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Risk-Appetite Discriminated Investors' Portfolio Optimization: Lessons from Pakistan Stock Exchange Listed Fertilizer Industry

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Abstract: *The main aim of this research is to assess the performance of risk-appetite discriminated investors in the PSX listed fertilizers industry, using RSM and non-RSM, to maximize their portfolios' wealth. The research period (18 November 2015–June 30, 2021) is well characterized by the presence of two distinct volatility-related bull-regime and bear-regime, and it is divided into two groups: in-sample and out-sample. Throughout the out-sample time, different models are used to forecast the cumulative wealth of each investor. This cumulative wealth and the Sharpe ratios are calculated using the various models (RSM and Non-RSM). In stocks by using RSM the cumulated ending wealth of risk-averse investors, risk-neutral investors and risk-taker investors are 1.56, 1.54, and 1.53 respectively which is higher than the Non-RSM and their Sharpe ratios remains zero in both models. Investors may benefit from this study's asset allocation and limited capital apportionment to vary their portfolios. As a result, market regulators and policymakers may be better equipped to create and implement rules that safeguard stakeholders from unintended consequences, such as a transfer to a new shift of regime. The distinctiveness of this study derives from its attention on risk-appetite investors' portfolio wealth maximization issue, which is explored through technical analysis utilizing two entirely different models in the developing market's fertilizer stocks.*

Keywords: Regime-switching models (RSM), Performance assessment, Portfolio optimization, Fertilizer industry, Risk-appetite.

Introduction

Investigations into financial theory have been developing since the last few decades, which irritate the judgment of investors in the financial business sector through new models. Investors, according to traditional financial theories, do not face difficulties when making investment decisions because they are educated, attentive and reliable (He, He, & Wen, 2019).

Random Matrix Theory has been used in the past to optimize portfolios, but employing the Regime Switching model in association with RMT filters is a new thought that

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will further demonstrate the flexibility of the Regime Switching approach (Iqbal, 2018). Modern Portfolio Theory (MPT) claimed if you add to a diverse portfolio a collection of assets that correlate less, you may lower the risk without losing return. Modern portfolio theory and capital asset pricing model predict that the size of data that are provided to investors is not confused and their social money factors do not exclude them. Regardless, a few investigations into the created capital business sectors discovered that numerous marvels regarding corporate share decisions are incomprehensible. Typically, investors in capital asset trades make a variety of significant decisions; the most well-known are making investment decisions to maximize their wealth; others are considering market timing procedures to supplement their wealth (Alquraan, Alqisie, & Al Shorafa, 2016).

Risk-taking is an important aspect of today's business, as investors need to be informed, and normal decisions about risks they need to pursue the organization's goals. Investors should have the choice to characterize their risk appetite, risk struggle and risk focuses to successfully adjust their strategy and risk a panel process to achieve a competitive advantage. An investor must see how much risk it takes and how he determines how to adjust risks and openings before a defined strategy is planned and executed. At a time when the risk appetite has undoubtedly been characterized by the investor, it becomes their liability to convey the risk appetite throughout the investor to ensure that these activities of the firm are in line at all levels with the risk that the investor will recognize (Epetimehin, 2013). Saleem and Ahmad-Zaluki (2021) suggested on the basis of risk appetite, investors are classified into risk aversion (avoid to take risk), risk takers (agree to take risk) and risk neutral (don't consider while making investment decisions).The current study shows that the risk feelings of investors (for example their risk prize) are frequently represented by the compromise of risk-return where the weakness of the market clarifies risk.

Iqbal, Ahmad, Akhtar, and Ismail (2020) concluded that in asset allocation using regime-switching models can do better than mean-variance or non-regime switching models in sub-continent countries because of their defensive attitude besides "low performance" and "high correlation" in bear markets, even when short-selling is also like this. Therefore, the effectiveness of different methods for investors to deal with risks and their investment decisions are not satisfactory. Therefore, this study uses two different models RSM and Non-RSM to evaluate the performance of investors in making investment decisions in terms of risk appetite.

Investor risk appetite determinants are critical to (1) providing more reliable financial advice at the appropriate risk stage for each investor's means, which we believe is critical, particularly concerning Fintech financial advisory; and (2) enabling supervisors to ensure an investor's appropriate risk stage via their portfolio as is. In fact, with the literature on the risk persistence of investors in mind, the supervisors can decide a few groups of risks arising from people who are in keeping with their social demographic properties. This allows us to confirm whether or not the amount of risk taken through buyers' means for the duration of the asset allocation is dependable on the risk cluster they belong to; (3) identify funding products that do not overlook investors' reactions during macroeconomic adjustments and (4) enable financial consultants to carefully select financing products for their asset (Lippi & Rossi, 2020).

