	-33.86	33.68	0.88	10.85	-17.13	-12.12	-5.16	0.95	7.03	13.01	17.07
SDev	24.90	24.94	0.97	4.40	6.97	4.71	2.45	1.03	2.16	4.33	6.31
Large-Cap Stocks											
Daily Returns											
Mean	-17.03	15.23	0.06	1.94	-2.81	-1.93	-0.84	0.07	0.98	2.02	2.85
Median	-13.77	13.11	0.06	1.87	-2.74	-1.86	-0.79	0.07	0.95	1.95	2.77
SDev	11.01	8.68	0.03	0.60	0.79	0.55	0.26	0.03	0.25	0.55	0.82
Monthly Returns											
Mean	-27.15	25.85	1.24	8.08	-12.31	-8.61	-3.32	1.49	5.91	10.10	13.10
Median	-23.00	22.08	1.22	7.58	-11.53	-8.01	-3.06	1.44	5.68	9.75	12.50
SDev	16.12	14.64	0.61	2.85	4.61	3.09	1.56	0.70	1.60	3.01	4.25

Table 1.2: Autocorrelation in Stock Returns

Cross-sectional average autocorrelation coefficients $\rho^\tau(k)$ for the daily and monthly continuously compounded returns on individual stocks. τ is the quantile of the return distribution. The rows below $\rho^\tau(1)$ report the 2.5% and 97.5% quantiles of the cross-sectional distribution of $\rho^\tau(1)$. The sample period is from December 31, 2009, to December 31, 2018.

	τ							Mean
$\rho^\tau(k)$	0.05	0.10	0.25	0.50	0.75	0.90	0.95	Return
				Small-Cap Stocks				
				Daily Returns				
$\rho^\tau(1)$	-0.1294	-0.1259	-0.1108	-0.0757	-0.0988	-0.0972	-0.0878	-0.1095
2.5%	-0.3820	-0.3327	-0.2598	-0.1828	-0.2389	-0.3128	-0.3537	-0.3106
97.5%	0.0700	0.0567	0.0284	0.0103	0.0211	0.0706	0.1138	0.0394
$\rho^\tau(2)$	-0.0587	-0.0514	-0.0393	-0.0176	-0.0329	-0.0383	-0.0363	-0.0432
$\rho^\tau(3)$	-0.0356	-0.0306	-0.0231	-0.0115	-0.0197	-0.0265	-0.0264	-0.0271
$\rho^\tau(4)$	-0.0215	-0.0166	-0.0118	-0.0045	-0.0086	-0.0108	-0.0101	-0.0126
$\rho^\tau(5)$	-0.0199	-0.0134	-0.0062	-0.0016	-0.0059	-0.0063	-0.0060	-0.0096
				Monthly Returns				
$\rho^\tau(1)$	-0.0119	-0.0306	-0.0363	-0.0429	-0.0390	-0.0332	-0.0151	-0.0383
2.5%	-0.5244	-0.4285	-0.3278	-0.2606	-0.3095	-0.4133	-0.4966	-0.2929
97.5%	0.4714	0.3539	0.2602	0.1635	0.2016	0.3697	0.4781	0.1978
$\rho^\tau(2)$	0.0138	0.0000	-0.0083	-0.0139	-0.0199	-0.0166	-0.0044	-0.0116
$\rho^\tau(3)$	0.0243	0.0177	0.0143	0.0107	0.0100	0.0074	0.0090	0.0142
$\rho^\tau(4)$	0.0036	-0.0112	-0.0116	-0.0216	-0.0273	-0.0381	-0.0373	-0.0247
$\rho^\tau(5)$	0.0064	-0.0027	0.0019	-0.0064	-0.0123	-0.0203	-0.0196	-0.0121
				Mid-Cap Stocks				
				Daily Returns				
$\rho^\tau(1)$	-0.0258	-0.0250	-0.0342	-0.0423	-0.0540	-0.0648	-0.0737	-0.0468
2.5%	-0.1994	-0.1733	-0.1453	-0.1565	-0.1762	-0.2106	-0.2484	-0.1892
97.5%	0.1113	0.0993	0.0522	0.0329	0.0381	0.0483	0.0772	0.0502
$\rho^\tau(2)$	0.0092	0.0092	0.0082	-0.0014	-0.0144	-0.0254	-0.0322	-0.0048
$\rho^\tau(3)$	0.0056	0.0040	0.0034	-0.0037	-0.0144	-0.0286	-0.0334	-0.0067
$\rho^\tau(4)$	0.0280	0.0221	0.0100	-0.0047	-0.0204	-0.0274	-0.0270	-0.0011
$\rho^\tau(5)$	0.0105	0.0066	-0.0007	-0.0093	-0.0204	-0.0295	-0.0338	-0.0103
				Monthly Returns				
$\rho^\tau(1)$	0.0149	-0.0091	-0.0338	-0.0678	-0.0867	-0.1102	-0.1060	-0.0609
2.5%	-0.4646	-0.4155	-0.3312	-0.3186	-0.3323	-0.4169	-0.4737	-0.2568
97.5%	0.5444	0.4045	0.2643	0.1683	0.1869	0.2326	0.3509	0.1536
$\rho^\tau(2)$	0.0551	0.0282	0.0074	-0.0229	-0.0427	-0.0592	-0.0584	-0.0171
$\rho^\tau(3)$	0.0222	0.0040	-0.0021	-0.0147	-0.0142	-0.0001	0.0069	-0.0040
$\rho^\tau(4)$	0.0116	0.0042	0.0026	-0.0132	-0.0141	-0.0121	-0.0119	-0.0056
$\rho^\tau(5)$	-0.0138	-0.0149	-0.0154	-0.0204	-0.0217	-0.0314	-0.0442	-0.0253

Table 1.2 (Continued)

$\rho^{\tau}(k)$	τ 0.05	0.10	0.25	0.50	0.75	0.90	0.95	Mean Return
				Large-Cap Stocks				
				Daily Returns				
$\rho^{\tau}(1)$	0.0326	0.0216	-0.0052	-0.0297	-0.0454	-0.0570	-0.0730	-0.0270
2.5%	-0.1253	-0.0867	-0.0902	-0.1020	-0.1248	-0.1746	-0.2135	-0.1421
97.5%	0.1622	0.1071	0.0614	0.0298	0.0291	0.0265	0.0429	0.0488
$\rho^{\tau}(2)$	0.0382	0.0299	0.0123	-0.0108	-0.0338	-0.0488	-0.0541	-0.0073
$\rho^{\tau}(3)$	0.0193	0.0115	0.0032	-0.0093	-0.0275	-0.0472	-0.0581	-0.0145
$\rho^{\tau}(4)$	0.0522	0.0401	0.0150	-0.0099	-0.0316	-0.0471	-0.0488	0.0000
$\rho^{\tau}(5)$	0.0056	0.0052	-0.0006	-0.0131	-0.0280	-0.0421	-0.0472	-0.0166
				Monthly Returns				
$\rho^{\tau}(1)$	0.0700	0.0544	0.0017	-0.0565	-0.1126	-0.1630	-0.1840	-0.0606
2.5%	-0.4248	-0.3596	-0.3003	-0.2889	-0.3347	-0.4515	-0.5411	-0.2483
97.5%	0.5518	0.4203	0.2738	0.1493	0.1338	0.1567	0.2424	0.1456
$\rho^{\tau}(2)$	0.0631	0.0561	0.0145	-0.0223	-0.0539	-0.0800	-0.0930	-0.0231
$\rho^{\tau}(3)$	0.0067	0.0129	0.0002	0.0004	-0.0102	-0.0201	-0.0174	-0.0034
$\rho^{\tau}(4)$	0.0313	0.0239	0.0052	-0.0044	-0.0137	-0.0215	-0.0197	-0.0100
$\rho^{\tau}(5)$	0.0094	-0.0011	-0.0081	-0.0129	-0.0205	-0.0363	-0.0372	-0.0182

Table 1.3: Percentage of Stocks with Predictable Daily Returns

Percentage of stocks for which the random walk model is rejected at the 5% significance level. τ is the quantile of the return distribution. RM, BM1, and BM2 stand for the Rational Model, the Behavioural Model 1, and the Behavioural Model 2, respectively. The difference between the percentage of stocks with predictable returns for the behavioural model and the model with the rational investor is reported in square brackets immediately below the row for the behavioural model. Rows "d^+" and "d^-" display the percentage of stocks for which the considered heuristics, respectively, raise and lower the return predictability. The sample period is from December 31, 2009, to December 31, 2018.

Model	τ							Mean
	0.05	0.10	0.25	0.50	0.75	0.90	0.95	Return
Small-Cap Stocks								
A. Stocks with Decreasing Volatility of Returns								
RM	72.54	70.47	66.32	31.09	56.48	59.07	55.44	63.21
BM1	62.69	56.48	37.82	4.66	30.57	46.63	49.22	42.49
	[-9.84]	[-13.99]	[-28.50]	[-26.42]	[-25.91]	[-12.44]	[-6.22]	[-20.73]
d^+	4.15	1.04	0.52	0.00	0.52	3.63	6.74	0.00
d^-	13.99	15.03	29.02	26.42	26.42	16.06	12.95	20.73
BM2	67.36	64.25	59.59	24.35	50.78	51.81	47.67	52.85
	[-5.18]	[-6.22]	[-6.74]	[-6.74]	[-5.70]	[-7.25]	[-7.77]	[-10.36]
d^+	4.15	3.63	2.07	3.11	2.07	4.15	4.66	2.59
d^-	9.33	9.84	8.81	9.84	7.77	11.40	12.44	12.95
B. Stocks with Increasing Volatility of Returns								
RM	65.74	60.19	58.80	31.48	56.02	54.63	61.11	50.93
BM1	75.46	68.98	70.83	76.85	63.89	63.89	74.54	66.20
	[9.72]	[8.80]	[12.04]	[45.37]	[7.87]	[9.26]	[13.43]	[15.28]
d^+	16.67	12.96	12.50	45.37	10.65	15.28	19.91	15.28
d^-	6.94	4.17	0.46	0.00	2.78	6.02	6.48	0.00
BM2	81.48	75.00	71.76	62.04	66.67	68.98	82.41	67.59
	[15.74]	[14.81]	[12.96]	[30.56]	[10.65]	[14.35]	[21.30]	[16.67]
d^+	18.52	18.98	18.52	31.94	17.13	22.22	25.93	22.22
d^-	2.78	4.17	5.56	1.39	6.48	7.87	4.63	5.56

TABLE 1.3 (CONTINUED)

Model	τ							Mean
	0.05	0.10	0.25	0.50	0.75	0.90	0.95	Return
Mid-Cap Stocks								
A. Stocks with Decreasing Volatility of Returns								
RM	39.90	27.59	15.76	18.23	34.48	51.72	57.64	27.09
BM1	29.06	17.24	11.33	4.43	17.24	38.42	55.17	18.23
	[-10.84]	[-10.34]	[-4.43]	[-13.79]	[-17.24]	[-13.30]	[-2.46]	[-8.87]
d^+	4.93	1.48	0.49	0.00	0.00	0.49	4.93	0.00
d^-	15.76	11.82	4.93	13.79	17.24	13.79	7.39	8.87
BM2	30.54	21.18	14.29	9.85	28.08	41.38	52.71	21.67
	[-9.36]	[-6.40]	[-1.48]	[-8.37]	[-6.40]	[-10.34]	[-4.93]	[-5.42]
d^+	3.45	1.48	0.99	0.00	0.99	0.99	4.93	0.00
d^-	12.81	7.88	2.46	8.37	7.39	11.33	9.85	5.42
B. Stocks with Increasing Volatility of Returns								
RM	46.60	36.89	22.33	20.39	38.83	62.62	68.93	29.61
BM1	62.14	43.20	35.44	51.46	59.22	72.33	77.67	47.57
	[15.53]	[6.31]	[13.11]	[31.07]	[20.39]	[9.71]	[8.74]	[17.96]
d^+	20.87	13.11	13.59	31.07	20.39	14.08	13.59	17.96
d^-	5.34	6.80	0.49	0.00	0.00	4.37	4.85	0.00
BM2	73.79	58.25	37.86	37.38	53.40	68.93	78.16	48.06
	[27.18]	[21.36]	[15.53]	[16.99]	[14.56]	[6.31]	[9.22]	[18.45]
d^+	32.04	26.21	20.87	19.90	19.90	16.50	18.45	22.33
d^-	4.85	4.85	5.34	2.91	5.34	10.19	9.22	3.88
Large-Cap Stocks								
A. Stocks with Decreasing Volatility of Returns								
RM	35.87	18.48	4.35	3.26	27.17	51.09	60.87	13.04
BM1	31.52	8.70	1.09	1.09	8.70	40.22	55.43	3.26
	[-4.35]	[-9.78]	[-3.26]	[-2.17]	[-18.48]	[-10.87]	[-5.43]	[-9.78]
d^+	5.43	1.09	0.00	0.00	0.00	2.17	3.26	0.00
d^-	9.78	10.87	3.26	2.17	18.48	13.04	8.70	9.78
BM2	39.13	19.57	3.26	1.09	18.48	46.74	54.35	8.70
	[3.26]	[1.09]	[-1.09]	[-2.17]	[-8.70]	[-4.35]	[-6.52]	[-4.35]
d^+	7.61	4.35	0.00	0.00	2.17	1.09	4.35	0.00
d^-	4.35	3.26	1.09	2.17	10.87	5.43	10.87	4.35
B. Stocks with Increasing Volatility of Returns								
RM	62.78	41.64	5.36	11.36	54.57	76.66	85.49	14.51
BM1	71.92	51.10	25.87	58.99	73.82	80.13	84.54	32.18
	[9.15]	[9.46]	[20.50]	[47.63]	[19.24]	[3.47]	[-0.95]	[17.67]
d^+	18.30	18.30	21.14	47.63	22.08	9.46	6.62	17.67
d^-	9.15	8.83	0.63	0.00	2.84	5.99	7.57	0.00
BM2	83.91	76.97	49.53	36.59	68.14	82.33	89.27	38.49
	[21.14]	[35.33]	[44.16]	[25.24]	[13.56]	[5.68]	[3.79]	[23.97]
d^+	25.87	37.22	44.48	27.13	20.50	13.25	8.83	28.39
d^-	4.73	1.89	0.32	1.89	6.94	7.57	5.05	4.42

Table 1.4: Percentage of Stocks with Predictable Monthly Returns

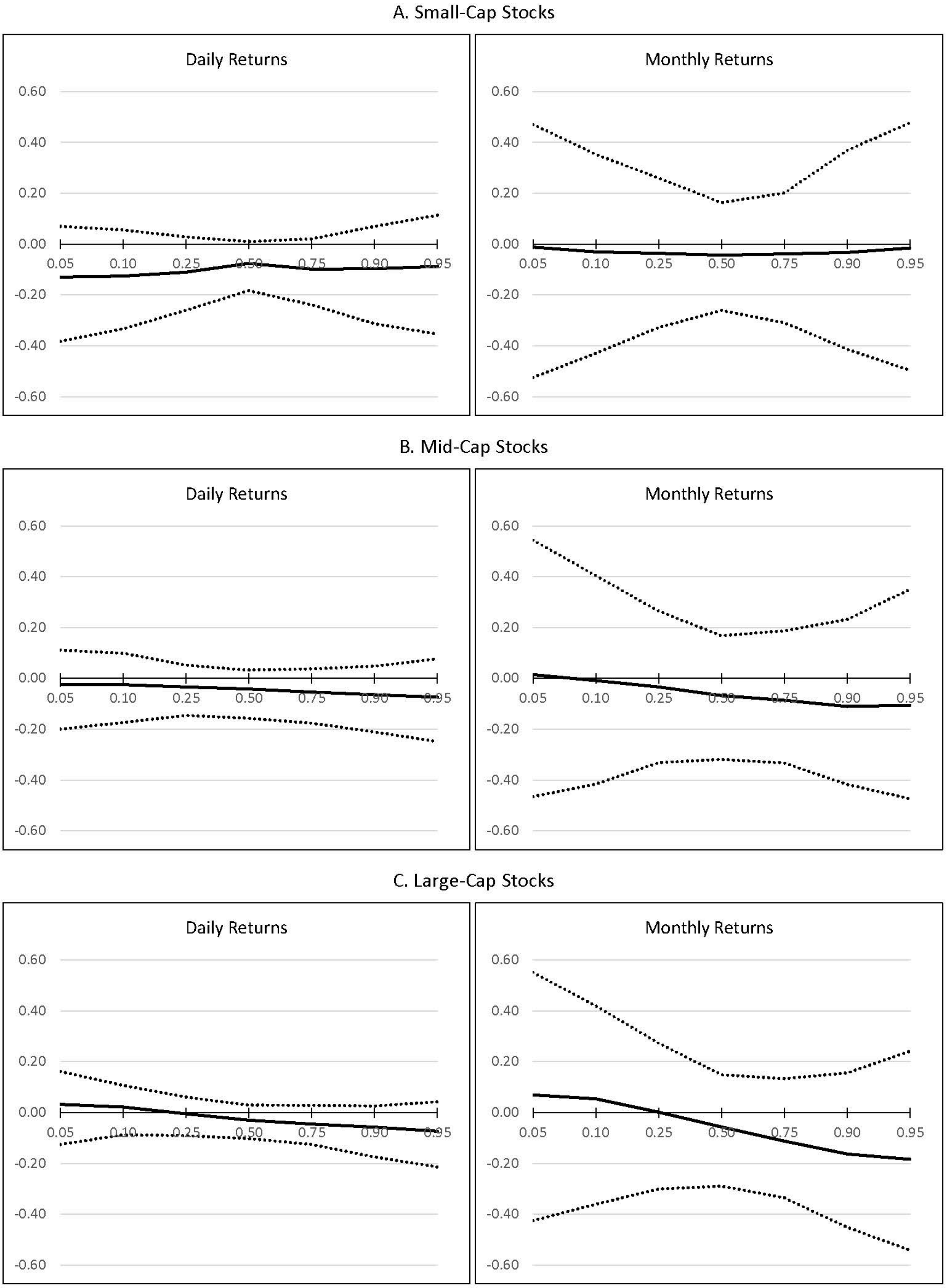
Percentage of stocks for which the random walk model is rejected at the 5% significance level. τ is the quantile of the return distribution. RM, BM1, and BM2 stand for the Rational Model, the Behavioural Model 1, and the Behavioural Model 2, respectively. The difference between the percentage of stocks with predictable returns for the behavioural model and the model with the rational investor is reported in square brackets immediately below the row for the behavioural model. Rows "d^+" and "d^-" display the percentage of stocks for which the considered heuristics, respectively, raise and lower the return predictability. The sample period is from December 31, 2009, to December 31, 2018.

Model	τ							Mean
	0.05	0.10	0.25	0.50	0.75	0.90	0.95	Return
				Small-Cap Stocks				
			A. Stocks with Decreasing Volatility of Returns					
RM	44.67	28.33	10.33	3.67	13.00	32.33	57.00	5.00
BM1	37.00	20.67	7.33	2.33	9.33	24.00	45.67	2.00
	[-7.67]	[-7.67]	[-3.00]	[-1.33]	[-3.67]	[-8.33]	[-11.33]	[-3.00]
d^+	2.00	0.67	0.00	0.00	0.00	1.33	1.67	0.00
d^-	9.67	8.33	3.00	1.33	3.67	9.67	13.00	3.00
BM2	34.33	22.33	8.00	3.00	11.00	26.67	47.67	2.00
	[-10.33]	[-6.00]	[-2.33]	[-0.67]	[-2.00]	[-5.67]	[-9.33]	[-3.00]
d^+	2.00	1.00	0.33	0.00	1.00	2.33	2.67	0.00
d^-	12.33	7.00	2.67	0.67	3.00	8.00	12.00	3.00
			B. Stocks with Increasing Volatility of Returns					
RM	51.38	27.52	14.68	3.67	9.17	36.70	47.71	5.50
BM1	61.47	42.20	31.19	38.53	37.61	52.29	62.39	25.69
	[10.09]	[14.68]	[16.51]	[34.86]	[28.44]	[15.60]	[14.68]	[20.18]
d^+	13.76	22.02	19.27	34.86	28.44	22.94	20.18	20.18
d^-	3.67	7.34	2.75	0.00	0.00	7.34	5.50	0.00
BM2	59.63	48.62	34.86	33.94	33.03	54.13	60.55	22.94
	[8.26]	[21.10]	[20.18]	[30.28]	[23.85]	[17.43]	[12.84]	[17.43]
d^+	12.84	25.69	22.94	31.19	24.77	23.85	20.18	17.43
d^-	4.59	4.59	2.75	0.92	0.92	6.42	7.34	0.00

Table 1.4 (Continued)

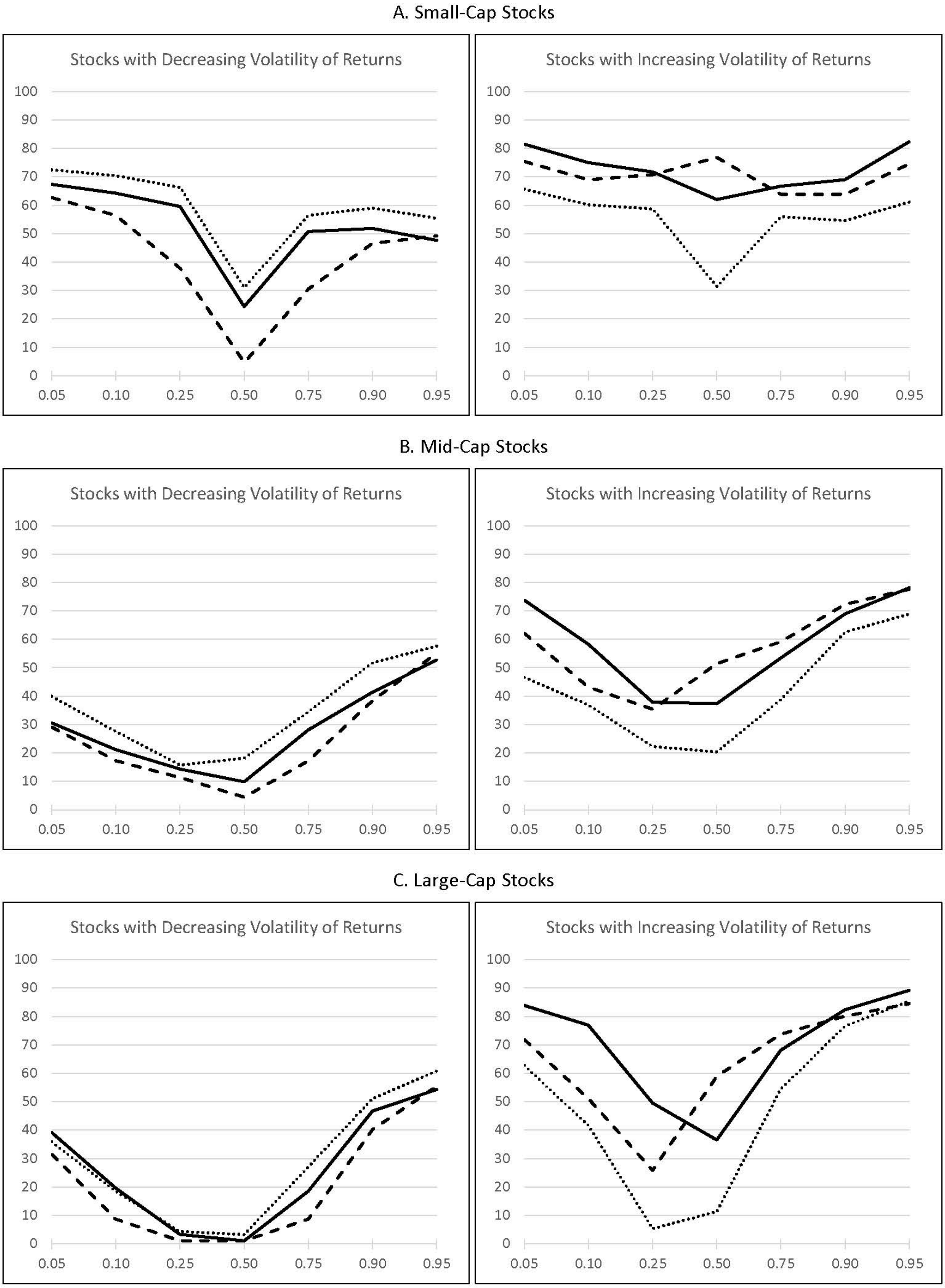
Model	τ							Mean
	0.05	0.10	0.25	0.50	0.75	0.90	0.95	Return
				Mid-Cap Stocks				
				A. Stocks with Decreasing Volatility of Returns				
RM	54.58	31.37	14.05	11.76	18.30	34.64	45.10	6.21
BM1	46.73	26.47	11.44	7.84	16.01	30.39	39.87	4.58
	[-7.84]	[-4.90]	[-2.61]	[-3.92]	[-2.29]	[-4.25]	[-5.23]	[-1.63]
d^+	1.63	0.98	0.65	0.00	0.33	2.29	2.29	0.00
d^-	9.48	5.88	3.27	3.92	2.61	6.54	7.52	1.63
BM2	46.73	27.78	12.09	10.78	17.65	31.05	41.50	4.90
	[-7.84]	[-3.59]	[-1.96]	[-0.98]	[-0.65]	[-3.59]	[-3.59]	[-1.31]
d^+	1.96	1.96	1.31	1.31	1.31	2.94	3.59	0.00
d^-	9.80	5.56	3.27	2.29	1.96	6.54	7.19	1.31
				B. Stocks with Increasing Volatility of Returns				
RM	58.25	33.98	17.48	17.48	23.30	36.89	47.57	9.71
BM1	63.11	42.72	33.98	34.95	37.86	38.83	50.49	25.24
	[4.85]	[8.74]	[16.50]	[17.48]	[14.56]	[1.94]	[2.91]	[15.53]
d^+	10.68	13.59	18.45	17.48	15.53	7.77	9.71	15.53
d^-	5.83	4.85	1.94	0.00	0.97	5.83	6.80	0.00
BM2	61.17	58.25	34.95	33.98	40.78	49.51	57.28	24.27
	[2.91]	[24.27]	[17.48]	[16.50]	[17.48]	[12.62]	[9.71]	[14.56]
d^+	10.68	29.13	19.42	16.50	22.33	18.45	13.59	14.56
d^-	7.77	4.85	1.94	0.00	4.85	5.83	3.88	0.00
				Large-Cap Stocks				
				A. Stocks with Decreasing Volatility of Returns				
RM	52.54	37.32	18.84	10.51	22.46	38.77	54.71	9.78
BM1	47.10	32.97	15.58	8.70	19.20	35.51	50.00	7.97
	[-5.43]	[-4.35]	[-3.26]	[-1.81]	[-3.26]	[-3.26]	[-4.71]	[-1.81]
d^+	2.17	1.81	0.72	0.00	0.72	2.17	2.17	0.00
d^-	7.61	6.16	3.99	1.81	3.99	5.43	6.88	1.81
BM2	49.28	34.42	16.67	10.51	21.38	35.87	48.55	8.33
	[-3.26]	[-2.90]	[-2.17]	[0.00]	[-1.09]	[-2.90]	[-6.16]	[-1.45]
d^+	2.54	2.17	1.09	0.72	1.45	2.90	1.09	0.00
d^-	5.80	5.07	3.26	0.72	2.54	5.80	7.25	1.45
				B. Stocks with Increasing Volatility of Returns				
RM	51.13	39.10	18.80	12.03	24.06	48.12	57.14	6.77
BM1	62.41	46.62	38.35	38.35	42.11	51.13	60.15	21.05
	[11.28]	[7.52]	[19.55]	[26.32]	[18.05]	[3.01]	[3.01]	[14.29]
d^+	16.54	15.79	21.05	26.32	19.55	10.53	8.27	14.29
d^-	5.26	8.27	1.50	0.00	1.50	7.52	5.26	0.00
BM2	63.91	55.64	37.59	29.32	45.11	57.89	63.16	24.81
	[12.78]	[16.54]	[18.80]	[17.29]	[21.05]	[9.77]	[6.02]	[18.05]
d^+	18.80	24.06	20.30	18.05	23.31	16.54	13.53	18.05
d^-	6.02	7.52	1.50	0.75	2.26	6.77	7.52	0.00

Figure 1.1: Cross-sectional Distribution



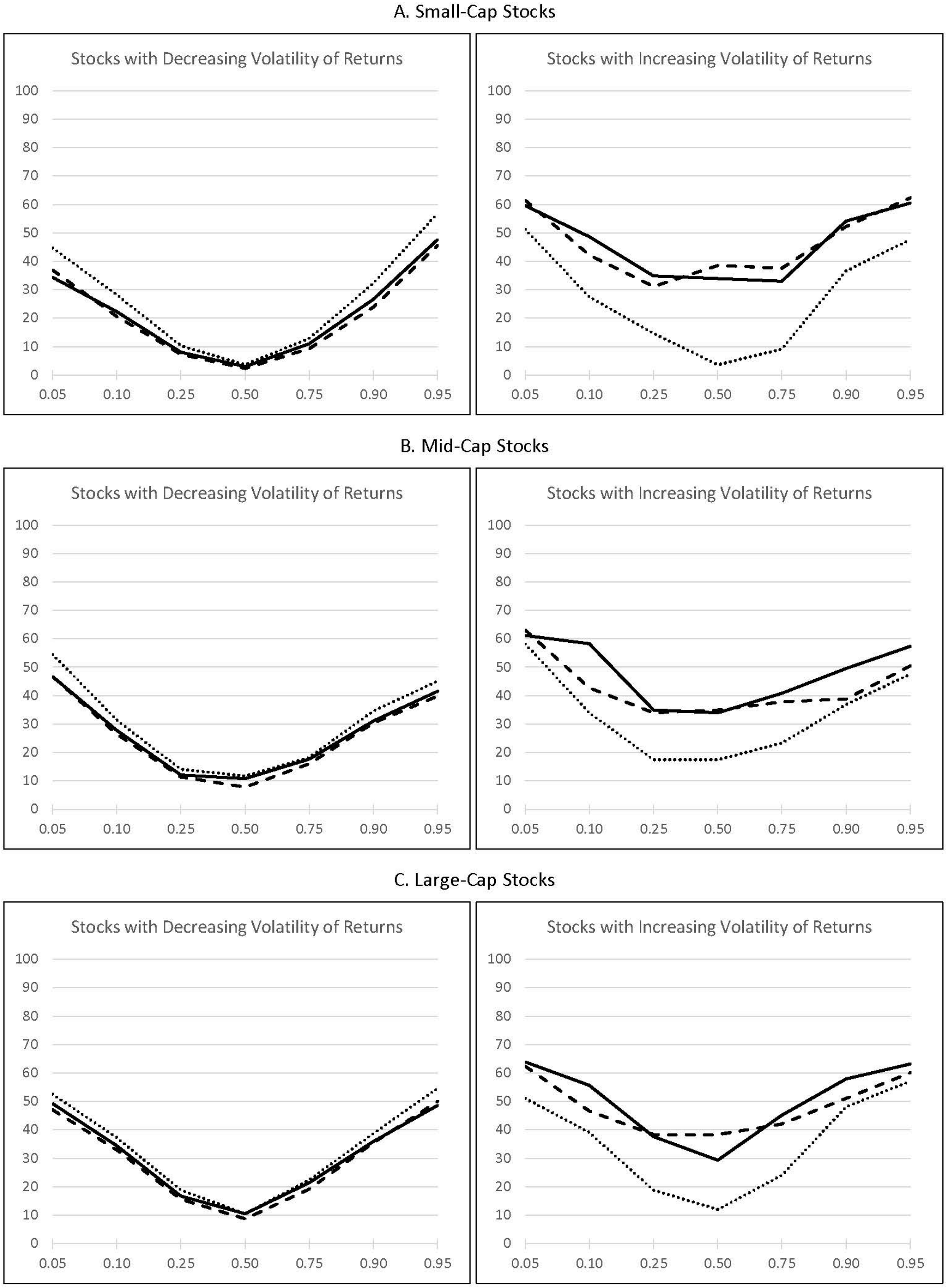
The average (solid line) and the 0.025 and 0.975 quantiles (dotted lines) of the cross-sectional distribution of $\rho^{\tau}(1)$ for $\tau = 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95$.

Figure 1.2: Random Walk model rejection with Daily Returns



Daily returns. Percentage of stocks for which the random walk model is rejected at the 5% significance level under the conventional assumption of rationality (dotted line), confidence/doubt (dashed line), confidence/doubt and the availability heuristic (solid line) for various quantiles of the return distribution.

Figure 1.3: Random Walk model rejection with Monthly Returns



Monthly returns. Percentage of stocks for which the random walk model is rejected at the 5% significance level under the conventional assumption of rationality (dotted line), confidence/doubt (dashed line), confidence/doubt and the availability heuristic (solid line) for various quantiles of the return distribution.

2 Behavioural Value-at-Risk

2.1 Introduction

The growing instabilities in financial markets over the last few decades have influenced the need for a more sophisticated risk management tool. Financial literature defines risk as the degree of uncertainty about future net returns, which are broadly classified into several categories (See van den Goorbergh et al. (1999), Manganelli and Engle (2001), Lai and Xing (2008)). There are three types of risk in finance, which are business risk, strategic risk, and financial risk. Financial risk is further broken down into five categories[1]: credit risk, operational risk, liquidity risk, legal risk, and market risk. Although all kinds of financial risks are important, the recent financial crisis put the focus entirely on the analysis of market risk.

The only widespread standard measure of market risk in the financial sector is Value at Risk (VaR). It provides an estimate of the maximum expected loss in the portfolio value over a target horizon, for a particular confidence level. VaR has been developed in the early 1990s in the industry to provide senior management with a single number that can easily portray information about the risk of a portfolio. Despite several other competing risk measures proposed in the literature, VaR has been endorsed by the Basel Committee on Banking Supervision (BCBS) as the tool for determining market risk capital. After the success of the Morgan (1996) - RiskMetrics database, it has been used widely to measure the risk of the loss on a specific portfolio of a financial asset.

VaR, which serves as the sole example of the distributional based analysis of return, has many applications from risk management to regulatory purposes. Banks are allowed to have their regulatory required capital based on their own internal VaR forecasts. It is also used to manage risk by setting a trading limit to each trader based on the trader's portfolio value. Berkowitz et al. (2011) further explain the importance of VaR in portfolio choice. If a manager sees VaR increasing, it signals for the closing of a position that eventually guides the portfolio choice to a certain extent. In theory, optimal investment policy is set with optimal portfolio weights that can be found by maximizing the expected return or expected utility of terminal wealth subject to a maximum VaR.

