SENIOR RESEARCH

Topic: A Sectorial Analysis of Moments in the SET: Forecasting Returns with Volatility and Skewness

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Abstract

The purpose of this research is to examine the forecasting performance of higher order moments, namely volatility and skewness, on stock returns in the the Stock Exchange of Thailand. Basing on sectorial indices of the Stock Exchange of Thailand, four forecast models: (1) random walk model, (2) Fama-French (1993) three-factor model, (3) "higher-order-moments" model, and (4) extended Fama-French (1993) three-factor model with higher order moment variables, are analysed using rolling window estimation. Then, using root mean square forecast error (RMSFE) as a benchmark, the "higher-order-moments" model is found to have the lowest sets of the root mean square forecast error (RMSFE); hence, it is concluded to be the best forecast model.

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I. Introduction

The question of whether stock returns can be forecasted has always been a controversial subject in the financial studies of asset pricing. While researches in the past (Kendall (1953), Cootonner (1964), Godfrey, Granger and Morgenstern (1964), etc.) concluded that returns in the stock market could not be forecasted, it is still widely believed that expected returns are influenced by some economic and financial factors. Countless asset-pricing concepts and models have been developed, using different economic and financial factors to forecast stock returns in the future.

The purpose of this research is to examine the forecasting performance of higher order moments, namely volatility and skewness, on returns in sectorial indices in the Stock Exchange of Thailand.

Volatility and skewness are extremely vital in finance, especially in risk management. Stock return volatility (the second order moment) is a measure of fluctuation of stock returns around the mean, which can be measured by standard deviation. The greater the volatility of stock returns implies higher risk associated with the investment. On the other hand, skewness of stock returns (the third order moment) is a measure of the asymmetry of return distribution, where a negative skewness indicates a high chance of losses in the investment.

Over the years, volatility has been a well-known subject of discussion; however, a little attention has been paid to skewness and its relationship towards stock returns. Skewness of returns reflects herding or bandwagon behaviour of investors, where ones follow the actions of others. For instance, when investors start buying a stock because others are buying it, it automatically drives the average price and the average return up making the distribution skews to the right (a positive skewness). Therefore, a very high skewness implies a development of bubble in the market for that stock, and a greater risk associated with the investment.

This research is based on sectorial indices of the Stock Exchange of Thailand, where four forecast models: (1) random walk model, (2) Fama-French (1993) three-factor model, (3) "higher-order-moments" model, and (4) extended Fama-French (1993) three-factor model with higher order moment variables, are analysed using rolling window estimation. Then, using root mean square forecast error (RMSFE) as a benchmark, the model with the lowest sets of the root mean square forecast error (RMSFE) is concluded to be the best forecast model.

The remainder of the paper is organised as follows. Section II discusses reviews previous literature on the asset-pricing concepts and models. Section III lists the testable forecast models. Section IV describes data involved. Section V explains the construction of the main variables and the analysis method. Section VI evaluates the forecasting performance of each model, and discusses the results of robustness tests. Lastly, section VII provides a conclusion.

II. Literature Review

Over the years, several asset-pricing concepts and models have been developed, in the hope of forecasting returns in the stock market. But due to the time constraint, only significant models were mentioned in this literature review.

Firstly, Kendall (1953) proposed Random Walk theory as he examined movement of security and commodity prices over time, and observed that stock prices move randomly. In addition, Efficient Market Hypothesis (EMH), a concept developed by Fama (1965), states that it is impossible to beat the market since all relevant information are reflected in the share prices. Consequently, future market trends cannot be predicted through fundamental or technical analysis.

Secondly, Sharpe (1964) built the capital asset pricing model (CAPM) to describe the relationship between risk and return, in which the expected stock return equals the risk-free rate plus a risk premium. The model have received a lot of criticisms and many have tried to improve it, one of which was the Fama-French (1993) Three-factor model, which suggested that stock prices are best modelled using the (i): market portfolio return; (ii): the difference between the return on a portfolio of small stocks and the return on a portfolio of big stocks; and (iii) the difference between the return on a portfolio of high-book-to-market stocks and the return on a portfolio of low-book-to-market stocks.

Lastly, Kraus and Literzenberger (1976) constructed a model incorporating the higher order moments in the CAPM model called Kraus-Litzenberger (1976) three-moment capital asset pricing or K-L model. Kraus-Litzenberger (1976), Friend and Westerfield (1980), and Sears and Wei (1988) tested the model using cross-sectional regressions to estimate the risk-adjusted returns. However, the resulting estimations were found to be biased. Then, Baron-Adesi (1985) used Gibbons' (1982) multivariate approach to test the consistency of quadratic market specification to the K-L model. Using Hansen's (1982) generalised method of moments (GMM) approach, Lim (1999) revealed that monthly stock returns partially reflect the systematic skewness. Harvey and Siddique (2000) and Dittmar (2002) found three and four-moment CAPM models could explain the cross-sectional movement of stock returns in the US stock market, as well as having a great impact on forecasting returns.