The stock market in Pakistan has the imperative trading volume in all the financial markets of the region as one of the most important emerging markets in South Asia. The researchers are therefore hoping that the study results will improve investors' decisions by identifying the most important components of the risk-appetite, which can affect their market (Alquraan et al., 2016).

This study builds on the work of writers like Guidolin and Timmermann (2005), This study' RSM is unique in several ways, involved in the manufacturing of the regime matrices. The assumption that asset returns are regularly distributed is a solid approach. To go outside the strong assumption of normality, a Regime Switching Model appears to be the best answer, because asset returns distributions may be constructed with numerous regimes, each of which is associated with a distinct normal distribution. Furthermore, mean-variance models are mostly built on a buy-and-hold investing approach, which makes it difficult for an investor to make effective portfolio changes when new information becomes available. Again, this is rarely the case for investors who wish to maintain a close eye on the progress of financial markets since they may need to adjust their portfolios at different points when new information becomes available. This research assists market regulators and policymakers in formulating/implementing regulations that protect stakeholders from subsequent disasters (typically when the market changes regimes).

A study's scope identifies the boundaries of the subject area that will be researched and how the investigation will be conducted. The research aims to find out if the risk appetites of investors and their firms' financial performance are linked. This investigation was restricted to organizations the researcher could have access to and could find the financial information they needed. Additionally, the appetite for risk held by the investors will be evaluated.

The regime-switching methodology used here is outstanding for the most part; first, this review processes alphas, betas, mean, and sigma and supports in identifying which regime model is in use. Second, it uses RMT methods to filter the regime-based filter probability as well as smooth probability. When the market regime changes it uses the mean and standard deviations of the supplies from multiple market periods. Portfolio optimization and weight allocation have changed dramatically as a result of advancements in regimes, including how they are chosen and whether a long or short period is appropriate. The research will concentrate on these factors:

- There are five indices in the Pakistan stock exchange but the KSE ALL share index is used to collect the data about fertilizer companies.
- Investors in capital apportionment and asset allocation decisions with a restricted source of capital.
- The portfolio wealth maximization issue is examined of discriminated risk-appetite investors for using two completely different models (RSM and Non-RSM) in the emerging markets.

Literature Review

Over the last few decades, Pakistan's fertilizer sector has seen significant structural changes. Fertilizer use is critical to the agricultural economy. Pakistan's annual fertilizer production was recorded 8mln tons in 2020. As one of Pakistan's leading industries, it is widely considered to be one of the country's fastest-growing, as well as one of the highly excellent for employment (about 44 percent of the workforce is employed in agriculture), biggest income producer, and provides roughly 25% of the country's GDP (Economic survey of Pakistan, 2021). The Fertilizer sector is the major and the largest sector on Pakistan Stock Exchange. Pakistan's economy is heavily dependent on fertilizer production. The fertilizer business in Pakistan imports and sells a variety of fertilizers. The National Fertilizer Company (NFC) is a publicly-traded company that has been a major producer of fertilizer for the majority of Pakistan's existence. The primary component of the agriculture industry, which is the foundation of Pakistan's economy, is fertilizer. Currently, Pakistan makes up around one-third of global agricultural output. The fertilizer industry must be maintained in a competitive way in order to grow and advance the nation's agricultural sector. Assessing the profitability, company growth, and sector's financial stability is the key objective of the financial analysis (Masood, 2014).

Regime-switching models can match the tendency of financial markets to often change their behavior abruptly and the phenomenon that the new behavior of financial variables often persists for several periods after such a change. Regime-switching models are popular in financial modeling for several reasons. First, the idea of changes to the regime is ordinary and perceptive. Certainly, the new request of regime switching in Hamilton (1989) foremost jobs are recession and economic expansion, and the regime logically captures the long-term trend of economic activity cycles (Ang & Timmermann, 2012). Iqbal et al. (2020) also discussed that because of their huge volume and number of transactions, developing market stock indexes such as Bangladesh, Pakistan, and India are strongly weighted by trading in the top 10 businesses. Compared to developed markets, volatility is higher in emerging markets. Comparing the FTSE-100 with developing/emerging markets on the Subcontinent, the RS CAPM Strategy revealed some useful regime indicators.