VaR has many advantages for which it has become popular over the years. Nieppola et al. (2009) affirm that VaR has two important and appealing characteristics: (i) it provides a common consistent measure of risk for different positions and instrument types; and (ii) it takes into account the corre-

[1] *Credit risk* is the risk of potential loss due to the inability of a client to meet the promised obligations. *Operational risk* relates to the risk of fraud and regulatory risk that arise due to the errors in instructing payments or settling transactions. *Liquidity risk* happens due to an unexpectedly large and stressful negative cash flow over a short period for a firm with mostly non-liquid assets that suddenly need some liquidity. *Legal risk* arises from uncertainty about the ability to enforce contracts. *Market risk* is caused by the changes in market conditions that increase the uncertainty of future earnings.

lation between different risk factors. VaR is forward-looking by definition that gives the advantage to forecast future volatility (Taylor, 2005). Furthermore, VaR as limits is comparable across asset classes because the VaR of a position reflects both the notional size of the position as well as the risk per dollar invested (Blanco and Blomstrom, 1999). Another advantage of VaR is that it can be seen as a coherent risk measure for a large class of continuous distributions[2].

There are a variety of approaches to estimate VaR that Manganelli and Engle (2001) broadly categorized as parametric[3], semi-parametric[4], and non-parametric[5]. There is empirical evidence that the distribution of financial price changes usually has fatter tails than those suggested by the normal distribution. Since VaR measure is designed explicitly to capture performance at the lower tails of price change distributions, this may cause VaR measures to underestimate the true portfolio risk. Engle and Manganelli (2004) confirm that if the VaR is not properly estimated, this may lead financial institutions to overestimate (or underestimate) their market risks and consequently to maintain excessively high (low) capital levels. This results in an inefficient capital allocation affecting the profitability or the financial stability of the firm.

VaR has been adopted in many researches in an attempt to obtain precise VaR forecasts (Richardson et al. (1997), Hendricks (1997), Rockafellar et al. (2000), Berkowitz and O'brien (2002), Danielsson et al. (2005), Giacomini and Komunjer (2005), Ibragimov and Walden (2007), Issler and Lima (2009), Berkowitz et al. (2011), Gaglianone et al. (2012), and among others). While the approaches may vary significantly, all the forecasting models estimate market risks in current positions with detailed measures. The large-scale use and acceptance of VaR models have developed substantial literature that explains and examines statistical descriptions of VaR with different models and approaches[6]. Nevertheless, these estimations are quite statistically challenging and none of the methodologies gives satisfactory solutions about the potential maximum loss on a portfolio. Furthermore, little empirical study has been conducted on the current risk models in use, such as VaR output, profit, and loss distributions of trading firms.

[2] See Danielsson et al. (2005), Ibragimov and Walden (2007), and Gaglianone et al. (2012).
It satisfies the following properties; (i) subadditivity (the risk measure of a portfolio cannot be greater than the sum of the risk measures of the smaller portfolios that comprise it); (ii) homogeneity (the risk measure is proportional to the scale of the portfolio); (ii) monotonicity (if portfolio Y dominates X, in the sense that each payoff of Y is at least as large as the corresponding payoff of X, i.e., $X \leq Y$, then X must be of lesser or equal risk); and (iv) risk-free condition (adding a risk-free instrument to a portfolio decreases the risk by the size of the investment in the risk-free instrument).

[3] Danielsson and De Vries (1997), Barone-Adesi et al. (1998), Diebold et al. (1998), Embrechts et al. (1999), and McNeil and Frey (2000)

[4] Koenker and Zhao (1996), Taylor (1999), Chernozhukov and Umantsev (2001), Christoffersen et al. (2001), Engle and Manganelli (2004), and Komunjer (2005)

[5] Bhattacharya and Gangopadhyay (1990), and White (1992)

[6] Check CVaR (Conditional Value-at-Risk) of Rockafellar and Uryasev (2002) and CAViaR (Conditional Autoregressive Value-at-Risk) of Engle and Manganelli (2004)

The first direct evidence on the performance of banks' VaR models is provided by Berkowitz and O'brien (2002). VaR estimates are prone to be conservative relative to the 99th percentile of profit and losses. In general, losses significantly exceed the VaR, and those cases are inclined to form clusters. The survey of Pérignon and Smith (2007) depicts that 73% of the banks among 60 US, Canadian, and large international banks over 1996-2005 have used the historical simulation (HS) approach of VaR. Historical simulation is a non-parametric method to generate VaR by using the empirical distribution of past returns. The historical data contains the information of price distributions with fat tails, whose impact on the portfolio's performance is reflected in the VaR measure.

The conventional HS approach weighs all observations equally assuming investors are rational thinkers. After the success of the Morgan (1996) - RiskMetrics database, VaR is calculated with the exponentially weighted moving average (EWMA) approach that assigns geometrically declining weights to past observations. This is called the weighted historical simulation (WHS) approach that combines HS with exponentially declining weights. Alternatively, Richardson et al. (1997) term it as the hybrid approach. The process of assigning the highest weight to the latest observation and the least to the oldest makes the model capture the dynamic features of volatility. This phenomenon in psychology is known as availability heuristics.

The notion of assigning different weights to every possible outcome by the investor's subjective beliefs[7] is referred to as irrational behaviour. The investor's beliefs are formed when an agent uses heuristics in making investment decisions. Recent researches present behavioural heuristics as a powerful instrument for solving many financial problems. For example, Abel (2002), and Semenov (2009a) prove that pessimism, doubt, and availability heuristic in the consumption-based CAPM can better explain the large historical average equity risk premium.

The contribution of this study lies in the introduction of behavioural VaR that employs multiple behavioural heuristics in the existing VaR approach. In contrast to previous studies on VaR, we do not attempt to establish a new VaR approach. Rather, we utilize the existing recognized WHS approach to explore the forecasting ability of VaR by various behavioural heuristics that are proven to be essential in stock return analysis. First, we compute investor's subjective beliefs according to decision heuristics that evaluate asset returns with respect to a prespecified reference level or target return[8]. Then, we make out-of-sample VaR forecasts using the *rolling* (moving window) method under investor's beliefs about the probability of future net return with respect to a given target

[7]Semenov (2009a) defines the expected value of uncertain outcomes as linear to the subjective probabilities, which are significantly different from the objective probabilities.

[8]In behavioural finance, target return level captures the disposition effect, which explains why investors tend to sell stocks that gained value and to hold on stocks that lost value (Hon-Snir et al., 2012; Shefrin and Statman, 1985).

return.

The next crucial issue is how to assess the performance of behavioural heuristics in the VaR model. Backtest helps to ensure whether the models in use can detect the underlying risk successfully. Most financial institutions now depend on the backtest results to manage risk and to improve their models continuously. Among the several existing backtests, Kupiec (1995), Christoffersen (1998), and Engle and Manganelli (2004) are famous for the formal testing of statistical properties. These tests are based on the orthogonal conditions between some instruments and binary variable, which is simply a hit indicator of losses that exceed VaR.

The binary variable, which is constructed to represent rare events, suffers in finite samples due to the lack of information on extreme events that may not reject a misspecified model. A typical solution for this is either to increase sample size or construct a new backtest that uses more information (Gaglianone et al., 2012). Many recent studies propose new evaluation techniques that examine whether a forecasting model is correctly specified or whether a sequence of forecasts satisfies certain optimality conditions[9]. Unlike previous researches, we do not attempt to formulate any new backtesting technique. We solve the issue by taking sufficient long data and assess the VaR forecasting ability of behavioural heuristics with the simplest Kupiec (1995) - backtest.

VaR is usually estimated for portfolios because investors invest in portfolios consisting of multiple stocks. We use the daily net return of 5 major US stock market indices collected from the first trading day of 2009 to the last trading day of 2019. Since the data comprises US stock market indices, we compute the cross-sectional joint Mean Square Error (MSE) loss function to assess the behavioural VaR model at the particular lower percentile of the return distribution. This is statistically efficient as VaR is calculated with sufficiently large data in each sub-sample; the initial 1768 observations are used to generate the last 1000 VaR forecasts.

The empirical results display that, in comparison to the conventional equal weighting strategy of rationality, decision heuristics provide better VaR forecast with the established WHS approach. We will further investigate which heuristics either single or in pairs provide the most accurate VaR forecast. This will recommend the new weighting strategy for WHS that can be implemented in financial institutions.

This study is organized as follows: Section 2.2 describes the importance of irrational behaviour in investment decisions and explains how to formulate them when an investor exhibits one or more heuristics simultaneously. Section 2.3 demonstrates first the estimation and evaluation process,

[9]See Christoffersen and Pelletier (2004), Haas (2005), Giacomini and Komunjer (2005), Wong (2008), Wong (2010), Candelon et al. (2010), Berkowitz et al. (2011), Corbetta and Peri (2016)

second the summary of data, and finally the empirical analysis based on the comparison of results obtained under the conventional assumption of rationality and the assumption of behavioural heuristics. Section 2.4 summarizes and concludes.

2.2 The Importance of Behavioural Heuristics

2.2.1 Behavioural Heuristics Background

Financial and economic researches are usually experimented by assuming people are rational in making decisions. This allows them to weigh uncertain outcomes by their objective probabilities. Experimental evidence supports the systematic biases of an agent's beliefs, which implies that an individual is not always rational. An agent usually uses short-cuts and simple rule of thumb in making financial decisions that require extremely high computational skills. These short-cuts are known as "decision heuristics" (Tversky and Kahneman (1974), Stracca (2004)). This causes the subjective probabilities to deviate substantially from the fundamental objective probabilities resulting in irrational investment decisions (Semenov, 2012). Recent studies show that investor behaviour attributed to an agent's beliefs about the probabilities of future events is a powerful problem solving tool in a wide range of financial disciplines.

The importance of investor behaviour is probably first perceived in the expected utility theory of Markowitz (1952). The main intuition for maximizing the mean, while minimizing the variance of a portfolio comes from the phenomenon that investor prefers higher expected returns and lower risk. The phenomenon of buying and selling assets due to expectations plays an important role in the setting of financial market prices. Shiller (2015) also, argues that financial-economic theory poorly defines the true value of the markets because it largely depends on the public's decision factors. The fluctuations in the stock market, bond market, and real estate market in the 2007-9 world financial crisis are labeled as irrational exuberance.

Many theories of investor's decision under uncertainty have been developed over the years. These theories are based on people's preferences with respect to choices and the probabilities of uncertain outcomes. The famous prospect theory of Kahneman and Tversky (1979) affirms that investors make decisions based on gains and losses relative to some reference points, rather than the final value of the wealth. Gains compared to a specific reference level, or target return are carriers of positive utility, while losses are carriers of negative utility. The dependence on a reference point to make investment decision also captures the disposition effect[10]. It is the investor's tendency to sell stocks that gained value and to hold on to stocks that lost value. Loss aversion is an example of the change in investor's preferences when the return falls below a specific target return.

Loss aversion is the tendency of people to be more sensitive for losses than gains of equivalent absolute value. In financial literature, risk associated with losses is referred to as downside risk. The likelihood that return falls below a target level is treated by investors as risk. Contrarily, the likelihood of return to be above a target level is perceived as upside potential. When investors expect to lose money, they are most likely to select riskier investment decisions just to averse losses. The reference dependent decision heuristics are also known as "anchoring and adjustment heuristics". This is because an investor commences investment decisions with a particular reference point ("anchor") and makes adjustments relative to the starting point. Abreu (2014) defines anchoring as the human nature to rely too heavily on, or "anchor" on one piece of information in decision making.

Availability heuristic is an example of psychological bias that influences investors to rely on information that is readily available and intuitive relative to information that is less salient and more abstract. Under an uncertain situation, it allows determining the likelihood of an event according to the easiness of recalling similar instances. In general, it is assumed that "recent occurrences" are likely to be relatively more available compared to "earlier experiences" (Hon-Snir et al., 2012; Tversky and Kahneman, 1973, 1974). After the introduction of RiskMetrics by Morgan (1996), availability heuristic has been discussed in many financial researches[11]. In particular, Semenov (2009b) shows the success of availability heuristic in the forecast of risk factor beta Conditional VaR.

Other frequently observed heuristics are optimism, pessimism, overconfidence, and doubt. These heuristics lead people to judge based on extreme outcomes[12]. Extreme changes in the price of an asset will enable an agent to profit on unexpected upswings and save at the occurrence of an abnormal low. Many financial researches successfully present behavioural heuristics as an instrument for solving asset pricing anomalies. Abel (2002) and Semenov (2009a) present that pessimism, doubt, and availability heuristic in the consumption-based CAPM can better explain the large historical average equity risk premium.

Decision taken based on the heuristics leads to irrational behaviour that can be captured through investor's subjective beliefs. When maximizing the expected utility of an uncertain prospect, an in-

[10]Kliger and Kudryavtsev (2008) find that investors update their reference points on stocks and subsequently exhibit *disposition effect* with respect to those reference points.

[11]See Shiller (1999), Ganzach (2000), Daniel et al. (2002), Frieder (2004), Barber and Odean (2007), Lee et al. (2008), Kliger and Kudryavtsev (2010)

[12]The state of extreme events with unexpected high or low returns (or prices) indicates that the asset will eventually revert to its normal state.

vestor weights possible outcomes by his subjective probabilities that deviate substantially from the fundamental objective probabilities resulting in irrational investment decisions. Financial institutions forecast market risk on a portfolio using the exponentially weighted moving average (EWMA) that assigns geometrically declining weights on past observations (Richardson et al., 1997). This phenomenon is known in psychology as the availability heuristic. The opposite of availability heuristic is conservatism, which happens when investors do not trust the available information and put the least weight to the recent outcomes.

Overconfident investors overestimate the probabilities of the asset returns that are close to the target return and underestimate the likelihood of extreme returns. By contrast, investors with doubt underestimate the probabilities of asset returns that are close to the target return. Optimism allows investors to put higher subjective probabilities of occurring to larger returns compared to low returns. In opposite to optimism, pessimism investors assign higher weights to smaller returns relative to larger returns.

We examine the effect of optimism, pessimism, overconfidence, doubt, conservatism, and availability heuristics. These six mental shortcuts comprise three distinct pairs of mutually exclusive decision heuristics: (a) optimism/ pessimism, (b) overconfidence/ doubt, and (c) conservatism/ availability. At any particular point in time, it is unknown whether the representative investor is rational or not, each of pairs of heuristics may be regarded as a complement of rationality. The subjective probabilities of returns conditional on different combinations of heuristics are calculated by ranking the historical returns in descending order based on the weighted sum of the performance values of each return scenario from the selected decision criteria taken as the deviations of the returns from a specified target level.

Since we measure the market risk with the behavioural heuristics explained in the paper "Investor Behaviour and the Predictability of Stock Returns" (coauthored with A. Semenov), we also assume that investors make decisions based on the comparison of stock returns with some target references. The three target points that are considered here are the zero return, the historical average market portfolio return, and the preceding day's stock return. Since the data for this study comprises market indices, average historical asset return will be equal to average market return as a target point. The first two target points are fixed over time, while the third one depends on time.

2.2.2 Investor's Subjective Probabilities

"Investor Behaviour and the Predictability of Stock Returns" (coauthored with A. Semenov) provides a detailed explanation of how to compute the total subjective probabilities when two or more behavioural heuristics are used by the investor simultaneously. We utilize the concept in computing the total subjective probabilities of asset returns when one or more pairs of mutually exclusive heuristics act together with rationality.

Single pair of mutually exclusive heuristics: Suppose X is denoted as the return on an asset, and R as rationality. Let A_1 and A_2 in event $A = (A_1, A_2)$ be the two mutually exclusive heuristics. The total investor's subjective probability of the return X equals the asset return r_s (for scenario $s = 1, ..., S$), $P(X = r_s)$, is simply the summation of the intersection terms shown as below:

$$
\begin{aligned}
P(X = r_s) &= P(X = r_s \cap R) + P(X = r_s \cap A_1) + P(X = r_s \cap A_2) \\
&= P(X = r_s \mid R)P(R) + P(X = r_s \mid A_1)P(A_1) + P(X = r_s \mid A_2)P(A_2) \qquad (2.1)
\end{aligned}
$$

Each intersection term is the product of the prior belief and the conditional subjective probability of a given decision heuristic. The prior belief about rationality is $P(R)$ and about the pair of heuristics are $P(A_1)$ and $P(A_2)$. Events R and $A = (A_1, A_2)$ are mutually exclusive by the law of total probability, i.e. $P(R) + P(A_1) + P(A_2) = 1$. $P(R)$ can vary from 0 to 1, which leaves $P(A_1)$ to vary from 0 to $1 - P(R)$. This eventually leaves $P(A_2)$ to be $[1 - P(R) - P(A_1)]$.

The total investor's subjective probability of the return, $P(X = r_s)$, is a convex combination of the objective probability under rationality, $P(X = r_s \mid R)$ and the subjective probabilities under behavioural heuristics $P(X = r_s \mid A_i)$, where $i = 1, 2$. The above equation can be decomposed to:

$$
\begin{aligned}
P(X = r_s) = P(X = r_s \mid R)P(R) + P(X = r_s \mid A_1)P(A_1) \\
+P(X = r_s \mid A_2)[1 - P(R) - P(A_1)] \qquad (2.2)
\end{aligned}
$$

Under the conventional assumption of the investor's rationality, $P(R) = 1$ and $P(A_i) = 0$ so that the probability of return in any scenario equals the objective probability:

$$
P(X = r_s) = P(X = r_s \mid R) = \frac{1}{T} \qquad (2.3)
$$

where T is the sample size.

Each conditional subjective probability, $P(X = r_s \mid A_i)$, is taken under the assumption that investor uses heuristic A_i for i=1,2. Under behavioural heuristics, investor ranks the observed historical asset return r_s according to some decision criterion. We assume the conditional subjective probability of the historical asset return r_s declines exponentially with the rank $s = 1, ..., S$ of the return under heuristic A_i ($i = 1, 2$). The following exponentially weighted moving average (EWMA) function is used to compute the subjective probability under each decision heuristic:

$$P(X = r_s \mid A_i) = \frac{\theta^{s-1}(1-\theta)}{1-\theta^T}, 0 < \theta < 1, s = 1, ..., T \tag{2.4}$$

where $0 < \theta < 1$ is the decay factor. $lim_{\theta \to 1} P(X = r_s \mid A_i) = 1/T$, i.e., the probability of the return under rationality. The smaller the value of θ, the faster the decrease in $P(X = r_s \mid A_i)$ as s increases. $\frac{(1-\theta)}{1-\theta^T}$ ensures that the cumulative subjective weight for the whole return distribution does not exceed 1.

Two pairs of mutually exclusive heuristics: Assuming there are K pairs of mutually exclusive heuristics and denote these heuristics by A_i^k, with $k = 1, ..., K$ and $i = 1, 2$ for each n. The heuristics in each pair are mutually exclusive. However, each heuristic in one pair is not necessarily mutually exclusive with the heuristic in another pair. The total subjective probability $P(X = r_s)$ is a convex combination of the objective probability, $P(X = r_s \mid R)$ and the subjective probabilities conditional on that the investor uses K heuristics A_i^k simultaneously, provided $A_i^k \cap R = \emptyset$ for all $i = 1, 2$ and $k = 1, ..., K$, and $A_1^k \cap A_2^k = \emptyset$ for all $k = 1, ..., K$. The prior beliefs that the investor is rational $P(R)$ and the heuristics.

For example when there are two pairs of mutually exclusive heuristics, A_1^1, A_2^1 and A_1^2, A_2^2, the total probability that $X = r_s$, where r_s is the asset return for scenario s = (1,...,S), is[13]:

$$\begin{aligned} P(X = r_s) &= P(X = r_s \mid R)P(R) + P(X = r_s \mid A_1^1 \cap A_1^2)P(A_1^1 \cap A_1^2) \\ &+P(X = r_s \mid A_1^1 \cap A_2^2)[P(A_1^1) - P(A_1^1 \cap A_1^2)] + P(X = r_s \mid A_2^1 \cap A_1^2)[P(A_1^2) - P(A_1^1 \cap A_1^2)] \\ &+P(X = r_s \mid A_2^1 \cap A_2^2)([1 - P(R) - P(A_1^1)] - [P(A_1^2) - P(A_1^1 \cap A_1^2)]) \end{aligned} \tag{2.5}$$

This equation means that $P(X = r_s)$ is determined by the probability that the investor is rational, $P(R)$, the probabilities of heuristics A_1^1 and A_1^2, $P(A_1^1)$ and $P(A_1^2)$, the probability that the investors behaviour is subject to heuristics A_1^1 and A_1^2 simultaneously, $P(A_1^1 \cap A_1^2)$, as well as the probability that $X = r_s$ conditional on that the agent is rational, $P(X = r_s \mid R)$, and the subjec-

[13]It has been simplified from $P(X = r_s) = P(X = r_s \mid R)P(R) + P(X = r_s \mid A_1^1 \cap A_1^2)P(A_1^1 \cap A_1^2) + P(X = r_s \mid A_1^1 \cap A_2^2)P(A_1^1 \cap A_2^2) + P(X = r_s \mid A_2^1 \cap A_1^2)P(A_2^1 \cap A_1^2) + P(X = r_s \mid A_2^1 \cap A_2^2)P(A_2^1 \cap A_2^2)$

tive probabilities of $X = r_s$ conditional on that the agents behaviour is subject to two heuristics simultaneously, $P(X = r_s \mid A_i^1 \cap A_i^2)$ for $i = 1, 2$.

Before computing the conditional subjective probabilities $P(X = r_s \mid A_i^1 \cap A_i^2)$, we need to find the performance value of each heuristic, v_{ti}. Now we assume that the investor's behaviour is subject to two or more heuristics (i.e., decision criteria) A_i $(i = 1, ..., K)$ simultaneously. Let h_{ti} be the value corresponding to scenario r_t when the scenario is evaluated in terms of the decision criterion A_i. For each A_i, h_{ti} is a particular function of $\tilde{r_t} = r_t - a_t$, with a_t as target return[14]. For each scenario r_t, the performance value v_{ti} depends on h_{ti} when the scenario is evaluated in terms of a decision criterion A_i.

$$v_{ti} = \frac{h_{ti} - h_i^{min}}{h_i^{max} - h_i^{min}} \tag{2.6}$$

if, under A_i, a higher probability is assigned to the scenario with a greater value of h_{ti}, and as

$$v_{ti} = \frac{h_i^{max} - h_{ti}}{h_i^{max} - h_i^{min}} \tag{2.7}$$

if, according to the decision criterion A_i, a higher probability of occurring is assigned to the scenario with a smaller value of h_{ti}. Here, h_i^{min} and h_i^{max} are, respectively, the smallest and largest (across the scenarios r_t $(t = 1, ..., T)$ values of h_{ti}.

Since $0 \leq v_{ti} \leq 1$ for all *t* and *i*, this allows us to express in the same units the performance values of different scenarios for all the decision criteria A_i. When the decision criteria are considered simultaneously, the total performance value of scenario r_t may be computed as

$$V_t = \sum_{i=1}^{I} w_i v_{ti} \tag{2.8}$$

where w_i is the relative weight of importance of criterion A_i. The total importance of different scenarios, V_t $(t = 1, ..., T)$, may be ranked from 1 to *T*, with rank *d* = 1 assigned to the scenario r_t with the highest value of V_t and *d* = *T* assigned to the scenario with the lowest total importance V_t.

By analogy with the case of a single behavioural heuristic as shown in [2.4], the subjective probability of each scenario r_t (*t* = 1,...,T) conditional on that the investor uses *K* heuristics jointly

[14] a_t is taken as 0, $\tilde{r_t}$, and r_{t-1}. Under pessimism and optimism, h_{ti} is the asset return itself i.e., $h_{ti} = r_t$ when target return is zero, otherwise $h_{ti} = r_t - a_t$ when target return is non-zero. In the case of overconfidence and doubt, h_{ti} is the absolute deviation of the asset return r_t from its target return a_t, i.e., $h_{ti} = \mid r_t - a_t \mid = \mid \tilde{r_t} \mid$, when target return is asset mean. For availability heuristics and conservatism, h_{ti} is simply the rank of time for the corresponding asset return, i.e., $h_{ti} = t$.

is computed as:

$$P(X = r_t \mid \cap_{i=1}^{K} A_i) = \frac{\theta^{d-1}(1-\theta)}{1-\theta^T} \tag{2.9}$$

where d is the rank of the total performance value of r_t, V_t.

2.3 Empirical Investigation

2.3.1 Data

The data contains the daily adjusted closing prices of 5 major US stock market equity indices from 12/31/2008 to 12//31/2019. Information on the historical stock prices are readily available from Datastream and YAHOO finance website. This aids in calculating the net returns of the asset for a complete 11 years. The reason to consider indices is that investors invest in portfolios instead on individual stocks to diversify their positions. Another reason to choose these major broad-based US indices is that they offer a greater comprehensive representation of the US stock market. The 5 market indexes that are studied in the paper are DJI - Dow Jones Industrial Average, GSPC - S&P 500, IXIC - NASDAQ Composite, NYA - NYSE Composite, and XAX - NYSE AMEX Composite.

Table 2.1 reports the descriptive summary statistics for daily net returns on the individual stock market index over the entire sample period.

[Table 2.1]

2.3.2 Model and Methodology

The Model

Manganelli and Engle (2001) define risk over net returns. Thus, the model uses daily net rate of returns to forecast VaR. The net returns are calculated from the adjusted closing prices of the market index portfolio using the following equation:

$$r_{t+1} = \frac{(P_{t+1} - P_t)}{P_t} \tag{2.10}$$

In general, VaR is defined to the τ percentile of the portfolios profit or loss distribution:

$$VaR_t(\tau) = -F^{-1}(\tau \mid \Omega_t) \tag{2.11}$$

where $F^{-1}(\tau \mid \Omega_t)$ refers to the percentile of the profit and loss distribution that varies over time as market conditions, depicted in Ω_t, changes. The negative sign is a normalization that quotes VaR in terms of positive dollar amounts of losses[15].

The two most widespread VaR estimation approaches are historical simulation (HS) and weighted historical simulation (WHS). HS is a non-parametric method that estimates VaR directly from the empirical percentiles of the past return distribution. The historical data contains the information of price distributions with fat tails, whose impact on the portfolio's performance is reflected in the VaR measure. The main advantage of using HS is that it is easy to implement and conceptualize. Unlike other parametric approaches, it does not require any distributional assumption about return distribution.

However, one of the main weaknesses of HS is that sufficient long time series of historical data on asset return is required to calculate VaR with some significant precision. The "conditional coverage" of the Basel Committee (BCBS, 1996a) is based on filtering a serially correlated and heteroskedastic time series return in the I.I.D. sequence. This causes in loss of important pieces of information. In order to overcome this problem, long time series of historical asset returns are used to simulate the desirably long forward distribution of VaR risk measures.

Another weakness of HS is in the use of flat equal weights to all the observations, which results in the loss of important information depicted by the conditional distribution of returns. The WHS approach assigns exponentially declining weights[16] to past returns in order to calculate conditional return at risk. The declining weights assist in capturing the cyclical behaviour of the asset return. The existing WHS approach captures the notion of the availability heuristic, where recent observation is given more weight compared to the relative past. It is also known as the *hybrid* approach[17].

We take a long sample of historical time series of the market index. Then, the sample returns are split into an estimation sample and an evaluation sample for each technique. The estimation sample is used to compute the investor's subjective beliefs and to forecast VaR at its relevant percentile of the return distribution. The evaluation sample is the forward distribution of VaR estimates. The evaluation sample helps to conduct a backtest in order to assess the adequacy of the investor's subjective beliefs in VaR forecasting. The former has to be sufficiently large enough to estimate VaR with a reliable degree of precision. The latter needs to have an adequate number of observations that can extensively represent extreme events to do the backtesting accurately. There is always the issue of trade-off between the choice of sample split[18] with the effect of estimation error on forecast

[15]See Campbell (2005)

[16]Morgan (1996) refers it to as exponential soothing.

[17]See Richardson et al. (1997), Alexander (2009) and Daníelsson (2011)

[18]See van den Goorbergh et al. (1999), and Hansen and Timmermann (2012). Many economists recommend taking

precision. The sample has to split in such a way that it generates the maximum achievable power.

HS is then conducted by simply taking sample percentiles over a moving sample. It is a good resampling method that is based on the assumption that history is repeating itself. If we observe data from day 1 to day t, and $r_{j,t}$ is the return of portfolio *j* on day t, then we get a series of return $\{r_{j,t+1-m}\}_{m=1}^{M}$. The value of risk for asset j with coverage rate τ is calculated as the $(100.\tau)\%$ of the sequence of past portfolio returns.

$$\widehat{VaR}_{j,t+1}^{\tau} = percentile\left[\{r_{j,t+1-m}\}_{m=1}^{M}, (100.\tau)\%\right] \tag{2.12}$$

HS forecast VaR for τ = 0.01, 0.05 by assigning equal weights to all the observations in the moving sample. This is the case of complete rationality, for which the conditional probability is given in equation (2.3) and the P(R) is equal to 1.

As explained in Section 2.2.2, the subjective probability $P(X = r_{j,t})$ for WHS is a function of return r_{jt} from the period t and target return on stock j, a_{jt}. We consider three possible values of a_{jt}. They are the zero return, the historical portfolio return, and the preceding day's portfolio return. Zero is selected as a target return because we assume investors identify negative returns as losses and positive returns as gains[19]. The historical mean of the asset return, $\bar{r_j} = \frac{1}{T}\sum_{t=1}^{T} r_{jt}$, as target return captures the significance of mean reversion theorem[20]. It claims that asset prices and returns eventually revert to its historical averages. The preceding day's portfolio return, $r_{j,t-1}$, as target return can be explained by the "the law of small numbers"[21]. It is a special case of mean-target model in which investors make judgments about the asset performance based on the most recent return only[22]. The first target return is same for all market portfolio indices. Whereas, the last two target returns are firm-specific.

Estimation and Testing Methodology

We use the following three stage estimation and testing procedure. In the first stage, we use the grid search technique to find the forward distribution of VaR measures with HS approach (2.12) and

multiple splits of the sample in an attempt to obtain more consistent and accurate estimates. Some events may have an influence on asset returns during a small period of time, but not as a whole. However, dividing samples multiple times in turn suffers from the lack of information on rare events in finite subsamples that invalidate the purpose of acquiring precise VaR measures.

[19] Benartzi and Thaler (1995)

[20] Hogan and Warren (1972), Hogan and Warren (1974)

[21] Tversky and Kahneman (1971)

[22] Weber and Camerer (1998) and Oehler et al. (2002) explain why the last period price is important as the reference point.

WHS approach at the chosen confidence level for each market portfolio index. In the second stage, we conduct the backtesting using the forecasted VaR sequence obtained in the first stage for each portfolio at each confidence level and for each value of decay factor θ. Finally, in the third stage, we calculate the Mean Squared Error using the backtest results for all the five market indices to assess the risk forecasting ability performance of behavioural heuristics at each corresponding percentile and for each θ.

Estimating Out-of-Sample VaR Forecast: In order to make the out-of-sample VaR forecast, we first compute the total subjective probabilities[23]. Under the departure of investor's rational behaviour, we commence an investigation with the simplest case of single pair of mutually exclusive heuristics, $\tilde{A} = \{A_1, A_2\}$. The three pairs of mutually exclusive heuristics in $\tilde{A}$ are: (a) pessimism/optimism, (b) overconfidence/doubt, and (c) conservatism/availability.

We calculate the total subjective probability for single pair of mutually exclusive heuristics with equation (2.2.2). It depends on $P(X = r_{jt} \mid R) = \frac{1}{T}$ for all t in the moving sample, $P(X = r_{jt} \mid A_i)$ for i=1,2, and the prior beliefs P(R), and $P(A_i)$. $P(X = r_{jt} \mid A_i)$ is estimated with equation (2.4) that depends on θ. For simplicity, we assume θ to be same across the heuristics.

The prior beliefs P(R), and $P(A_i)$, and θ are all unobservable. We use grid search technique for the unobserved variables. θ is set to vary from 0.999 with decrements 0.001 for the mutually exclusive heuristics $\tilde{A}$ and target return $a = a_{jt}$. Then we let P(R), and $P(A_1)$ to take values from 0 to 1 with increments of 0.1 on that $P(A_2) = 1 - P(R) - P(A_2)$ is non-negative and is not greater than 1. This provides 66 distinct sets of probabilities P(R), $P(A_1)$, and $P(A_2)$ for each value of θ and at each confidence level, ($\tau = 0.01, 0.05$).

It is assumed that P(R), $P(A_1)$, and $P(A_1)$ are all non-negative and smaller than 1. There are three extreme cases. Under the conventional assumption of rationality, $P(R) = 1$ and $P(A_1) = P(A_2) = 0$. The other two extreme cases are when investor use a heuristic either A_1 or A_2 with certainty. This happens when $P(A_1) = 1$ and $P(R) = P(A_2) = 0$, or when $P(A_2) = 1$ then $P(R) = P(A_1) = 0$.

The rolling (moving window) forecast method is employed to obtain out-of-sample VaR forecasts. The moving window out-of-sample forecast uses sample of return distribution $[r]_{s=1}^{T-n}$ for $t = 1, ..., (T - n)$ to produce the first VaR forecast with a window width of (T-n).[24] It is assumed

[23] See Section 2.2.2

[24] See van den Goorbergh et al. (1999). The choice of the window size (T-n) is open to debate. With a short window size, VaR estimates become very sensitive to accidental outcomes from the recent past. Whereas, a long window size has the disadvantage that past data are included which might no longer be relevant to the current situation.
The data contains 2768 observations, i.e. T=2768. A reasonable choice of observation size in forward distribution is $n = T/3$ and the moving window width is $T - n = 2T/3$. We choose to forecast the last 1000 VaR sequence, which

that the return distribution will remain same in the next period to generate a forecast of return at $t = T - n + 1$. This forecast is the relevant percentile of the asset return distribution weighted by the investor's subjective probabilities. This means VaR forecast at time $t = T - n + 1$ is:

$$\left(\widehat{VaR}^{\tau}_{j,T-n+1} \mid F_{T-n}\right) = -\widehat{W} r^{\tau}_{j,T-n} \tag{2.13}$$

In order to estimate next day's VaR at time $T - n$ with confidence level $\tau\%$, we use historical return conditional on an information set F_{T-n}. For each market portfolio in j, the estimated weight $\widehat{W}$ represents the total subjective probability, $P(X = r_{jt})$ with $t = 1, ..., (T - n)$ and τ = 0.01, 0.05. HS puts the same weight to all observations in the chosen window. Equation (2.12) shows that $P(X = r_{jt} \mid R) = 1/(T - n)$ and P(R) = 1. In WHS, $\widehat{W}$ is equal to the total subjective probability obtained from equation (2.2.2) for single pair of mutually exclusive heuristics.

Similarly, in order to generate the second VaR forecast of index at $t = T - n + 2$, it uses information in $t = 2, ..., (T - n + 1)$ with the same moving window width. In this way, the window is moved one time period ahead to determine (T-n)-step ahead forecast that corresponds to the relevant weighted percentile of the index. In the end, to forecast the final T-th return, it uses information in $t = n, ..., (T - 1)$. Since the window width, T-n, is same as before, HS assigns $P(X = r_{jt} \mid R) = 1/(T-n)$ to all observation in the new window. The weight remains unaffected. While for WHS, $\widehat{W}$ is estimated again from equation (2.2.2) with the new ranking of the returns from its target return in the window.