III. Models

For the purpose of this research, four forecast models: (1) random walk model, (2) Fama-French (1993) three-factor model, (3) "higher-order-moments" model, and (4) the extension of Fama-French (1993) three-factor model with higher order moment variables, were estimated.

Model 1: *Random walk model*

Random walk model is one of the simplest models, yet it is widely used in the area of finance. By definition, prices are said to follow a random walk when there is no correlation between price movement and subsequent ones. In other words, the expected stock price is forecasted to equal the price in the previous day.

$$E(P_{i,t}) = P_{i,t-1} + \varepsilon_{i,t} \quad ,$$

where $P_{i,t}$ and $P_{i,t-1}$ are the prices of the i-th index in day t and day $t-1$, respectively, and ε_t is the error term in day t. So, the risk-adjusted return of each index is expected to be 0 in any day t.

$$E(R_{i,t}) = 0 \quad \forall\, i, t \quad .$$

If the hypothesis of the random walk model holds, there would be no need to use any model to forecast stock returns in the future, since that only factor that makes the price deviate from its previous one is an unanticipated shock.

Model 2: *Fama-French (1993) Three-factor model*

Fama-French (1993) three-factor model is an advancement of the Capital Asset Pricing Model (CAPM), incorporating three distinct risks found in the equity market to explain a portfolio return: market, size and value risks.

$$E(R_{i,t}) = \beta_{1,i,t}(R_{m,t}) + \beta_{2,i,t}(SMB_{i,t-1}) + \beta_{3,i,t}(HML_{i,t-1}) + \varepsilon_{i,t} \quad ,$$

where $R_{m,t}$ is the risk-adjusted market return in day t, $SMB_{i,t-1}$ is the excess risk-adjusted returns of a portfolio of three smallest market-capitalisation stocks and a portfolio of three biggest market-capitalisation stocks of the i-th sector in day t, and $HML_{i,t-1}$ is the excess risk-adjusted returns of a portfolio of three highest book-to-market stocks and a portfolio of three lowest book-to-market stocks of the i-th sector in day t.

The Fama-French (1993) three-factor model captures three risk associated in the stock market. First, market risk is the overall risk from investing the stock market. This is the risk that investors cannot diversify if they were to invest in the stock market as it has impacts on all stocks in the market. Second, size risk is the risk of investing in stocks of companies with different sizes, which can be measured using market capitalisation. Stocks with small market capitalisation are considered to be riskier because they are more susceptible to shocks. Third, value risk refers to the risk of investing in stocks of companies with different price levels. This risk can be measured by book-to-market ratio that identifies if the stocks are over or under-valued.

Model 3: *"Higher-order-moments" model*

I construct "Higher-order-moments" model to test the forecasting ability of higher order moments: volatility and skewness. This model estimate return of the i-th sector in day t with the two higher-order-moment variables.

$$E(R_{i,t}) = \beta_{1,i,t}(VOL^{s}_{i,t-1}) + \beta_{2,i,t}(SKEW^{s}_{i,t-1}) + \varepsilon_{i,t} \ ,$$

$VOL^{s}_{i,t-1}$ and $SKEW^{s}_{i,t-1}$ are s-day rolling volatility and skewness of past daily returns up to day $t-1$ of the i-th sector, respectively.

Volatility of stock returns is a measurement of variation of the returns around the average. Also, it can be used to explain a risk of not gaining the return as high as expected. Skewness of stock returns, on the other hand, refers to the shape of the return distribution.

To look at this another way, skewness reflects herding or bandwagon psychology of investors and the existence of bubble in the market for a particular stock. As more and more investors buy a certain stock, it pushes the average price and the average return up, making the return distribution skew to the right. Such behaviour generates a bubble in the market for that stock. Hence, the positive skewness implies greater risk of bubble.

To put it more simply, the two higher order moment variables explain risks of the stock market investment. Due to investors' risk aversion, they expect greater returns on the riskier stocks; higher volatility and skewness.

Model 4: *the extended Fama-French (1993) three-factor model with higher order moment variables*

The last model considered in this research is the combination of the Fama-French (1993) three-factor and the "Higher-order-moments" models.

$$E(R_{i,t}) = \beta_{1,i,t}(R_{m,t})+\beta_{2,i,t}(SMB_{i,t-1})+\beta_{3,i,t}(HML_{i,t-1})+\beta_{4,i,t}(VOL^{s}_{i,t-1})+\beta 5_{,i,t}(SKEW^{s}_{i,t-1})+\varepsilon_{i,t},$$

where $R_{m,t}$ is the risk-adjusted market return in day t, $SMB_{i,t-1}$ is the excess risk-adjusted returns of a portfolio of three smallest market-capitalisation stocks and a portfolio of three biggest market-capitalisation stocks of the i-th sector in day t, and $HML_{i,t-1}$ is the excess risk-adjusted returns of a portfolio of three highest book-to-market stocks and a portfolio of three lowest book-to-market stocks of the i-th sector in day t, and $VOL^{s}_{i,t-1}$ and $SKEW^{s}_{i,t-1}$ are s-day rolling volatility and skewness of past daily returns up to day $t-1$ of the i-th sector, respectively.