Hamilton (1989) considered many others for the initial time (Ang & Bekaert, 2002; Ang & Timmermann, 2012; Huang, 2003) based on the fictitious rationality of key manufacturers to Pereiro and González-Rozada (2015) recorded, price of certain assets is particularly difficult to predict because of the non-linearity known as institutional change, which is subject to discrete and sudden changes from one state or system to another from time to time very different, and vice versa. When the non-RS strategy failed, they discovered many facts. In the literature, these models are classified the regime-switching and based on asymmetric in sequence. Kristoufek and Vosvrda (2018) regarded deviation from traditional assumptions of market participants as a major improvement. Rejeb and Arfaoui (2019) study whether the Islamic stock index is more explosive or the conventional stock index. The study used the GARCH model and concluded Islamic stock index is more effective than the conventional stock in terms of informational efficiency and risk, during the recent financial instability period.

In early research on finance, the pricing of assets was given the greatest attention.

However, researchers have recently begun to focus on other factors instead of rationality that may affect the investment decision. Nofsinger (2001) study concluded that Asian investors were more affected than Western investors by behavioral bias. Investors are always rational for standard finance and economics theories, make logical decisions and consider all relevant aspects of investment opportunity before making investment decisions. However, in practice economic, sociological, and financial factors affect investors' decision-making. Edward Bowman is a supplier of investor's risk issues in decision-making mentioned in many papers discussed later. Bowman (1980) contradiction between perceived risk and return and reality has been recognized. In general, higher risk leads to increased profitability, and the lower the risk, the bigger the return is expected to be for companies.

Shapira (2002) research also discussed the consequences of decision-making and gave examples of individual traders who were fired for making risky auction decisions in auctions. This is an important point after performing poor performances. When taking risks is the only way to overcome productivity. The ambiguity lies in choosing a high-risk option, if the consequences of not reaching the goal are the same, in this case giving up, then the individual has no reverse risk, only the organization. More and more people believed that changing attitudes towards risk prices of assets is the key factor. Coudert and Gex (2008) stated that "increasing the risk aversion will increase the risk premium of an asset commensurate with the volatility of the asset return." For this reason, time-varying risk aversion can perform a vital function in the amplification of the likely sequential difference (Bekaert, Engstrom, & Xing, 2009).

Bollerslev, Tauchen, and Zhou (2009) determined the variance risk premium based on the threat quality assessment of the market's return an aggregate risk aversion proxy, may clarify "stock market returns." Bekaert and Hoerova (2014) established "variance premium has a significant impact on stock returns."Because various stocks have different investors and their performance depends on the unusual prospect. Risk perception changes are connected to changes in subjective expectations, risks, and portfolio performance. The body of research dedicated to asset value risk premiums and risk aversion has been increasing, fewer studies are focused directly on the effectiveness of investment decisions of investors, particularly their appetite for risk. Therefore, this research attempts to close this gap. The strategy formulation based on the same data could present new opportunities useful insight. This knowledge is helpful (1) limited asset allocation investors and asset allocation decisions, (2) regulatory agencies formulating regulations to protect the market from subsequent disasters caused by changes in the market system, and policymakers in formulating policies. Therefore, it is necessary to study the issue of investors' stock prices, which is essential for optimizing the wealth of the investment portfolio to maximize the final wealth.

Methodology

The sample study contains all stocks of fertilizer firms that appear on the (KSE_ALL) index at the commencement of this research and that will not be omitted to await the date ended.

The test period begins on 18/11/2015 and ends on 30/06/2021 as no authentic/official categorization is available for all PSX listed KSE ALL inventories before this date. The lay down criteria have allowed all the fertilizer industry in which '06' stocks to be classified in which Arif Habib Corporation Limited (AHCL), Fauji Fertilizer Bin Qasim Ltd. (FFBL), Fauji Fertilizer company ltd (FFC), Engro Corporation Ltd. (ENGRO) Fatima Fertilizer Co. Ltd. (FATIMA), and Engro fertilizer Ltd. (EFERT). As defined above, the following stocks were qualified for the sample as a benchmark is covering KSE ALL companies and a risk-free KIBOR rate.

