Senior Research

Topic: Testing Asset Pricing Models: Evidence from Thailand

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Date: 16 May 2018

Senior Research Submitted in Partial Fulfillment of the Requirements for the Bachelor of Arts degree in Economics (International Program)

The Bachelor of Arts Program in Economics
Faculty of Economics
Chulalongkorn University
Academic Year 2017

Approved By:

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Abstract

This research investigates the performance of eight asset pricing models in the Stock Exchange of Thailand including Fama-French three-factor model (3FF), 5FF, and Cahart's four-factor model. Two models are formed by replacing relative momentum in Cahart's model with absolute and probabilistic momentum respectively. The other three models are formed by discarding factors from the 5FF model. These models are tested on three sets of 25 portfolios. By comparing average absolute intercepts $(\mathrm{A}|a_i|)$ produced by the multi-variate regression of each model, we find that the model that includes probabilistic momentum factor is the best model to explain the return of Thai stocks. However, after comparing $\mathrm{A}|a_i|$ to magnitude and dispersion unexplained by average returns, we find that $\mathrm{A}|a_i|$ is larger than unexplained return dispersion. This means that the asset pricing models are inadequate for predicting Thai stocks' return. The average returns of 25 portfolios have more predictive accuracy than all models.

We find that asset pricing models can indicate risk exposures in various portfolios. Stocks with different characteristics are exposed to different types of risks. Additionally, this study also form two trading strategies inspired by factor construction methods. We found that investing in stocks from small, heavy investing and profitable firms and investing in stocks with strong positive momentum yield exceptionally good and consistent returns.

Content

Section 1: Introduction

Factor asset pricing models have been developed since 1980's. They are built based on financial theories to determine the prices of stocks in any market. There are several popular asset pricing models such as Capital Asset Pricing Model (Sharpe, 1964 and Linter, 1965) and Fama-French three-factor model (Fama & French, 1992). The objective of this study is to test the ability of asset pricing models to explain Thai stock returns. As the model performances depend on various risk factors, this research also investigates relationships among the risk factors as well as analyzing factors' effects on stock returns in different portfolio formations.

Studying these models is important for both investors and academia. Investors utilize asset pricing models to manage risks in their portfolio. For example, investors can simply use beta derived from CAPM to help them make investment decisions. As factor asset pricing models become more complicated, they contain more risk factors. The three-factor asset pricing model adds two more risk factors to CAPM, which are size and book to market ratio (Fama & French 1992). Then, investors can use the new model to identify more type of risk exposures other than beta.

Another importance of asset pricing models for investors is the interpretation of the model intercepts. Scholars would try to create the lowest intercepts implying the model generates low unexplained returns. However, investors can use model's intercept to evaluate trading strategies. As the model adopt multi-variate regression analysis, factors included in the model can be control variables for their effects on stock prices. This means that the trading portfolios with high model intercept after controlling for risk factors are attractive portfolios. They can generate excess returns after controlling for all types of identified risks. Hence, the development of a diverse asset pricing models helps investors trade safely, systematically and efficiently.

This study also discusses the implications and applications of the models to assist investing activities. In section 5, the author discuss how factor trading strategy can be constructed. After that, portfolios are formed according to the strategy and a model is used to indicate risk exposures of trading strategy as well as evaluating the returns.

Scholars also use factor asset pricing models to study relationships of factors affecting stock returns. Firstly, the models help researchers further develop asset pricing models per se. They use these models to identify a new factor, which can significantly reduce the amount of unexplained returns. Scholars could try adding various factors into the model and test whether the model accuracy is improved. This would not be possible without a good prior knowledge on pricing factors and existing robust model. Secondly, a robust model can be used to separate and identify structure of stock returns. This helps them develop empirical support for return theories.

There are lots of studies indicating that asset pricing models work well in the US. The models could leave little unexplained returns for some portfolio allocations. Furthermore, there are several researches which test asset pricing models in continental level including emerging markets and developed markets. However, there have been only few studies done in Thailand, which has one of the oldest stock market in South East Asian region. Therefore, the author investigates the performance of asset pricing models in Thailand as well as studies the relationships of pricing factors. The findings in this study will be compared to the theories and empirical results found in the US.