As we move the window one step ahead to forecast VaR, the $\widehat{W}$ is unaffected under HS. However, to make one step ahead VaR forecast with WHS, $\widehat{W}$ is re-estimated each time we move the window and distorts the ranking of return by dropping one observation and adding a new observation. The $\widehat{W}$ are adjusted as the window moves forward with the new ranking of the returns according to the decision criterion in $\tilde{A}$ and target return $a = a_{jt}$.

For two pairs of mutually exclusive heuristics $\tilde{A} = \{\{A^1_1, A^1_2\}, \{A^2_1, A^2_2\}\}$, $\widehat{W}$ is estimated from equation (2.2.2). For simplicity we assume the decay factor θ is same across the heuristics and the relative weight of importance *w* equal to 0.5 for all heuristics. Using the grid search technique, the prior belief that the investor is rational, $P(R)$ is set to vary from 0 to 1 with 0.1 increments. Since heuristics and rationality are mutually exclusive, $P(A^1_1)$ and $P(A^2_1)$ are both set to 0, 0.1, etc., until $1 - P(R)$. Hence, $P(A^1_1 \cap A^2_1)$ is set to 0, 0.1, etc., until *min* $(P(A^1_1), P(A^2_1))$. This provides

implies n=1000. The moving window width is 1768. Each 1-step ahead VaR forecast is produced with the same number of observations.

1001 distinct combinations of heuristics in $\tilde{A}$. With the same grid search technique, the conditional subjective probabilities, $P(X = r_t \mid \cap_{i=1}^{K} A_i)$ for all i are estimated with θ varying from 0.999 with decrements 0.001.

Evaluating Performance with Backtest: The accuracy and reliability of a risk measure depend on the predictability of unexpected future losses. The standard way to assess VaR involves backtesting or reality check. The formal statistical approach of backtesting consists in verifying whether actual losses are in line with projected losses, or leads to VaR violations. In order to monitor the frequency of violations, the Basel Committee (BCBS, 1996b) has set up a regulatory backtesting framework for internal VaR models that is known as the traffic light approach.[25]

All the existing backtest helps to identify misspecified VaR model with hit indicator that only signals whether a particular threshold has exceeded or not. The VaR violation sequence can be defined by the hit indicator as below:

$$H_{j,t}(\tau) = \begin{cases} 1 & \text{if } r_{j,t} < -\widehat{VaR}_{j,t|t-1}(\tau) \\ 0 & \text{if } r_{j,t} \geq -\widehat{VaR}_{j,t|t-1}(\tau) \end{cases}$$

Backtesting involves a systematic comparison of the historical model-generated VaR forecasts with the actual returns. It is assumed that the forward distributions of asset returns may be well proxied by the simulated historical distributions. According to the definition, the probability of exceeding VaR should equal to $Pr[H_{j,t}(\tau) = 1 \mid F_{t-1}] = \tau$.

We assess the ability of behavioural heuristics to predict VaR using the widespread Kupiec backtest Kupiec (1995). It is one of the earliest and simplest backtesting method, which allows for an intuitive interpretation and comparison of various VaR models. It is nonparametric in nature and is based on the proportion of failures (known as POF test). The test examines whether proportion $\hat{p_j} \equiv \frac{n_j}{N}$, where N is the sample size in the backtesting window and n_j is the number of violations in asset j of $n_j = \sum_{t=1}^{N} H_{j,t}$, is statistically consistent with the confidence level τ.

The VaR model is accepted if the POF, $\hat{p_j}$, over the specific time interval does not significantly differ from the confidence level, τ. Under this unconditional coverage test, the null hypothesis is given as:

$$H_o : Pr[H_{j,t}(\tau) = 1] = E[H_{j,t}(\tau)] = \hat{p_j} \tag{2.14}$$

Alternatively, if $\hat{p_j}$ in the sample is statistically different from the confidence level τ then null hypothesis is rejected. This implies that the proposed model is incapable of estimating accurate VaR

[25] See Jorion (2000)

measures. The sequence of VaR violation follows Bernoulli distribution[26].

For each combination of heuristics in $\tilde{A}$ and target return a_{jt}, the conditional forward distribution of $\widehat{VaR}_j^{\tau}$ estimates (τ = 0.01, 0.05), is compared with the actual returns to record the hit indicator for a particular value of θ. We conduct the backtest by computing the POF $\hat{p_j}$ in asset j, which is a single number obtained for each combination of heuristics in $\tilde{A}$, target return a_{jt}, and decay factor θ. The POF $\hat{p_j}$ are arranged in vector of size the numbers of combination in pairs of heuristics in $\tilde{A}$ by the number of decay factors θ under scrutiny at each confidence level (τ = 0.01, 0.05)[27].

Testing Model Accuracy with Mean Squared Error: Mean squared error (MSE) of an estimator is defined to measure the average of the squares of the difference between the estimated value and the actual (target) value. The main objective is to minimize MSE, which of a value of zero means an estimator predicts the actual parameter with perfect accuracy. It is used for comparative purposes, to determine the best predictive model. MSE is frequently used in empirical researches to assess any forecasting model for its statistical consistency. We use MSE to assess the ability of behavioural heuristics to forecast VaR.

Danielsson et al. (2005), and Ibragimov and Walden (2007) show that for a large class of distributions of continuous random variables, VaR is coherent and satisfies subadditivity properties. The POF, $\hat{p_j}$ obtained for VaR backtest for all asset J are evaluated together at a particular confidence level τ with MSE. The MSE is formulated as the weighted average square of the relative distance between the proportion of violations and its respective percentile.

$$MSE_{\tau} = \sum_{j=1}^{J=5} \frac{(\frac{X_j}{\hat{X_\tau}} - 1)^2}{n} \tag{2.15}$$

where $\frac{X_j}{\hat{X_\tau}}$ measures the relative distance[28] of the POF, $\hat{p_j}$, from its respective percentile of VaR estimation and n=5 because 1% and 5% VaR are observed separately for 5 market indices.

In general, an investor may react differently towards risk measured at different percentiles. For example, 1% risk is generally higher than 5% risk. Assuming that the investor makes decision under

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[26]See Hitaj et al. (2018). It can be verified with likelihood ratio (LR) test. $LR_{POF} = -2ln\left(\frac{(1-\tau)^{N-n}\tau^n}{(1-(\frac{n}{N}))^{N-n}(\frac{n}{N})^n}\right) \sim \chi_1^2$ Asymptotically, as the number of observation in backtesting window N increases to infinity, the test will be distributed as a χ^2 with 1 degrees of freedom. The model is rejected, if the LR_{POF} statistic exceeds the critical value of the χ_1^2.

[27]For any single pair of mutually exclusive heuristics and target return, $\hat{p_j}$ is (66 X 15), when VaR_j^{τ} at a particular percentile (τ = 0.01, 0.05) is assessed for each asset j. For any two pairs of mutually exclusive heuristics and target return, $\hat{p_j}$ is (1001 X 15), when VaR_j^{τ} for each asset j is assessed separately for τ = 0.01, and 0.05.

[28]Alternatively, MSE can be calculated with $MSE_{\tau} = \sum_{j=1}^{J=5} \frac{(X_j - \hat{X_\tau})^2}{j}$, where $\hat{X_\tau} = 1$ for 1% VaR backtest and $\hat{X_\tau} = 5$ for 5% VaR backtest

psychological biases, an investor may not invest by looking at 1% VaR. However, the same investor is likely to invest based on 5% VaR. Each heuristic has a diverse effect across the distribution of the asset return. Thus, MSE is estimated separately for VaR 1% and 5%.

Theoretically, both 1% and 5% of an asset return are on the left side of the distribution, which are usually negative. The negative return on an investment is always treated as a loss. For example, a loss averse investor may react in the same way to avoid the risk of loss regardless of its magnitude. This motivates us to evaluate the performance of behavioural heuristics in VaR model for both 1% and 5% jointly. This helps to identify the heuristics that precisely measure VaR at the left tail of the return distribution. This purpose is achieved by formulating the joint MSE that searches for the better risk predicting heuristic as a whole.

$$MSE_{joint} = \frac{1}{2}[MSE_{1\%} + MSE_{5\%}] \tag{2.16}$$

Alternatively, this can be computed from equation [2.15] with j=10 and $\hat{X}_\tau$ equals to the relevant percentile. We identify all the combinations of heuristics in $\tilde{A}$ that give the lowest MSE. Fundamentally, we make cross-sectional comparisons across all the probabilities sets $P(\tilde{A})$ and θ to obtain the minimum MSE for any pair of heuristics and target return. MSE is a reliable consistent measure that allows us to contrast results from single pair and two pairs of mutually exclusive heuristics. This helps to identify the heuristics that provide the most accurate VaR forecast with the existing WHS approach.

2.3.3 Empirical Results

Table 2.2 reports the minimum MSE for various combinations of single pair of mutually exclusive heuristics attained in $\tilde{A}$. We denote $P^*(\tilde{A})$ as the set of probabilities and the corresponding θ^* as the decay factor, which provides the cross-sectional minimum mean squared error MSE^*_τ at τ percentile. MSE for τ equals to 1%, and 5% correspond to Kupiec's POF-backtest for VaR forecast at 1%, and 5% respectively. The minimum MSE for the joint test is presented in rows of τ equals to (1%+5%).

[Table 2.2]

Table 2.2 panel A exhibits the MSE under the conventional assumption of rationality. Panels B - G of table 2.2 present the minimum values of MSE for all the single pair of mutually exclusive heuristics and target return, a_{jt}. All the reported sets of heuristics perform significantly better in forecasting VaR than that under the assumption of rationality. The MSE for VaR forecasts with the standard rationality approach is 0.118 at 1%, 0.03352 at 5%, and 0.07576 for joint. Panel B, reports the results for rationality, pessimism, and optimism with target returns equal to zero and historical stock mean[29]. At 1% the MSE^* is 0.032, at 5% it is 0.01168, and for joint it is 0.0228. These values of MSE are substantially lower than those obtained with full rationality assumption. The $P^*(\tilde{A})$ for $MSE^*_{(1\%+5\%)}$ indicates that the assumption of more optimistic investors in the market gives financial institutions greater power in VaR forecasts.

Panel C reports the results for rationality, pessimism, and optimism with the preceding day's return as the target level. The MSE^* at 1% is 0.022, at 5% is 0.01136 and for the joint is 0.02504. It also displays the importance of pessimism and optimism in the improvement of VaR forecasts. It has a similar pattern as observed in panel B. There is an inverse relation between rationality and optimism. However, with the joint test, it is confirmed that optimism improves VaR forecasting in general at the left-tail of the return distribution. In all cases, better VaR forecasts are achieved with a lesser degree of pessimism. Pessimistic investors fear the risk of losses, for which they do not invest during bear markets. On the other hand, an optimistic investor expects of earning higher returns from risky investment, and in advance precisely measures the maximum losses. Pessimistic investors assign higher probabilities to the negative returns, as they expect of negative outcomes more than optimistic investors. Thus, pessimistic investor under-react to any declining price signals, and optimistic investor overreact to such price signal.

Panels D - F display the results for rationality, overconfidence, and doubt. Comparing across the target returns, the lowest MSE^* at 1% is 0.03, at 5% is 0.00888 and for joint is 0.02204. These values at their relevant percentile are evidently lower than the corresponding values under full rationality. Overconfidence and doubt also provide a more accurate VaR forecast than that with the conventional equal weighing HS approach. The improved VaR forecast is obtained when the investor exhibits a greater degree of overconfidence. $P^*(\tilde{A})$ shows that for the left-tail distribution, assuming markets have more overconfident investors aids in forecasting VaR with higher precision. According to Odean (1998b), markets are full of overconfident investors, who comprehend falling price signals as an opportunity for investment. They are the only people who invest even when the prices are falling. Overconfident investors overreact to any price information[30] that enable them to better predict the maximum risk of losses from any investment. While the investor who doubts the

[29]As forecasting window moves forward by one observation each time, the target return $a_{jt} = \bar{r}_j$ changes with the alteration of the observations in the window.

[30]See Daniel et al. (1997)

potential loss is expected to be inactive as they under-react to any falling prices.

Panel G presents the results for rationality, conservatism, and availability heuristics. The minimum MSE is obtained with 100% availability heuristics for the lower percentile of the return distribution. This corresponds to the conventional WHS approach that heavily weighs the recent observation compared to the distant past. The MSE^* at 1% is 0.004, at 5% is 0.00552, and for the joint is 0.00816. These values are the smallest at its relevant percentile when compared among the single pair of mutually exclusive heuristics. Markets with more knowledgeable investors are capable of forecasting VaR more accurately. However, this does not nullify the higher forecasting ability of other heuristics. It is deduced that optimism, overconfidence, and availability heuristic provide correct VaR measures that could never be obtained under the assumption of rationality. The results from table II reassure the empirical evidence of superior VaR forecast with availability heuristic.

[Table 2.3]

Table 2.3 also reports the cross-sectional minimum MSE^*_τ, but for two pairs of mutually exclusive heuristics. Panels A - C evaluate the results for rationality, pessimism/optimism, and overconfidence/doubt. The lowest MSE^* at 1% is 0.014, at 5% is 0.01024, and for the joint is 0.01332. With these pairs of heuristics, 1% VaR is better attained when target returns are historical mean stock return and preceding day's return. For the overall left-tail of the distribution, VaR is more precisely estimated when the target return is the preceding day's return. Regardless of the target return, $P^*(\tilde{A})$ indicates that VaR forecasting accuracy increases when the lowest weights are assigned towards rationality, and pessimism-doubt. The reason is that the investor who possesses both pessimism and doubt are assigning higher weights to the most negative returns that are farther away from the mean. As a result if they receive any information of declining prices, they under-react to the news.

Panel D and E exhibit results for rationality, pessimism/optimism, and conservatism/ availability heuristic. For any target return, these pairs of heuristics provide a highly accurate VaR forecast than that when rationality or any single pair of heuristics is considered. The lowest MSE^* at 1% is 0.002, at 5% is 0.00032, and for the joint is 0.00236, all of which are significantly close to zero. When MSE is near zero, it proposes the perfect VaR forecasting approach. Therefore, these particular pairs of behavioural heuristics have substantial strength in forecasting VaR at the lower percentile. The least weights towards rationality and pessimism-conservatism and the more weights towards optimism-availability forecast VaR with the highest degree of precision. Pessimistic investors who are not informed about the current intuitive market conditions fear loss due to market risk that prevents them from investing. Meanwhile, the optimistic investors who rely on the available information can accurately perceive the potential risk on their portfolios. They take the opportunity of lower prices in their buying-selling strategies of assets during the bear market.

Panels F - H involve rationality, conservatism/availability, and overconfidence/doubt. The lowest MSE^* at 1% is 0.002, at 5% is 0.0004, and for the joint is 0.00268. These pairs of mutually exclusive heuristics also significantly improve the VaR forecast precision with any target return[31]. $P^*(\tilde{A})$ proves that exact VaR estimates are attained with minimal or no weights on rationality and conservatism-doubt and the highest weights on availability-overconfidence. This explains the same phenomenon that an uninformed investor who doubts the future asset price movement will constantly fear of losses whether the market is performing well or in distress. When the prices are falling, investors who are either rational or exhibit doubt and conservatism under-react to the price changes. On the other hand, more knowledgeable and overconfident[32] investors overreact to news that helps them better postulate the high risk and return trade-off on any investment decisions. They are more capable to identify the maximum potential losses that could incur when the market prices are going down.

Results from tables 2.2 and 2.3 confirm that the best VaR forecasts are achieved when investors are assumed to rely more on the available information[33]. We compare the minimum values of MSE^* across all the single and two pairs of mutually exclusive heuristics at their respective percentile. It is evident that all the reported combinations of heuristics efficiently forecast VaR with the established WHS than could be obtained with HS under the conventional assumption of rationality. From table II, it is noticed that the availability heuristic alone can forecast VaR with significant precision, which is consistent with the Morgan (1996) - RiskMetrics database. From table III, optimism-availability and overconfidence-availability are the only two pairs of heuristics that separately provide the most accurate VaR estimates at the left tail of the distribution. The empirical results strongly suggest that these two pairs can forecast VaR with higher accuracy than the established availability heuristic.

Empirical results prove that the performance of the availability heuristic in the VaR forecast is overrated when compared to the performances of optimism-availability heuristic and overconfidence-availability heuristic. The existing VaR estimation approaches are prescribed to adopt the availability heuristic in pairs with either optimism or overconfidence for a significant increase in forecasting pre-

[31] Comparing these three tables, the preceding day's return as reference level slightly performs better to forecast risk at the left-tail of the distribution.

[32] See Daniel et al. (1998, 1997) and Odean (1998b). They propose that markets are full of overconfident traders who use price movements as information and react accordingly in their buying and selling strategies.

[33] Tversky and Kahneman (1971) explains this with "the law of small numbers". When the investor sees few periods of low returns, the law of small numbers makes him believe that the returns will continue to be low in the future.

cision. During the financial crisis, an informed investor with optimism or overconfidence can better apprehend the maximum loss that may incur on any investment. It is expected that the informed-optimistic investors and the informed-overconfident investors will actively trade by utilizing the given information of price movement in the decisions of investment strategies.

2.4 Concluding Remarks

VaR is the widespread measure of the maximum expected loss in the portfolio over a given time horizon that will not be exceeded with a given probability. If VaR is not properly estimated, this leads to an inefficient allocation of financial resources. The majority of the financial institutions use HS and WHS to forecast VaR. The standard HS approach uses the idea of rationality that gives equal importance to all observations. WHS utilizes the concept of the availability heuristic, which assigns heavier weight to recent outcomes relative to the distant past.

The contribution of this research lies in the introduction of some important decision heuristics to the VaR estimating technique. We attempt to utilize the existing WHS approach to explore whether behavioural heuristics can forecast VaR with a higher degree of precision. First, we compute investor's subjective beliefs according to some decision criteria that evaluate asset returns with respect to a prespecified target return. Then, we make out-of-sample VaR forecasts at the lower percentile using the *rolling* (moving window) method under investor's beliefs about the probability of future net return. We assess the forecasting ability of behavioural heuristics with the simplest and statistically efficient Kupiec's backtest for individual portfolios. Finally, we use MSE to compare the performances across various heuristics.

The empirical results display that, in contrast to the conventional assumption of rationality in HS, behavioural heuristics single and in mutually exclusive pairs forecast VaR more accurately with the established WHS approach. Optimism-availability heuristic and overconfidence-availability heuristic are the two pairs of heuristics that separately estimate VaR with the highest precision at the left tail of the return distribution. An optimistic investor who relies on the available intuitive information can better comprehend the potential market risks on investment and will invest even when the prices are falling. Similarly, more informed and overconfident investors are expected to postulate the potential high risk and return trade-off on any investment.

Consistent with the earlier findings, we find evidence of higher VaR forecasting ability when an investor exhibits availability heuristic. However, the performance of availability heuristic in the VaR forecast is overrated when compared to the performances of optimism-availability heuristic and overconfidence-availability heuristic. The existing VaR estimation approaches are prescribed to adopt availability heuristic in pairs with either optimism or overconfidence for a significant increase in forecasting precision.

Table 2.1: Descriptive Summary Statistics

The table presents the descriptive summary statistics for the time-series return distribution on each stock market index *j*. DJI is Dow Jones Industrial Average, GSPC is S&P 500, IXIC is NASDAQ Composite, NYA is NYSE Composite, and XAX is NYSE AMEX Composite. POF is the proportion of failure performed with the Kupiec's VaR backtest. It indicates the number of times (in percent) returns on each stock index *j* fall below its VaR that is estimated with HS at 1% and 5%.

Statistics	**DJI**	**GSPC**	**IXIC**	**NYA**	**XAX**
Mean	0.0005	0.0005	0.0007	0.0004	0.0003
Standard Deviation	0.0096	0.0103	0.0116	0.0106	0.0102
Variance	0.0001	0.0001	0.0001	0.0001	0.0001
Skewness	-0.2083	-0.2345	-0.2066	-0.2900	-0.3394
Kurtosis	7.5645	8.0668	6.6746	8.3392	5.5903
Minimum	-0.0555	-0.0666	-0.0690	-0.0705	-0.0632
Maximum	0.0684	0.0708	0.0707	0.0732	0.0557
1% percentile	-0.0291	-0.0310	-0.0341	-0.0324	-0.0284
5% percentile	-0.0154	-0.0166	-0.0194	-0.0170	-0.0165
Median	0.0006	0.0007	0.0010	0.0006	0.0007
95% percentile	0.0145	0.0154	0.0177	0.0157	0.0159
99percentile	0.0260	0.0292	0.0319	0.0296	0.0253
POF at 1%	1.60%	1.30%	1.30%	0.90%	0.80%
POF at 5%	4.20%	4.30%	5.10%	3.40%	4.30%
Observation			2769		
Sample			12/31/2008-12/31/2019		

Table 2.2: THE MINIMUM MSE FOR SINGLE PAIR OF MUTUALLY EXCLUSIVE HEURISTICS

The estimation results for various combinations of single pair of mutually exclusive heuristics and target return a_{jt}. $\bar{r_j}$ is the time series average returns on the stock index *j*, and $r_{j,t-1}$ is the preceding day's return on stock index *j*. $P^*(\tilde{A})$ is the set of probabilities at the corresponding decay factor θ^* that provides the cross-sectional (across all $P(\tilde{A})$ and θ) minimum value of mean squared error MSE^*_τ at confidence level τ percentile. R represents rationality, A^1_1 is the first set, and A^1_2 is the second set of heuristics in a single pair of mutually exclusive heuristics. MSE at τ equals to 1%, and 5% correspond to POF-backtest of VaR at 1%, and 5% respectively. τ equals to (1%+5%) is the joint MSE test.

	$P^*(\tilde{A})$				
τ %	R	A^1_1	A^1_2	θ^*	MSE^*_τ
Panel A: Rationality					
τ =1%	1.0	0.0	0.0	-	0.118
τ =5%	1.0	0.0	0.0	-	0.03352
τ =(1%+5%)	1.0	0.0	0.0	-	0.07576
Panel B: Pessimism (A^1_1) / Optimism (A^1_2), with a_{jt}=0, $\bar{r_j}$					
τ = 1%	0.0	0.1	0.9	0.993	0.032
	0.0	0.5	0.5	0.999	0.032
	0.1	0.3	0.6	0.998	0.032
	0.2	0.1	0.7	0.994	0.032
	0.2	0.2	0.6	0.997	0.032
	0.2	0.4	0.4	0.999	0.032
	0.3	0.4	0.3	0.999	0.032
	0.4	0.1	0.5	0.995	0.032
	0.5	0.1	0.4	0.996	0.032
	0.5	0.2	0.3	0.998	0.032
	0.5	0.3	0.2	0.999	0.032
	0.7	0.1	0.2	0.997	0.032
	0.8	0.2	0.0	0.999	0.032
	0.9	0.1	0.0	0.998	0.032
τ = 5%	0.8	0.0	0.2	0.997	0.01168
τ = (1%+5%)	0.0	0.1	0.9	0.993	0.0228
Panel C: Pessimism (A^1_1) / Optimism (A^1_2), with a_{jt}=$r_{j,t-1}$					
τ = 1%	0.4	0.1	0.5	0.993	0.022
	0.5	0.1	0.4	0.995	0.022
	0.6	0.1	0.3	0.995	0.022
τ = 5%	0.1	0.2	0.7	0.998	0.01136
	0.8	0.0	0.2	0.990	0.01136
τ = (1%+5%)	0.1	0.1	0.8	0.991	0.02504

Table 2.2 (Continued)

	$P^{*}(\tilde{A})$				
τ %	R	A_1^1	A_2^1	θ^*	MSE_τ^*
Panel D: Overconfidence (A_1^1) / Doubt (A_2^1), with a_{jt}=0					
τ = 1%	0.0	0.5	0.5	0.999	0.032
	0.1	0.6	0.3	0.998	0.032
	0.2	0.4	0.4	0.999	0.032
	0.2	0.6	0.2	0.997	0.032
	0.2	0.7	0.1	0.994	0.032
	0.3	0.3	0.4	0.999	0.032
	0.4	0.5	0.1	0.995	0.032
	0.5	0.2	0.3	0.999	0.032
	0.5	0.3	0.2	0.998	0.032
	0.5	0.4	0.1	0.996	0.032
	0.7	0.2	0.1	0.997	0.032
	0.8	0.0	0.2	0.999	0.032
	0.9	0.0	0.1	0.998	0.032
τ = 5%	0.1	0.8	0.1	0.992	0.01104
τ = (1%+5%)	0.1	0.8	0.1	0.992	0.02252
Panel E: Overconfidence (A_1^1) / Doubt (A_2^1), with a_{jt} = $\bar{r}_j$					
τ = 1%	0.0	0.5	0.5	0.999	0.032
	0.1	0.6	0.3	0.998	0.032
	0.2	0.4	0.4	0.999	0.032
	0.2	0.6	0.2	0.997	0.032
	0.2	0.7	0.1	0.994	0.032
	0.3	0.3	0.4	0.999	0.032
	0.4	0.5	0.1	0.995	0.032
	0.5	0.2	0.3	0.999	0.032
	0.5	0.3	0.2	0.998	0.032
	0.5	0.4	0.1	0.996	0.032
	0.7	0.2	0.1	0.997	0.032
	0.8	0.0	0.2	0.999	0.032
	0.9	0.0	0.1	0.998	0.032
τ = 5%	0.0	0.9	0.1	0.990	0.00888
τ = (1%+5%)	0.2	0.7	0.1	0.994	0.02204

TABLE 2.2 (CONTINUED)

	$P^*(\tilde{A})$				
τ %	R	A_1^1	A_2^1	θ^*	MSE^*_τ
Panel F: Overconfidence (A_1^1) / Doubt (A_2^1), with a_{jt}=$r_{j,t-1}$					
τ = 1%	0.1	0.6	0.3	0.997	0.03
	0.5	0.4	0.1	0.992	0.03
	0.6	0.3	0.1	0.992	0.03
	0.7	0.2	0.1	0.994	0.028
τ =5%	0.1	0.7	0.2	0.999	0.01136
τ =(1%+5%)	0.3	0.6	0.1	0.990	0.02268
Panel G: Conservatism (A_1^1) / Availability (A_2^1)					
τ =1%	0.0	0.0	1.0	0.997	0.004
τ = 5%	0.0	0.0	1.0	0.988	0.00552
τ = (1%+5%)	0.0	0.0	1.0	0.996	0.00816

*

Table 2.3: The Minimum MSE for Two Pairs of Mutually Exclusive Heuristics

The estimation results for various combinations of two pairs of mutually exclusive heuristics and the three possible values of target return a_{jt} (0, $\bar{r_j}$, and $r_{j,t-1}$). The sets of probabilities $P^*(\tilde{A})$, and the decay factor θ^*, which corresponds to the cross-sectional minimum MSE^*_τ at τ percentile. R represents rationality, A^1_1, and A^1_2 are the sets of heuristics in the first pair of mutually exclusive heuristics, and A^2_1, and A^2_2 are the sets of heuristics in the second pair of mutually exclusive heuristics.

	$P^*(\tilde{A})$										
τ%	R	A^1_1	A^1_2	A^2_1	A^2_2	$A^1_1 \cap A^2_1$	$A^1_1 \cap A^2_2$	$A^1_2 \cap A^2_1$	$A^1_2 \cap A^2_2$	θ^*	MSE^*_τ
Panel A: Pessimism (A^1_1) / Optimism (A^1_2) and Overconfidence (A^2_1) / Doubt (A^2_2), with $a_{jt} = 0$											
τ=1%	0.0	0.1	0.9	0.5	0.5	0.1	0.0	0.4	0.5	0.998	0.02
	0.0	0.2	0.8	0.5	0.5	0.2	0.0	0.3	0.5	0.998	0.02
	0.0	0.2	0.8	0.6	0.4	0.0	0.2	0.6	0.2	0.998	0.02
	0.0	0.3	0.7	0.4	0.6	0.1	0.2	0.3	0.4	0.999	0.02
	0.0	0.3	0.7	0.5	0.5	0.3	0.0	0.2	0.5	0.998	0.02
	0.0	0.3	0.7	0.6	0.4	0.1	0.2	0.5	0.2	0.998	0.02
	0.0	0.4	0.6	0.5	0.5	0.4	0.0	0.1	0.5	0.998	0.02
	0.0	0.4	0.6	0.6	0.4	0.2	0.2	0.4	0.2	0.998	0.02
	0.0	0.5	0.5	0.5	0.5	0.5	0.0	0.0	0.5	0.998	0.02
	0.1	0.0	0.9	0.5	0.4	0.0	0.0	0.5	0.4	0.997	0.02
	0.1	0.1	0.8	0.5	0.4	0.1	0.0	0.4	0.4	0.997	0.02
	0.1	0.1	0.8	0.7	0.2	0.0	0.1	0.7	0.1	0.995	0.02
	0.1	0.2	0.7	0.3	0.6	0.2	0.0	0.1	0.6	0.999	0.02
	0.1	0.2	0.7	0.5	0.4	0.2	0.0	0.3	0.4	0.997	0.02
	0.1	0.2	0.7	0.7	0.2	0.1	0.1	0.6	0.1	0.995	0.02
	0.1	0.3	0.6	0.3	0.6	0.3	0.0	0.0	0.6	0.999	0.02
	0.1	0.3	0.6	0.5	0.4	0.3	0.0	0.2	0.4	0.997	0.02
	0.1	0.3	0.6	0.7	0.2	0.2	0.1	0.5	0.1	0.995	0.02
	0.1	0.4	0.5	0.5	0.4	0.4	0.0	0.1	0.4	0.997	0.02
	0.1	0.4	0.5	0.7	0.2	0.3	0.1	0.4	0.1	0.995	0.02
	0.1	0.5	0.4	0.5	0.4	0.5	0.0	0.0	0.4	0.997	0.02
	0.1	0.5	0.4	0.7	0.2	0.4	0.1	0.3	0.1	0.995	0.02
	0.1	0.6	0.3	0.5	0.4	0.5	0.1	0.0	0.3	0.998	0.02
	0.1	0.6	0.3	0.7	0.2	0.5	0.1	0.2	0.1	0.995	0.02
	0.1	0.7	0.2	0.7	0.2	0.6	0.1	0.1	0.1	0.995	0.02
	0.1	0.8	0.1	0.7	0.2	0.7	0.1	0.0	0.1	0.995	0.02
	0.2	0.4	0.4	0.3	0.5	0.2	0.2	0.1	0.3	0.999	0.02
	0.4	0.0	0.6	0.3	0.3	0.0	0.0	0.3	0.3	0.997	0.02
	0.4	0.1	0.5	0.3	0.3	0.0	0.1	0.3	0.2	0.998	0.02
	0.4	0.1	0.5	0.3	0.3	0.1	0.0	0.2	0.3	0.997	0.02
	0.4	0.2	0.4	0.3	0.3	0.2	0.0	0.1	0.3	0.997	0.02
	0.4	0.3	0.3	0.3	0.3	0.3	0.0	0.0	0.3	0.997	0.02
	0.5	0.1	0.4	0.1	0.4	0.0	0.1	0.1	0.3	0.999	0.02
	0.7	0.0	0.3	0.1	0.2	0.0	0.0	0.1	0.2	0.997	0.02
	0.7	0.1	0.2	0.1	0.2	0.1	0.0	0.0	0.2	0.997	0.02
τ=5%	0.3	0.6	0.1	0.6	0.1	0.5	0.1	0.1	0.0	0.997	0.01072
τ=(1%+5%)	0.4	0.0	0.6	0.3	0.3	0.0	0.0	0.3	0.3	0.997	0.01728

Table 2.3 (Continued)

	$P^*(\tilde{A})$										
τ%	R	A_1^1	A_2^1	A_1^2	A_2^2	$A_1^1 \cap A_1^2$	$A_1^1 \cap A_2^2$	$A_2^1 \cap A_1^2$	$A_2^1 \cap A_2^2$	θ^*	MSE_τ^*
Panel B: Pessimism (A_1^1) / Optimism (A_2^1) and Overconfidence (A_1^2) / Doubt (A_2^2), with $a_{jt} = \bar{r_j}$											
τ=1%	0.1	0.0	0.9	0.6	0.3	0.0	0.0	0.6	0.3	0.994	0.014
	0.1	0.1	0.8	0.6	0.3	0.1	0.0	0.5	0.3	0.994	0.014
	0.1	0.2	0.7	0.6	0.3	0.2	0.0	0.4	0.3	0.994	0.014
	0.1	0.3	0.6	0.6	0.3	0.3	0.0	0.3	0.3	0.994	0.014
	0.1	0.4	0.5	0.6	0.3	0.4	0.0	0.2	0.3	0.994	0.014
	0.1	0.5	0.4	0.6	0.3	0.5	0.0	0.1	0.3	0.994	0.014
	0.1	0.6	0.3	0.6	0.3	0.6	0.0	0.0	0.3	0.994	0.014
τ=5%	0.3	0.4	0.3	0.4	0.3	0.4	0.0	0.0	0.3	0.997	0.01048
τ=(1%+5%)	0.7	0.0	0.3	0.1	0.2	0.0	0.0	0.1	0.2	0.986	0.01596
	0.7	0.1	0.2	0.1	0.2	0.1	0.0	0.0	0.2	0.986	0.01596
Panel C: Pessimism (A_1^1) / Optimism (A_2^1) and Overconfidence (A_1^2) / Doubt (A_2^2), with $a_{jt} = r_{j,t-1}$											
τ=1%	0.0	0.6	0.4	0.6	0.4	0.5	0.1	0.1	0.3	0.992	0.014
	0.0	0.7	0.3	0.6	0.4	0.6	0.1	0.0	0.3	0.992	0.014
	0.1	0.4	0.5	0.4	0.5	0.3	0.1	0.1	0.4	0.996	0.014
	0.1	0.5	0.4	0.4	0.5	0.4	0.1	0.0	0.4	0.996	0.014
	0.1	0.5	0.4	0.5	0.4	0.4	0.1	0.1	0.3	0.994	0.014
	0.1	0.6	0.3	0.5	0.4	0.5	0.1	0.0	0.3	0.994	0.014
τ=5%	0.0	0.8	0.2	0.7	0.3	0.7	0.1	0.0	0.2	0.994	0.01024
τ=(1%+5%)	0.0	0.7	0.3	0.6	0.4	0.6	0.1	0.0	0.3	0.992	0.01332
Panel D: Pessimism (A_1^1) / Optimism (A_2^1) and Conservatism (A_1^2) / Availability (A_2^2), with $a_{jt} = 0, \bar{r_j}$											
τ=1%	0.1	0.2	0.7	0.0	0.9	0.0	0.2	0.0	0.7	0.992	0.002
	0.1	0.2	0.7	0.1	0.8	0.0	0.2	0.1	0.6	0.992	0.002
τ=5%	0.1	0.2	0.7	0.2	0.7	0.0	0.2	0.2	0.5	0.989	0.00032
τ=(1%+5%)	0.0	0.3	0.7	0.2	0.8	0.0	0.3	0.2	0.5	0.995	0.00476
Panel E: Pessimism (A_1^1) / Optimism (A_2^1) and Conservatism (A_1^2) / Availability (A_2^2), with $a_{jt} = r_{j,t-1}$											
τ=1%	0.0	0.3	0.7	0.1	0.9	0.0	0.3	0.1	0.6	0.993	0.002
τ=5%	0.1	0.2	0.7	0.3	0.6	0.0	0.2	0.3	0.4	0.986	0.00088
τ=(1%+5%)	0.0	0.3	0.7	0.1	0.9	0.0	0.3	0.1	0.6	0.993	0.00236