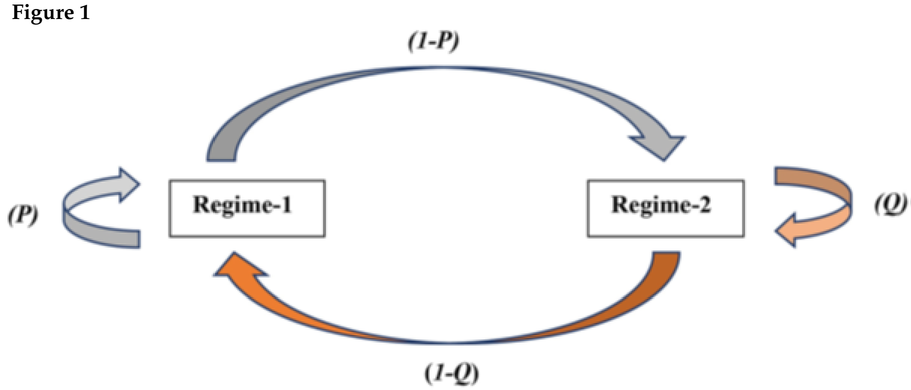
Regime Change Strategy

In RS models, the number of stated regimes is considered a critical consideration. The judgments on the approximations of the fundamental states are complicated as a result of their unknown character. So the 'first-order Markov process' is applied for two states in the simulation"State-1 or regime-1": a bull market with low volatility high profits and"State-2 or regime-2": a bear market with poor profits and high market volatility).

The two-state RS model indicates that it is derived from two normally distributed data with varying means, correlations, and variances from one state to the next. Parameters are required to estimate model specifications/system indications, which are then used to calculate transition probabilities using the greatest probability estimate. Every day, when the regime-switching KSE ALL index (benchmark index) changes following the Markov chain (interchange among the "regime-1 and the regime-2"), the portable portfolio of the RS model is rebalanced.

Transition Probabilities Indicating Two Regimes

Figure 1



Notes: If at time t, the market is in Regime – 1 then the probability of staying in the same state at time $t + 1$ is P; if at the time t, it is in Regime – 2 then the probability of staying in the same state at time $t + 1$ is Q; if at time t it is in Regime – 1 then the likelihood to move to the Regime – 2 at time $t + 1$ is $1 - P$; and if at time t it is in State – 2 then the probability of moving to the State – 1 at time t + 1 is $1 - Q$

The traditional CAPM equation differs from the CAPM equation depending on the regime in which it is applied:

$$r_{it} = \alpha_i + \beta_i r_{mt} + \epsilon_{it} \tag{1}$$

There are a number of variables, including the risk-free rate r_{it}, the time period (t), the slopes of the data (i.e., the intercepts), and the market index return r_{mt}.

Out-Sample and In-Sample Data Criteria

For computing initial values that are entered, the sample is divided into two parts: the in-sample (from 18/11/2015 to 21/112016) and out sample (from 22/11/2016 to 30/06/2021). Regime-Switching Model is use along with CAPM Model while for out-sample data Rs. 1 is invested to get initial values. The sharp ratio will be obtained for comparison purpose.

Data Collection and Analysis

To calculate the variance, standard deviation, kurtosis, mean, and skewness as well as the OLS regression, covariance, and correlation to determine stock returns, first divide the data into two samples and load all the in sample and out sample data. Compare the graphs of RSM and Non-RSM at the end to determine which model performs better.

Descriptive Analysis

Three panels are devoted to the statistical data description of the sampled stocks' returns as well as the returns of their respective benchmarks, including standard deviation, variance, kurtosis, mean, and skewness.

For each stock's return and its out sample's benchmark, Mean, variance, standard deviation, and skewness are all displayed in Part A. The average return on the stocks is negative in 83 percent of cases, which means that the stocks are in a loss period but they are all within a few percentage points of zero. While FFBL has a low negative mean return (-0.0234%), its standard deviation is the largest (1.5849%). ENGRO (0.008%) has an average mean return value that is close to zero. The average negative return for FFBL is the lowest (-0.0574%), while the standard deviation is the largest (2.5639%) in Part B. Stocks with the positive average mean returns are also close to zero on the other side. In the case of FFC and EFERT, excess kurtosis (kurtosis value >3) indicates that these two stocks have a positive kurtosis (peaked-curve) and higher prices. The average mean return is negative for the period under consideration for about 83 percent of the stocks (5 of 6). It has the lowest negative mean return (-0.0095%) and the highest standard deviation (FFBL) of any portfolio in the FFC group (2.42%). ENGRO (0.0014%) has the only average return value close to zero with a positive value of the average mean return. Excess kurtosis, which indicates positive kurtosis greater values, can only be seen in one stock (EFERT), which is leptokurtic (with a kurtosis value exceeding 3). When looking at Part B and Part C in Table 1, however, there are some extremely interesting changes. Among the 50 percent of the stocks and their benchmarks in Part B (out-sample), the average mean returns are positive but close to zero.