I included the volatility and skewness of stock returns into the Fama-French (1993) three-factor model to test if this model can beat the other three forecast models, since it incorporates more risk measures.

IV. Data

The four forecast models are estimated using daily returns of sectorial indices of the Stock Exchange of Thailand, which includes: Agro & Food industry (AGRO), Consumption Products (CONSUMP), Financials (FINCIAL), Industrials (INDUS), Property & Construction (PROPCON), Resources (RESOURC), Service (SERVICE), and Technology (TECH). The sample spans from January 1st 2010 to August 31st 2015; thus, the number of data points of each sectorial index is 1,291. As a robustness check, the same models are ran using sectorial stocks in the SET50.

Table 1: Brief summary of the sectorial data

Sectorial Indices	Number of Companies in the Index (As of November 6th, 2015)	Companies Listed in the SET50 (As of November 6th, 2015)
AGRO	50	CBG, CPF, MINT, M, TU
CONSUMP	40	-
FINCIAL	59	BBL, KBANK, KTB, TCAP TMB, SAWAD, SCB
INDUS	86	IVL, PTTGC
PROPCON	132	CK, CPN, ITD, LH, PS, SCC, TPIPL, WHA
RESOURC	39	BANPU, BCP, EGCO, GLOW, IRPC, PTT, PTTEP, RATCH, TOP, TTW
SERVICE	101	AOT, BA, BDMS, BEC, BMCL, BH, BTS, CENTEL, CPALL, HMPRO, ROBINS
TECH	43	ADVANC, DTAC, DELTA, INTUCH, JAS, THCOM, TRUE

Table 2: Summary statistics of the sectorial indices

	AGRO	CONSUMP	FINCIAL	INDUS	PROPCON	RESOURC	SERVICE	TECH
Average Price	359.220	130.621	158.008	114.934	108.788	175.019	250.723	163.582
Std. Dev. Price	70.1895	21.7029	35.3546	18.4742	29.0474	15.4795	94.1783	58.8784
Averge Return	0.00046	0.00037	0.00041	0.00027	0.00055	0.00001	0.00093	0.00074
Std. Dev. Return	0.01126	0.00731	0.01367	0.01513	0.01187	0.01378	0.01097	0.01417

According to the summary statistics, AGRO has the highest average price, and PROPCON has the lowest average price. In terms of average returns, all sectorial indices yield positive. While price of SERVICE price varies the most over time, its return of INDUS is the most fluctuated. In addition, there is a negative relationship between standard deviations of price and average returns; the more fluctuated the price, the higher the average return.

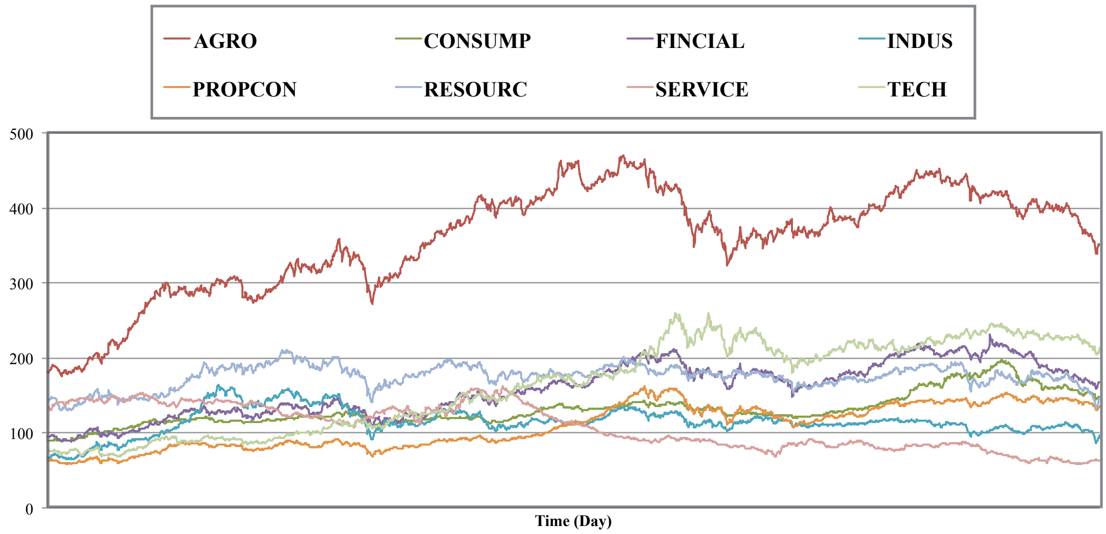

Figure 1: Price movement of the sectorial indices from January 1st 2010 to August 31st 2015

Overall, there is no clear trend of price movement across sectorial indices. The prices of AGRO, CONSUMP, FINCIAL, INDUS, PROPCON, and TECH have increased in the course of 5 years; however, RESOURC price has varied around the initial price. Finally, the price of SERVICE have fallen below the price in January 1st 2010.