Table 2.3 (Continued)

						$P^*(\tilde{A})$					
τ%	R	A_1^1	A_2^1	A_1^2	A_2^2	$A_1^1 \cap A_1^2$	$A_1^1 \cap A_2^2$	$A_2^1 \cap A_1^2$	$A_2^1 \cap A_2^2$	θ^*	MSE_τ^*
Panel F: Conservatism (A_1^1) / Availability (A_2^1) and Overconfidence (A_1^2) / Doubt (A_2^2), with $a_{jt} = 0$											
τ=1%	0.0	0.0	1.0	0.8	0.2	0.0	0.0	0.8	0.2	0.994	0.012
	0.0	0.0	1.0	0.9	0.1	0.0	0.0	0.9	0.1	0.985	0.012
	0.0	0.1	0.9	0.8	0.2	0.1	0.0	0.7	0.2	0.994	0.012
	0.0	0.1	0.9	0.9	0.1	0.1	0.0	0.8	0.1	0.985	0.012
	0.0	0.2	0.8	0.8	0.2	0.2	0.0	0.6	0.2	0.994	0.012
	0.0	0.2	0.8	0.9	0.1	0.2	0.0	0.7	0.1	0.985	0.012
	0.0	0.3	0.7	0.8	0.2	0.3	0.0	0.5	0.2	0.994	0.012
	0.0	0.3	0.7	0.9	0.1	0.3	0.0	0.6	0.1	0.985	0.012
	0.0	0.4	0.6	0.9	0.1	0.4	0.0	0.5	0.1	0.985	0.012
	0.0	0.5	0.5	0.8	0.2	0.5	0.0	0.3	0.2	0.994	0.012
	0.0	0.5	0.5	0.9	0.1	0.5	0.0	0.4	0.1	0.985	0.012
	0.0	0.6	0.4	0.8	0.2	0.6	0.0	0.2	0.2	0.994	0.012
	0.0	0.6	0.4	0.9	0.1	0.6	0.0	0.3	0.1	0.985	0.012
	0.0	0.7	0.3	0.9	0.1	0.7	0.0	0.2	0.1	0.985	0.012
	0.0	0.8	0.2	0.9	0.1	0.8	0.0	0.1	0.1	0.985	0.012
	0.0	0.9	0.1	0.9	0.1	0.9	0.0	0.0	0.1	0.985	0.012
	0.1	0.0	0.9	0.8	0.1	0.0	0.0	0.8	0.1	0.987	0.012
	0.1	0.1	0.8	0.8	0.1	0.1	0.0	0.7	0.1	0.987	0.012
	0.1	0.2	0.7	0.8	0.1	0.2	0.0	0.6	0.1	0.987	0.012
	0.1	0.3	0.6	0.8	0.1	0.3	0.0	0.5	0.1	0.987	0.012
	0.1	0.4	0.5	0.8	0.1	0.4	0.0	0.4	0.1	0.987	0.012
	0.1	0.5	0.4	0.8	0.1	0.5	0.0	0.3	0.1	0.987	0.012
	0.1	0.6	0.3	0.8	0.1	0.6	0.0	0.2	0.1	0.987	0.012
	0.1	0.7	0.2	0.8	0.1	0.7	0.0	0.1	0.1	0.987	0.012
	0.1	0.8	0.1	0.8	0.1	0.8	0.0	0.0	0.1	0.987	0.012
τ=5%	0.0	0.3	0.7	0.8	0.2	0.3	0.0	0.5	0.2	0.989	0.0008
τ=(1%+5%)	0.2	0.2	0.6	0.6	0.2	0.2	0.0	0.4	0.2	0.995	0.015

Table 2.3 (Continued)

							$P^*(\tilde{A})$				
τ%	R	A_1^1	A_2^1	A_1^2	A_2^2	$A_1^1 \cap A_1^2$	$A_1^1 \cap A_2^2$	$A_2^1 \cap A_1^2$	$A_2^1 \cap A_2^2$	θ^*	MSE_τ^*
Panel G: Conservatism (A_1^1) / Availability (A_2^1) and Overconfidence (A_1^2) / Doubt (A_2^2), with $a_{jt} = \bar{r_j}$											
τ=1%	0.0	0.0	1.0	0.8	0.2	0.0	0.0	0.8	0.2	0.994	0.012
	0.0	0.0	1.0	0.9	0.1	0.0	0.0	0.9	0.1	0.985	0.012
	0.0	0.1	0.9	0.8	0.2	0.1	0.0	0.7	0.2	0.994	0.012
	0.0	0.1	0.9	0.9	0.1	0.1	0.0	0.8	0.1	0.985	0.012
	0.0	0.2	0.8	0.8	0.2	0.2	0.0	0.6	0.2	0.994	0.012
	0.0	0.2	0.8	0.9	0.1	0.2	0.0	0.7	0.1	0.985	0.012
	0.0	0.3	0.7	0.9	0.1	0.3	0.0	0.6	0.1	0.985	0.012
	0.0	0.4	0.6	0.9	0.1	0.4	0.0	0.5	0.1	0.985	0.012
	0.0	0.5	0.5	0.8	0.2	0.5	0.0	0.3	0.2	0.994	0.012
	0.0	0.5	0.5	0.9	0.1	0.5	0.0	0.4	0.1	0.985	0.012
	0.0	0.6	0.4	0.9	0.1	0.6	0.0	0.3	0.1	0.985	0.012
	0.0	0.7	0.3	0.9	0.1	0.7	0.0	0.2	0.1	0.985	0.012
	0.0	0.8	0.2	0.9	0.1	0.8	0.0	0.1	0.1	0.985	0.012
	0.0	0.9	0.1	0.9	0.1	0.9	0.0	0.0	0.1	0.985	0.012
	0.1	0.0	0.9	0.8	0.1	0.0	0.0	0.8	0.1	0.988	0.012
	0.1	0.1	0.8	0.8	0.1	0.1	0.0	0.7	0.1	0.988	0.012
	0.1	0.2	0.7	0.8	0.1	0.2	0.0	0.6	0.1	0.988	0.012
	0.1	0.3	0.6	0.8	0.1	0.3	0.0	0.5	0.1	0.988	0.012
	0.1	0.4	0.5	0.8	0.1	0.4	0.0	0.4	0.1	0.988	0.012
	0.1	0.5	0.4	0.8	0.1	0.5	0.0	0.3	0.1	0.988	0.012
	0.1	0.6	0.3	0.8	0.1	0.6	0.0	0.2	0.1	0.988	0.012
	0.1	0.7	0.2	0.8	0.1	0.7	0.0	0.1	0.1	0.988	0.012
	0.1	0.8	0.1	0.8	0.1	0.8	0.0	0.0	0.1	0.988	0.012
τ=5%	0.0	0.1	0.9	0.8	0.2	0.1	0.0	0.7	0.2	0.989	0.0004
τ=(1%+5%)	0.0	0.1	0.9	0.7	0.3	0.0	0.1	0.7	0.2	0.997	0.0138
Panel H: Conservatism (A_1^1) / Availability (A_2^1) and Overconfidence (A_1^2) / Doubt (A_2^2), with $a_{jt} = r_{j,t-1}$											
τ=1%	0.1	0.1	0.8	0.7	0.2	0.1	0.0	0.6	0.2	0.991	0.002
	0.2	0.1	0.7	0.6	0.2	0.1	0.0	0.5	0.2	0.992	0.002
τ=5%	0.0	0.2	0.8	0.8	0.2	0.2	0.0	0.6	0.2	0.985	0.00096
τ=(1%+5%)	0.1	0.1	0.8	0.7	0.2	0.1	0.0	0.6	0.2	0.991	0.00268

3 Higher-Order Return Moments under Irrational Behaviour

3.1 Introduction

An extensive literature documents the departure from the normality of asset return distribution. However, returns are generally assumed as normally distributed in theoretical models of financial researches for convenience. Bond and Patel (2003) mention that this assumption is incompatible with the analysis of most financial data. Empirical evidence of financial markets has shown that large movements occur more frequently than would be observed with normally distributed returns and that returns tend to be of the same sign than of opposite signs. Financial series is proven to be skewed and fat-tailed (Bollerslev (1987), Mandelbrot (1997), Das and Sundaram (1997), Perez-Quiros and Timmermann (2001), Alizadeh and Gabrielsen (2011), and many other). By definition, skewness is a measure of asymmetry, and kurtosis is a measure of the steepness of a probability distribution indicating the thickness of the tails.

It is well established that stock return distributions exhibit negative skewness and excess kurtosis. Negative skewness means the left-hand side of the return distribution is accentuated. This suggests that the market puts a higher probability to decreases than increases in asset pricing. Conversely, excess kurtosis makes extreme observations more likely than in the normal case. This implies that the market assigns a higher probability to outliers than in normal distribution (See León et al. (2005)). Therefore, failing to account for these distributional characteristics of the return series will have serious implications in risk management, Value-at-Risk (VaR) estimation, derivatives pricing, security valuation, trading and hedging activities, portfolio selection, and asset allocation. The existence of asymmetries in stock return distribution is widely accepted[1]; however, what causes it is still uncertain.

Earlier studies have identified the presence of negative skewness with the volatility in the equity markets[2]. This property is known as *asymmetric volatility* that is the positive association of volatility with negative asset returns. The presence of asymmetric volatility is more pronounced during the stock market crashes when the massive decreases in stock prices are accompanied by a substantial increase in market volatility (Wu, 2001). Later, many alternative economic theories have been developed to explain the market return asymmetries, such as leverage-effects, volatility-feedback,

[1] Fang and Lai (1997), Jurczenko et al. (2005), Jurczenko and Maillet (2006), Chung et al. (2006), Guidolin and Timmermann (2008), Bhandari and Das (2009), Maringer and Parpas (2009), Harvey et al. (2010), Kostakis et al. (2012), Sihem and Slaheddine (2014), Chen et al. (2020), and Javed et al. (2021)

[2] Pindyck (1983), French et al. (1987), Campbell and Hentschel (1992), Engle and Ng (1993), Braun et al. (1995), Duffee (1995), Koutmos and Booth (1995), Hong and Stein (1999a), Bekaert and Wu (2000), Wu (2001), Dennis et al. (2006), McAleer et al. (2007), Goudarzi and Ramanarayanan (2011)

and bubble theories that are based on the representative investor framework[3].

Hong and Stein (1999a) first propose an alternative theory based on investor heterogeneity that can explain the asymmetries in stock return distribution. The model is built on the assumption that there are differences of opinion among investors, who face short-sales constraints. They claim that the return distribution becomes more negatively skewed when trading volume is high. Extant literature has considered trading volume as a proxy for the intensity of disagreement, which rises with the degree of heterogeneity among investors (Varian (1989), Harris and Raviv (1993), Kandel and Pearson (1995), Odean (1998b), and Hong and Stein (2003)).

With this motivation, Chen et al. (2001) examine the differences-of-opinion theory by forecasting the unconditional skewness in daily returns of individual stocks with the series of cross-sectional regression specifications. The investor heterogeneity is attributed to the recent deviation of turnover from its trend. Their empirical investigation finds that negative skewness is more pronounced in stocks that have experienced either an increase in turnover or high past returns. However, the estimation approach of Chen et al. (2001) has been criticized. They compute the sample skewness in daily returns using non-overlapping 6-month period data, which leads to statistical power loss due to insufficient sample size. It is also too restrictive to assume that the skewness measure is fixed within the given 6-month period.

Hueng and McDonald (2005) suggest that skewness is expected to be time-varying across the 6-month periods. They propose an alternative measure of asymmetry that changes every day with daily available information. Instead of using the unconditional sample skewness in 6-month periods, they employ a parametric model to compute the conditional skewness[4]. They find that higher prior turnover either predicts a more positively skewed distribution for future market returns or does not have a statistically significant predicting power on market skewness. They do not support the prediction of Hong and Stein (2003) model and mark trading volume as a bad proxy for opinion divergence. However, this conclusion may not be appropriate as Hueng and McDonald (2005) compare their conditional skewness forecasting model with the unconditional skewness forecasting model of Chen et al. (2001).

[3]See Chen et al. (2001). The *leverage effect* is one of the explanations, which states a decline in prices raises the operating and financial leverage that further increases the volatility of subsequent returns. The *volatility feedback* mechanism is another theory. It explains that the arrival of any kind of information (good news or bad news) in the market increases the risk premium that escalates the market volatility. The *stochastic bubble model* also explains the asymmetries in market returns, where the least likely event produces large negative returns. All these theories concentrate on the mechanisms in the aggregate, which has been formulated as a representative-agent model.

[4]The GARCH model is used to estimate the daily conditional skewness. Hueng and McDonald (2005) utilize the theoretical guidance from the Hong-Stein model and the empirical evidence from Chen et al. (2001) in specifying the time-varying asymmetry parameter and selecting the explanatory variables. Their results are consistent with the prediction of past returns, but not with that of turnover.

To verify this issue, we measure time-varying skewness with the overlapping approach like Hueng and McDonald (2005) and then investigate whether opinion divergence can predict the unconditional negative skewness. The non-overlapping approach of Chen et al. (2001) is also used. We then contrast the results from the overlapping model with the estimates from the non-overlapping model to confirm whether trading volume can predict negative skewness. We further investigate whether trading volume can also explain excess kurtosis, which is another major source of asymmetry in stock return distribution.

Besides proposing the theory of investor heterogeneity, Hong and Stein (1999a) have demonstrated a behavioural notion. The existence of negative skewness and excess kurtosis indicates that stock markets are susceptible to crashes. Hong and Stein (1999a) identify market crashes as "behavioural" because it relies on less-than-fully rational behaviour of investors. Therefore, the rational theories cannot explain the asymmetries in stock market return. By definition of the market crash[5], the significant decline in prices of all stocks happens when the majority of investors overreact and behave in the same way. Whereas, trading volume reflects the intensity of opinion divergence among investors, which is incongruous to the prevailing behaviour during a market crash. We propose employing some behavioural factors that describe how investors' irrational behaviour during extreme market conditions may influence negative skewness and excess kurtosis of stock returns.

Behavioural finance literature has identified that the behaviour of investors is systematic rather than random. Investors tend to follow the advice of financial experts, track stock price patterns, actively trade stocks, sell winning stocks and hold on to losing stocks that increase their tax liabilities. Posner (2012) observes that traders are not interested in what they think about the company's future earnings are expected to reach, rather mostly interested in whether other traders think the stocks will rise or fall in value. When other traders consider a stock to be undervalued, an investor finds it a good reason to buy it without looking at the company's prospect income. This is called "momentum trading" - buying when others are buying, selling when others are selling. Momentum trading is very dangerous for the economy as it can start asset price bubbles[6] that lead to stock market crashes with an eventual economic crisis. The irrational behaviour with respect to momentum

[5]Hong and Stein (1999a) define the word "crash" with three distinct elements. First, a crash is an unusually large movement in stock prices that happens in the absence of any major public news event. Second, the large price movement is negative that directly induces asymmetry in stock returns. Finally, a crash is widely contagious in the market, which means a massive drop of a single stock price causes the' subsequent decline in prices of all stocks that are highly correlated.

[6]Posner (2012) has defined the bubble as a disequilibrium event with a steep increase in price that continues for a long time, and then after peaking, sharply fall in price. Large price movements happen when a bulk of traders react in the same way and it becomes difficult to find anyone on the other side willing to buy or sell stocks. The bubble bursting is purely a psychological phenomenon, as when enough traders become fearful and want to get out of the market, they sell off their winning position and prick the bubble.

trading, bubble bursting, selling winning stocks, and holding on to losing stocks can significantly affect the stock return distribution (See Daniel et al. (1998), Odean (1998b)). Therefore, our proposed behavioural factors based on investors' biased investment decisions during momentum trading that force them to behave in the same way are deemed to explain the higher-order return moments.

Our study contributes to the literature by exploring whether investors' irrational behaviour through various behavioural factors can predict the third (skewness) and the fourth (kurtosis) moments of the stock return distribution. Previous studies have examined the inverse relationship in which non-normality of return influences investor's preference towards asset allocation[7]. It is proven that investors are averse to negative skewness and excess kurtosis (Kimball, 1993; Maringer and Parpas, 2009; Scott and Horvath, 1980). This helps us to analyse the relationship between our proposed behavioural factors and the asymmetric parameter. Our empirical results confirm that negative skewness generates from market overreaction due to price change signal, herding intensity, momentum return, and off-optimistic season. We also observe that excess kurtosis originates from market overreaction, herding intensity, and the disparity between winning stocks and losing stocks.

The remaining of this paper is organized as follows. Section 3.2 discusses the behavioural theories and formulates the behavioural factors that demonstrate how investors' behaviour in the market causes asymmetry in stock return distribution. Section 3.3 describes the data used for analysis, presents the models and methodology, and compares the empirical results. Section 3.4 concludes.

3.2 Irrationality and Behavioural Factors

Investor's irrational behaviour in investment is the foremost source of booms and busts in the market. Stock market crashes from time to time due to significant asset price drops are driven by the biased investment decisions of a large number of investors, who react in the same way. This motivates us to present the following behavioural propositions based on investors' biased investment decisions that appear during momentum trading. These propositions utilize some acclaimed behavioural theories to derive behavioural factors that may affect stock return distribution.

Proposition 1: Regret - Price Signal

[7]See Jurczenko et al. (2005), Jondeau and Rockinger (2006). Taylor series expansion is used to approximate the expected utility as a function of higher moments. They establish the theoretical foundations of a mean–variance–skewness–kurtosis decision criterion. In addition, Kleniati et al. (2009) claim that the investor seeks to maximize the expected return and the skewness of the portfolio and minimize the variance and kurtosis, subject to budget and no short-selling constraints. With asymmetric returns, an investor is willing to accept lower expected return and higher volatility in exchange for higher skewness and lower kurtosis (Dittmar, 2002; Harvey and Siddique, 2000; Martellini and Ziemann, 2010; Mitton and Vorkink, 2007).

The regret theory of Ricciardi and Simon (2000) asserts that investors usually avoid selling stocks that have declined in value to avoid the regret of making a bad investment decision and the discomfort of acknowledging the loss. Loss aversion is another explanation to avoid loss or discomfort. Merkle (2020) finds that a large part of investors' financial loss aversion[8] results from the projection bias. Camerer (2005) argues that loss aversion represents an emotional overreaction towards losses driven by fear.

This tendency of an investor to hold onto losing investments too long, while sell winners too soon are also referred to as the "disposition effect" in behavioural finance (Ackert, 2014; Odean, 1998a). Investors are hesitant to realize losses but quick to realize gains. Ritter (2003) explains this phenomenon with an example in which, if someone buys a stock at $30 that then drops to $22 before rising to $28, most people do not want to sell until the stock gets to above $30. The disposition effect shows the tendency of investors to update their reference points[9].

In the prospect theory of Kahneman and Tversky (1979), investors do not look at the final value of wealth, instead make decisions based on the gains and losses in comparison to some reference points. This indicates that the decision to long, short, or hold depends on the investor's position on that asset. Many researchers have examined investors' decisions by looking at the price differential. For example, Hirshleifer et al. (1994) demonstrate that investors' trading strategies are highly correlated with the price differential and its movement. Daniel et al. (1998) and Odean (1998b) argue that financial markets have more overconfident investors, who follow price changes to get information signals[10]. Ackert et al. (2006) investigate investor's behaviour by looking at price changes in response to changes in market wealth.

Our first behavioural factor is the daily price differential on individual stock that signals whether the investment position is winning or losing. We define *POS* as the indicator of gain and loss on a particular stock. *POS* is computed as the daily price change on stock *i*:

$$POS_{i,t} = P_{i,t} - P_{i,t-1} \tag{3.1}$$

[8]Merkle (2020) describes loss aversion as the greater sensitivity to losses as compared to gains. In other words, the expected negative feeling associated with a loss is larger than the expected positive feeling with a gain of equal size. It has been found that loss aversion is strong for anticipated outcomes with investors reacting over twice as sensitive to negative expected returns as to positive expected returns.

[9]See Abreu (2014); Kliger and Kudryavtsev (2008). This is also known as "anchoring and adjustment" because an investor makes investment decisions with a particular reference point called "anchor" and adjusts relative to the starting point.

[10]Odean (1998b) confirms that investors in financial markets are usually overconfident. The difficult task of buying and selling financial assets to earn higher returns makes investors more overconfident. Furthermore, selection bias and survivorship bias in the financial markets lead to more overconfident market participants. Overconfidence causes price-taking investors to have differing posterior beliefs.

where $P_{i,t}$ is the adjusted closing price of stock *i* at time *t*. The position of winning is attained when $P_{i,t} - P_{i,t-1} > 0$, and the position of losing is identified when $P_{i,t} - P_{i,t-1} < 0$. The reference point is the previous day price on the stock.

Cont and Bouchaud (1997) allege that the heavy tail observed in the distribution of stock returns is due to large fluctuations in prices and bursts of volatility. It is difficult to explain only in terms of variations in fundamental economic variables. Hence, trading volume that reflects the differences of opinion across investors, may not directly impact the market asymmetries. The stock price change can be a better alternative. Harris and Raviv (1993) and Cao and Ou-Yang (2008) demonstrate that trading volume and absolute price changes are positively serially correlated[11][12]. Kandel and Pearson (1995) and Huberman and Regev (2001) observe that the trading volume of a stock can be positive even if its price does not change. The negative asymmetries in stock returns are because of the significant price changes rather than the trading volume, which can be significantly high even when there is no price change.

Proposition 2: Herding - Following Market

Momentum trading also arises from "herd behaviour". It is the behaviour of investors trading in the same direction of the market and following other investors. Herding behaviour defies the efficient market hypothesis (EMH) under which all the assets are fairly priced as investors make informed decisions. Investors with herding behaviour copy the actions of others[13]. Since they disregard their own judgment in investment decisions, this ensues asset mispricing and inefficient market condition characterized by speculative bubbles [14]. Christie and Huang (1995) provide evidence of herding during periods of extreme market condition.

Herding behaviour is of two types: unintentional (spurious) herding that arises due to changes in fundamentals, and intentional (true) herding that results from following the behaviour of other investors[15]. In general, herding behaviour is influenced by investors' fear of their investment decisions. According to Asch (1952), disagreement of opinion causes anxiety and a desire to seek

[11]Harris and Raviv (1993) suggest that in the presence of options, the trading volume of the stock is related not only to its price change but also to lagged price changes. They find that when speculators overestimate (underestimate) the information they received, the consecutive price changes exhibit negative (positive) serial correlation.

[12]The empirical findings of Cao and Ou-Yang (2008) further show that even if there are no differences of opinion or no signals about stock's payoff, there may still be trading in the stock due to differences of opinion about the payoffs of other related stocks. This implies that the trading volume of a stock depends not only on its own stock price change but also on the price changes of related stocks.

[13]See Scharfstein and Stein (1990), Lakonishok et al. (1992), Grinblatt et al. (1995), Bikhchandani and Sharma (2001), Walter and Moritz Weber (2006), Holmes et al. (2013), Malik and Elahi (2014)

[14]See Christie and Huang (1995), Prosad et al. (2012)

[15]See Bikhchandani and Sharma (2001), Walter and Moritz Weber (2006), Holmes et al. (2013), and Malik and Elahi (2014).

consensus. The attempt to seek consensus is herding behaviour that requires a re-evaluation of the validity of one's opinions and observations. There is evidence that herding intensity increases with the credibility of the consensus, the concern with one's reputation, the lack of confidence in one's own ability, and the difficulty in forecasting earnings (Olsen (1996), Cote and Goodstein (1999), and Welch (2000)). Camerer (2005) also asserts that loss aversion due to fear of losses makes it easier for investors to herd by investing in the most popular assets.

Investors are additionally seen to herd when they use private information to decide whether or not to conform or deviate[16]. Thus, Hirshleifer et al. (1994) observe that the herding tendency increases if investors are overconfident about the information they receive early. The observed pattern shows that initially, an investor doubts about his own ability and fears losses. This compels him to herd. To herd, an investor needs to observe other investors and gather information, which he then uses with overconfidence. Thus, herding behaviour encapsulates investor's psychological biases of doubt, fear, and overconfidence. However, herding behaviour leads to more optimistically biased earnings forecasts and reduced perceptions of risk as earnings become more unpredictable. This results in abnormally low stock returns with more uncertain earnings (Huang and Wang (2017), Economou et al. (2018)).

The early evidence of herding in financial markets that led to the first major financial bubble in the 17th century is the tulip mania in Holland. Many recent studies have found the existence of herd behaviour in speculative markets[17]. Herding behaviour is significantly detected when the market is under stress during extreme conditions. For example, Hwang and Salmon (2001) observe that herding is more apparent before a crisis. Researchers have found pronounced herding behaviour during down-market periods[18], and also significant asymmetric herding during up-market periods[19]. Moreover, Cont and Bouchaud (1997) suggest that the excess kurtosis in asset returns is related to collective phenomena of herd behaviour. Since herding is one of the main reasons for market crashes, it is associated with the asymmetries in stock return distribution.

Various models of herd behaviour have been developed over time. Many of those models only provide theoretical arguments. The two recognized methods to capture herding behaviour in the empirical analysis are *CSSD* of Christie and Huang (1995) and *CSAD* of Chang et al. (2000). Christie

[16]See Scharfstein and Stein (1990), Banerjee (1992), Bikhchandani et al. (1992) Trueman (1994), and Hirshleifer et al. (1994)

[17]See Scharfstein and Stein (1990), Trueman (1994), Grinblatt et al. (1995), Welch (2000), Caparrelli et al. (2004), Basu et al. (2011), Prosad et al. (2012), and Malik and Elahi (2014)

[18]See Chang et al. (2000), Demirer et al. (2010), Chiang and Zheng (2010), Chen (2013), Philippas et al. (2013), Mobarek et al. (2014)

[19]See Tan et al. (2008), Economou et al. (2011), Economou et al. (2015)

and Huang (1995) provide the first formal test to identify herding behaviour in the market with cross-sectional standard deviation (*CSSD*). It is a measure of the average proximity of individual asset returns to the realized market average. They suggest the existence of herding behaviour in periods of market extremes is because investors do not use their own judgment and follow the aggregate market movement. While Chang et al. (2000) use cross-sectional absolute deviation (*CSAD*) to detect herd behaviour. *CSAD* is a widespread measure of return dispersion in the market, that shows a non-linear relationship.

We employ *CSAD* of Chang et al. (2000) to detect herd behaviour as it is more popular and is simply taken as the cross-sectional weighted average of the absolute deviation of returns from market return.

$$CSAD_t = \frac{1}{n}\sum_{i=1}^{n} |r_{it} - r_{mt}| \tag{3.2}$$

r_{mt} is the return on the CRSP index, and r_{it} is the return on the individual stock. Herding intensity is reduced as the dispersion between individual asset returns and overall market return falls.

Proposition 3: Price Momentum - Momentum Return

According to the theory of cognitive dissonance, some investors experience dissonance during the investment process of buying, selling, or holding assets (Goetzmann and Peles, 1997). Several studies have shown that investors invest more quickly in leading funds with strong performance gains than in lagging funds with poor investment returns. Investors are also changing their investment styles to modern internet-based investment[20], which is simply based on price momentum. Price momentum is the rate of change in price movement over a period of time that shows the strength of a trend. Investors use momentum when analyzing the trend as it indicates the strength and weakness in the asset price.

Many researchers have explained price momentum with behavioural theories that use investor's biased reactions to information. Several studies characterize price momentum as an underreaction[21]. Conversely, numerous researches suggest that the initial momentum gain in price is because of the market overreaction[22]. The underreaction of asset prices to news is observed in the short run, while overreaction is seen in the long run[23]. Bloomfield and Libby (1996) observe that the impact of price signal in the market depends on what fraction of traders receive that signal. In general, underreactions occur when all or majority of traders undervalue a signal; whereas overreactions

[20]Ricciardi and Simon (2000) believe that these internet investors contributed to the financial speculative bubble burst in March 2000 causing prices to decline by 70% for most stocks.

[21]See Jegadeesh and Titman (1993), Chan et al. (1996), Barberis et al. (1998), Hong and Stein (1999b)

[22]See De Long et al. (1990), Daniel et al. (1997), Lee and Swaminathan (2000)

[23]See Hong and Stein (1999b), and Hong et al. (2000)

happen when a major fraction of active traders significantly overvalue a signal.

The valuation errors in response to the underreaction and overreaction in the market appear from the investors' cognitive biases[24]. Daniel et al. (1997) suggest that the market underreaction and overreaction result from the psychological biases of overconfidence and self-attribution. They observe that when investors are overconfident about the precision of their private information and also exhibit biased self-attribution, it causes asymmetric shifts in investors' confidence as a function of their investment outcomes. Markets also reflect the same systematic biases as their participants. They demonstrate that stocks with excess volatility and uncertainty increase overconfidence among investors, and are subject to greater mispricing and public event-based return predictability.

Daniel et al. (1997) further show how investors' overreaction to stock price signal can be analysed with the covariance of price changes. Assuming the arrival of a private signal on date 1, overconfidence causes the stock price to overreact to new information. At date 2 the noisy public information signal arrives, the inefficient deviation of the price is partially corrected. The overreaction and correction implies that the covariance between date 1 price change and the date 2 price change is negative, i.e. $cov(P_2 - P_1, P_1 - P_0) < 0$. The overreaction to the private signal is fully corrected upon release of the date 3 public signal, so $cov(P_3 - P_1, P_1 - P_0) < 0$. Finally, the continuing correction starting at date 2 and ending at date 3 causes price changes to the public signal to be positively correlated, i.e $cov(P_3 - P_2, P_2 - P_1) > 0$. If investors are overconfident, price changes are unconditionally negatively autocorrelated at both short and long lags.

The opposite is seen if investor confidence changes owing to biased self-attribution. Because of the biased self-attribution stock price changes will exhibit unconditional short-lag positive autocorrelation ('momentum') and long-lag negative autocorrelation('reversal'). This implies that overreaction phase (not correction phase) can contribute positively to short-term momentum: $cov(P_2 - P_1, P_1 - P_0) > 0$. The mispricing is corrected on the subsequent dates causing overreactions to be reversed in the long-term: $cov(P_3 - P_1, P_1 - P_0) < 0$ and $cov(P_3 - P_2, P_2 - P_1) < 0$.

Investors' overreaction due to psychological bias cause significant mispricing and stock price fluctuations that can potentially explain the negative asymmetry of stock return. Unlike Daniel et al. (1997), we are not interested in finding whether the overreaction brings positive or negative

[24] For example, Barberis et al. (1998) demonstrate that the conservatism bias leads to initial underreaction as it prevents investors to update their prior beliefs immediately after receiving new information about a firm. There are also some investors, who suffer from the representativeness bias that leads to delayed overreaction. While, Odean (1998b) observe that markets with overconfident price-taking traders underreact to abstract, statistical, and highly relevant information, and overreact to salient, anecdotal, and less relevant information. Daniel et al. (1998, 1997) propose that informed investors exhibit overconfidence and biased self-attribution, for which they underreact to public information but overreact to private information. Conrad and Kaul (1998) affirm that overconfident investors overestimate the precision of his private information signal, but not of publicly received information.

momentum. With daily price change as a new signal, we only explore the effect of overreaction by looking at the $cov(P_2 - P_1, P_1 - P_0)$. We don't look at reversals that involve correction because they may not reflect the reaction to the significant asset price decline. Since the daily price change is measured by POS, we define COV of stock *i* at time *t* as:

$$COV_{i,t} = cov(P_2 - P_1, P_1 - P_0) = cov(POS_{i,t+1}, POS_{i,t}) \tag{3.3}$$

Overreaction due to overconfidence increases volatility around private signals that can increase or decrease volatility around public signals, but always increases unconditional volatility[25]. To explore the effect of investors' overreaction due to overconfidence, we also employ the volatility in the daily price change ($P_{i,t} - P_{i,t-1}$). Since the daily price change is measured by POS, we define the volatility as the variance of POS on stock *i* over the prior 6 month period. Thus, $VarPOS_{i,t}$ is:

$$VarPOS_{i,t} = \frac{1}{(n-1)} \sum_{t=1}^{n} (POS_{it} - E(POS_{it}))^2 \tag{3.4}$$

Biased reactions among the bulk of traders cause asset mispricing and serially correlated returns. For instance, with respect to some signals, overconfident investors may push up the prices of the winners above their fundamental values. The delayed overreaction leads to momentum profits that are eventually reversed. Hong and Stein (1999b) observe that investors initially underreact to news, but with gradual price adjustments underreaction turns into overreaction due to the activities of momentum traders. Odean (1998b) demonstrates that price adjustments in response to market reactions cause reversals as investors prefer to sell winners and hold losers.

The evidence in the financial market shows that investors long (buy) shares when stock exhibits bullish momentum (rising price) and short (sell) shares when stock exhibits bearish momentum (falling price). Jegadeesh and Titman (1993) have first identified that the momentum anomaly gives statistically and economically significant profits just by buying stocks with recent high returns and selling stocks with recent low returns. Chordia and Shivakumar (2006) and Heston and Sadka (2008) notice that investors can make abnormal profits for some certain period by using the winner-loser strategies built on price momentum analogy, which involves buying past winners and selling past losers. While, De Bondt and Thaler (1985, 1987) suggest that the opposite strategies of buying past

[25] See Daniel et al. (1997), and Odean (1998b). Overconfidence causes wider swings at date 1 away from fundamentals that produce excess price volatility around private signals $var(P_1 - P_0)$. The wide date 1 swings due to overconfidence need greater corrective price moves at dates 2 and 3, which can either increase or decrease the subsequent volatility around public signals.

losers and selling past winners achieve abnormal returns due to investor's reaction to information.

We follow Jegadeesh and Titman (1993) and Lee and Swaminathan (2000) to attain the winner-loser strategy. We sort all stocks in the sample based on returns in some prior performance period (K months) and group them into ten equally weighted portfolio stocks based on these ranks. According to the cross-sectional rank, we define extreme winners (*WIN*) as the cross-sectional weighted average of the average returns in the prior performance period for stocks in the top decile and compute extreme losers (*LOS*) by considering stocks in the bottom decile. Thus, the foremost step to analyse the momentum effect is to form decile portfolios by equally weighting all firms in the decile rankings.

For ranking, the daily stock returns for a prior K-month period are taken as equal-weighted average returns from strategies implemented in the current month and the previous K - 1 months. For example, when K=3, the daily return is based on an equal-weighted average of asset returns from this month's strategy, last month's strategy, and the strategy from two months ago. This is equivalent to revising the weights (approximately) one-third of the asset each month and carrying over the rest from the previous month.