Table 1
Descriptive Statistics

Classification	AHCL	FFBL	FFC	ENGRO	FATIMA	EFERT	KSE ALL
Part A: In sample							
Variance	0.000346	0.000251	0.00015	0.000189	0.000246	0.000157	0.000049
Mean	-0.001138	-0.000234	-0.000574	0.000008	-0.001266	-0.001172	0.000694
Kurtosis	0.832186	2.784727	3.839574	2.049048	1.128239	2.318016	2.091887
Standard Deviation	0.018612	0.015849	0.012252	0.013746	0.015674	0.01252	0.000049
Skewness	-0.046805	0.316619	0.172962	0.459989	0.038082	-0.066913	0.271625
Part B: Out sample							
Variance	0.000572	0.000657	0.000235	0.000311	0.000333	0.000252	0.000104
Mean	-0.000053	-0.000597	0.000013	0.000026	-0.000142	0.000095	-0.000158
Kurtosis	0.879039	1.179958	3.814165	2.820576	2.353825	4.523918	3.456018
Standard Deviation	0.023926	0.025639	0.015336	0.017638	0.018262	0.015877	0.010186
Skewness	0.235967	0.014807	-0.054047	-0.20031	-0.205792	-0.561213	-0.665352
Part C: Whole sample							
Variance	0.000534	0.000584	0.000219	0.000289	0.000318	0.000235	9.391882
Mean	-0.000208	-0.000539	-0.000095	0.000014	-0.000343	-0.000131	-0.000001
Kurtosis	0.975224	1.530194	3.956136	2.908648	2.269271	4.490559	3.748787
Standard Deviation	0.023102	0.024166	0.014823	0.016998	0.017819	0.015328	9.691172
Skewness	0.224482	0.026471	-0.024392	-0.138801	-0.169281	-0.503154	-0.639338

Part A shows the in-sample, part B shows out-sample and Part C shows the whole sample data. In this table clearly showed that values can be changed from negative to positive when moving from in-sample to out-sample.

Regression Analysis

The OLS regression is related to the Capital Asset Pricing Model (CAPM) to find the Slope

Table 2
OLS Regression

Classification	AHCL	FFBL	FFC	ENGRO	FATIMA	EFERT
Part A: In sample						
"Intercept"	0.000791	0.000709	0.000748	0.000684	0.000788	0.000879
"Slope"	0.091179	0.097345	0.115028	0.164438	0.081569	0.166202
"Standard error slope	0.006772	0.006809	0.006838	0.006605	0.006863	0.006664
"R-Squared"	0.207815	0.062385	0.081301	0.115299	0.182845	0.597652
Part B: Out sample						
"Intercept"	-0.000151	-0.000058	-0.000154	-0.000156	-0.000124	-0.000174
"Slope"	0.117207	0.154871	0.227926	0.280534	0.193211	0.22986
"Standard error slope	0.009793	0.009382	0.00957	0.008905	0.009558	0.009512
"R-Squared"	0.680409	0.588102	0.006466	0.43947	0.451428	0.01631
Part C: Whole sample						
"Intercept"	0.000023	0.00008	0.000018	-0.000005	0.000059	0.000028
"Slope"	0.113875	0.150521	0.213781	0.266973	0.17724	0.221379
"Standard error slope	0.009327	0.008983	0.009159	0.008563	0.009162	0.009078
"R-Squared"	0.082504	0.040773	0.037575	0.335431	0.038339	0.015878

of the data, Standard error of the data, Intercept, and R-Squared of the data in three ways (In-sample, Out-sample, and Whole sample of the stocks) in the table below.

The R-SQ value of FFBL is 6% in in-sample when moving from in-sample to out-sample the R-SQ value change to 58% which shows the regime-switching behavior in the stocks. The findings of the in-sample phase are compared to those of the out-of-sample period in order to verify parameter stability and consistency. When the length of the in-sample and out-of-sample periods was shifted, the findings remain consistent.