The daily return of the i-th index in day t is computed as follows:

$$r_{i,t} = \ln (P_{i,t}) - \ln (P_{i,t-1}) \quad ,$$

where $P_{i,t}$ is the closing price of the i-th index in day t, sourced from the Stock Exchange of Thailand via Set Smart.

In addition, I compute the risk-adjusted daily return of the i-th index in day t as:

$$R_{i,t} = r_{i,t} - r_{f,t} \quad ,$$

where $r_{f,t}$ is the daily 3-month treasury bill return rate in day t, which, in this paper, is assumed to be risk-free return, sourced from the Bank of Thailand. I defined daily returns of the SET as the market returns (r_m).

To construct the models with higher order moments, j-day rolling volatility, and skewness of the i-th index are computed as follows:

$$AVG^j_i = \overline{R^j_t} = \frac{\sum_{t=1}^{j} R_{i,t}}{j} \quad ,$$

$$VOL^j_i = \sqrt{\frac{\sum_{t=1}^{j}\left(R_{i,t} - \overline{R^j_t}\right)^2}{j}} \, ,$$

$$SKEW^j_i = \sqrt{j}\, \frac{\sum_{t=1}^{j}\left(R_{i,t} - \overline{R^j_t}\right)^3}{\left[\sum_{t=1}^{j}\left(R_{i,t} - \overline{R^j_t}\right)^2\right]^{3/2}} \, ,$$

where $R_{i,t}$ is the risk-adjusted daily return of the i-th index in day t. Then, fixing the length of the window, I keep rolling the window 1 day forward till the last data point.

V. Methodology

Taking into account that financial time series data can be time-varying, it may not be reasonable to assume that parameters of a model are constant over time. Hence, rolling window analysis of time series models is a common technique to assess stability and forecast accuracy of the models.

Intuitively, the rolling window analysis is one of the best methods to evaluate forecasting performance of forecast models because it does not assume that the estimated parameters are persistent, and that it does not overfit the estimations. Also, by changing window sizes, the consistency of forecast models' accuracy ranking indicates the robustness of the evaluation.

In context of rolling window estimation, the full sample is split into sets of fixed rolling window time dimension, in this case, 60, 90 and 120 days. For each rolling window subsample, I estimate each model and using the estimated parameters and last values of the subsample to forecast return in 1 period ahead.

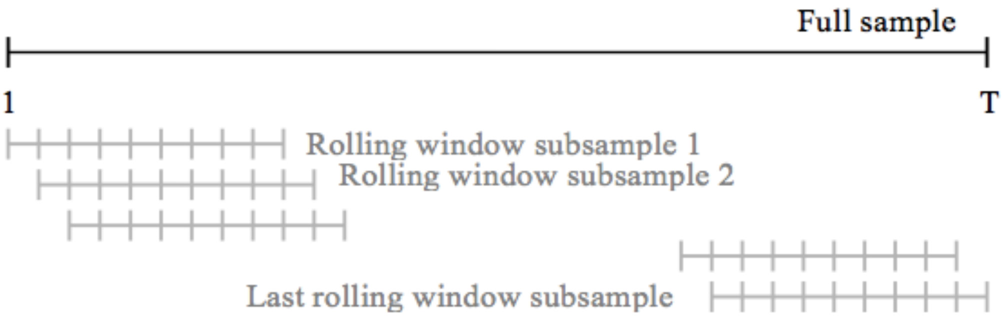

Figure 2: Illustration of rolling window estimation

After estimating forecasted returns, I compute forecast error for each forecast and the root mean square forecast errors of *j*-th rolling window for the i-th sector as follows:

$$RMSFE^{j}{}_{i} = \sqrt{\frac{\sum_{t=1}^{j}\left(R_t - \widehat{R_t}\right)^2}{j}} \quad ,$$

where R_t and $\widehat{R_t}$ are period *t*-th return and period *t*-th forecasted return, respectively. Finally, I compare the root mean share forecast errors among the models, and the model with the lowest sets of the root mean share forecast errors has the best forecast performance.

V. Results

I use root mean square forecast error (RMSFE) as a benchmark to evaluate the forecasting performance of the four forecast models, where the model with the lowest sets of the root mean square forecast error is the best forecast model. To check if the rankings are consistent, I compare the root mean square forecast errors of all forecast models across eight sectorial indices of the Stock Exchange of Thailand. While the main contribution to the findings of this research is the 90-day rolling moments and 90-day rolling window estimation, it is worthwhile to look at the results of the 60 and 120-day rolling moment and rolling window estimations to check the robustness of the findings.