In Lee and Swaminathan (2000), R10 represents the extreme winner stocks with the highest returns, and R1 representing the extreme loser stocks with the lowest returns during the previous K months. Thus, *WIN* is taken as the expected value of prior K months average returns for stocks in R10. Similarly, *LOS* is computed as the expected value of prior K months average returns for stocks in R1.

$$WIN_t = E[(\frac{1}{K}\sum_{t=K}^{K-1} r_{it}) \mid i \in R10] \tag{3.5}$$

$$LOS_t = E[(\frac{1}{K}\sum_{t=K}^{K-1} r_{it}) \mid i \in R1] \tag{3.6}$$

where *E*(.) is the cross-sectional equal weighted average return for stocks in R10 and R1. In each period *t*, we find WIN_t and LOS_t after finding the cross-sectional ranks of all stocks based on their prior K months equal weighted average returns. This will generate two time-series sequences: WIN_t with the highest positive returns, and LOS_t with the lowest negative returns. The momentum return (*PMN*) is then calculated with the difference between the return of the winning portfolio stocks (WIN_t) and the return of the losing portfolio stocks (LOS_t).

$$PMN_t = WIN_t - LOS_t \tag{3.7}$$

Like Chordia and Shivakumar (2006), we also denote this momentum return as *PMN*, which is for positive minus negative. It is also known as a zero investment portfolio that captures the price momentum phenomenon in time series and cross-sectional asset pricing tests. *WIN*, *LOS* and *PMN* help in identifying the winner-loser strategy that lead investors to make biased investment decisions.

Alternatively, Lee and Swaminathan (2000) suggest that trading volume can predict cross-sectional returns for various price momentum portfolios. Following Lee and Swaminathan (2000), we sort all the stocks based on their average daily turnover over the past K months and divide them into three volume portfolios, V1 to V3. V1 represents the lowest trading volume portfolio, and V3 represents the highest trading volume portfolio. We denote *HVR* for average high volume stocks return, which is computed by taking the cross-sectional expectation of prior K months average returns for stocks in V3. Similarly, we denote *LVR* for average low volume stocks return, which is obtained by taking the cross-sectional expectation of prior K months average returns for stocks in V1.

$$HVR_t = E[(\frac{1}{K}\sum_{t=K}^{K-1} r_{it}) \mid i \in V3] \tag{3.8}$$

$$LVR_t = E[(\frac{1}{K}\sum_{t=K}^{K-1} r_{it}) \mid i \in V1] \tag{3.9}$$

The findings of Lee and Swaminathan (2000) show that low volume stocks outperform high volume stocks. In contrast to the past, the high (low) volume stocks earn lower (higher) future returns. They provide strong evidence that the information of trading volume is related to market misperceptions of the firm's future earnings prospects. This is the reason low (high) volume stocks tend to be under- (over-) valued by the market. This implies that investors' expectations affect not only a stock's returns but also its trading activity. When stocks decline in popularity, their trading volume drops, and investors neglect them. While when stocks increase in popularity, their trading volume increases.

Investors' biased behaviour in underreaction and delayed overreaction attribute to the negative post-holding period returns of the momentum portfolio (Jegadeesh and Titman, 2001). Schwert (2003) defines the momentum as an exceptional anomaly that may persist for a long time. Chordia and Shivakumar (2002) find that with momentum strategies returns are positive only during expansionary periods, and are negative during recessions. Momentum return is expected to explain the substantial decrease in stock prices that may develop asymmetry in return distribution exhibiting negative skewness and excess kurtosis.

Proposition 4: Seasonality Effect - Mood Swings

The relationship between seasonality and stock market overreaction results from investor's biased investment decisions (De Bondt and Thaler, 1985; Zarowin, 1990). Kamstra et al. (2017) identify the strong association between the investor's mood or sentiment and the seasonality effect for different types of assets[26]. Investors prefer to flow funds to safer funds in the autumn, and risky funds in the spring, controlling for other regularities. The finding of Kramer and Weber (2012) also assert that individuals are on average significantly more financially risk-averse in the fall/winter than in the summer.

Bergsma and Jiang (2016) provide evidence that positive holiday moods, in conjunction with cash infusions before a cultural New Year, produce elevated stock prices, particularly among those stocks most preferred and traded by individual investors. The January effect is an eminent example of such an anomaly in the stock market. An extensive literature documents the January effect on stock performance (Rozeff and Kinney Jr (1976), Gultekin and Gultekin (1983), Keim (1983), Reinganum (1983), Tinic and West (1984), Ricciardi and Simon (2000) Bouman and Jacobsen (2002), Kamstra et al. (2003), and Heston and Sadka (2008)). Investors are in a good mood for which they expect above average gains in January. This happens because cash infusions in the form of employee bonuses at the cultural year-end and new money supply from retirement contributions, influence investor's optimistic holiday mood towards stock prices. In the presence of borrowing constraints, stock investment is made by a cash infusion that leads to abnormal returns around the cultural New Year. Similarly, at the beginning of the tax year, returns on stocks are unusually high as investors actively trade stocks to avoid capital gain tax[27].

Heston and Sadka (2008) demonstrate that the seasonality effect can explain the winner-loser strategies, which investors use in buying and selling stocks based on the historical trend. Seasonality effect on investment in the financial market is of two types: up-season, and down-season. In the up-season, investors are in a good mood and optimistic about investments. In the down-season, the market experiences more losses as investors are mostly pessimistic.

[26] The connection between seasonality and investors' mood is known as seasonal affective disorder (SAD) (Kamstra et al., 2017). Molin et al. (1996); Young et al. (1997) observe that winter blues and seasonal depression are associated with increased financial risk aversion. The flows to different fund categories (e.g., equity versus money market), controlling for known influences such as return chasing, capital gains tax avoidance, liquidity needs, year-end effects, and advertising expenditures, are strongly dependent on the season and interact with the relative riskiness of the categories. Households are seen to move money into relatively safe fund categories during the fall, and into riskier fund categories during the spring.

[27] See Shleifer (2000), and Posner (2012). The tendency of investors to sell winning stocks, and hold on to losing stocks at the tax year-end, increase their tax liabilities that can offset the capital gain tax. De Bondt and Thaler (1985, 1987) and Jegadeesh and Titman (1993) also observe that long-term losers outperform the long-term winners only in January due to the investor's reaction to information and tax-loss selling at the tax year-end.

In the up-season, investors are generally optimistic due to the January effect and holiday mood. In the U.S. the tax month is in January, for which tax-loss selling and January effect are seen with abnormal high returns on stocks. In addition, Kamstra et al. (2017) find returns to be higher from November to February. We denote *upS* for up-season, which takes the value 1 when the trading month is November to February and the trading day is 1 day before and after a major U.S. public holiday[28], or 0 otherwise.

While, in the down-season, there are larger declines in prices than increases. Kamstra et al. (2010) notice that average stock market returns on Mondays are lower due to the leverage effect[29]. Moreover, Ogden (2003) finds that the market experiences losses in April through September. Hence, we denote *downS* for down-season, which equals 1 when the trading month is April to September and the trading day is Monday, or 0 otherwise.

3.3 Empirical Investigation

3.3.1 Data

The empirical examination is based on the daily data of individual stock prices and their trading volume from the sample period December 31, 2009 to December 31, 2018. The stocks are all the NYSE, Nasdaq, and AMEX - commonly traded stocks with no missing returns during the sample period. The historical closing prices and the trading volume of the selected stocks are obtained from CRSP. To investigate whether models are sensitive to firm size, data are segregated into three groups of size-sorted stocks. A stock is defined as large-, mid-, or small-cap when its end-of-sample-period market value falls into, respectively, the highest, central, or lowest market capitalization quintile of all stocks in the sample. The return on the CRSP index for the same sample period is considered as a proxy for the market return. The risk-free return is the 3-month Treasury bill obtained from the FRED.

Table 3.1 reports the summary statistics for the time-series distributions of log returns on the individual stock. The cross-sectional distribution of skewness exhibits a size effect as skewness is negative and left-skewed for large and mid-cap stocks, and positive and right-skewed for small-cap stocks. The cross-sectional distribution of kurtosis is always leptokurtic.

[28]The 10 major federal holidays in the U.S. are New Years Day, Martin Luther King Day, Presidents Day, Good Friday, Memorial Day, Independence Day, Labor Day, Columbus Day, Veterans Day, Thanksgiving, and Christmas Day.

[29]For instance, intraday changes in leverage have a higher impact on volatility. The reason returns on Monday are negatively skewed is because a decline in prices on Monday morning increases the leverage and eventually volatility by Monday afternoon.

[Table 3.1]

3.3.2 Estimation and Testing Methodology

The Models

Following Chen et al. (2001), we investigate the predictability of next period higher-order stock return moments with the same factors as in their baseline regression model. We have two predictability models: (i) one period ahead negative skewness, and (ii) one period ahead excess kurtosis. In our baseline models, we also use $SIGMA_{it}$, $LOGSIZE_{it}$, $DTURNOVER_{it}$, and RET_{it} with its past five lagged return variables RET_{it-1},...,RET_{it-5} to predict NSk_{it+1} and $ExKr_{it+1}$. Both the models exhibit that the current observation of asymmetric parameter predicts the one-period ahead forecast. This means NSk_{it} is used to explain NSk_{it+1}, and $ExKr_{it}$ for $ExKr_{it+1}$.

The negative coefficient of skewness is measured as the negative ratio of the third moment of daily returns to the standard deviation of daily returns raised to power three. In a small sub-sample, the unbiased estimation of skewness[30] depends on the standardized deviation of each return observation from its target mean return raised to the power three.

$$NSk_{it} = -\frac{n}{(n-1)(n-2)} \sum_{t=1}^{n} \left(\frac{r_{it} - \mu}{s_i} \right)^3 \tag{3.10}$$

The unbiased excess kurtosis[31] is defined over the standardized deviation of each return observation from its mean raised to the power four.

$$ExKr_{it} = \left[\frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \left(\frac{r_{it} - \mu}{s_i} \right)^4 \right] - \frac{3(n-1)^2}{(n-2)(n-3)} \tag{3.11}$$

where n is the number of observation in the sub-sample, r_{it} is the daily return of stock *i* in period *t*. μ is its moving average over the 6 month period. s_{it} is the standard deviation[32] of stock *i* in the sub-sample of 6 month period. The daily return has been taken as (1) log-returns, (2) market-adjusted returns, (3) excess returns, and (4) beta-adjusted returns. NSk_{it}, $ExKr_{it}$, $SIGMA_{it}$ and RET_{it} are computed based on the target daily return series.

We estimate all the covariates in the same way as explained in Chen et al. (2001). We employ both overlapping and non-overlapping approaches. The overlapping approach helps to overcome

[30] See Bono et al. (2020); Rimoldini (2013)

[31] See Ivanovski et al. (2015), and Bono et al. (2020)

[32] The variance over the 6 month period is: $s_{it}^2 = \frac{1}{(n-1)} \sum_{t=1}^{n} (r_{it} - \mu)^2$

the problem of poor statistical significance, and the non-overlapping approach is used to ensure the previous findings. $SIGMA_{it}$ is the daily standard deviation of stock *i*'s daily returns in the 6 month period *t*, which is directly acquired from s_{it}. $LOGSIZE_{it}$ is the log of market capitalization of stock *i* at the end of period *t*. $DTURNOVER_{it}$ is the average daily turnover in the six-month period *t*, detrended by a moving average of turnover in the prior 18 months. The daily turnover coefficient for $DTURNOVER_{it}$ is taken as the ratio of total trading volume relative to the total number of shares outstanding. RET_{it} is the cumulative return on stock *i* over the 6 month period *t*. The past five lagged returns RET_{it-1},...,RET_{it-5} are then obtained from RET_{it} [33].

The baseline regression models[34] predict NSk_{it+1}, and $ExKr_{it+1}$ using the same factors as in Chen et al. (2001). We estimate the baseline regression models with both overlapping returns, and non-overlapping returns. Each baseline regression model is compared with our proposed behavioural models, in which each behavioural factor is added individually with the set of independent variables of the baseline model. Following Chen et al. (2001) we conduct the series of cross-sectional forecasting by involving panel data analysis with fixed effect model, which provides the same results as from pooled regression when time variants are controlled. In addition, panel data analysis are experimented with both random effect (RE) model and fixed effect (FE) model. The consistent appropriate model for predicting the higher order return moments is confirmed by the Hausman test.

Behavioural Factor Model

The behavioural factors from the previous section 3.2 are used in the baseline regression models. These factors are added individually as a control variable in the baseline regression models to examine which behavioural factors predict negative skewness and excess kurtosis. The statistically significant behavioural factors that are uncorrelated with each other are added together as covariates in the multiple behavioural factor model. This helps to explore whether investors' irrational behaviour can predict higher-order stock return moments.

Our behavioural factors can be segregated into two categories: (A) firm-specific factor that varies across the stocks, and (B) systematic factors that move with the market affecting all stocks in the same way. POS_{it}, $VarPOS_{it}$, and COV_{it} are firm-specific factors. We estimate POS_{it} first for each

[33] Each lagged variable in RET_{it-1},...,RET_{it-5} is lagged by daily observation with overlapping approach, and by 6 month return with non-overlapping approach.

[34] The baseline model for negative skewnesss: $NSk_{it+1} = \alpha_N NSk_{it} + \alpha_S Sigma_{it} + \alpha_L LOGSIZE_{it} + \alpha_D DTURNOVER_{it} + \alpha_0 RET_{it} + \alpha_1 RET_{it-1} + \alpha_2 RET_{it-2} + \alpha_3 RET_{it-3} + \alpha_4 RET_{it-4} + \alpha_{RET5} RET_{it-5} + \epsilon$ The beaseline model for excess kurtosis replaces NSk_{it} with $ExKr_{it}$, and NSk_{it+1} with $ExKr_{it+1}$

stock and then estimate $VarPOS_{it}$, and COV_{it} as they directly depend on the price differential of each stock. $CSAD_t$, LOS_t, WIN_t, PMN_t, LVR_t, HVR_t, upS_t, and $downS_t$ are systematic market factors that are same in period for all stocks. Each of these behavioural factors represents multiple behavioural heuristics as explained in the proposition.

LOS_t, WIN_t, PMN_t, LVR_t, and HVR_t depend on the return types. First, we compute the average return of stocks over the 6 month period[35]. Then, we find the the cross-sectional ranks of stocks based on the 6 month average return for LOS_t, and WIN_t and based on the 6 month average daily turnover for LVR_t, and HVR_t. LOS_t, WIN_t, LVR_t, and HVR_t are estimated as the expectation of the 6 month average return for those stocks that are sorted based on the cross-sectional ranks. PMN_t is calculated by subtracting LOS_t from WIN_t.

3.3.3 Empirical Results

The Hausman test confirms that the FE model is the appropriate forecasting model for both NSk_{it+1} and $ExKr_{it+1}$. In addition, the FE model is consistently selected with both overlapping and non-overlapping returns. The empirical results from the FE model are presented here that make our analysis comparable with Chen et al. (2001).

The baseline regression models with panel data forecasting of NSk_{it+1}, and $ExKr_{it+1}$ are presented in the first four columns of each table in table 3.2. The models with their respective significant factors are also estimated and presented in the last four columns of each table. Each table is identified by the model and the estimation approach, i.e. overlapping and non-overlapping returns.

[Table 3.2]

In panel A, forecasting NSk_{it+1} with overlapping returns of all market stocks, all the predictors except $SIGMA_{it}$ and RET_{it-4} are statistically significant. Panel B makes panel data forecasting of NSk_{it+1} with non-overlapping returns. None of the covariates are significant except for $LOGSIZE_{it}$ and some of the lagged returns. The coefficient of $LOGSIZE_{it}$ is always positive in both overlapping and non-overlapping approaches, indicating that negative skewness is more likely for larger stocks. The significant coefficients of past returns indicate that stocks, which have experienced a larger surge in past returns regardless of being negative and positive, are predicted to be more negatively skewed. Moreover, $DTURNOVER_{it}$ is statically insignificant with the pro-

[35] LOS_t, WIN_t, LVR_t, and HVR_t depend on the prior K-month performance period. Following Jegadeesh and Titman (1993, 2001), many researchers have considered K=6, to determine the profitability in momentum trading that defines the winner-loser strategies. We also consider K=6 months as it is consistent with the sampling period of Chen et al. (2001) and Hueng and McDonald (2005) in estimating negative skewness.

posed approach of Chen et al. (2001). Panels C and D display the forecasting of $ExKr_{it+1}$ with overlapping and non-overlapping returns respectively. $ExKr_{it}$, $SIGMA_{it}$, RET_{it}, and RET_{it-4} are only significant with all types of returns in both the panels. Highly volatile stocks are likely to have excess kurtosis.

[Table 3.3]

Table 3.3 represents the baseline model forecasting by firm size for market-adjusted returns. Panel A shows the panel data forecasting of NSk_{it+1} with both overlapping and non-overlapping market-adjusted returns. For all sized firms, NSk_{it}, $LOGSIZE_{it}$, and RET_{it} are significant with overlapping returns, and $LOGSIZE_{it}$ with non-overlapping returns. No size effect is seen with respect to $LOGSIZE_{it}$. The larger stocks in each size sorted group is more negatively skewed. Again, the insignificance of $DTURNOVER_{it}$ invalidates the claim of Chen et al. (2001) that higher prior turnover predicts negative skewness. Panel B displays the panel data forecasting of $ExKr_{it+1}$ with both overlapping and non-overlapping market-adjusted returns. Only overlapping returns exhibit some predictability with significant $ExKr_{it}$, $LOGSIZE_{it}$, and RET_{it}. In table 3.2 panel C, $LOGSIZE_{it}$ is also seen to be significant with market adjusted overlapping returns. It can be concluded that only $LOGSIZE_{it}$, and RET_{it} are significant predictors of both NSk_{it+1}, and $ExKr_{it+1}$ for all size sorted and market stocks.

[Table 3.4]

Table 3.4 displays the results of panel data forecasting of NSk_{it+1} when a single behavioural factor is added to the baseline model. The results are similar across all return types. For convenience, the behavioural models for market-adjusted returns are only presented. Each column of table 3.4 indicates the behavioural factor used in the model depicted by the marker BEHAVIOUR. Panels A - D present the single behavioural forecasting model for overlapping returns. POS_{it}, $VarPOS_{it}$, and COV_{it} are significant mostly for mid and small-cap stocks. However, their coefficients are almost close to zero[36], suggesting that investors' reaction based on these firm-specific factor has negligible impact on negative skewness. The other most frequently significant factors among all size-sorted groups of stocks and return types are LOS_t, PMN_t, LVR_t, HVR_t, $CSAD_t$, and upS_t.

The coefficients of LOS_t, LVR_t, HVR_t, and upS_t are negative. When returns fall on losing stocks, less popular low volume stocks, and more popular high volume stocks, it indicates of a falling market. This may turn to recession and market crash for which negative skewness will rise. The

[36]The first digit of the coefficients appears from 7th to 13th decimal places.

negative coefficient of upS_t implies that optimistic investment decision during holidays increases return on stocks that decreases negative skewness. While, $CSAD_t$, and PMN_t, show positive relation with negative skewness. $CSAD_t$ shows the cross-sectional dispersion of all stocks from the market, and PMN_t attains the disparity between the winners and losers in the market. The higher disparity in the market is the major source of negative skewness in stock return distribution.

Panels E - G present the single behavioural forecasting model for non-overlapping returns. $VarPOS_{it}$, COV_{it}, $CSAD_t$, PMN_t, and upS_t are statistically significant for most groups of stocks and types of returns. These significant factors also show the same relation as they exhibit in forecasting NSk_{it+1} with overlapping returns. Considering both overlapping and non-overlapping returns, $CSAD_t$ has strong predictive power for large stocks and upS_t for small stocks. Unlike overlapping returns, non-overlapping returns can only investigate the effect of one type of the season due to insufficient observation. upS_t is more frequently significant with all types of returns and size-sorted groups than $downS_t$. When testing upS_t with non-overlapping returns $downS_t$ does not vary over time as all the observations are in the down-season. This means $downS_t$ and upS_t are not mutually exclusive as some holidays fall during the down season, which may bring short-term upswing/optimism in the market.

[Table 3.5]

Table 3.5 presents the panel data forecasting of $ExKr_{it+1}$ with single behavioural factor. The results for overlapping returns are in panels A -D. Most behavioural factors are statistically significant when each of them is added to the baseline model of excess kurtosis. POS_{it}, $VarPOS_{it}$, and COV_{it} are again mostly significant for smaller stocks with minimal impact. $CSAD_t$, LOS_t, WIN_t, PMN_t, HVR_t, and LVR_t, are highly significant among all the size-sorted groups of stocks and return types. $CSAD_t$ is negatively associated with excess kurtosis. Whereas, LOS_t, WIN_t, PMN_t, HVR_t, and LVR_t, all increases excess kurtosis. The higher returns on losers, winners, less popular low volume stocks and more popular high volume stocks increase excess kurtosis. PMN_t increases excess kurtosis for large and mid-cap stocks but decreases for small-cap stocks. upS_t decreases excess kurtosis for large-cap stocks. Lastly, panels E - G for non-overlapping returns show that $ExKr_{it+1}$ is predicted by COV_{it} in small-cap stocks and by LOS_t, WIN_t, PMN_t, and HVR_t in large and mid-cap stocks. However, the results of non-overlapping returns are highly unreliable due to poor statistical power as the models have very low R^2 consistently for all groups of stocks and its return types.

POS_{it}, $VarPOS_{it}$, and COV_{it} have almost zero impact on negative skewness and kurtosis. This is because loss aversion due to disposition effect and overreaction due to overconfidence act in the opposite direction. Loss averse investors, who fear losses, hold onto stocks when the prices are below the buying price (for daily traders if $POS_{it} < 0$) and sell when the prices are above the buying price (for daily traders if $POS_{it} > 0$). According to Daniel et al. (1997), overconfident investors with self-attribution take this price change as the price signal. The falling price in $POS_{it} < 0$, signals them to sell stocks now and buy in the next period when prices are lower. The rising price in $POS_{it} > 0$, influences them to buy stocks now and sell later when prices are higher. There may be temporal uncertainty in the market due to price signals. Investors' overreaction, captured in $VarPOS_{it}$, and COV_{it}, corrects the price in the long run.

LOS_t, WIN_t, HVR_t, and LVR_t are negatively related to negative skewness and positively related to excess kurtosis. The returns on winners are positive and losers are negative. When the returns on these extreme assets are rising, it signals investors about positive market movement that increases their confidence in investment decisions. Higher returns increase the demand for most stocks, which pushes up the prices above the fundamental values and leads to market overreaction. This overreaction causes the market to be bullish that declines negative skewness and raises excess kurtosis. Alternatively, when the returns of winners and losers are falling, investors lose confidence from the market. They tend to sell off their stocks to averse losses, which pushes down the prices. Their overreaction makes the market bearish that increases negative skewness.

Similarly, when past returns on low volume and high volume stocks rise, demand for both the stocks increase[37]. Some investors will buy less popular low volume stocks as they are undervalued. While other investors prefer to invest in more popular high volume stocks with an expectation of higher future profit. Both types of investors build the upward price momentum in response to higher past returns that decrease negative skewness and increase excess kurtosis. The alternative is true for the opposite.

LOS_t, WIN_t, HVR_t, and LVR_t provide information about the market trend. However, they move negative skewness and excess kurtosis in the opposite direction. Herding intensity, $CSAD_t$ also has inverse impacts. It is positively related to negative skewness and negatively with excess kurtosis. Whereas, PMN_t and upS_t move negative skewness and excess kurtosis in the same direction.

PMN_t, which is WIN_t minus LOS_t, increases negative skewness and excess kurtosis as the

[37]See De Bondt and Thaler (1985, 1987), Heston and Sadka (2008)

disparity between these extreme assets increases. Disparity signals about market volatility. The higher cross-sectional dispersion between them is caused when the average past returns of winners increases and losers fall. According to the cognitive dissonance theory, higher disparity encourages investors to invest in strong performing winners with confidence and decreases the demand for low performing losers. This pushes up the prices of winners above the fundamental values and decreases the prices of losers. Market overreaction due to heightened disparity increases negative skewness and excess kurtosis of most stocks. On the other hand, optimism in upS_t always reduces negative skewness and excess kurtosis.

[Table 3.6]

Table 3.6 displays the cross-sectional correlation matrix among the behavioural factors of overlapping and non-overlapping returns. The correlation matrix helps in selecting multiple behavioural factors, that can be added together in the baseline forecasting model. If the absolute correlation coefficient between any two factors is approximately close to or greater than 0.5, those two factors are considered to be strongly correlated. When such highly correlated explanatory factors are included jointly in the baseline model, the problem of multicollinearity arises. First, we identify all the significant behavioural factors that have been individually added to the baseline models. Considering only the significant behavioural factors for each forecasting model across all size-sorted stock groups and return types, we then select the factors that are uncorrelated to each other.

For overlapping returns, POS_{it}, $VarPOS_{it}$, COV_{it}, $CSAD_t$, HVR_t, and upS_t are selected for the panel forecasting of NSk_{it+1} and $ExKr_{it+1}$. HVR_t is selected over other return momentum variables because it is highly correlated with WIN_t, LOS_t, PMN_t, and LVR_t. For non-overlapping returns, $VarPOS_{it}$, $CSAD_t$, and upS_t are chosen for the panel forecasting of NSk_{it+1}, and COV_{it}, PMN_t, and HVR_t for $ExKr_{it+1}$.

[Table 3.7]

Table 3.7 presents the significant multiple behavioural factor models. We include the chosen behavioural factors to the complete baseline predictive model and also to the baseline model with only its significant factors. For overlapping model of NSk_{it+1}, panel A shows that COV_{it}, $CSAD_t$, HVR_t, and upS_t are more frequently statistically significant. For non-overlapping model of NSk_{it+1}, $CSAD_t$, and upS_t are always significant as shown in panel B. Both confirm that COV_{it}, $CSAD_t$, HVR_t, and upS_t can forecast the unconditional negative skewness of stock return distribution.

The overlapping model of $ExKr_{it+1}$ in panel C indicates that COV_{it}, and $CSAD_t$ are commonly statically significant than HVR_t, and upS_t. The results in panel D with non-overlapping model of $ExKr_{it+1}$, reveal that PMN_t can better forecast the unconditional excess kurtosis. Both these results prove that COV_{it}, $CSAD_t$, and PMN_t are the major source of excess kurtosis.

Our empirical evidence identifies that market overreaction, herding intensity, momentum return on high volume stocks, and optimistic seasons can forecast negative skewness with significant statistical power. We also observe that market overreaction, herding intensity, and the cross-sectional disparity between winning and losing stocks can forecast excess kurtosis. Negative skewness is positively associated with investors' reaction to price signal and herding decisions, and is inversely related to the upward trend on momentum stocks and optimistic season. While excess kurtosis is positively correlated with investors' overreaction and disparity in returns on momentum stocks, but negatively related to herding intensity.

The covariance on stock price movements portraying investors' overreaction due to price signal marginally increases both negative skewness and excess kurtosis. The herding intensity increases negative skewness but decreases excess kurtosis. When herding intensity escalates, it increases the returns on the winning stocks[38], which in turn expands the disparity between winning and losing stocks. The growing disparity increases excess kurtosis that may exceed the decrease in excess kurtosis due to higher herding intensity[39]. Hence, the asymmetric distribution of stock returns due to the existence of negative skewness and excess kurtosis is explained by the investors' overreaction to price signal, herding intensity in the market, and an indicator of momentum return. In contrast to the firm-specific factors, the systematic market factors due to the biased reaction of majority investors make stock return distribution more asymmetric.[40]

3.4 Conclusion

Financial returns are proven to be negatively skewed and fat-tailed. Negative skewness implies that the left-hand side of the return distribution is more pronounced as the market puts a higher

[38]See Grinblatt et al. (1995). They find significant evidence of cross-sectional dispersion across individual funds in their tendency to buy past winners and to trade with the herd. They observe strong relation between the tendency to buy past winners and performance.

[39]Table 3.5 indicates that the coefficients of PMN_t are usually greater than the coefficients of $CSAD_t$. When the market is under stress, investors tend to herd more with overconfidence as they doubt themselves and like to invest in better performing winning stocks. This increases the disparity between winning and losing stocks even more inflating excess kurtosis.

[40]This result is consistent with other estimation approaches, such as pooled regression and random effect model. Like Cont and Bouchaud (1997), we find the significant asymmetries in stock returns are not due to the fundamental firm-specific factors but rather due to the overall market aggression.

probability to decreases over increases in asset pricing. Excess kurtosis results when extreme observations appear more often than usual. The existence of negative skewness and excess kurtosis implies that stock markets are susceptible to crashes. The crash has been identified as a behavioural phenomenon as it depends on the way investors behave in the market.

Chen et al. (2001) explore the ability of differences-of-opinion among investors to forecast unconditional negative skewness of individual stocks. Since they use the non-overlapping estimation approach, it leads to statistical power loss due to insufficient data. It is also too restrictive to assume that skewness is fixed in the proposed sub-period. Thus, we use both overlapping and non-overlapping estimation approach to explain the unconditional negative skewness and excess kurtosis. In addition, Hueng and McDonald (2005) mark trading volume as a bad proxy of opinion divergence as it could not forecast their proposed skewness. We propose to use different behavioural heuristics through various behavioural factors deemed to influence the third (skewness) and fourth (kurtosis) moments of the stock return distribution. Our behavioural factors are derived from four behavioural proposition-based on momentum trading.

The baseline regression models find the coefficient of turnover is insignificant for different size-sorted groups of individual stocks. The panel data forecasting of negative skewness invalidates the claim of Chen et al. (2001) as higher turnover can neither predict negative skewness nor excess kurtosis. The multiple behavioural factor model confirms that market overreaction, herding intensity, momentum return on high volume stocks, and optimistic seasons are statistically significant in forecasting negative skewness. Empirical evidence also suggests that excess kurtosis is explained by market overreaction, herding intensity, and the cross-sectional disparity between winning and losing stocks.

Overreaction to price signal marginally increases both negative skewness and excess kurtosis. Herding intensity increases negative skewness but decreases excess kurtosis. During extreme market conditions, the decrease in excess kurtosis due to herding is surpassed by the increase in excess kurtosis due to disparity in stock returns. The higher disparity between the winners and losers increases both negative skewness and excess kurtosis. While optimistic season reduces both negative skewness and excess kurtosis. In conclusion, the existence of negative skewness and excess kurtosis is determined by investors' overreaction to price signal, herding intensity in the market, and an indicator of momentum return. The systematic market factors due to the bulk of investors' biased reactions are the major source of asymmetry in stock returns.

Table 3.1: Summary Statistics of Stock Returns

The cross-sectional mean, median, and standard deviation of the summary statistics for the time-series distributions of individual stock returns. The expected values of skewness for large and mid-cap stocks are negative and skewed to the left. While for small-cap stocks, the expected skewness is positive and skewed to the right. The average kurtosis for any stock is always positive and skewed to the right.

Summary statistics for the time-series distribution				
Statistics	Mean	Sdev	Skewness	Kurtosis
		Large-cap Stocks		
Mean	0.0006	0.0194	-0.2811	17.9477
Median	0.0006	0.0187	-0.1778	10.6080
Standard Deviation	0.0003	0.0060	1.3138	40.7385
		Mid-cap Stocks		
Mean	0.0004	0.0278	-0.2970	26.9594
Median	0.0004	0.0259	-0.0408	12.8676
Standard Deviation	0.0005	0.0089	2.4106	74.2463
		Small-cap Stocks		
Mean	-0.0001	0.0458	0.5667	30.8733
Median	0.0001	0.0375	0.4007	16.9332
Standard Deviation	0.0009	0.0671	1.6975	45.6665

Table 3.2: Panel Data Forecasting of Baseline Regression Model

NSk_{it+1} is the dependent variable in panels A and B, and $ExKr_{it+1}$ in panels C and D. The independent variables are $SIGMA_{it}$, $LOGSIZE_{it}$, $DTURNOVER_{it}$, RET_{it}, RET_{it-1},..., RET_{it-5}, and own lagged variable, which are shown in Column 1. The FE panel data regression estimates for market-adjusted returns are presented in columns 2 and 6, for log returns in columns 3 and 7, for excess returns in columns 4 and 8, and for beta-adjusted in columns 5 and 9. Columns 6-9 display the baseline regression model estimates with only the 1% and 5% significant covariates found from the full baseline regression model estimation shown in columns 2-5.