Covariance and Correlation

Table 3 displays data for the whole sample period. The ENGRO and the benchmark return KSE_ALL have minimum covariance while FFBL has the highest covariance with benchmark return. FFBL and ENGRO show maximum covariance among each other while AHCL and EFERT show minimum covariance. Table 3 also shows the correlation matrix in which ENGRO and EFERT show the highest correlation (51.62%) and AHCL and EFERT show minimum correlation (22.17%) as covariance. When correlating with benchmark return ENGRO (46.82%) shows the highest correlation with benchmark return and AHCL (27.14%) shows minimum correlation with a benchmark return of the stocks which shows a weaker relationship as compared to other stocks.

Table 3
Covariance and Correlation

Name of Stocks	AHCL	FFBL	FFC	ENGRO	FATIMA	EFERT	KSE_ALL
				Covariance Matrix			
AHCL	0.000533	0.000157	0.000085	0.000106	0.000112	0.000078	0.000061
FFBL	0.000157	0.000583	0.000169	0.00017	0.000136	0.000142	0.000088
FFC	0.000085	0.000169	0.000219	0.000121	0.000093	0.000113	0.000047
ENGRO	0.000106	0.00017	0.000121	0.000289	0.000106	0.000134	0.000077
FATIMA	0.000112	0.000136	0.000093	0.000106	0.000317	0.000088	0.000056
EFERT	0.000078	0.000142	0.000113	0.000134	0.000088	0.000235	0.000052
KSE_ALL	0.000061	0.000088	0.000047	0.000077	0.000056	0.000052	0.000094
				Correlation Matrix			
AHCL	1	0.280933	0.249155	0.270372	0.273369	0.22166	0.271472
FFBL	0.280933	1	0.472599	0.415484	0.316536	0.384001	0.375336
FFC	0.249155	0.472599	1	0.480977	0.352851	0.499863	0.326993
ENGRO	0.270372	0.415484	0.480977	1	0.349312	0.516186	0.468266
FATIMA	0.273369	0.316536	0.352851	0.349312	1	0.321677	0.32588
EFERT	0.22166	0.384001	0.499863	0.516186	0.321677	1	0.350131
KSE_ALL	0.271472	0.375336	0.326993	0.468266	0.32588	0.350131	1

Asymmetric Bull and Bear Market Periods

Table 4 shows asymmetrical returns by all stocks to their components across various bull and bear market periods. The bull market phase (regime 1) has lower standard deviations and greater mean returns than the bear market phase (regime 2), which has high standard deviations and low mean returns. The mean and standard deviations of the benchmark and companies are also provided in four panels to support our claim regarding the asymmetric returns of the stocks (Part A: bear period (18/11/2015 – 30/12/2016); Part B: bull period (02/01/2017 – 23/01/2018); Part C: bear period (24/01/2018 – 26/12/2019); and Part D: bull period (27/12/2019 – 30/06/2021) that are explained in Table 4.

Table 4
Asymmetric bull and bear market periods

Time Period	Part A: Bear Period 18/11/2015-30/12/2016		Part B: Bull Period 02/01/2017-23/01/2018		Part C: Bear Period 24/01/2018-26/12/2019		Part D: Bull Period 27/12/2019-30/06/2021	
Name of Stocks	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D
AHCL	-0.000698	0.018029	0.000689	0.01893	-0.000247	0.022909	0.000525	0.028752
FFBL	-0.000269	0.015442	0.001044	0.019826	-0.001538	0.024987	0.000871	0.030411
FFC	-0.000409	0.011868	0.000708	0.016889	-0.000267	0.015236	0.000131	0.014721
ENGRO	0.000417	0.013535	0.000211	0.019331	-0.000221	0.016252	0.000391	0.018435
FATIMA	-0.000761	0.015676	0.000495	0.019766	-0.000507	0.017247	0.000283	0.000961
EFERT	-0.000747	0.01269	0.00004	0.016328	0.000091	0.015099	0.000077	0.016644
KSE_ALL	0.001025	0.00683	0.003288	0.001298	-0.000493	0.009328	0.011611	0.01062

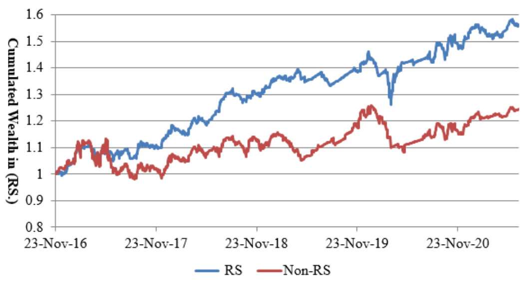
Investors Cumulated Wealth through RS and Non-RS Models

Each investor started an investment of 1.00 Rs. through models of RS and Non-RS models. As displayed in Figure (A), the RS and Non-RS models initially coincide, but after the 1/3rd of observations, the regime-switching models' cumulated wealth strategy moves upward, while the mean-variance or non-regime switching models' cumulated wealth investment strategy moves downward. Thus, when risk-averse investors invested through RSM rather than non-RSM, their cumulative wealth remained higher.