Tables 2: Root Mean Square Forecast Errors of 90-day Rolling Moments and 90-day Rolling Window Estimation: Sectorial Indices and SET50 Sectorial Stocks

(2a) Sectorial Indices

	AGRO	CONSUMP	FINCIAL	INDUS	PROPCON	RESOURC	SERVICE	TECH
Model 1	1.5531	1.0131	1.8823	2.0908	1.6232	1.9399	1.5111	1.9696
Model 2	1.3596	0.8116	1.7813	1.9476	1.4919	1.8497	1.3588	1.7446
Model 3	**1.2046**	**0.7376**	**1.4080**	**1.5025**	**1.1972**	**1.4027**	**1.1301**	**1.4242**
Model 4	1.9204	1.0298	2.9096	3.2317	5.7608	2.2642	1.7782	2.2193

(2b) SET50 Sectorial Stocks

	AGRO	CONSUMP	FINCIAL	INDUS	PROPCON	RESOURC	SERVICE	TECH
Model 1	0.0145	-	0.0134	0.0321	0.0483	0.0483	0.0121	0.0285
Model 2	0.0156	-	0.0130	0.0312	0.0160	0.0112	0.0104	0.0296
Model 3	**0.0111**	-	**0.0106**	**0.0250**	0.0157	**0.0103**	**0.0100**	**0.0258**
Model 4	0.0148	-	0.0131	0.0320	**0.0156**	0.0106	0.0108	0.0293

The results from the sectorial indices of the 90-day rolling moments and 90-day rolling window estimation suggest that the "Higher-order-moments" model is the best forecast model among the four, follows by the Fama-French (1993) Three-factor model, the

Random walk model, and, lastly, the extended Fama-French (1993) three-factor model with higher order moment variables. Additionally, The ranking of the root mean square forecast errors among the four forecast models are rigid cross sectorial indices.

Given the fact that the results from the sectorial indices could be driven by speculative stocks, I conduct the same test for stocks that are listed in the SET50 for each sector using , assuming that the list remain throughout the period. The root mean square forecast errors of the "Higher-order-moments" model are still the lowest for all sector, except PROPCON, where it is sightly higher that the root mean forecast error of the extended Fama-French (1993) three-factor model with higher order moment variables. However, the accuracy rankings vary for different sector. For AGRO and TECH SET50 stocks, the second best model is the Random walk model, follows by the extended Fama-French (1993) three-factor model with higher order moment variables, and the Fama-French (1993) three-factor model. In the case of FINCIAL, INDUS, and SERVICE, the Fama-French (1993) three-factor model is the second best forecast model, follows by the extended Fama-French (1993) three-factor model with higher order moment variables, and the Random walk model. Finally, in the case of PROPCON SET50 stocks, the extended Fama-French (1993) three-factor model with higher order moment variables is ranked first, follows by the "Higher-order-moments" model, the Fama-French (1993) three-factor model, and, lastly, the Random walk model.

Overall, it is clear that the models for the SET50 sectorial stocks have lower root mean square forecast error compared to the ones for sectorial indices. One possible explanation for this is that price and return of speculative stocks move in a pattern; so the movement themselves can be explained by some financial factors.

Tables 3: Root Mean Square Forecast Errors of
60-day Rolling Moments and 60-day Rolling Window, and
120-day Rolling Moments and 120-day Rolling Window Estimation :
Sectorial Indices and SET50 Sectorial Stocks

(3a) 60-day Rolling Moments and 60-day Rolling Window Estimation: Sectorial Indices

	AGRO	CONSUMP	FINCIAL	INDUS	PROPCON	RESOURC	SERVICE	TECH
Model 1	1.5531	1.0131	1.8823	2.0908	1.6232	1.9399	1.5111	1.9696
Model 2	1.3588	0.8686	1.8052	1.9714	1.4729	1.8333	1.5518	1.7560
Model 3	**1.1140**	**0.7422**	**1.3820**	**1.5057**	**1.1805**	**1.4182**	**1.1242**	**1.4227**
Model 4	1.4825	0.9336	1.8560	2.0272	1.5290	1.8522	2.0893	1.9093

(3b) 60-day Rolling Moments and 60-day Rolling Window Estimation: SET50 Sectorial Stocks

	AGRO	CONSUMP	FINCIAL	INDUS	PROPCON	RESOURC	SERVICE	TECH
Model 1	0.0145	-	**0.0134**	0.0321	0.0483	0.0483	**0.0121**	**0.0285**
Model 2	0.0169	-	0.0146	0.0333	**0.0146**	**0.0113**	0.0134	0.0312
Model 3	**0.0108**	-	0.0139	**0.0235**	0.0175	0.0175	0.0168	0.0315
Model 4	0.0168	-	0.0146	0.0336	0.0484	0.0147	0.1971	0.0329

(3c) 120-day Rolling Moments and 120-day Rolling Window Estimation: Sectorial Indices