	Panel A: Forecasting NSk with overlapping returns							
NSk_{it+1}	Market-Adj	Log Ret	Excess Ret	Beta-Adj	Market-Adj	Log Ret	Excess Ret	Beta-Adj
NSk_{it}	0.9904***	0.9899***	0.9899***	0.9904***	0.9904***	0.9899***	0.9899***	0.9904***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$SIGMA_{it}$	0.0003	-0.0011	-0.0011	-0.0006				
	(0.0051)	(0.0044)	(0.0044)	(0.0051)				
$LOGSIZE_{it}$	0.0030***	0.0032***	0.0032***	0.0030***	0.0030***	0.0032***	0.0032***	0.0031***
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)
$DTURNOVER_{it}$	0.0240***	0.0176**	0.0176**	0.0253***	0.0241***	0.0175**	0.0174**	0.0253***
	(0.0093)	(0.0080)	(0.0080)	(0.0094)	(0.0093)	(0.0080)	(0.0080)	(0.0094)
RET_{it}	0.0583***	0.0537***	0.0537***	0.0600***	0.0582***	0.0537***	0.0537***	0.0599***
	(0.0022)	(0.0018)	(0.0018)	(0.0022)	(0.0022)	(0.0018)	(0.0018)	(0.0022)
RET_{it-1}	-0.0193***	-0.0231***	-0.0231***	-0.0199***	-0.0194***	-0.0231***	-0.0231***	-0.0200***
	(0.0026)	(0.0022)	(0.0022)	(0.0026)	(0.0026)	(0.0022)	(0.0022)	(0.0026)
RET_{it-2}	-0.0208***	-0.0144***	-0.0144***	-0.0215***	-0.0210***	-0.0144***	-0.0144***	-0.0217***
	(0.0026)	(0.0022)	(0.0022)	(0.0026)	(0.0026)	(0.0022)	(0.0022)	(0.0026)
RET_{it-3}	-0.0060**	-0.0055**	-0.0055**	-0.0066**	-0.0067***	-0.0052**	-0.0052**	-0.0074***
	(0.0026)	(0.0022)	(0.0022)	(0.0026)	(0.0024)	(0.0021)	(0.0021)	(0.0025)
RET_{it-4}	-0.0018	0.0008	0.0008	-0.0022				
	(0.0026)	(0.0022)	(0.0022)	(0.0026)				
RET_{it-5}	-0.0057***	-0.0091***	-0.0091***	-0.0052**	-0.0065***	-0.0088***	-0.0088***	-0.0061***
	(0.0022)	(0.0018)	(0.0018)	(0.0022)	(0.0018)	(0.0015)	(0.0015)	(0.0018)
CONSTANT	-0.0628***	-0.0669***	-0.0670***	-0.0638***	-0.0627***	-0.0671***	-0.0672***	-0.0639***
	(0.0053)	(0.0046)	(0.0046)	(0.0054)	(0.0053)	(0.0046)	(0.0046)	(0.0053)
Observations	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326
No. of stocks	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227
R^2	0.9797	0.9786	0.9786	0.9796	0.9797	0.9786	0.9786	0.9796
Adjusted R^2	0.980	0.979	0.979	0.980	0.980	0.979	0.979	0.980

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.2 (Continued)

	Panel B: Forecasting NSk with non-overlapping returns							
NSk_{it+1}	Market-Adj	Log Ret	Excess Ret	Beta-Adj	Market-Adj	Log Ret	Excess Ret	Beta-Adj
NSk_{it}	-0.0018	-0.0046	-0.0046	0.0020				
	(0.0151)	(0.0158)	(0.0157)	(0.0150)				
$SIGMA_{it}$	0.1324	0.0972	0.0971	-0.0371				
	(0.8259)	(0.7161)	(0.7161)	(0.8278)				
$LOGSIZE_{it}$	0.6222***	0.6265***	0.6265***	0.6314***	0.5926***	0.5942***	0.5942***	0.6035***
	(0.0601)	(0.0508)	(0.0508)	(0.0600)	(0.0486)	(0.0459)	(0.0459)	(0.0487)
$DTURNOVER_{it}$	1.5734	1.5841	1.5841	1.6224				
	(1.4252)	(1.2416)	(1.2416)	(1.4274)				
RET_{it}	-0.1068	-0.1634**	-0.1634**	-0.1041		-0.0832	-0.0833	
	(0.0907)	(0.0770)	(0.0769)	(0.0903)		(0.0660)	(0.0660)	
RET_{it-1}	0.2650***	0.1665**	0.1664**	0.2515***	0.2843***	0.1713**	0.1712**	0.2699***
	(0.0906)	(0.0751)	(0.0751)	(0.0913)	(0.0818)	(0.0696)	(0.0696)	(0.0831)
RET_{it-2}	-0.0584	-0.1047	-0.1047	-0.0561				
	(0.0864)	(0.0722)	(0.0722)	(0.0858)				
RET_{it-3}	0.2839***	0.2241***	0.2241***	0.2781***	0.3053***	0.2431***	0.2430***	0.2990***
	(0.0859)	(0.0657)	(0.0657)	(0.0875)	(0.0799)	(0.0631)	(0.0631)	(0.0812)
RET_{it-4}	-0.0873	-0.1231*	-0.1233*	-0.0762				
	(0.0831)	(0.0714)	(0.0714)	(0.0825)				
RET_{it-5}	0.0694	0.0833	0.0834	0.0729				
	(0.0723)	(0.0576)	(0.0576)	(0.0730)				
CONSTANT	-12.9902***	-13.0763***	-13.0757***	-13.1786***	-12.3649***	-12.4091***	-12.4098***	-12.5928***
	(1.2574)	(1.0531)	(1.0525)	(1.2559)	(1.0140)	(0.9539)	(0.9537)	(1.0164)
Observations	7,362	7,362	7,362	7,362	7,362	7,362	7,362	7,362
No. of stocks	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227
R^2	0.0439	0.0500	0.0500	0.0442	0.0431	0.0484	0.0484	0.0434
Adjusted R^2	-0.149	-0.142	-0.142	-0.149	-0.149	-0.142	-0.142	-0.148

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3.2 (Continued)

	Panel C: Forecasting ExKr with overlapping returns							
$ExKr_{it+1}$	Market-Adj	Log Ret	Excess Ret	Beta-Adj	Market-Adj	Log Ret	Excess Ret	Beta-Adj
$ExKr_{it}$	0.9888***	0.9889***	0.9889***	0.9887***	0.9888***	0.9890***	0.9890***	0.9887***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$SIGMA_{it}$	-0.0966***	-0.1423***	-0.1422***	-0.0798**	-0.0956***	-0.1458***	-0.1459***	-0.0792**
	(0.0337)	(0.0291)	(0.0291)	(0.0342)	(0.0337)	(0.0288)	(0.0288)	(0.0341)
$LOGSIZE_{it}$	0.0060***	0.0016	0.0016	0.0042**	0.0059***			0.0041**
	(0.0017)	(0.0015)	(0.0015)	(0.0017)	(0.0017)			(0.0017)
$DTURNOVER_{it}$	0.0342	0.0686	0.0681	0.0247				
	(0.0612)	(0.0530)	(0.0530)	(0.0619)				
RET_{it}	-0.0604***	-0.0342***	-0.0343***	-0.0623***	-0.0741***	-0.0428***	-0.0429***	-0.0755***
	(0.0143)	(0.0121)	(0.0121)	(0.0145)	(0.0118)	(0.0097)	(0.0097)	(0.0120)
RET_{it-1}	-0.0278	-0.0251*	-0.0251*	-0.0275				
	(0.0170)	(0.0144)	(0.0144)	(0.0172)				
RET_{it-2}	0.0424**	0.0469***	0.0469***	0.0392**	0.0271**	0.0431***	0.0430***	0.0251*
	(0.0171)	(0.0146)	(0.0146)	(0.0174)	(0.0138)	(0.0097)	(0.0097)	(0.0140)
RET_{it-3}	-0.0181	-0.0234	-0.0234	-0.0154				
	(0.0171)	(0.0146)	(0.0146)	(0.0174)				
RET_{it-4}	0.0191	0.0150	0.0150	0.0179				
	(0.0169)	(0.0144)	(0.0144)	(0.0172)				
RET_{it-5}	0.0324**	0.0212*	0.0212*	0.0363**	0.0345***			0.0386***
	(0.0143)	(0.0120)	(0.0120)	(0.0145)	(0.0106)			(0.0108)
CONSTANT	-0.0404	0.0340	0.0333	-0.0006	-0.0396	0.0674***	0.0674***	0.0000
	(0.0351)	(0.0304)	(0.0304)	(0.0354)	(0.0350)	(0.0012)	(0.0012)	(0.0354)
Observations	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326
No. of stocks	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227
R^2	0.9775	0.9776	0.9776	0.9773	0.9775	0.9776	0.9776	0.9773
Adjusted R^2	0.977	0.978	0.978	0.977	0.977	0.978	0.978	0.977

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 3.2 (CONTINUED)

	Panel D: Forecasting ExKr with non-overlapping returns							
$ExKr_{it+1}$	Market-Adj	Log Ret	Excess Ret	Beta-Adj	Market-Adj	Log Ret	Excess Ret	Beta-Adj
$ExKr_{it}$	0.0421***	0.0423***	0.0422***	0.0429***	0.0371***	0.0424***	0.0424***	0.0380***
	(0.0143)	(0.0148)	(0.0148)	(0.0142)	(0.0142)	(0.0148)	(0.0148)	(0.0141)
$SIGMA_{it}$	-10.2484*	-11.3095**	-11.3017**	-8.9502*		-12.8296***	-12.8296***	
	(5.2810)	(4.7104)	(4.7103)	(5.2981)		(4.6689)	(4.6688)	
$LOGSIZE_{it}$	0.0984	0.5526*	0.5563*	-0.1342				
	(0.3809)	(0.3316)	(0.3314)	(0.3804)				
$DTURNOVER_{it}$	-10.4049	-10.1609	-10.1548	-10.6705				
	(9.0274)	(8.0994)	(8.0993)	(9.0412)				
RET_{it}	-1.6453***	-2.2279***	-2.2389***	-1.4625***	-1.4137***	-1.7989***	-1.8080***	-1.5145***
	(0.5412)	(0.4698)	(0.4692)	(0.5391)	(0.4613)	(0.4133)	(0.4131)	(0.4635)
$RET2_{it-1}$	0.1995	-0.4689	-0.4750	0.4108				
	(0.5732)	(0.4888)	(0.4887)	(0.5774)				
RET_{it-2}	-1.5611***	-2.1014***	-2.1057***	-1.3815**	-1.4360***	-1.9354***	-1.9387***	-1.3124***
	(0.5470)	(0.4710)	(0.4708)	(0.5435)	(0.4878)	(0.4379)	(0.4378)	(0.4880)
$RET4_{it-3}$	0.2174	-1.1148***	-1.1146***	0.4834		-0.8506**	-0.8482**	
	(0.5438)	(0.4288)	(0.4288)	(0.5540)		(0.3824)	(0.3826)	
RET_{it-4}	-0.5544	-1.1889**	-1.1890**	-0.5396		-1.0828**	-1.0822**	
	(0.5261)	(0.4654)	(0.4652)	(0.5222)		(0.4416)	(0.4415)	
RET_{it-5}	0.8028*	0.4288	0.4300	1.0078**				1.0348**
	(0.4574)	(0.3742)	(0.3744)	(0.4618)				(0.4329)
CONSTANT	5.9676	-4.6040	-4.6805	10.8585	7.7988***	6.9225***	6.9214***	7.8729***
	(7.9642)	(6.8669)	(6.8633)	(7.9535)	(0.1594)	(0.1824)	(0.1823)	(0.1608)
Observations	7,362	7,362	7,362	7,362	7,362	7,362	7,362	7,362
No. of stocks	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227
R^2	0.0055	0.0088	0.0089	0.0057	0.0036	0.0077	0.0078	0.0045
Adjusted R^2	-0.195	-0.191	-0.191	-0.195	-0.196	-0.192	-0.192	-0.195

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3.3: Panel Data Forecasting of Baseline Regression Model by Firm Size

The dependent variable in panel A is NSk_{it+1}, and in panel B is $ExKr_{it+1}$. The independent variables are $SIGMA_{it}$, $LOGSIZE_{it}$, $DTURNOVER_{it}$, RET_{it}, RET_{it-1},..., RET_{it-5}, and own-lagged variable indicated in Column 1. Except for $LOGSIZE_{it}$ and $DTURNOVER_{it}$ (which do not depend on stock prices or returns), all the other variables are estimated based on market-adjusted returns. The FE panel data regression estimates for overlapping returns are presented in columns 2-4, and for non-overlapping returns in columns 5-7.

Panel A: Forecasting NSk with Market-Adjusted Returns

	Overlapping			Non-Overlapping		
NSk_{it+1}	Large	Mid	Small	Large	Mid	Small
NSk_{it}	0.9905***	0.9911***	0.9889***	0.0247	-0.0162	0.0070
	(0.0002)	(0.0002)	(0.0002)	(0.0270)	(0.0275)	(0.0264)
$SIGMA_{it}$	-0.1038*	0.0533	-0.0026	12.9588	2.9093	-0.0099
	(0.0602)	(0.0350)	(0.0052)	(10.7229)	(6.7809)	(0.7643)
$LOGSIZE_{it}$	0.0031***	0.0043***	0.0024***	0.7055***	0.8845***	0.4273***
	(0.0005)	(0.0006)	(0.0004)	(0.1166)	(0.1312)	(0.0817)
$DTURNOVER_{it}$	0.0504	0.0292	0.0199**	-3.5177	27.5313***	0.6183
	(0.1035)	(0.0780)	(0.0095)	(13.1424)	(9.7740)	(1.3110)
RET_{it}	0.0386***	-0.0171**	0.0697***	0.3271	-0.3438	0.0152
	(0.0108)	(0.0075)	(0.0024)	(0.2764)	(0.2113)	(0.1082)
RET_{it-1}	-0.0542***	0.0154	-0.0185***	0.4908**	0.0155	0.4079***
	(0.0152)	(0.0106)	(0.0027)	(0.2437)	(0.1915)	(0.1133)
RET_{it-2}	0.0130	0.0045	-0.0245***	0.1783	-0.3532*	0.0367
	(0.0152)	(0.0106)	(0.0027)	(0.2463)	(0.1945)	(0.1032)
RET_{it-3}	-0.0316**	0.0099	-0.0084***	0.8426***	0.2376	0.2815***
	(0.0152)	(0.0106)	(0.0027)	(0.2363)	(0.1828)	(0.1052)
RET_{it-4}	-0.0134	-0.0148	-0.0031	-0.5441**	-0.2230	0.0459
	(0.0152)	(0.0106)	(0.0027)	(0.2506)	(0.1899)	(0.0963)
RET_{it-5}	0.0473***	0.0047	-0.0107***	0.0883	0.2190	0.0652
	(0.0108)	(0.0075)	(0.0023)	(0.2233)	(0.1638)	(0.0829)
CONSTANT	-0.0722***	-0.0888***	-0.0453***	-16.7482***	-18.3038***	-7.9287***
	(0.0124)	(0.0119)	(0.0065)	(2.7720)	(2.7437)	(1.5193)
Observations	874,442	874,442	874,442	2,454	2,454	2,454
No. of stocks	409	409	409	409	409	409
R^2	0.9808	0.9814	0.9760	0.0430	0.0462	0.0661
Adjusted R^2	0.981	0.981	0.976	-0.154	-0.150	-0.126

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.3 (Continued)

Panel B: Forecasting ExKr with Market-Adjusted Return						
	Overlapping			Non-Overlapping		
ExKr_{it+1}	Large	Mid	Small	Large	Mid	Small
ExKr_{it}	0.9893***	0.9892***	0.9877***	0.0201	0.0692**	0.0351
	(0.0002)	(0.0002)	(0.0002)	(0.0258)	(0.0291)	(0.0252)
SIGMA_{it}	0.1289	0.1688	-0.1010***	25.8749	-61.0538	-9.8313*
	(0.4238)	(0.2560)	(0.0360)	(69.7689)	(46.4952)	(5.5363)
LOGSIZE_{it}	0.0148***	0.0254***	-0.0074***	0.0431	2.2639***	-1.1896**
	(0.0033)	(0.0038)	(0.0024)	(0.6874)	(0.8171)	(0.5856)
DTURNOVER_{it}	-2.2649***	0.4275	0.0322	1.6179	88.0407	-14.4910
	(0.6539)	(0.5129)	(0.0656)	(76.4490)	(60.1274)	(9.4054)
RET_{it}	0.1419**	-0.1835***	-0.0520***	-3.1580**	-1.0587	-1.0198
	(0.0682)	(0.0492)	(0.0163)	(1.4492)	(1.2030)	(0.7296)
RET_{it-1}	-0.2144**	0.0900	-0.0335*	-2.6762*	-1.2339	1.5380*
	(0.0958)	(0.0694)	(0.0187)	(1.4095)	(1.1760)	(0.8105)
RET_{it-2}	0.1115	0.0640	0.0357*	-2.1441	-1.3389	-1.0495
	(0.0958)	(0.0694)	(0.0190)	(1.4254)	(1.1973)	(0.7393)
RET_{it-3}	-0.0644	-0.0138	-0.0191	-0.6294	-0.7696	0.9866
	(0.0958)	(0.0694)	(0.0190)	(1.3668)	(1.1262)	(0.7540)
RET_{it-4}	-0.0111	0.1012	0.0181	-0.3054	-0.8998	-0.0272
	(0.0958)	(0.0694)	(0.0187)	(1.4520)	(1.1695)	(0.6909)
RET_{it-5}	-0.0002	-0.0782	0.0499***	-0.3989	0.0634	1.3785**
	(0.0682)	(0.0492)	(0.0162)	(1.2936)	(1.0081)	(0.5933)
CONSTANT	-0.2720***	-0.4388***	0.2189***	6.7001	-37.0964**	29.3240***
	(0.0798)	(0.0805)	(0.0450)	(16.3874)	(17.1123)	(10.8894)
Observations	874,442	874,442	874,442	2,454	2,454	2,454
No. of stocks	409	409	409	409	409	409
R^2	0.9785	0.9785	0.9755	0.0061	0.0103	0.0152
Adjusted R^2	0.979	0.979	0.975	-0.198	-0.193	-0.187

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.4: Forecasting Negative Skewness with Single Behavioural Factor

This table presents the FE panel data regression forecasting of NSk_{it+1} with variables computed with market-adjusted returns. Column 1 identifies the dependent variable and the independent variables. The factor $BEHAVIOUR_t$ uses the behavioural factor indicated at the top of each column. $BEHAVIOUR_t$ represents POS_{it}, $VarPOS_{it}$, COV_{it}, $CSAD_t$, LOS_t, WIN_t, PMN_t, LVR_t, HVR_t, UPS_t, and $DOWNS_t$. Unlike overlapping returns, non-overlapping returns can only investigate the effect of UPS_t due to limited observation.

	Panel A: Overlapping Market-Adjusted Returns of Aggregate Market Stocks										
NSk_{it+1}	POS_{it}	$VarPOS_{it}$	COV_{it}	$CSAD_t$	LOS_t	WIN_t	PMN_t	LVR_t	HVR_t	UPS_t	$DOWNS_t$
NSk_{it}	0.9904***	0.9904***	0.9904***	0.9904***	0.9905***	0.9905***	0.9904***	0.9905***	0.9905***	0.9904***	0.9904***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$SIGMA_{it}$	0.0003	0.0004	0.0004	-0.0002	-0.0005	0.0003	-0.0005	0.0002	-0.0000	0.0004	0.0004
	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)
$LOGSIZE_{it}$	0.0030***	0.0030***	0.0030***	0.0032***	0.0028***	0.0030***	0.0028***	0.0030***	0.0027***	0.0030***	0.0030***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$DTURNOVER_{it}$	0.0240***	0.0241***	0.0241***	0.0246***	0.0234**	0.0242***	0.0232**	0.0243***	0.0233**	0.0240***	0.0240***
	(0.0093)	(0.0093)	(0.0093)	(0.0093)	(0.0093)	(0.0093)	(0.0093)	(0.0093)	(0.0093)	(0.0093)	(0.0093)
RET_{it}	0.0583***	0.0582***	0.0583***	0.0582***	0.0586***	0.0584***	0.0584***	0.0583***	0.0588***	0.0583***	0.0583***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
RET_{it-1}	-0.0194***	-0.0193***	-0.0193***	-0.0193***	-0.0192***	-0.0193***	-0.0193***	-0.0193***	-0.0192***	-0.0193***	-0.0193***
	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)
RET_{it-2}	-0.0208***	-0.0208***	-0.0208***	-0.0208***	-0.0208***	-0.0208***	-0.0208***	-0.0208***	-0.0208***	-0.0208***	-0.0208***
	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)
RET_{it-3}	-0.0061**	-0.0060**	-0.0060**	-0.0060**	-0.0060**	-0.0060**	-0.0060**	-0.0060**	-0.0060**	-0.0060**	-0.0060**
	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)
RET_{it-4}	-0.0019	-0.0018	-0.0018	-0.0019	-0.0018	-0.0018	-0.0018	-0.0018	-0.0018	-0.0018	-0.0018
	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)
RET_{it-5}	-0.0057***	-0.0057***	-0.0057***	-0.0057***	-0.0057***	-0.0057***	-0.0057***	-0.0057***	-0.0057***	-0.0057***	-0.0057***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
$BEHAVIOUR_t$	-0.0000	-0.0000**	0.0000***	0.2942***	-1.2160***	-1.0381***	1.2784***	-1.1005**	-2.6501***	-0.0004	0.0006**
	(0.0000)	(0.0000)	(0.0000)	(0.0445)	(0.1462)	(0.2625)	(0.1749)	(0.4839)	(0.2896)	(0.0003)	(0.0003)
CONSTANT	-0.0628***	-0.0637***	-0.0629***	-0.0723***	-0.0643***	-0.0587***	-0.0694***	-0.0637***	-0.0580***	-0.0626***	-0.0631***
	(0.0053)	(0.0053)	(0.0053)	(0.0055)	(0.0053)	(0.0054)	(0.0054)	(0.0053)	(0.0053)	(0.0053)	(0.0053)
Observations	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326
No. of stocks	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227
R^2	0.9797	0.9797	0.9797	0.9797	0.9797	0.9797	0.9797	0.9797	0.9797	0.9797	0.9797
Adjusted R^2	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.4 (Continued)

NSk_{it+1}	POS_{it}	$VarPOS_{it}$	COV_{it}	$CSAD_t$	LOS_t	WIN_t	PMN_t	LVR_t	HVR_t	UPS_t	$DOWNS_t$
	Panel B: Overlapping Market-Adjusted Returns of Large-cap Stocks										
NSk_{it}	0.9905***	0.9905***	0.9905***	0.9905***	0.9905***	0.9905***	0.9905***	0.9905***	0.9905***	0.9905***	0.9905***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$SIGMA_{it}$	-0.1039*	-0.1066*	-0.1040*	-0.1221**	-0.1517**	-0.1047*	-0.1608***	-0.1095*	-0.1318**	-0.1083*	-0.1042*
	(0.0602)	(0.0603)	(0.0602)	(0.0603)	(0.0613)	(0.0602)	(0.0617)	(0.0603)	(0.0607)	(0.0603)	(0.0603)
$LOGSIZE_{it}$	0.0031***	0.0031***	0.0031***	0.0038***	0.0023***	0.0031***	0.0022***	0.0032***	0.0024***	0.0031***	0.0031***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0005)	(0.0006)	(0.0005)	(0.0006)	(0.0005)	(0.0005)
$DTURNOVER_{it}$	0.0504	0.0506	0.0507	0.0199	0.0104	0.0330	0.0499	0.0283	0.0094	0.0523	0.0505
	(0.1035)	(0.1035)	(0.1035)	(0.1037)	(0.1039)	(0.1047)	(0.1035)	(0.1042)	(0.1041)	(0.1035)	(0.1035)
RET_{it}	0.0432***	0.0387***	0.0386***	0.0386***	0.0390***	0.0386***	0.0391***	0.0385***	0.0392***	0.0385***	0.0386***
	(0.0114)	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)
RET_{it-1}	-0.0587***	-0.0542***	-0.0542***	-0.0540***	-0.0541***	-0.0542***	-0.0541***	-0.0542***	-0.0541***	-0.0542***	-0.0542***
	(0.0156)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)
RET_{it-2}	0.0130	0.0130	0.0130	0.0130	0.0130	0.0130	0.0130	0.0131	0.0130	0.0130	0.0130
	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)
RET_{it-3}	-0.0315**	-0.0316**	-0.0316**	-0.0316**	-0.0316**	-0.0316**	-0.0316**	-0.0316**	-0.0316**	-0.0316**	-0.0316**
	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)
RET_{it-4}	-0.0135	-0.0134	-0.0134	-0.0134	-0.0134	-0.0134	-0.0134	-0.0134	-0.0134	-0.0134	-0.0134
	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)
RET_{it-5}	0.0474***	0.0473***	0.0473***	0.0470***	0.0474***	0.0474***	0.0474***	0.0474***	0.0474***	0.0474***	0.0473***
	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0108)
$BEHAVIOUR_t$	-0.0001	0.0000	-0.0000	0.3960***	-1.0801***	-0.4747	1.3453***	-1.4701*	-1.8667***	0.0008*	-0.0001
	(0.0001)	(0.0000)	(0.0000)	(0.0756)	(0.2618)	(0.4386)	(0.3181)	(0.8107)	(0.5145)	(0.0005)	(0.0005)
CONSTANT	-0.0724***	-0.0711***	-0.0722***	-0.0933***	-0.0576***	-0.0703***	-0.0595***	-0.0751***	-0.0558***	-0.0724***	-0.0721***
	(0.0124)	(0.0125)	(0.0124)	(0.0131)	(0.0129)	(0.0125)	(0.0128)	(0.0125)	(0.0132)	(0.0124)	(0.0124)
Observations	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442
No of stocks	409	409	409	409	409	409	409	409	409	409	409
R^2	0.9808	0.9808	0.9808	0.9808	0.9808	0.9808	0.9808	0.9808	0.9808	0.9808	0.9808
Adjusted R^2	0.981	0.981	0.981	0.981	0.981	0.981	0.981	0.981	0.981	0.981	0.981

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.4 (Continued)

NSk_{it+1}	POS_{it}	$VarPOS_{it}$	COV_{it}	$CSAD_t$	LOS_t	WIN_t	PMN_t	LVR_t	HVR_t	UPS_t	$DOWNS_t$
Panel C: Overlapping Market-Adjusted Returns of Mid-cap Stocks											
NSk_{it}	0.9911***	0.9912***	0.9912***	0.9911***	0.9911***	0.9911***	0.9911***	0.9911***	0.9911***	0.9911***	0.9911***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$SIGMA_{it}$	0.0563	-0.0350	-0.0437	0.0513	0.0349	0.0525	0.0330	0.0512	0.0425	0.0557	0.0544
	(0.0350)	(0.0387)	(0.0386)	(0.0351)	(0.0354)	(0.0350)	(0.0355)	(0.0351)	(0.0352)	(0.0351)	(0.0351)
$LOGSIZE_{it}$	0.0043***	0.0039***	0.0039***	0.0044***	0.0038***	0.0042***	0.0037***	0.0043***	0.0038***	0.0043***	0.0043***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
$DTURNOVER_{it}$	0.0274	0.0734	0.0775	0.0289	0.0361	0.0252	0.0465	0.0283	0.0260	0.0254	0.0277
	(0.0780)	(0.0785)	(0.0784)	(0.0780)	(0.0780)	(0.0781)	(0.0782)	(0.0780)	(0.0780)	(0.0781)	(0.0780)
RET_{it}	-0.0198***	-0.0154**	-0.0153**	-0.0172**	-0.0166**	-0.0170**	-0.0169**	-0.0171**	-0.0163**	-0.0171**	-0.0171**
	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)
RET_{it-1}	0.0178*	0.0154	0.0153	0.0155	0.0155	0.0154	0.0155	0.0154	0.0154	0.0154	0.0154
	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)
RET_{it-2}	0.0048	0.0045	0.0045	0.0046	0.0046	0.0045	0.0046	0.0045	0.0045	0.0045	0.0045
	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)
RET_{it-3}	0.0099	0.0099	0.0099	0.0099	0.0099	0.0099	0.0099	0.0099	0.0099	0.0100	0.0099
	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)
RET_{it-4}	-0.0147	-0.0148	-0.0148	-0.0147	-0.0147	-0.0148	-0.0147	-0.0148	-0.0147	-0.0147	-0.0148
	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)
RET_{it-5}	0.0047	0.0044	0.0044	0.0046	0.0047	0.0047	0.0047	0.0048	0.0046	0.0046	0.0047
	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)
$BEHAVIOUR_{it}$	0.0000***	0.0000***	0.0000***	0.1088	-0.9684***	-0.5057	1.1651***	-0.8881	-1.7932***	-0.0009*	0.0004
	(0.0000)	(0.0000)	(0.0000)	(0.0811)	(0.2699)	(0.4767)	(0.3244)	(0.8797)	(0.5345)	(0.0005)	(0.0005)
CONSTANT	-0.0890***	-0.0806***	-0.0800***	-0.0933***	-0.0834***	-0.0868***	-0.0869***	-0.0898***	-0.0801***	-0.0887***	-0.0892***
	(0.0119)	(0.0120)	(0.0120)	(0.0124)	(0.0120)	(0.0121)	(0.0119)	(0.0120)	(0.0122)	(0.0119)	(0.0119)
Observations	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442
No. of stocks	409	409	409	409	409	409	409	409	409	409	409
R^2	0.9814	0.9814	0.9814	0.9814	0.9814	0.9814	0.9814	0.9814	0.9814	0.9814	0.9814
Adjusted R^2	0.981	0.981	0.981	0.981	0.981	0.981	0.981	0.981	0.981	0.981	0.981

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.4 (Continued)

NSk_{it+1}	POS_{it}	$VarPOS_{it}$	COV_{it}	$CSAD_t$	LOS_t	WIN_t	PMN_t	LVR_t	HVR_t	UPS_t	$DOWNS_t$
	Panel D: Overlapping Market-Adjusted Returns of Small-cap Stocks										
NSk_{it}	0.9889***	0.9889***	0.9889***	0.9889***	0.9890***	0.9890***	0.9889***	0.9890***	0.9890***	0.9889***	0.9889***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$SIGMA_{it}$	-0.0026	-0.0025	-0.0026	-0.0033	-0.0016	-0.0023	-0.0019	-0.0027	-0.0010	-0.0025	-0.0025
	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)
$LOGSIZE_{it}$	0.0024***	0.0025***	0.0024***	0.0025***	0.0027***	0.0023***	0.0027***	0.0024***	0.0027***	0.0024***	0.0024***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
$DTURNOVER_{it}$	0.0199**	0.0200**	0.0199**	0.0203**	0.0209**	0.0209**	0.0201**	0.0203**	0.0210**	0.0198**	0.0199**
	(0.0095)	(0.0095)	(0.0095)	(0.0095)	(0.0095)	(0.0095)	(0.0095)	(0.0095)	(0.0095)	(0.0095)	(0.0095)
RET_{it}	0.0698***	0.0697***	0.0697***	0.0698***	0.0699***	0.0700***	0.0697***	0.0698***	0.0700***	0.0697***	0.0697***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
RET_{it-1}	-0.0186***	-0.0185***	-0.0185***	-0.0186***	-0.0184***	-0.0185***	-0.0185***	-0.0185***	-0.0184***	-0.0185***	-0.0186***
	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)
RET_{it-2}	-0.0245***	-0.0245***	-0.0245***	-0.0245***	-0.0244***	-0.0245***	-0.0245***	-0.0245***	-0.0244***	-0.0245***	-0.0245***
	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)
RET_{it-3}	-0.0084***	-0.0084***	-0.0084***	-0.0083***	-0.0084***	-0.0084***	-0.0084***	-0.0084***	-0.0084***	-0.0084***	-0.0084***
	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)
RET_{it-4}	-0.0031	-0.0031	-0.0031	-0.0031	-0.0031	-0.0031	-0.0031	-0.0031	-0.0031	-0.0031	-0.0031
	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)
RET_{it-5}	-0.0107***	-0.0107***	-0.0107***	-0.0107***	-0.0107***	-0.0106***	-0.0107***	-0.0107***	-0.0107***	-0.0107***	-0.0107***
	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)
$BEHAVIOUR_t$	-0.0000*	-0.0000**	0.0000***	0.4302***	-1.5990***	-2.1808***	1.3177***	-1.4928*	-4.0479***	-0.0011**	0.0014***
	(0.0000)	(0.0000)	(0.0000)	(0.0766)	(0.2560)	(0.4567)	(0.3075)	(0.8417)	(0.5040)	(0.0005)	(0.0005)
CONSTANT	-0.0453***	-0.0469***	-0.0456***	-0.0534***	-0.0580***	-0.0373***	-0.0606***	-0.0457***	-0.0520***	-0.0449***	-0.0462***
	(0.0065)	(0.0066)	(0.0065)	(0.0067)	(0.0068)	(0.0067)	(0.0074)	(0.0065)	(0.0066)	(0.0065)	(0.0065)
Observations	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442
No. of stocks	409	409	409	409	409	409	409	409	409	409	409
R^2	0.9760	0.9760	0.9760	0.9760	0.9760	0.9760	0.9760	0.9760	0.9760	0.9760	0.9760
Adjusted R^2	0.976	0.976	0.976	0.976	0.976	0.976	0.976	0.976	0.976	0.976	0.976

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3.4 (Continued)

NSk_{it+1}	POS_{it}	$VarPOS_{it}$	COV_{it}	$CSAD_t$	LOS_t	WIN_t	PMN_t	LVR_t	HVR_t	UPS_t
	Panel E: Non-overlapping Market-Adjusted Returns of Aggregate Market Stocks									
NSk_{it}	-0.0015	0.0009	-0.0006	-0.0024	-0.0024	-0.0030	-0.0040	-0.0018	-0.0014	-0.0031
	(0.0151)	(0.0151)	(0.0151)	(0.0152)	(0.0151)	(0.0152)	(0.0151)	(0.0151)	(0.0151)	(0.0151)
$SIGMA_{it}$	0.1197	0.1748	0.1923	0.1208	0.1000	0.0983	0.0524	0.1323	0.1491	0.0361
	(0.8260)	(0.8248)	(0.8259)	(0.8260)	(0.8256)	(0.8260)	(0.8256)	(0.8260)	(0.8260)	(0.8247)
$LOGSIZE_{it}$	0.6249***	0.6384***	0.6232***	0.6438***	0.5900***	0.6522***	0.6307***	0.6230***	0.6008***	0.6174***
	(0.0602)	(0.0601)	(0.0601)	(0.0641)	(0.0613)	(0.0628)	(0.0601)	(0.0621)	(0.0636)	(0.0600)
$DTURNOVER_{it}$	1.5790	1.5614	1.5615	1.6198	1.6219	1.6571	1.7382	1.5752	1.5606	1.7361
	(1.4253)	(1.4232)	(1.4246)	(1.4260)	(1.4246)	(1.4259)	(1.4249)	(1.4258)	(1.4253)	(1.4232)
RET_{it}	-0.1072	-0.1062	-0.1101	-0.1297	-0.0678	-0.1377	-0.1095	-0.1076	-0.0829	-0.0805
	(0.0907)	(0.0906)	(0.0907)	(0.0938)	(0.0918)	(0.0926)	(0.0906)	(0.0924)	(0.0936)	(0.0907)
RET_{it-1}	0.2647***	0.2656***	0.2667***	0.2465***	0.3029***	0.2391***	0.2681***	0.2642***	0.2833***	0.3008***
	(0.0906)	(0.0905)	(0.0906)	(0.0926)	(0.0917)	(0.0920)	(0.0906)	(0.0922)	(0.0924)	(0.0908)
RET_{it-2}	-0.0574	-0.0370	-0.0476	-0.0743	-0.0199	-0.0770	-0.0447	-0.0590	-0.0398	-0.0247
	(0.0864)	(0.0864)	(0.0864)	(0.0879)	(0.0875)	(0.0871)	(0.0864)	(0.0872)	(0.0882)	(0.0865)
RET_{it-3}	0.2855***	0.2791***	0.2827***	0.2707***	0.3192***	0.2752***	0.3081***	0.2836***	0.2993***	0.2875***
	(0.0859)	(0.0858)	(0.0858)	(0.0870)	(0.0869)	(0.0860)	(0.0861)	(0.0861)	(0.0872)	(0.0857)
RET_{it-4}	-0.0897	-0.0789	-0.0841	-0.0985	-0.0624	-0.0957	-0.0734	-0.0875	-0.0755	-0.0883
	(0.0831)	(0.0830)	(0.0831)	(0.0839)	(0.0836)	(0.0832)	(0.0831)	(0.0832)	(0.0839)	(0.0830)
RET_{it-5}	0.0660	0.0680	0.0790	0.0588	0.0786	0.0557	0.0598	0.0691	0.0785	0.0574
	(0.0724)	(0.0722)	(0.0724)	(0.0732)	(0.0724)	(0.0728)	(0.0723)	(0.0726)	(0.0729)	(0.0723)
$BEHAVIOUR_t$	0.0000	-0.0000***	-0.0000**	8.1543	-90.1679***	66.8097*	91.9991***	5.1560	-75.9368	-0.1979***
	(0.0000)	(0.0000)	(0.0000)	(8.4495)	(33.9469)	(40.5297)	(27.8020)	(104.6986)	(73.6195)	(0.0422)
CONSTANT	-13.0461***	-13.3258***	-13.0107***	-13.5677***	-12.6995***	-13.8491***	-13.8762***	-13.0045***	-12.5615***	-12.8198***
	(1.2589)	(1.2581)	(1.2568)	(1.3925)	(1.2615)	(1.3609)	(1.2846)	(1.2906)	(1.3243)	(1.2557)
Observations	7,362	7,362	7,362	7,362	7,362	7,362	7,362	7,362	7,362	7,362
No. of stocks	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227
R^2	0.0440	0.0467	0.0449	0.0440	0.0450	0.0443	0.0456	0.0439	0.0440	0.0473
Adjusted R^2	-0.149	-0.146	-0.148	-0.149	-0.148	-0.149	-0.147	-0.149	-0.149	-0.145