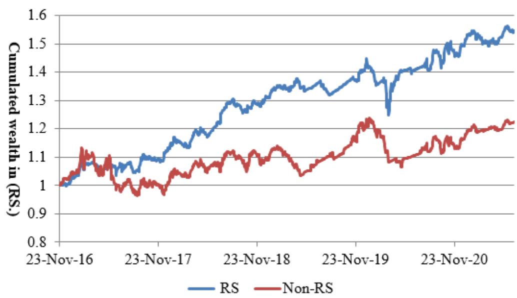
In figure (B), the RSM and non-RSM initially coincide, and then again after the 1/3rd of the observations, the regime-switching models cumulated wealth strategy moving upward and remaining at the end of the observations, and mean-variance models or non-regime switching models cumulated wealth investment strategy in the half of out-sample observations moving towards the bottom of the figure As a result, when risk-neutral investors invest through RS models, their cumulative wealth remains higher than when they invest through non-RS models. Non-RSM firstly coincides, but after 1/3rd of the observations, RSM cumulated wealth strategy moving upward and remained, while mean-variance models or non-regime switching models cumulated wealth investment strategy in the half of the out-sample observations moved towards the downward direction, as depicted by figure (C). Hence, As a result, when risk-taker investors invest through RS models, their cumulative wealth remains better when they invest through non-RS models.

Wealth of Risk-Appetite Investors Through Different Models

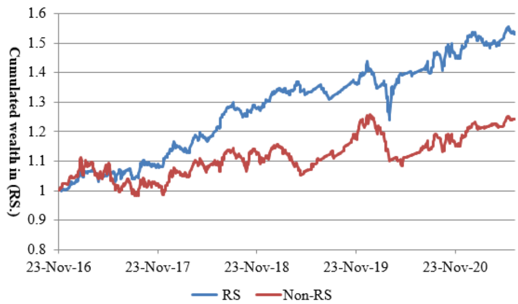
In Graph (M), see the total cumulative wealth of fertilizer companies over the time under consideration. According to this figure, the RSM of risk-appetite discriminated investors is moving upward, and in the case of when investor is risk averse, the value is higher than the other slopes; however, the Non-RSM curve is moving downward after 1/3rd of the observation in all types of risk, demonstrating that the RSM strategy is better to the Non-RSM strategy.


Cumulated Wealth in (RS.)
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
0.8
23-Nov-16
23-Nov-17
23-Nov-18
23-Nov-19
23-Nov-20
RS
Non-RS

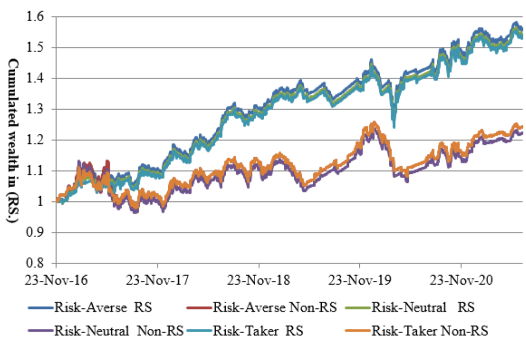
(a)


Cumulated wealth in (RS.)
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
0.8
23-Nov-16
23-Nov-17
23-Nov-18
23-Nov-19
23-Nov-20
RS
Non-RS

(b)


Cumulated wealth in (RS.)
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
0.8
23-Nov-16
23-Nov-17
23-Nov-18
23-Nov-19
23-Nov-20
RS
Non-RS

(c)


Cumulated wealth in (RS.)
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
0.8
23-Nov-16
23-Nov-17
23-Nov-18
23-Nov-19
23-Nov-20
Risk-Averse RS
Risk-Averse Non-RS
Risk-Neutral RS
Risk-Neutral Non-RS
Risk-Taker RS
Risk-Taker Non-RS

(d)

Ending Wealth of Investors and Sharpe Ratios through Different Models

Table 5 showed that in fertilizer stocks the investor ending wealth of risk-appetite discriminated investors (risk-averse, risk-neutral, and risk-taker) is 1.56, 1.54, and 1.53 respectively in RSM based strategy as compared to non-regime switching model which is 1.25, 1.23, and 1.24 respectively. But in the Sharpe ratio, all values in RSM and Non-RSM are zero which means the Sharpe ratio is not useful in this study to conclude which model strategy is better so it is shown that in stocks based on ending wealth the RSM based strategy is better than compared to the non-RSM based strategies.