	AGRO	CONSUMP	FINCIAL	INDUS	PROPCON	RESOURC	SERVICE	TECH
Model 1	1.5531	1.0131	1.8823	2.0908	1.6232	1.9399	1.5111	1.9696
Model 2	1.3722	0.7834	1.7869	1.9144	1.5103	1.8450	1.3618	1.7275
Model 3	**1.3514**	**0.8254**	**1.6142**	**1.7984**	**1.3043**	**1.5012**	**1.3654**	**1.5882**
Model 4	1.4916	0.8315	1.8168	2.0068	1.5423	1.8950	1.4268	1.7734

(3d) 120-day Rolling Moments and 120-day Rolling Window Estimation: SET50 Sectorial Stocks

	AGRO	CONSUMP	FINCIAL	INDUS	PROPCON	RESOURC	SERVICE	TECH
Model 1	0.0145	-	0.0134	0.0321	0.0483	0.0483	**0.0121**	0.0285
Model 2	0.0340	-	0.0147	0.0238	0.0262	**0.0162**	0.0231	0.0159
Model 3	**0.0142**	-	**0.0111**	**0.0219**	**0.0228**	0.0165	0.0464	**0.0129**
Model 4	0.0302	-	0.0146	0.0246	0.0317	0.0236	0.0682	0.0154

The rankings of the four forecast models still remain rigid for the analysis of sectorial indices in the 60 and 120-day rolling moment and rolling window estimations; the "Higher-order-moments" model is the best forecast model among the four, follows by the Fama-French (1993) Three-factor model, the Random walk model, and, lastly, the extended Fama-French (1993) three-factor model with higher order moment variables. But the results of 60-day Rolling Moments and 60-day Rolling Window, and 120-day Rolling Moments and 120-day Rolling Window Estimation: SET50 Sectorial Stocks reveal inconsistent forecasting performance rankings.

VI. Conclusion

All in all, the rolling window analysis of the sectorial indices of the Stock Exchange of Thailand suggests that using higher order moments, volatility and skewness, of past returns in a forecast model improves the forecasting performance. By comparing root mean square forecast error (RMSFE) of four forecast models: (1) random walk model, (2) Fama-French (1993) three-factor model, (3) "higher-order-moments" model, and (4) extended Fama-French (1993) three-factor model with higher order moment variables across sectorial indices, the "higher-order-moments" model is the model with the lowest sets of the root mean square forecast error (RMSFE); as a result, it is concluded to be the best forecast model.

However, the forecasting performance ranking is more rigid for the sectorial indices than the SET50 stocks. It is possible that SET50 is a more efficient market; in a sense that more information has already been obtained. Whereas the sectorial indices are still subject to speculative tendencies; so, the higher order moments capture the return movements better.

The findings of this research highlights the significance of higher order moments, volatility and skewness, in forecasting returns, as they can explain the risks that are associated in the stock market investment. Volatility captures the possibility of not gaining the expected return; the higher the volatility, the greater the possibility; therefore, the greater the risk. Skewness reflects the herding or bandwagon behaviour of investors,where ones follow the actions of others, which then indicates the development of bubble; the higher the skewness, the greater the risk.

Although this research has reached its aims, there are some limitations and rooms for further studies. First, the evaluation is only in the context of the sectorial indices of the Stock Exchange of Thailand; therefore, the conclusion may differ for portfolios with foreign stocks. Second, due to regulations of the Stock Exchange of Thailand, the data used in the analysis only span 5 years.

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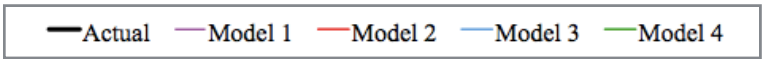
Appendix:
Actual and Forecasted Price Movement Estimated from the Four Forecast Models

To compare the forecasting performance of the four models against the actual price movements, the price of the i-th index in day t is calculated such that:

$$P_{i,t} = P_{i,t-1} \times (1+\widehat{R_t}) \quad \text{Given that } P_{i,0} = 1 \, , \quad \forall \ i = 1, 2, \ldots, 8,$$

where $\widehat{R_t}$ is estimated return of the i-th index in day t.



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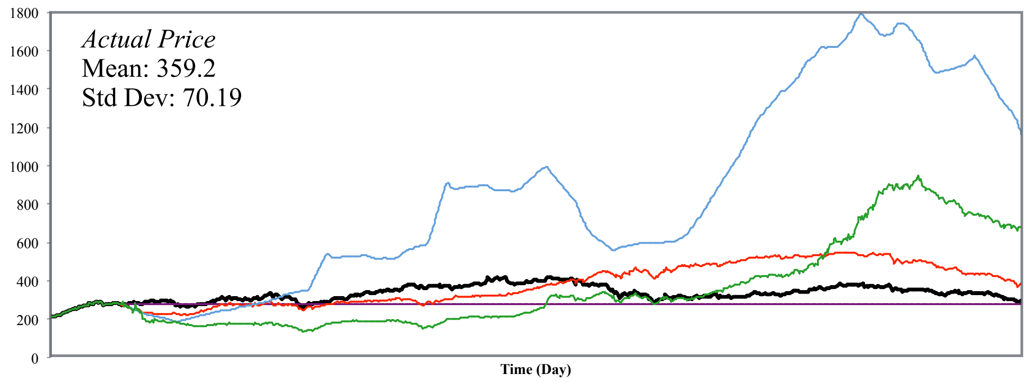