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.4 (Continued)

NSk_{it+1}	Panel F: Non-overlapping Market-Adjusted Returns of Large-cap Stocks									
	POS_{it}	$VarPOS_{it}$	COV_{it}	$CSAD_t$	LOS_t	WIN_t	PMN_t	LVR_t	HVR_t	UPS_t
NSk_{it}	0.0234	0.0245	0.0254	0.0224	0.0250	0.0226	0.0235	0.0241	0.0244	0.0235
	(0.0270)	(0.0270)	(0.0270)	(0.0270)	(0.0271)	(0.0271)	(0.0271)	(0.0270)	(0.0270)	(0.0270)
$SIGMA_{it}$	12.9189	13.8506	13.3920	18.7260*	13.5158	13.3725	11.8128	13.8790	15.8048	8.5838
	(10.7210)	(10.7339)	(10.7260)	(10.9967)	(11.2565)	(10.7301)	(10.9277)	(10.8838)	(10.9689)	(10.9795)
$LOGSIZE_{it}$	0.7257***	0.7295***	0.7150***	0.9751***	0.7192***	0.7694***	0.6952***	0.7379***	0.8564***	0.6518***
	(0.1176)	(0.1175)	(0.1168)	(0.1646)	(0.1439)	(0.1319)	(0.1181)	(0.1336)	(0.1693)	(0.1201)
$DTURNOVER_{it}$	-3.6053	-2.9922	-4.5968	-1.7344	-3.7193	-2.0438	-2.5589	-2.9634	-4.6124	-1.4215
	(13.1402)	(13.1419)	(13.1655)	(13.1509)	(13.2036)	(13.2188)	(13.2612)	(13.1922)	(13.1710)	(13.1846)
RET_{it}	0.2847	0.3162	0.3356	0.1452	0.3198	0.2758	0.3268	0.3036	0.2282	0.3576
	(0.2782)	(0.2764)	(0.2764)	(0.2871)	(0.2801)	(0.2808)	(0.2765)	(0.2805)	(0.2879)	(0.2768)
RET_{it-1}	0.4635*	0.4824**	0.4866**	0.3128	0.4821*	0.4496*	0.4971**	0.4708*	0.3876	0.5254**
	(0.2446)	(0.2437)	(0.2437)	(0.2553)	(0.2496)	(0.2470)	(0.2441)	(0.2471)	(0.2578)	(0.2443)
RET_{it-2}	0.1586	0.1805	0.1904	0.0988	0.1746	0.1552	0.1790	0.1678	0.1355	0.1873
	(0.2467)	(0.2462)	(0.2464)	(0.2484)	(0.2474)	(0.2473)	(0.2463)	(0.2472)	(0.2487)	(0.2462)
RET_{it-3}	0.8302***	0.8417***	0.8449***	0.7249***	0.8362***	0.8185***	0.8493***	0.8338***	0.7661***	0.8445***
	(0.2364)	(0.2362)	(0.2362)	(0.2414)	(0.2396)	(0.2374)	(0.2366)	(0.2370)	(0.2443)	(0.2361)
RET_{it-4}	-0.5387**	-0.5422**	-0.5420**	-0.6234**	-0.5471**	-0.5636**	-0.5437**	-0.5542**	-0.5772**	-0.5393**
	(0.2506)	(0.2505)	(0.2505)	(0.2526)	(0.2513)	(0.2513)	(0.2506)	(0.2515)	(0.2520)	(0.2504)
RET_{it-5}	0.0705	0.0876	0.0891	-0.0283	0.0860	0.0545	0.0822	0.0747	0.0429	0.0722
	(0.2237)	(0.2232)	(0.2233)	(0.2287)	(0.2238)	(0.2257)	(0.2236)	(0.2250)	(0.2263)	(0.2233)
$BEHAVIOUR_t$	0.0324	-0.0042	0.0264	45.1071**	11.4912	79.0783	26.4981	100.4639	211.8564	-0.1372*
	(0.0246)	(0.0026)	(0.0200)	(19.4638)	(70.4837)	(76.2731)	(48.4781)	(202.2957)	(172.4375)	(0.0749)
CONSTANT	-17.2255***	-17.3107***	-16.9749***	-23.8516***	-17.0291***	-18.5278***	-16.6968***	-17.4869***	-20.2764***	-15.3850***
	(2.7952)	(2.7939)	(2.7769)	(4.1307)	(3.2643)	(3.2604)	(2.7741)	(3.1463)	(3.9911)	(2.8686)
Observations	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454
No. of stocks	409	409	409	409	409	409	409	409	409	409
R^2	0.0438	0.0442	0.0438	0.0455	0.0430	0.0435	0.0431	0.0431	0.0437	0.0446
Adjusted R^2	-0.153	-0.153	-0.153	-0.151	-0.154	-0.154	-0.154	-0.154	-0.153	-0.152

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.4 (Continued)

NSk$_{it+1}$	POS$_{it}$	VarPOS$_{it}$	COV$_{it}$	CSAD$_t$	LOS$_t$	WIN$_t$	PMN$_t$	LVR$_t$	HVR$_t$	UPS$_t$
	Panel G: Non-overlapping Market-Adjusted Returns of Mid-cap Stocks									
NSk$_{it}$	-0.0164	-0.0161	-0.0162	-0.0215	-0.0165	-0.0209	-0.0196	-0.0188	-0.0172	-0.0171
	(0.0275)	(0.0275)	(0.0275)	(0.0275)	(0.0275)	(0.0274)	(0.0275)	(0.0275)	(0.0275)	(0.0275)
SIGMA$_{it}$	2.9414	2.8783	2.8794	7.3814	0.8415	4.7063	-0.6771	5.7940	4.2778	0.0459
	(6.7828)	(6.7846)	(6.7828)	(6.9506)	(6.9915)	(6.7730)	(6.8377)	(6.8680)	(6.9172)	(6.8787)
LOGSIZE$_{it}$	0.8846***	0.8839***	0.8841***	1.1219***	0.8199***	1.1084***	0.8731***	1.0241***	0.9641***	0.8496***
	(0.1312)	(0.1313)	(0.1312)	(0.1555)	(0.1416)	(0.1428)	(0.1309)	(0.1423)	(0.1534)	(0.1319)
DTURNOVER$_{it}$	27.5294***	27.5413***	27.5456***	27.2829***	28.7364***	29.7817***	31.6021***	27.8452***	27.0169***	29.6444***
	(9.7760)	(9.7765)	(9.7761)	(9.7575)	(9.8233)	(9.7570)	(9.8144)	(9.7620)	(9.7875)	(9.8029)
RET$_{it}$	-0.3431	-0.3431	-0.3443	-0.5644**	-0.2886	-0.5362**	-0.3348	-0.4656**	-0.4195*	-0.3007
	(0.2113)	(0.2114)	(0.2113)	(0.2248)	(0.2161)	(0.2162)	(0.2107)	(0.2165)	(0.2244)	(0.2118)
RET$_{it-1}$	0.0154	0.0158	0.0163	-0.1417	0.0501	-0.1938	-0.0322	-0.1186	-0.0287	0.0509
	(0.1915)	(0.1915)	(0.1915)	(0.1990)	(0.1936)	(0.1982)	(0.1914)	(0.1985)	(0.1965)	(0.1918)
RET$_{it-2}$	-0.3545*	-0.3531*	-0.3546*	-0.4712**	-0.3100	-0.4690**	-0.3252*	-0.4297**	-0.4010**	-0.3067
	(0.1945)	(0.1945)	(0.1946)	(0.1986)	(0.1977)	(0.1961)	(0.1941)	(0.1966)	(0.2003)	(0.1952)
RET$_{it-3}$	0.2389	0.2382	0.2386	0.1285	0.2825	0.1769	0.3023*	0.2024	0.1931	0.2414
	(0.1829)	(0.1829)	(0.1829)	(0.1865)	(0.1865)	(0.1828)	(0.1832)	(0.1831)	(0.1881)	(0.1826)
RET$_{it-4}$	-0.2235	-0.2230	-0.2232	-0.3073	-0.1934	-0.2677	-0.1832	-0.2609	-0.2482	-0.2165
	(0.1900)	(0.1900)	(0.1900)	(0.1919)	(0.1915)	(0.1896)	(0.1897)	(0.1903)	(0.1916)	(0.1897)
RET$_{it-5}$	0.2184	0.2197	0.2191	0.1089	0.2344	0.1058	0.1856	0.1538	0.1885	0.2192
	(0.1639)	(0.1639)	(0.1639)	(0.1681)	(0.1643)	(0.1658)	(0.1636)	(0.1656)	(0.1666)	(0.1636)
BEHAVIOUR$_t$	-0.0003	0.0000	-0.0000	51.2262***	-84.0583	315.7533***	189.6651***	532.3097**	156.4802	-0.1949**
	(0.0007)	(0.0000)	(0.0000)	(18.0669)	(69.3580)	(80.8473)	(53.6848)	(211.1567)	(156.2127)	(0.0817)
CONSTANT	-18.3055***	-18.2911***	-18.2946***	-24.0986***	-17.2857***	-24.0644***	-19.4667***	-21.0647***	-19.9399***	-17.4595***
	(2.7442)	(2.7452)	(2.7444)	(3.4174)	(2.8691)	(3.1066)	(2.7557)	(2.9509)	(3.1931)	(2.7633)
Observations	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454
No. of stocks	409	409	409	409	409	409	409	409	409	409
R^2	0.0462	0.0462	0.0462	0.0499	0.0469	0.0533	0.0520	0.0491	0.0466	0.0488
Adjusted R^2	-0.150	-0.150	-0.150	-0.146	-0.149	-0.142	-0.143	-0.147	-0.150	-0.147

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.4 (Continued)

NSk_{it+1}	POS_{it}	$VarPOS_{it}$	COV_{it}	$CSAD_t$	LOS_t	WIN_t	PMN_t	LVR_t	HVR_t	UPS_t
	Panel H: Non-overlapping Market-Adjusted Returns of Small-cap Stocks									
NSk_{it}	0.0077	0.0160	0.0122	0.0076	0.0071	0.0075	0.0065	0.0075	0.0083	0.0054
	(0.0264)	(0.0263)	(0.0264)	(0.0264)	(0.0264)	(0.0264)	(0.0264)	(0.0264)	(0.0264)	(0.0263)
$SIGMA_{it}$	-0.0232	0.0456	0.0687	0.0160	0.0205	0.0179	-0.0235	0.0240	0.0684	-0.0225
	(0.7646)	(0.7607)	(0.7635)	(0.7657)	(0.7641)	(0.7654)	(0.7645)	(0.7646)	(0.7654)	(0.7626)
$LOGSIZE_{it}$	0.4317***	0.4574***	0.4276***	0.4292***	0.4528***	0.4240***	0.4420***	0.4290***	0.4408***	0.4721***
	(0.0819)	(0.0816)	(0.0816)	(0.0818)	(0.0829)	(0.0818)	(0.0831)	(0.0817)	(0.0821)	(0.0827)
$DTURNOVER_{it}$	0.6279	0.6257	0.6086	0.6046	0.6975	0.5954	0.6765	0.6044	0.6264	0.7910
	(1.3112)	(1.3046)	(1.3088)	(1.3114)	(1.3110)	(1.3115)	(1.3124)	(1.3108)	(1.3104)	(1.3091)
RET_{it}	0.0140	0.0139	0.0139	0.0197	0.0150	0.0232	0.0073	0.0261	0.0238	0.0084
	(0.1082)	(0.1076)	(0.1080)	(0.1084)	(0.1081)	(0.1087)	(0.1085)	(0.1084)	(0.1082)	(0.1079)
RET_{it-1}	0.4068***	0.4039***	0.4106***	0.4066***	0.4027***	0.4093***	0.4042***	0.4101***	0.4015***	0.4056***
	(0.1133)	(0.1127)	(0.1131)	(0.1133)	(0.1133)	(0.1133)	(0.1134)	(0.1133)	(0.1133)	(0.1130)
RET_{it-2}	0.0369	0.0604	0.0530	0.0397	0.0471	0.0390	0.0391	0.0419	0.0464	0.0478
	(0.1032)	(0.1028)	(0.1032)	(0.1033)	(0.1033)	(0.1033)	(0.1032)	(0.1033)	(0.1033)	(0.1030)
RET_{it-3}	0.2826***	0.2721***	0.2811***	0.2800***	0.2809***	0.2767***	0.2859***	0.2718***	0.2775***	0.2562**
	(0.1052)	(0.1047)	(0.1050)	(0.1052)	(0.1051)	(0.1054)	(0.1053)	(0.1054)	(0.1051)	(0.1052)
RET_{it-4}	0.0422	0.0526	0.0510	0.0468	0.0496	0.0437	0.0497	0.0401	0.0497	0.0256
	(0.0964)	(0.0958)	(0.0961)	(0.0963)	(0.0962)	(0.0963)	(0.0964)	(0.0964)	(0.0963)	(0.0963)
RET_{it-5}	0.0606	0.0612	0.0805	0.0660	0.0556	0.0665	0.0596	0.0629	0.0641	0.0363
	(0.0831)	(0.0825)	(0.0829)	(0.0829)	(0.0830)	(0.0829)	(0.0831)	(0.0829)	(0.0828)	(0.0832)
$BEHAVIOUR_t$	0.0000	-0.0000***	-0.0000***	-7.2971	-96.9945*	-44.7092	43.7509	-209.2919	-184.2760*	-0.2163***
	(0.0000)	(0.0000)	(0.0000)	(12.3813)	(53.3115)	(60.8083)	(44.5976)	(158.6307)	(109.6060)	(0.0674)
CONSTANT	-8.0095***	-8.4734***	-7.9334***	-7.8511***	-8.8112***	-7.7145***	-8.5364***	-8.0344***	-8.2219***	-8.6820***
	(1.5230)	(1.5165)	(1.5167)	(1.5253)	(1.5941)	(1.5472)	(1.6408)	(1.5212)	(1.5286)	(1.5339)
Observations	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454
No. of stocks	409	409	409	409	409	409	409	409	409	409
R^2	0.0664	0.0758	0.0698	0.0663	0.0677	0.0664	0.0666	0.0669	0.0674	0.0709
Adjusted R^2	-0.126	-0.115	-0.122	-0.126	-0.124	-0.126	-0.126	-0.125	-0.125	-0.121

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.5: Forecasting Excess Kurtosis with Single Behavioural Factor

This table presents the FE panel data regression forecasting of ExKr_{it+1} with variables computed with market-adjusted returns. Column 1 indicates the dependent variable and the independent variables. The factor BEHAVIOUR_t uses the behavioural factor indicated at the top of each column. BEHAVIOUR_t represents POS_{it}, VarPOS_{it}, COV_{it}, CSAD_t, LOS_t, WIN_t, PMN_t, LVR_t, HVR_t, UPS_t, and DOWNS_t. Unlike overlapping returns, non-overlapping returns can only investigate the effect of UPS_t due to limited observation.

	Panel A: Overlapping Market-Adjusted Returns of Aggregate Market Stocks										
ExKr_{it+1}	POS_{it}	VarPOS_{it}	COV_{it}	CSAD_t	LOS_t	WIN_t	PMN_t	LVR_t	HVR_t	UPS_t	DOWNS_t
ExKr_{it}	0.9888***	0.9888***	0.9888***	0.9888***	0.9888***	0.9888***	0.9888***	0.9888***	0.9888***	0.9888***	0.9888***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
SIGMA_{it}	-0.0966***	-0.0966***	-0.0965***	-0.0912***	-0.0950***	-0.0952***	-0.0977***	-0.0924***	-0.0960***	-0.0960***	-0.0962***
	(0.0337)	(0.0337)	(0.0337)	(0.0337)	(0.0337)	(0.0337)	(0.0337)	(0.0337)	(0.0337)	(0.0337)	(0.0337)
LOGSIZE_{it}	0.0060***	0.0060***	0.0060***	0.0040**	0.0064***	0.0064***	0.0057***	0.0055***	0.0066***	0.0060***	0.0060***
	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
DTURNOVER_{it}	0.0342	0.0342	0.0347	0.0300	0.0357	0.0337	0.0328	0.0303	0.0363	0.0340	0.0341
	(0.0612)	(0.0612)	(0.0612)	(0.0612)	(0.0612)	(0.0612)	(0.0612)	(0.0612)	(0.0612)	(0.0612)	(0.0612)
RET_{it}	-0.0597***	-0.0604***	-0.0603***	-0.0602***	-0.0612***	-0.0622***	-0.0600***	-0.0611***	-0.0616***	-0.0603***	-0.0604***
	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)
RET_{it-1}	-0.0282*	-0.0278	-0.0277	-0.0279*	-0.0280*	-0.0283*	-0.0277	-0.0281*	-0.0281*	-0.0277	-0.0278
	(0.0170)	(0.0170)	(0.0170)	(0.0170)	(0.0170)	(0.0170)	(0.0170)	(0.0170)	(0.0170)	(0.0170)	(0.0170)
RET_{it-2}	0.0423**	0.0424**	0.0424**	0.0421**	0.0423**	0.0421**	0.0424**	0.0422**	0.0422**	0.0424**	0.0424**
	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)
RET_{it-3}	-0.0182	-0.0181	-0.0181	-0.0182	-0.0181	-0.0182	-0.0181	-0.0182	-0.0181	-0.0180	-0.0181
	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)
RET_{it-4}	0.0190	0.0191	0.0191	0.0192	0.0191	0.0190	0.0191	0.0190	0.0191	0.0191	0.0191
	(0.0169)	(0.0169)	(0.0169)	(0.0169)	(0.0169)	(0.0169)	(0.0169)	(0.0169)	(0.0169)	(0.0169)	(0.0169)
RET_{it-5}	0.0324**	0.0324**	0.0324**	0.0328**	0.0323**	0.0321**	0.0324**	0.0320**	0.0324**	0.0323**	0.0323**
	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)
BEHAVIOUR_t	-0.0000***	0.0000	0.0000***	-2.5302***	2.7508***	14.2209***	2.3798**	20.8069***	6.5200***	-0.0030	0.0017
	(0.0000)	(0.0000)	(0.0000)	(0.2945)	(0.9671)	(1.7361)	(1.1572)	(3.2035)	(1.9154)	(0.0019)	(0.0018)
CONSTANT	-0.0404	-0.0403	-0.0405	0.0409	-0.0369	-0.0957***	-0.0527	-0.0222	-0.0519	-0.0391	-0.0415
	(0.0351)	(0.0352)	(0.0351)	(0.0363)	(0.0351)	(0.0357)	(0.0356)	(0.0352)	(0.0352)	(0.0351)	(0.0351)
Observations	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326	2,623,326
No. of stocks	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227
R^2	0.9775	0.9775	0.9775	0.9775	0.9775	0.9775	0.9775	0.9775	0.9775	0.9775	0.9775
Adjusted R^2	0.977	0.977	0.977	0.977	0.977	0.977	0.977	0.977	0.977	0.977	0.977

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.5 (Continued)

	Panel B: Overlapping Market-Adjusted Returns of Large-cap Stocks										
$ExKr_{it+1}$	POS_{it}	$VarPOS_{it}$	COV_{it}	$CSAD_t$	LOS_t	WIN_t	PMN_t	LVR_t	HVR_t	UPS_t	$DOWNS_t$
$ExKr_{it}$	0.9893***	0.9893***	0.9893***	0.9893***	0.9893***	0.9893***	0.9893***	0.9893***	0.9893***	0.9893***	0.9893***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$SIGMA_{it}$	0.1299	0.1677	0.1287	0.3422	0.3862	0.2011	0.1380	0.2359	0.3832	0.1849	0.1626
	(0.4238)	(0.4244)	(0.4238)	(0.4252)	(0.4341)	(0.4241)	(0.4360)	(0.4254)	(0.4285)	(0.4242)	(0.4242)
$LOGSIZE_{it}$	0.0147***	0.0153***	0.0148***	0.0104***	0.0183***	0.0153***	0.0149***	0.0140***	0.0199***	0.0149***	0.0149***
	(0.0033)	(0.0033)	(0.0033)	(0.0034)	(0.0036)	(0.0033)	(0.0037)	(0.0033)	(0.0036)	(0.0033)	(0.0033)
$DTURNOVER_{it}$	-2.2646***	-2.2700***	-2.2647***	-2.0623***	-2.1138***	-1.8356***	-2.2652***	-2.0602***	-1.9971***	-2.2863***	-2.2712***
	(0.6539)	(0.6539)	(0.6539)	(0.6547)	(0.6562)	(0.6610)	(0.6539)	(0.6578)	(0.6573)	(0.6539)	(0.6539)
RET_{it}	0.1121	0.1414**	0.1419**	0.1413**	0.1399**	0.1418**	0.1418**	0.1427**	0.1382**	0.1427**	0.1428**
	(0.0717)	(0.0682)	(0.0682)	(0.0682)	(0.0682)	(0.0682)	(0.0682)	(0.0682)	(0.0682)	(0.0682)	(0.0682)
RET_{it-1}	-0.1847*	-0.2144**	-0.2144**	-0.2153**	-0.2145**	-0.2145**	-0.2144**	-0.2143**	-0.2146**	-0.2138**	-0.2148**
	(0.0982)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)
RET_{it-2}	0.1116	0.1115	0.1115	0.1115	0.1115	0.1113	0.1116	0.1113	0.1116	0.1116	0.1118
	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)
RET_{it-3}	-0.0647	-0.0645	-0.0644	-0.0639	-0.0644	-0.0643	-0.0644	-0.0645	-0.0643	-0.0646	-0.0645
	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)
RET_{it-4}	-0.0108	-0.0111	-0.0111	-0.0111	-0.0111	-0.0111	-0.0111	-0.0112	-0.0110	-0.0112	-0.0110
	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)	(0.0958)
RET_{it-5}	-0.0004	0.0001	-0.0002	0.0026	-0.0004	-0.0008	-0.0002	-0.0006	-0.0005	-0.0014	-0.0010
	(0.0682)	(0.0682)	(0.0682)	(0.0682)	(0.0682)	(0.0682)	(0.0682)	(0.0682)	(0.0682)	(0.0682)	(0.0682)
$BEHAVIOUR_t$	0.0009	-0.0000	-0.0000	-2.9149***	4.5296***	12.2604***	-0.1783	14.7099***	13.0836***	-0.0086***	0.0049*
	(0.0007)	(0.0000)	(0.0002)	(0.4778)	(1.6602)	(2.7687)	(2.0128)	(5.1328)	(3.2530)	(0.0029)	(0.0029)
CONSTANT	-0.2711***	-0.2851***	-0.2720***	-0.1236	-0.3380***	-0.3258***	-0.2738***	-0.2477***	-0.3920***	-0.2712***	-0.2772***
	(0.0798)	(0.0802)	(0.0799)	(0.0835)	(0.0834)	(0.0808)	(0.0824)	(0.0803)	(0.0852)	(0.0798)	(0.0799)
Observations	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442
No. of stocks	409	409	409	409	409	409	409	409	409	409	409
R^2	0.9785	0.9785	0.9785	0.9785	0.9785	0.9785	0.9785	0.9785	0.9785	0.9785	0.9785
Adjusted R^2	0.979	0.979	0.979	0.979	0.979	0.979	0.979	0.979	0.979	0.979	0.979

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 3.5 (CONTINUED)

	Panel C: Overlapping Market-Adjusted Returns of Mid-cap Stocks										
$ExKr_{it+1}$	POS_{it}	$VarPOS_{it}$	COV_{it}	$CSAD_t$	LOS_t	WIN_t	PMN_t	LVR_t	HVR_t	UPS_t	$DOWNS_t$
$ExKr_{it}$	0.9892***	0.9894***	0.9894***	0.9892***	0.9892***	0.9891***	0.9892***	0.9891***	0.9892***	0.9892***	0.9892***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$SIGMA_{it}$	0.2495	-0.5329*	-0.6177**	0.2162	0.1913	0.2302	0.0587	0.2588	0.1846	0.1761	0.1703
	(0.2560)	(0.2863)	(0.2847)	(0.2564)	(0.2591)	(0.2563)	(0.2591)	(0.2571)	(0.2572)	(0.2562)	(0.2562)
$LOGSIZE_{it}$	0.0256***	0.0225***	0.0223***	0.0233***	0.0259***	0.0261***	0.0227***	0.0248***	0.0259***	0.0254***	0.0254***
	(0.0038)	(0.0039)	(0.0038)	(0.0039)	(0.0039)	(0.0038)	(0.0039)	(0.0038)	(0.0039)	(0.0038)	(0.0038)
$DTURNOVER_{it}$	0.3795	0.7340	0.7692	0.4315	0.4201	0.5458	0.5150	0.4466	0.4311	0.4168	0.4258
	(0.5129)	(0.5160)	(0.5158)	(0.5129)	(0.5131)	(0.5135)	(0.5139)	(0.5130)	(0.5130)	(0.5131)	(0.5131)
RET_{it}	-0.2557***	-0.1733***	-0.1721***	-0.1828***	-0.1840***	-0.1874***	-0.1823***	-0.1832***	-0.1844***	-0.1834***	-0.1835***
	(0.0493)	(0.0492)	(0.0492)	(0.0492)	(0.0492)	(0.0492)	(0.0492)	(0.0492)	(0.0492)	(0.0492)	(0.0492)
RET_{it-1}	0.1545**	0.0899	0.0895	0.0885	0.0900	0.0897	0.0903	0.0893	0.0900	0.0902	0.0900
	(0.0695)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)
RET_{it-2}	0.0711	0.0639	0.0639	0.0634	0.0639	0.0635	0.0641	0.0634	0.0639	0.0639	0.0640
	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)
RET_{it-3}	-0.0143	-0.0137	-0.0138	-0.0126	-0.0138	-0.0136	-0.0139	-0.0138	-0.0137	-0.0137	-0.0138
	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)
RET_{it-4}	0.1026	0.1011	0.1011	0.1005	0.1011	0.1010	0.1013	0.1011	0.1012	0.1013	0.1012
	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)	(0.0694)
RET_{it-5}	-0.0785	-0.0804	-0.0801	-0.0771	-0.0781	-0.0786	-0.0784	-0.0797	-0.0781	-0.0785	-0.0782
	(0.0491)	(0.0492)	(0.0492)	(0.0492)	(0.0492)	(0.0492)	(0.0492)	(0.0492)	(0.0492)	(0.0492)	(0.0492)
$BEHAVIOUR_t$	0.0006***	0.0000***	0.0000***	-1.7959***	1.0017	15.8627***	5.9123***	21.8331***	2.2409	-0.0026	0.0005
	(0.0000)	(0.0000)	(0.0000)	(0.5337)	(1.7764)	(3.1328)	(2.1336)	(5.7986)	(3.5111)	(0.0033)	(0.0033)
CONSTANT	-0.4449***	-0.3674***	-0.3603***	-0.3677***	-0.4450***	-0.5074***	-0.4280***	-0.4193***	-0.4499***	-0.4387***	-0.4393***
	(0.0805)	(0.0816)	(0.0815)	(0.0832)	(0.0812)	(0.0816)	(0.0806)	(0.0807)	(0.0824)	(0.0805)	(0.0806)
Observations	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442
No. of stocks	409	409	409	409	409	409	409	409	409	409	409
R^2	0.9785	0.9785	0.9785	0.9785	0.9785	0.9785	0.9785	0.9785	0.9785	0.9785	0.9785
Adjusted R^2	0.979	0.979	0.979	0.979	0.979	0.979	0.979	0.979	0.979	0.979	0.979

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3.5 (Continued)

$ExKr_{it+1}$	POS_{it}	$VarPOS_{it}$	COV_{it}	$CSAD_t$	LOS_t	WIN_t	PMN_t	LVR_t	HVR_t	UPS_t	$DOWNS_t$
	Panel D: Overlapping Market-Adjusted Returns of Small-cap Stocks										
$ExKr_{it}$	0.9877***	0.9877***	0.9877***	0.9877***	0.9877***	0.9877***	0.9877***	0.9877***	0.9877***	0.9877***	0.9877***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$SIGMA_{it}$	-0.1010***	-0.1012***	-0.1010***	-0.0971***	-0.1059***	-0.1024***	-0.1036***	-0.0992***	-0.1067***	-0.1012***	-0.1010***
	(0.0360)	(0.0360)	(0.0360)	(0.0360)	(0.0360)	(0.0360)	(0.0360)	(0.0360)	(0.0360)	(0.0360)	(0.0360)
$LOGSIZE_{it}$	-0.0074***	-0.0076***	-0.0073***	-0.0077***	-0.0088***	-0.0071***	-0.0083***	-0.0072***	-0.0084***	-0.0074***	-0.0074***
	(0.0024)	(0.0025)	(0.0024)	(0.0024)	(0.0025)	(0.0024)	(0.0025)	(0.0024)	(0.0025)	(0.0024)	(0.0024)
$DTURNOVER_{it}$	0.0323	0.0318	0.0330	0.0304	0.0277	0.0267	0.0313	0.0273	0.0287	0.0323	0.0322
	(0.0656)	(0.0656)	(0.0656)	(0.0656)	(0.0656)	(0.0656)	(0.0656)	(0.0656)	(0.0656)	(0.0656)	(0.0656)
RET_{it}	-0.0512***	-0.0519***	-0.0518***	-0.0523***	-0.0529***	-0.0536***	-0.0520***	-0.0533***	-0.0529***	-0.0520***	-0.0520***
	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)
RET_{it-1}	-0.0340*	-0.0335*	-0.0334*	-0.0333*	-0.0340*	-0.0339*	-0.0336*	-0.0338*	-0.0340*	-0.0335*	-0.0335*
	(0.0187)	(0.0187)	(0.0187)	(0.0187)	(0.0187)	(0.0187)	(0.0187)	(0.0187)	(0.0187)	(0.0187)	(0.0187)
RET_{it-2}	0.0356*	0.0357*	0.0358*	0.0356*	0.0355*	0.0355*	0.0357*	0.0356*	0.0355*	0.0357*	0.0357*
	(0.0190)	(0.0190)	(0.0190)	(0.0190)	(0.0190)	(0.0190)	(0.0190)	(0.0190)	(0.0190)	(0.0190)	(0.0190)
RET_{it-3}	-0.0192	-0.0191	-0.0191	-0.0193	-0.0191	-0.0192	-0.0191	-0.0192	-0.0191	-0.0191	-0.0191
	(0.0190)	(0.0190)	(0.0190)	(0.0190)	(0.0190)	(0.0190)	(0.0190)	(0.0190)	(0.0190)	(0.0190)	(0.0190)
RET_{it-4}	0.0180	0.0180	0.0181	0.0181	0.0181	0.0180	0.0181	0.0180	0.0181	0.0181	0.0181
	(0.0187)	(0.0187)	(0.0187)	(0.0187)	(0.0187)	(0.0187)	(0.0187)	(0.0187)	(0.0187)	(0.0187)	(0.0187)
RET_{it-5}	0.0499***	0.0499***	0.0499***	0.0500***	0.0500***	0.0498***	0.0500***	0.0498***	0.0500***	0.0499***	0.0499***
	(0.0162)	(0.0162)	(0.0162)	(0.0162)	(0.0162)	(0.0162)	(0.0162)	(0.0162)	(0.0162)	(0.0162)	(0.0162)
$BEHAVIOUR_{it}$	-0.0000***	0.0000	0.0000***	-2.2066***	7.6669***	13.7009***	-4.8489**	20.1624***	13.9734***	0.0018	0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.5305)	(1.7725)	(3.1618)	(2.1288)	(5.8300)	(3.4889)	(0.0034)	(0.0033)
CONSTANT	0.2190***	0.2232***	0.2188***	0.2606***	0.2797***	0.1688***	0.2751***	0.2241***	0.2422***	0.2182***	0.2188***
	(0.0450)	(0.0452)	(0.0450)	(0.0461)	(0.0471)	(0.0464)	(0.0513)	(0.0450)	(0.0453)	(0.0450)	(0.0450)
Observations	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442	874,442
No. of stocks	409	409	409	409	409	409	409	409	409	409	409
R^2	0.9755	0.9755	0.9755	0.9755	0.9755	0.9755	0.9755	0.9755	0.9755	0.9755	0.9755
Adjusted R^2	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 3.5 (CONTINUED)