Table 5
Ending wealth and Sharpe Ratios

"Investors ending wealth in (RS.)/Sharpe Ratio"			
Models	**Risk Averse**	**Risk Neutral**	**Risk Taker**
Regime-Switching (RSM)	1.5623	1.5445	1.5354
Sharpe Ratio RSM	0	0	0
Non-Regime-Switching	1.2434	1.223	1.2438
Sharpe Ratio in Non-RSM	0	0	0

Discussion and Conclusion

There were very fascinating shifts are evident in the statistical description of the in-sample, out-sample, and whole-sample data. Consequently, around 80% of the stocks' mean returns became negative when the mean returns were changed from in-sample to out-sample. When the market went from in-sample to out-of-sample, all stock benchmark variances increased. Kurtosis and skewness both show similar changes. The RS behavior of equities is determined by the R-squared value of all companies. E.g., the R-squared value of the FFBL in the in-sample is 6 percent, which increases to 58 percent during the out-sample time and subsequently decreases to 4 percent for the whole-sample period, indicating that the stocks are behaving under the RS behavior.

On November 22, 2016, the day of the out-sample start, One rupee is invested in the stocks at the start, which explained two different volatility regimes: the short-term and the long-term. Regimes 1 and regime 2 are referred to as the ("bull regime") and the ("bear regime") respectively. Daily checks and studies are conducted to determine the cumulative wealth of each investment. This is done throughout the out-sample period (November 22, 2016–June 30, 2021) using different models. When comparing the cumulative daily wealth of stocks, it was discovered that RSM-based investments outperformed non-RSM-based investments. This shows that the RS models handle market challenges over all-weather situations (in both favorable and adverse conditions), which is crucial to determining the investors cumulative wealth, as observed by Pereiro and González-Rozada (2015).

If use RSM the risk-averse investor, the risk-neutral investor, and the risk-taker investor, cumulative ending wealth increases by 1.56, 1.54, and 1.53 times, respectively. If use the non-RSM cumulative ending wealth increases by 1.25, 1.23, and 1.24 times, respectively. As a result, the final wealth received by investors using RSM is bigger than the ending wealth obtained by investors through other models. The Sharpe ratio of investments based on RSM and investments based on non-RSM remains the same, which is 0. The zero Sharpe ratios means that the portfolio returns of investors are equal to risk-free rate of investment. Iqbal et al. (2020); Paolella, Polak, and Walker (2019); Saleem and Ahmad-Zaluki (2021) concluded that Sharpe ratios in regime-switching model are higher than the mean-variance or non-regime switching model which tells portfolio return of investors is higher than the risk rate but in this study both the models have zero values which mean that Sharpe ratios do not explain the hypotheses that which model is better of the investors for portfolio optimization. As a result, we conclude that investment strategies based on RSM outperformed in terms of cumulative ending wealth and cumulative daily wealth for the entire group of investors.

Investors may benefit from this study's asset allocation and limited capital apportionment to vary their portfolios. As a result, market regulators and policymakers may be better equipped to create and implement rules that safeguard stakeholders from unintended consequences, such as a transfer to a new shift of regime. As a result this study also helps the investors to invest through RSM or Non-RSM. This research includes all of the fertilizer firms that are publicly traded on the PSX.

Recommendations

Investors may benefit from this study's asset allocation and limited capital apportionment to vary their portfolios. As a result, market regulators and policymakers may be better equipped to create and implement rules that safeguard stakeholders from unintended consequences, such as a transfer to a new shift of regime. As a result this study also helps the investors to invest through RSM or Non-RSM. This research includes all of the fertilizer firms that are publicly traded on the PSX. For future researchers it is suggested that Developing and Emerging markets need further empirical studies to validate stylized facts already established in developed markets. Similarly, regime-switching models need to be checked for these markets. Other methods employed in Regime Switching Models can be compared with the model presented in the thesis for empirical verification and suggest which method is suitable for different markets.

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