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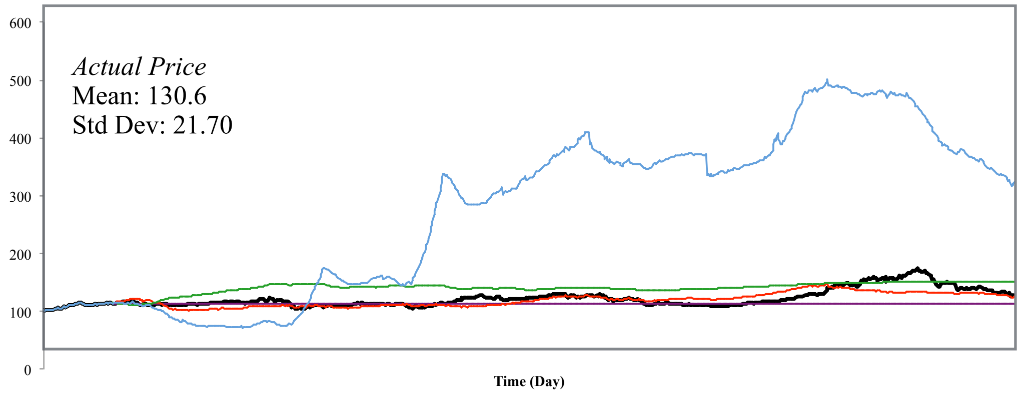

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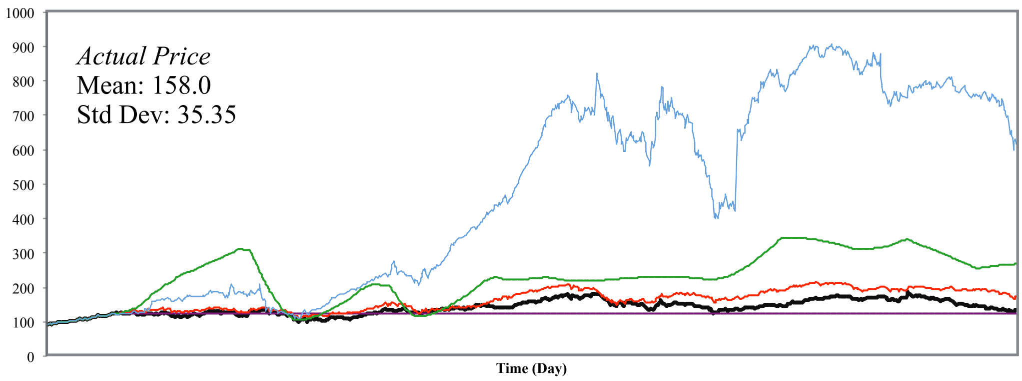

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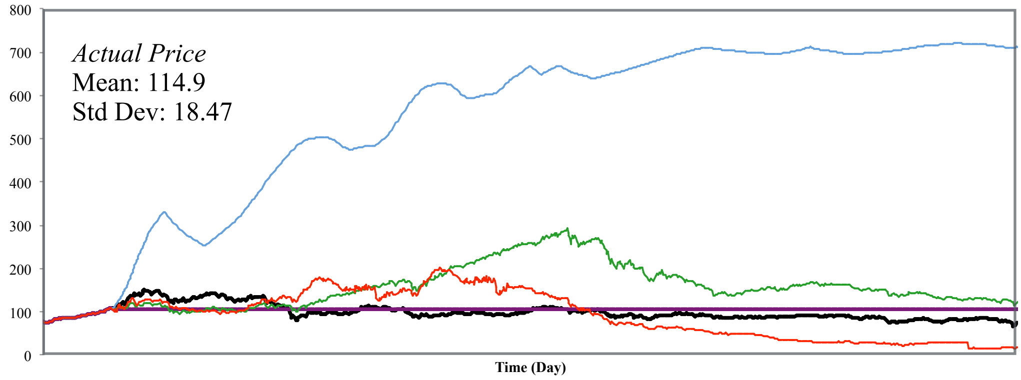