	Panel E: Non-overlapping Market-Adjusted Returns of Aggregate Market Stocks									
$ExKr_{it+1}$	POS_{it}	$VarPOS_{it}$	COV_{it}	$CSAD_t$	LOS_t	WIN_t	PMN_t	LVR_t	HVR_t	UPS_t
$ExKr_{it}$	0.0422***	0.0412***	0.0403***	0.0415***	0.0405***	0.0423***	0.0412***	0.0421***	0.0408***	0.0418***
	(0.0143)	(0.0144)	(0.0144)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)
$SIGMA_{it}$	-10.3544**	-10.2758*	-10.4492**	-10.0772*	-10.5078**	-10.4730**	-10.9284**	-10.2497*	-9.9436*	-10.4367**
	(5.2817)	(5.2810)	(5.2808)	(5.2810)	(5.2737)	(5.2823)	(5.2742)	(5.2815)	(5.2810)	(5.2819)
$LOGSIZE_{it}$	0.1197	0.0740	0.0960	-0.1506	-0.2324	0.2795	0.1748	0.1051	-0.1936	0.0889
	(0.3813)	(0.3816)	(0.3808)	(0.4060)	(0.3879)	(0.3978)	(0.3806)	(0.3935)	(0.4025)	(0.3809)
$DTURNOVER_{it}$	-10.3610	-10.3716	-10.3124	-10.9222	-9.8742	-9.9125	-8.9474	-10.3890	-10.5432	-10.0689
	(9.0273)	(9.0274)	(9.0255)	(9.0306)	(9.0152)	(9.0318)	(9.0179)	(9.0312)	(9.0247)	(9.0292)
RET_{it}	-1.6529***	-1.6387***	-1.6197***	-1.3938**	-1.2329**	-1.8173***	-1.6321***	-1.6524***	-1.3313**	-1.5863***
	(0.5412)	(0.5412)	(0.5413)	(0.5595)	(0.5487)	(0.5521)	(0.5403)	(0.5514)	(0.5590)	(0.5426)
RET_{it-1}	0.1981	0.1963	0.1875	0.4146	0.5880	0.0416	0.2203	0.1923	0.4517	0.2719
	(0.5731)	(0.5732)	(0.5731)	(0.5858)	(0.5793)	(0.5818)	(0.5722)	(0.5829)	(0.5840)	(0.5751)
RET_{it-2}	-1.5523***	-1.5961***	-1.6161***	-1.3771**	-1.1660**	-1.6732***	-1.4420***	-1.5662***	-1.3059**	-1.4924***
	(0.5470)	(0.5480)	(0.5476)	(0.5567)	(0.5537)	(0.5515)	(0.5467)	(0.5521)	(0.5586)	(0.5488)
RET_{it-3}	0.2304	0.2245	0.2221	0.3688	0.5816	0.1660	0.4319	0.2152	0.4285	0.2249
	(0.5439)	(0.5438)	(0.5437)	(0.5504)	(0.5494)	(0.5447)	(0.5448)	(0.5448)	(0.5517)	(0.5437)
RET_{it-4}	-0.5736	-0.5672	-0.5689	-0.4237	-0.2961	-0.6052	-0.4312	-0.5565	-0.3913	-0.5563
	(0.5263)	(0.5262)	(0.5260)	(0.5311)	(0.5287)	(0.5270)	(0.5259)	(0.5270)	(0.5309)	(0.5260)
RET_{it-5}	0.7763*	0.8042*	0.7555*	0.9272**	0.8965**	0.7179	0.7134	0.8000*	0.9288**	0.7774*
	(0.4580)	(0.4574)	(0.4579)	(0.4627)	(0.4572)	(0.4605)	(0.4570)	(0.4593)	(0.4607)	(0.4576)
$BEHAVIOUR_{it}$	0.0000	0.0000	0.0000*	-94.4617*	-930.9736***	403.0702	813.5261***	44.8934	-1,042.6356**	-0.4058
	(0.0000)	(0.0000)	(0.0000)	(53.4488)	(214.7318)	(256.3026)	(175.6950)	(662.5048)	(466.0765)	(0.2674)
CONSTANT	5.5291	6.4780	6.0309	12.6466	8.9394	0.7892	-1.8867	5.8431	11.8306	6.3124
	(7.9734)	(7.9788)	(7.9625)	(8.8141)	(7.9821)	(8.6172)	(8.1299)	(8.1740)	(8.3819)	(7.9666)
Observations	7,362	7,362	7,362	7,362	7,362	7,362	7,362	7,362	7,362	7,362
No. of stocks	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227	1,227
R^2	0.0057	0.0057	0.0061	0.0060	0.0086	0.0059	0.0090	0.0055	0.0063	0.0059
Adjusted R^2	-0.195	-0.195	-0.195	-0.195	-0.192	-0.195	-0.191	-0.195	-0.194	-0.195

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.5 (Continued)

	Panel F: Non-overlapping Market-Adjusted Returns of Large-cap Stocks									
$ExKr_{it+1}$	POS_{it}	$VarPOS_{it}$	COV_{it}	$CSAD_t$	LOS_t	WIN_t	PMN_t	LVR_t	HVR_t	UPS_t
$ExKr_{it}$	0.0209	0.0204	0.0197	0.0197	0.0229	0.0188	0.0229	0.0186	0.0171	0.0185
	(0.0258)	(0.0258)	(0.0258)	(0.0260)	(0.0261)	(0.0258)	(0.0259)	(0.0260)	(0.0259)	(0.0259)
$SIGMA_{it}$	24.2369	28.2695	24.4555	27.7747	7.6311	30.4907	5.0429	33.0562	49.7465	36.7915
	(69.6953)	(69.8264)	(69.7847)	(72.2579)	(74.0538)	(69.8270)	(71.3091)	(71.2269)	(71.5260)	(71.8250)
$LOGSIZE_{it}$	0.2502	0.1186	0.0047	0.1140	-0.3327	0.5587	-0.1213	0.2425	1.1325	0.1602
	(0.6923)	(0.6929)	(0.6886)	(0.9804)	(0.8566)	(0.7771)	(0.6972)	(0.7936)	(0.9978)	(0.7113)
$DTURNOVER_{it}$	0.4461	3.4268	5.9903	1.9191	7.7093	12.0902	16.1361	4.1814	-7.3540	-3.1354
	(76.3662)	(76.4813)	(76.5803)	(76.5253)	(76.9049)	(76.7843)	(77.1254)	(76.6327)	(76.6571)	(76.8185)
RET_{it}	-3.5341**	-3.1893**	-3.1830**	-3.2031**	-2.9284**	-3.4945**	-3.0711**	-3.2852**	-3.8634**	-3.2366**
	(1.4564)	(1.4497)	(1.4494)	(1.5164)	(1.4826)	(1.4681)	(1.4502)	(1.4714)	(1.5226)	(1.4546)
RET_{it-1}	-2.9655**	-2.7038*	-2.6597*	-2.7220*	-2.4500*	-3.0112**	-2.5928*	-2.7961*	-3.4117**	-2.7449*
	(1.4133)	(1.4099)	(1.4096)	(1.4804)	(1.4428)	(1.4287)	(1.4104)	(1.4298)	(1.4913)	(1.4138)
RET_{it-2}	-2.3407	-2.1364	-2.1951	-2.1645	-2.0427	-2.3207	-2.1233	-2.2054	-2.4503*	-2.1649
	(1.4263)	(1.4255)	(1.4263)	(1.4398)	(1.4322)	(1.4304)	(1.4251)	(1.4308)	(1.4394)	(1.4259)
RET_{it-3}	-0.7507	-0.6317	-0.6381	-0.6596	-0.4552	-0.8136	-0.5187	-0.6808	-1.1752	-0.6357
	(1.3663)	(1.3669)	(1.3669)	(1.3991)	(1.3874)	(1.3726)	(1.3688)	(1.3709)	(1.4137)	(1.3671)
RET_{it-4}	-0.2509	-0.2990	-0.3155	-0.3265	-0.2224	-0.4657	-0.2982	-0.3687	-0.5474	-0.3176
	(1.4506)	(1.4521)	(1.4521)	(1.4671)	(1.4566)	(1.4560)	(1.4517)	(1.4577)	(1.4604)	(1.4523)
RET_{it-5}	-0.5821	-0.4011	-0.4026	-0.4288	-0.3378	-0.6664	-0.4879	-0.4798	-0.7229	-0.3666
	(1.2945)	(1.2937)	(1.2936)	(1.3272)	(1.2964)	(1.3069)	(1.2948)	(1.3038)	(1.3110)	(1.2948)
$BEHAVIOUR_t$	0.3341**	-0.0134	-0.1134	11.5417	-303.0779	626.3434	394.3265	592.6085	1,508.2227	0.2796
	(0.1424)	(0.0153)	(0.1159)	(113.8356)	(412.0378)	(440.7317)	(280.5216)	(1,177.9967)	(1,001.5514)	(0.4359)
CONSTANT	1.8351	4.9336	7.6150	4.8356	14.4458	-7.6176	7.7644	2.1425	-18.8014	3.7269
	(16.5001)	(16.5118)	(16.4142)	(24.6339)	(19.4807)	(19.2331)	(16.4009)	(18.7276)	(23.5618)	(17.0327)
Observations	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454
No. of stocks	409	409	409	409	409	409	409	409	409	409
R^2	0.0088	0.0065	0.0066	0.0061	0.0064	0.0071	0.0071	0.0063	0.0072	0.0063
Adjusted R^2	-0.195	-0.198	-0.198	-0.199	-0.198	-0.197	-0.197	-0.198	-0.197	-0.198

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.5 (Continued)

	Panel G: Non-overlapping Market-Adjusted Returns of Mid-cap Stocks									
$ExKr_{it+1}$	POS_{it}	$VarPOS_{it}$	COV_{it}	$CSAD_t$	LOS_t	WIN_t	PMN_t	LVR_t	HVR_t	UPS_t
$ExKr_{it}$	0.0692**	0.0692**	0.0692**	0.0703**	0.0804***	0.0663**	0.0744**	0.0676**	0.0738**	0.0760***
	(0.0291)	(0.0291)	(0.0291)	(0.0292)	(0.0290)	(0.0291)	(0.0289)	(0.0292)	(0.0291)	(0.0291)
$SIGMA_{it}$	-61.0415	-61.2794	-61.2367	-66.1908	-123.6031***	-52.1710	-101.2644**	-55.1743	-88.1039*	-94.9852**
	(46.5063)	(46.5233)	(46.5099)	(47.8516)	(47.7466)	(46.5622)	(46.6665)	(47.2765)	(47.3615)	(47.1434)
$LOGSIZE_{it}$	2.2638***	2.2597***	2.2617***	2.0226**	0.5180	3.1821***	2.1328***	2.5070***	0.8393	1.8839**
	(0.8173)	(0.8176)	(0.8173)	(0.9738)	(0.8788)	(0.8916)	(0.8111)	(0.8900)	(0.9550)	(0.8200)
$DTURNOVER_{it}$	88.0293	88.1127	88.1080	88.3569	119.5323**	96.8616	127.9459**	88.5174	97.3297	109.1212*
	(60.1418)	(60.1431)	(60.1414)	(60.1431)	(60.0548)	(60.1452)	(60.0678)	(60.1392)	(60.1083)	(60.1619)
RET_{it}	-1.0553	-1.0564	-1.0603	-0.8500	0.4708	-1.7919	-0.8387	-1.2590	0.2442	-0.5617
	(1.2035)	(1.2033)	(1.2033)	(1.2875)	(1.2312)	(1.2352)	(1.1943)	(1.2377)	(1.2839)	(1.2056)
RET_{it-1}	-1.2343	-1.2319	-1.2302	-1.0760	-0.3366	-2.0859*	-1.7285	-1.4617	-0.4493	-0.8873
	(1.1763)	(1.1764)	(1.1764)	(1.2262)	(1.1813)	(1.2209)	(1.1701)	(1.2217)	(1.2054)	(1.1753)
RET_{it-2}	-1.3421	-1.3389	-1.3455	-1.2215	-0.1877	-1.8055	-1.0471	-1.4691	-0.4943	-0.8609
	(1.1977)	(1.1976)	(1.1978)	(1.2249)	(1.2102)	(1.2095)	(1.1891)	(1.2122)	(1.2309)	(1.1994)
RET_{it-3}	-0.7665	-0.7663	-0.7651	-0.6624	0.3897	-1.0128	-0.1405	-0.8273	0.0106	-0.7447
	(1.1266)	(1.1266)	(1.1265)	(1.1507)	(1.1411)	(1.1287)	(1.1229)	(1.1294)	(1.1566)	(1.1223)
RET_{it-4}	-0.9011	-0.8996	-0.9010	-0.8161	-0.1265	-1.0807	-0.5078	-0.9637	-0.4565	-0.8365
	(1.1698)	(1.1698)	(1.1698)	(1.1841)	(1.1716)	(1.1701)	(1.1625)	(1.1733)	(1.1776)	(1.1655)
RET_{it-5}	0.0618	0.0681	0.0641	0.1751	0.4753	-0.4007	-0.2719	-0.0492	0.6097	0.0693
	(1.0084)	(1.0087)	(1.0083)	(1.0377)	(1.0049)	(1.0230)	(1.0020)	(1.0214)	(1.0242)	(1.0046)
$BEHAVIOUR_t$	-0.0007	0.0000	-0.0000	-50.8488	-2,209.3306***	1,273.9532**	1,884.2753***	899.7656	-2,756.0311***	-1.9615***
	(0.0045)	(0.0000)	(0.0001)	(111.6093)	(425.5607)	(498.7453)	(328.8703)	(1,304.9122)	(960.9860)	(0.5029)
CONSTANT	-37.0937**	-37.0109**	-37.0477**	-31.2236	-9.2900	-60.6560***	-48.2258***	-41.9196**	-7.7938	-27.9727
	(17.1164)	(17.1231)	(17.1170)	(21.4268)	(17.8278)	(19.4193)	(17.0908)	(18.4888)	(19.9045)	(17.2126)
Observations	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454
No. of stocks	409	409	409	409	409	409	409	409	409	409
R^2	0.0103	0.0103	0.0103	0.0104	0.0232	0.0134	0.0260	0.0105	0.0143	0.0176
Adjusted R^2	-0.194	-0.194	-0.194	-0.193	-0.178	-0.190	-0.175	-0.193	-0.189	-0.185

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.5 (Continued)

	Panel H: Non-overlapping Market-Adjusted Returns of Small-cap Stocks									
$ExKr_{it+1}$	POS_{it}	$VarPOS_{it}$	COV_{it}	$CSAD_t$	LOS_t	WIN_t	PMN_t	LVR_t	HVR_t	UPS_t
$ExKr_{it}$	0.0355	0.0318	0.0293	0.0351	0.0353	0.0351	0.0353	0.0350	0.0349	0.0345
	(0.0252)	(0.0253)	(0.0253)	(0.0252)	(0.0252)	(0.0252)	(0.0252)	(0.0252)	(0.0252)	(0.0252)
$SIGMA_{it}$	-9.9546*	-9.8469*	-10.0482*	-9.5096*	-9.7520*	-9.8575*	-9.9055*	-9.8549*	-9.6273*	-9.7787*
	(5.5381)	(5.5354)	(5.5336)	(5.5452)	(5.5380)	(5.5445)	(5.5381)	(5.5403)	(5.5480)	(5.5358)
$LOGSIZE_{it}$	-1.1515**	-1.2519**	-1.1933**	-1.1651**	-1.1172*	-1.1866**	-1.1176*	-1.1909**	-1.1555**	-1.3102**
	(0.5871)	(0.5875)	(0.5852)	(0.5861)	(0.5943)	(0.5866)	(0.5954)	(0.5858)	(0.5886)	(0.5941)
$DTURNOVER_{it}$	-14.4182	-14.4525	-14.3512	-14.6637	-14.2696	-14.4698	-14.2082	-14.4799	-14.4690	-14.9506
	(9.4061)	(9.4039)	(9.3992)	(9.4068)	(9.4115)	(9.4103)	(9.4161)	(9.4080)	(9.4070)	(9.4121)
RET_{it}	-1.0383	-0.9904	-0.9747	-0.9735	-1.0208	-1.0265	-1.0555	-1.0273	-1.0029	-1.0069
	(0.7299)	(0.7298)	(0.7294)	(0.7310)	(0.7296)	(0.7332)	(0.7316)	(0.7318)	(0.7302)	(0.7295)
RET_{it-1}	1.5298*	1.5426*	1.5203*	1.5235*	1.5232*	1.5366*	1.5190*	1.5364*	1.5230*	1.5457*
	(0.8106)	(0.8104)	(0.8100)	(0.8106)	(0.8109)	(0.8108)	(0.8111)	(0.8108)	(0.8110)	(0.8104)
RET_{it-2}	-1.0465	-1.1057	-1.1431	-1.0118	-1.0200	-1.0517	-1.0380	-1.0534	-1.0249	-1.0790
	(0.7394)	(0.7405)	(0.7404)	(0.7403)	(0.7406)	(0.7399)	(0.7396)	(0.7401)	(0.7406)	(0.7397)
RET_{it-3}	0.9958	1.0064	0.9901	0.9690	0.9850	0.9910	1.0080	0.9938	0.9767	1.0551
	(0.7541)	(0.7540)	(0.7534)	(0.7542)	(0.7541)	(0.7555)	(0.7547)	(0.7560)	(0.7543)	(0.7560)
RET_{it-4}	-0.0585	-0.0374	-0.0462	-0.0158	-0.0171	-0.0252	-0.0090	-0.0229	-0.0172	0.0284
	(0.6917)	(0.6908)	(0.6905)	(0.6910)	(0.6911)	(0.6914)	(0.6915)	(0.6918)	(0.6912)	(0.6923)
RET_{it-5}	1.3409**	1.3852**	1.3013**	1.3898**	1.3513**	1.3772**	1.3506**	1.3801**	1.3766**	1.4573**
	(0.5947)	(0.5932)	(0.5942)	(0.5934)	(0.5946)	(0.5936)	(0.5948)	(0.5936)	(0.5934)	(0.5968)
$BEHAVIOUR_t$	0.0000	0.0000	0.0000*	-90.4185	-275.2644	41.2171	214.5265	154.3523	-462.0635	0.5831
	(0.0000)	(0.0000)	(0.0000)	(88.6936)	(382.4814)	(435.8482)	(319.7323)	(1,137.7221)	(785.9819)	(0.4839)
CONSTANT	28.6306***	30.4738***	29.4187***	30.2750***	26.8181**	29.1272***	26.3466**	29.4027***	28.5850***	31.3515***
	(10.9161)	(10.9239)	(10.8821)	(10.9292)	(11.4338)	(11.0892)	(11.7603)	(10.9075)	(10.9635)	(11.0175)
Observations	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454	2,454
No. of stocks	409	409	409	409	409	409	409	409	409	409
R^2	0.0156	0.0160	0.0170	0.0157	0.0154	0.0152	0.0154	0.0152	0.0153	0.0159
Adjusted R^2	-0.187	-0.187	-0.186	-0.187	-0.187	-0.188	-0.187	-0.188	-0.188	-0.187

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.6: Correlation Matrix

This table displays the cross-sectional correlation across the behavioural factors. Here LOS_t, WIN_t, PMN_t, LVR_t, and HVR_t are computed based on market-adjusted returns. The cross-sectional correlation matrix for other return types exhibits similar relation.

Panel A: Overlapping returns

	POS_{it}	$VarPOS_{it}$	COV_{it}	$CSAD_t$	LOS_t	WIN_t	PMN_t	LVR_t	HVR_t	UPS_t	$DOWNS_t$
POS_{it}	1.0000										
$VarPOS_{it}$	-0.0190	1.0000									
COV_{it}	-0.0367	-0.0565	1.0000								
$CSAD_t$	-0.0003	0.0025	-0.0003	1.0000							
LOS_t	-0.0003	0.0075	-0.0038	-0.2950	1.0000						
WIN_t	0.0002	0.0035	-0.0029	-0.1852	0.5536	1.0000					
PMN_t	0.0005	-0.0067	0.0026	0.2307	-0.8316	0.0022	1.0000				
LVR_t	-0.0009	0.0012	-0.0045	-0.2001	0.4891	0.8022	-0.0523	1.0000			
HVR_t	0.0004	0.0090	-0.0028	-0.2672	0.9184	0.6695	-0.6562	0.4698	1.0000		
UPS_t	0.0003	-0.0005	-0.0006	0.1134	-0.1095	-0.1036	0.0624	-0.1352	-0.0505	1.0000	
$DOWNS_t$	0.0004	0.0008	-0.0003	-0.1133	0.0859	0.0946	-0.0401	0.1083	0.0532	-0.5338	1.0000

Panel B: Non-overlapping returns

	POS_{it}	$VarPOS_{it}$	COV_{it}	$CSAD_t$	LOS_t	WIN_t	PMN_t	LVR_t	HVR_t	UPS_t	$DOWNS_t$
POS_{it}	1.0000										
$VarPOS_{it}$	-0.3769	1.0000									
COV_{it}	0.0045	0.7645	1.0000								
$CSAD_t$	-0.0059	0.0205	0.0171	1.0000							
LOS_t	-0.0006	0.0153	0.0093	0.5929	1.0000						
WIN_t	0.0024	0.0157	0.0142	0.8063	0.1703	1.0000					
PMN_t	0.0022	-0.0015	0.0023	0.0814	-0.7113	0.5714	1.0000				
LVR_t	0.0019	0.0191	0.0186	0.8971	0.4296	0.9323	0.3072	1.0000			
HVR_t	0.0007	0.0194	0.0140	0.8249	0.8580	0.5525	-0.3204	0.6795	1.0000		
UPS_t	0.0107	0.0148	0.0162	0.4173	0.8346	0.1929	-0.5575	0.4552	0.7236	1.0000	
$DOWNS_t$	-	-	-	-	-	-	-	-	-	-	-

Table 3.7: Multiple Behavioural Factor Forecasting Model

This table presents the FE panel data regression estimates, which are obtained when the forecasted NSk_{it+1} and $ExKr_{it+1}$ are computed with market-adjusted returns and then examined by multiple significant uncorrelated behavioural factors. The behavioural factors are first added with the full baseline regression model, and then with the significant covariates in the baseline regression model.

	Panel A: Forecasting Negative Skewness with Overlapping Market-Adjusted Returns							
NSk_{it+1}	All		Large		Mid		Small	
NSk_{it}	0.9904***	0.9904***	0.9905***	0.9905***	0.9912***	0.9912***	0.9889***	0.9889***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$SIGMA_{it}$	-0.0000		-0.1395**		-0.0544		-0.0013	
	(0.0051)		(0.0608)		(0.0390)		(0.0052)	
$LOGSIZE_{it}$	0.0030***	0.0030***	0.0033***	0.0036***	0.0036***	0.0039***	0.0028***	0.0028***
	(0.0003)	(0.0003)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0004)	(0.0004)
$DTURNOVER_{it}$	0.0238**	0.0238**	0.0050		0.0695		0.0211**	0.0211**
	(0.0093)	(0.0093)	(0.1041)		(0.0785)		(0.0095)	(0.0095)
RET_{it}	0.0587***	0.0587***	0.0429***	0.0426***	-0.0173**	0.0049***	0.0700***	0.0698***
	(0.0022)	(0.0022)	(0.0114)	(0.0114)	(0.0075)	(0.0012)	(0.0024)	(0.0024)
RET_{it-1}	-0.0192***	-0.0193***	-0.0581***	-0.0516***	0.0181*		-0.0185***	-0.0186***
	(0.0026)	(0.0026)	(0.0156)	(0.0136)	(0.0106)		(0.0027)	(0.0027)
RET_{it-2}	-0.0208***	-0.0209***	0.0130		0.0048		-0.0244***	-0.0248***
	(0.0026)	(0.0026)	(0.0152)		(0.0106)		(0.0027)	(0.0027)
RET_{it-3}	-0.0060**	-0.0067***	-0.0316**	-0.0318***	0.0099		-0.0083***	-0.0094***
	(0.0026)	(0.0024)	(0.0152)	(0.0108)	(0.0106)		(0.0027)	(0.0026)
RET_{it-4}	-0.0019		-0.0135		-0.0146		-0.0031	
	(0.0026)		(0.0152)		(0.0106)		(0.0027)	
RET_{it-5}	-0.0057***	-0.0066***	0.0472***	0.0409***	0.0042		-0.0107***	-0.0121***
	(0.0022)	(0.0018)	(0.0108)	(0.0077)	(0.0075)		(0.0023)	(0.0020)
POS_{it}	-0.0000	-0.0000	-0.0001	-0.0001	0.0000***	0.0000***	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$VarPOS_{it}$	-0.0000*	-0.0000*	0.0000	0.0000	-0.0000*	-0.0000*	-0.0000**	-0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
COV_{it}	0.0000***	0.0000***	-0.0000	-0.0000	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$CSAD_t$	0.2078***	0.2078***	0.3292***	0.3267***	0.0619	0.0588	0.3167***	0.3160***
	(0.0467)	(0.0467)	(0.0819)	(0.0819)	(0.0859)	(0.0859)	(0.0798)	(0.0798)
HVR_t	-2.2898***	-2.2898***	-0.9850*	-0.7879	-1.9409***	-1.8787***	-3.5668***	-3.5727***
	(0.3023)	(0.3023)	(0.5543)	(0.5455)	(0.5638)	(0.5608)	(0.5226)	(0.5220)
UPS_t	-0.0007**	-0.0007**	0.0005	0.0005	-0.0009*	-0.0010*	-0.0015***	-0.0015***
	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
CONSTANT	-0.0660***	-0.0660***	-0.0803***	-0.0903***	-0.0732***	-0.0810***	-0.0583***	-0.0585***
	(0.0056)	(0.0056)	(0.0146)	(0.0139)	(0.0131)	(0.0120)	(0.0067)	(0.0066)
Observations	2,623,326	2,623,326	874,442	874,442	874,442	874,442	874,442	874,442
No. of stocks	1,227	1,227	409	409	409	409	409	409
R^2	0.9797	0.9797	0.9808	0.9808	0.9814	0.9814	0.9760	0.9760
Adjusted R^2	0.980	0.980	0.981	0.981	0.981	0.981	0.976	0.976

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.7 (Continued)

NSk_{it+1}	Panel B: Forecasting Negative Skewness with Non-Overlapping Market-Adjusted Returns							
	All		Large		Mid		Small	
NSk_{it}	-0.0033		0.0188		-0.0265		0.0132	
	(0.0151)		(0.0270)		(0.0275)		(0.0263)	
$SIGMA_{it}$	-0.0035		15.1079		5.0406		-0.0155	
	(0.8232)		(11.0948)		(6.9516)		(0.7605)	
$LOGSIZE_{it}$	0.7217***	0.6579***	1.0521***	0.9686***	1.2156***	0.9937***	0.5050***	0.5190***
	(0.0648)	(0.0503)	(0.1659)	(0.1414)	(0.1567)	(0.1047)	(0.0826)	(0.0586)
$DTURNOVER_{it}$	1.9765		3.4711		31.0391***	30.7118***	0.8469	
	(1.4216)		(13.2170)		(9.7689)	(9.3526)	(1.3036)	
RET_{it}	-0.1654*		0.0889		-0.6315***		-0.0021	
	(0.0935)		(0.2869)		(0.2247)		(0.1078)	
RET_{it-1}	0.2381***	0.2908***	0.2683	0.2699	-0.1813		0.4038***	0.3831***
	(0.0923)	(0.0819)	(0.2551)	(0.2356)	(0.1986)		(0.1125)	(0.0939)
RET_{it-2}	-0.0563		0.0740		-0.4645**		0.0678	
	(0.0877)		(0.2480)		(0.1979)		(0.1027)	
RET_{it-3}	0.2295***	0.2783***	0.6638***	0.6583***	0.0630		0.2459**	0.2230**
	(0.0868)	(0.0797)	(0.2417)	(0.2334)	(0.1866)		(0.1047)	(0.0897)
RET_{it-4}	-0.1266		-0.6559***	-0.6449***	-0.3517*		0.0279	
	(0.0838)		(0.2523)	(0.2448)	(0.1916)		(0.0959)	
RET_{it-5}	0.0074		-0.1204		0.0364		0.0269	
	(0.0733)		(0.2301)		(0.1685)		(0.0829)	
$VarPOS_{it}$	-0.0000***	-0.0000***	-0.0044*	-0.0041	0.0000	0.0000	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0026)	(0.0026)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$CSAD_t$	33.8293***	28.9091***	69.4768***	60.8746***	85.5916***	66.8573***	13.2734	13.0974
	(9.3972)	(8.9288)	(21.0086)	(19.0161)	(19.9395)	(17.6713)	(13.5204)	(13.3950)
UPS_t	-0.2707***	-0.2630***	-0.2409***	-0.2494***	-0.3605***	-0.3569***	-0.2458***	-0.2436***
	(0.0469)	(0.0464)	(0.0808)	(0.0788)	(0.0901)	(0.0887)	(0.0737)	(0.0725)
CONSTANT	-15.4969***	-14.0849***	-25.8945***	-23.6038***	-26.4062***	-21.4163***	-9.4739***	-9.7428***
	(1.4141)	(1.0904)	(4.1669)	(3.5112)	(3.4541)	(2.2684)	(1.5519)	(1.0870)
Observations	7,362	7,362	2,454	2,454	2,454	2,454	2,454	2,454
No. of stocks	1,227	1,227	409	409	409	409	409	409
R^2	0.0521	0.0511	0.0509	0.0491	0.0574	0.0514	0.0809	0.0802
Adjusted R^2	-0.140	-0.140	-0.146	-0.144	-0.138	-0.141	-0.110	-0.107

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3.7 (Continued)

	Panel C: Forecasting Excess Kurtosis with Overlapping Market-Adjusted Returns							
$ExKr_{it+1}$	All		Large		Mid		Small	
$ExKr_{it}$	0.9888***	0.9888***	0.9892***	0.9893***	0.9894***	0.9892***	0.9877***	0.9877***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$SIGMA_{it}$	-0.0910***	-0.0902***	0.5126		-0.6025**		-0.1029***	-0.1023***
	(0.0337)	(0.0337)	(0.4295)		(0.2887)		(0.0360)	(0.0360)
$LOGSIZE_{it}$	0.0042**	0.0042**	0.0142***	0.0128***	0.0196***	0.0234***	-0.0087***	-0.0088***
	(0.0017)	(0.0017)	(0.0038)	(0.0036)	(0.0041)	(0.0037)	(0.0025)	(0.0025)
$DTURNOVER_{it}$	0.0312		-1.9830***	-1.7288***	0.7531		0.0284	
	(0.0612)		(0.6575)	(0.6241)	(0.5161)		(0.0656)	
RET_{it}	-0.0597***	-0.0737***	0.1143	0.1157	-0.2441***	-0.0119	-0.0519***	-0.0590***
	(0.0143)	(0.0118)	(0.0717)	(0.0716)	(0.0494)	(0.0072)	(0.0163)	(0.0107)
RET_{it-1}	-0.0284*		-0.1897*	-0.1531**	0.1548**		-0.0342*	
	(0.0170)		(0.0982)	(0.0716)	(0.0695)		(0.0187)	
RET_{it-2}	0.0420**	0.0264*	0.1116		0.0708		0.0353*	
	(0.0171)	(0.0138)	(0.0958)		(0.0694)		(0.0190)	
RET_{it-3}	-0.0182		-0.0643		-0.0132		-0.0194	
	(0.0171)		(0.0958)		(0.0694)		(0.0190)	
RET_{it-4}	0.0191		-0.0108		0.1020		0.0181	
	(0.0169)		(0.0958)		(0.0694)		(0.0187)	
RET_{it-5}	0.0328**	0.0348***	0.0011		-0.0790		0.0502***	0.0566***
	(0.0143)	(0.0106)	(0.0682)		(0.0492)		(0.0162)	(0.0106)
POS_{it}	-0.0000***	-0.0000***	0.0008	0.0008	0.0006***	0.0006***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0007)	(0.0007)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$VarPOS_{it}$	0.0000	0.0000	-0.0000	-0.0000	-0.0000**	-0.0000***	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
COV_{it}	0.0000***	0.0000***	-0.0000	-0.0000	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0002)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$CSAD_{t}$	-2.4234***	-2.4250***	-2.4161***	-2.4040***	-1.6870***	-1.7339***	-1.8351***	-1.8386***
	(0.3090)	(0.3090)	(0.5166)	(0.5163)	(0.5652)	(0.5648)	(0.5530)	(0.5530)
HVR_{t}	1.9606	1.9284	6.5602*	6.0230*	-2.9216	-2.3221	10.9872***	10.9794***
	(1.9992)	(1.9990)	(3.4994)	(3.4715)	(3.7016)	(3.6824)	(3.6178)	(3.6173)
UPS_{t}	-0.0012	-0.0012	-0.0066**	-0.0065**	-0.0010	-0.0013	0.0037	0.0037
	(0.0019)	(0.0019)	(0.0030)	(0.0030)	(0.0034)	(0.0034)	(0.0034)	(0.0034)
CONSTANT	0.0351	0.0360	-0.2197**	-0.1802**	-0.2781***	-0.3679***	0.2753***	0.2765***
	(0.0370)	(0.0369)	(0.0937)	(0.0879)	(0.0880)	(0.0791)	(0.0464)	(0.0463)
Observations	2,623,326	2,623,326	874,442	874,442	874,442	874,442	874,442	874,442
No. of stocks	1,227	1,227	409	409	409	409	409	409
R^2	0.9775	0.9775	0.9785	0.9785	0.9785	0.9785	0.9755	0.9755
Adjusted R^2	0.977	0.977	0.979	0.979	0.979	0.979	0.975	0.975

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3.7 (Continued)

	Panel D: Forecasting Excess Kurtosis with Non-Overlapping Market-Adjusted Returns							
$ExKr_{it+1}$	All		Large		Mid		Small	
$ExKr_{it}$	0.0390***	0.0337**	0.0196		0.0757***	0.0519**	0.0292	
	(0.0143)	(0.0142)	(0.0259)		(0.0289)	(0.0256)	(0.0253)	
$SIGMA_{it}$	-10.9913**		28.1830		-108.1624**		-9.9385*	
	(5.2781)		(72.2093)		(47.2602)		(5.5507)	
$LOGSIZE_{it}$	0.0725		1.3485		1.6485*	1.8698***	-1.1117*	-0.9314**
	(0.4074)		(1.0055)		(0.9630)	(0.6386)	(0.5958)	(0.3855)
$DTURNOVER_{it}$	-8.9826		14.4758		128.7170**		-14.1211	
	(9.0183)		(77.2303)		(60.0903)		(9.4122)	
RET_{it}	-1.5044***	-1.3304***	-4.0810***	-2.8419**	-0.4022		-0.9877	
	(0.5606)	(0.4627)	(1.5247)	(1.3525)	(1.2831)		(0.7332)	
RET_{it-1}	0.2896		-3.6081**		-1.4269		1.4937*	
	(0.5843)		(1.4940)		(1.2142)		(0.8110)	
RET_{it-2}	-1.4203**	-1.3271***	-2.6092*		-0.7738		-1.1147	
	(0.5586)	(0.4889)	(1.4403)		(1.2255)		(0.7418)	
RET_{it-3}	0.4934		-1.2682		0.0908		0.9981	
	(0.5511)		(1.4133)		(1.1502)		(0.7549)	
RET_{it-4}	-0.3994		-0.6572		-0.3787		-0.0244	
	(0.5301)		(1.4603)		(1.1711)		(0.6913)	
RET_{it-5}	0.7123		-1.0078		-0.0625		1.2788**	1.1301**
	(0.4625)		(1.3176)		(1.0271)		(0.5959)	(0.5327)
COV_{it}	0.0000*	0.0000**	-0.1103	-0.1060	-0.0000	-0.0000	0.0000*	0.0000**
	(0.0000)	(0.0000)	(0.1158)	(0.1154)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
PMN_t	767.4110***	748.9169***	589.0697**	539.9241*	1,768.8975***	1,595.8460***	160.7420	96.2834
	(187.7483)	(183.3319)	(296.4589)	(286.3048)	(351.5040)	(341.7937)	(335.2257)	(331.8418)
HVR_t	-341.1884	-400.2372	2,199.2180**	1,051.8337	-952.1654	-888.2575	-375.2581	-764.7034
	(497.4609)	(463.7381)	(1,058.3322)	(721.0605)	(1,020.6259)	(909.0682)	(824.1660)	(819.9117)
CONSTANT	0.5406	1.9314	-28.0053	4.1800*	-37.4168*	-42.5033***	26.5879**	23.4066***
	(8.8256)	(1.3964)	(24.0906)	(2.1757)	(20.6469)	(13.7707)	(11.7554)	(7.9935)
Observations	7,362	7,362	2,454	2,454	2,454	2,454	2,454	2,454
No. of stocks	1,227	1,227	409	409	409	409	409	409
R^2	0.0097	0.0078	0.0096	0.0045	0.0264	0.0218	0.0173	0.0078
Adjusted R^2	-0.191	-0.192	-0.196	-0.196	-0.175	-0.176	-0.186	-0.193

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

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