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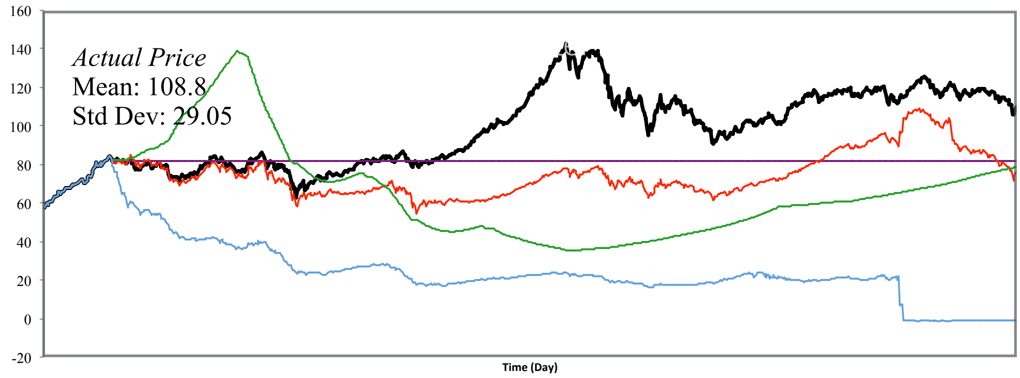

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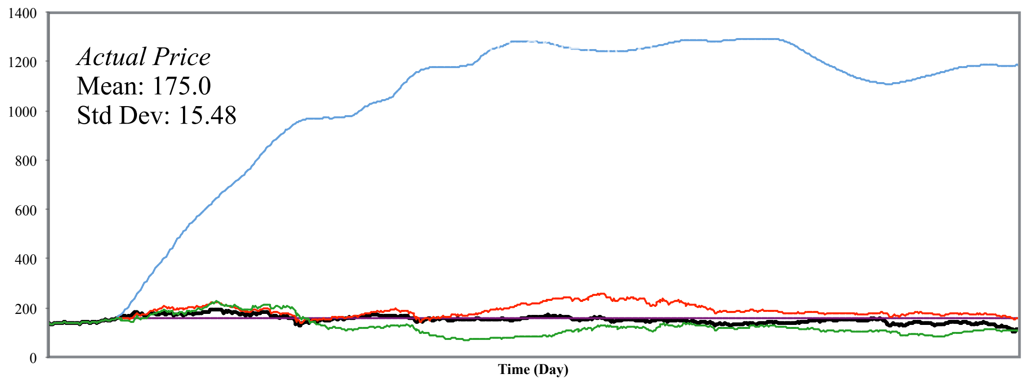

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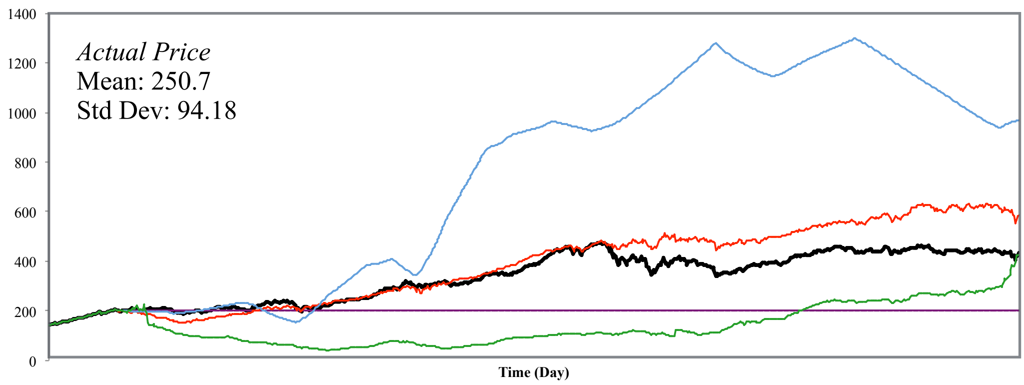

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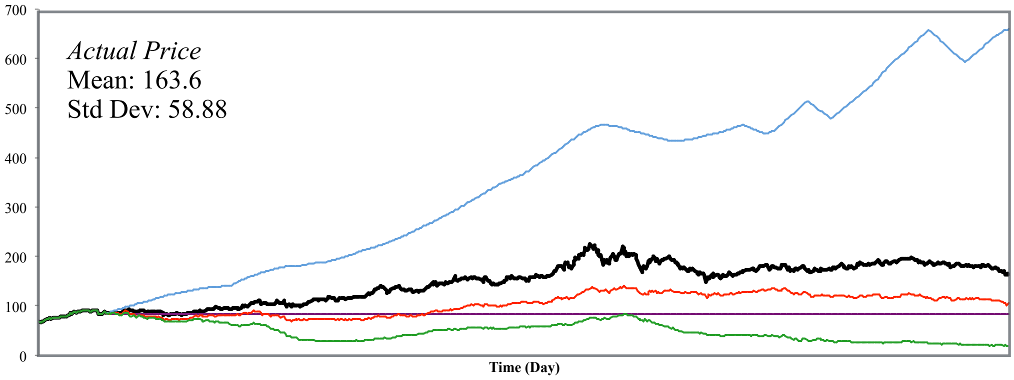
700
600
500
400
300
200
100
0
Actual Price
Mean: 163.6
Std Dev: 58.88
Time (Day)