The importance of this research is in its contribution to build an asset pricing model that fits Thai stock market or the Stock Exchange of Thailand. Constructing an effective model in Thailand, which adequately includes significant factors, can help create better theories describing Thai stocks. For Thai investor, this research could help them identify relevant risk factors and form a good trading strategy in Thai stock market.

Section 2: Literature Review

2.1) Capital Asset Pricing Models (CAPM)

The Sharpe (1964) – Linter (1965) capital asset pricing model (CAPM) is built upon mean-variance portfolio. It postulates a linear trade-off between expected returns and risk measured by beta. The model implies that portfolio risk can be diversified except for "systematic risk" or the market risk. Investors would ask for higher returns when holding portfolio with high systematic risk.

CAPM can be written as follows:

$$R_{it} - R_{Ft} = a_i \ + \ b_i(R_{Mt} - R_{Ft}) + e_{it}$$

$R_{it} - R_{Ft}$ is an excess return or the portfolio's return minus risk-free rate (R_{Ft}). a_i is the intercept of the equation, which is the return unexplained by the model. When a portfolio is well diversified, a_i should be virtually equal to zero according to CAPM (Merton, 1973). b_i is known as beta describing a linear relationship between market return and the portfolio's return. $R_{Mt} - R_{Ft}$ represents market performance relatively to risk free rate.

2.2) Development of Fama-French Three Factor Model

2.2.1) Theory

Fama and French (1992) study risk factors affecting stock and bond returns. They indicated two relevant risk factors besides the market risk. The first risk factor is size of the firm measured by market capitalization. The second factor is value, which is measured by book-to-market ratio. Firms with low BE/ME will have low earnings on asset.

To test the influence of risks on returns, they formed 6 portfolios sorted on size and BE/ME ratio. Every June of each year, the stocks are ranked on size. Stocks with market capitalization higher than the median of NYSE would be put in "big" portfolios. If the size is lower than the median, they will be put in "small" portfolios. For BE/ME, stocks above 70 percentiles of NYSE would be considered as "high" BE/ME stocks or "growth stocks". Stocks below 30 percentiles of NYSE would be considered as "low" BE/ME or "value stocks". As a result, six portfolios are formed (S/L, S/M, S/H, B/L, B/M, B/H where S is small, B is big, H M L are high, medium and low book-to-market ratio respectively). Their value-weighted returns are calculated monthly.

Once portfolios are formed, factors can be constructed. Size factor or SMB (Small Minus Big) are formed by calculating monthly returns of S/L + S/M + S/H - B/L - B/M - B/H. Value factor or HML (High Minus Low) are formed by calculating monthly returns S/H + B/H - S/L - B/L.

Fama-French Three factors model can be written as follows:

$$R_{it} - R_{Ft} = a_i \ + \ b_i\big(R_{Mt} - R_f\big) + s_i(SMB_t) + \ h_i(HML_t) + e_{it}$$

The samples in their study suggest that bigger stocks generally have smaller returns. Additionally, value stocks usually have higher returns than growth stocks. Augmenting CAPM with size and value factor, Fama and French could reduce the model's intercepts. They also found that slopes of market factor become lower and closer to 1. These suggest size and value factor could explain differences in stocks return.

2.2.2) Empirical Evidence

In Thai stock exchange, size and value are statistically significant factors to determine returns (Chancharat, Valadkhani, & Harvie, 2007). Slopes of size factor increase for portfolios that contain smaller stocks. This means bigger stocks are less exposed to size risk. Value stocks report small positive HML coefficients while growth stocks have larger HML negative slopes.

2.3) Development of Cahart's Four Factor model

2.3.1) Theory

Cahart's (1997) observed mutual funds' performance and found a strong persistence in their return. He found that one-year past return is positively correlated to the next year return. To back up his argument, Cahart sorted fund portfolios according to sum of its one-year past return. He formed momentum factor by using equal-weighted returns of stocks in the highest 30 percentile of one-year past return minus with equal-weighted returns of stock in the lowest 30 percentile of one-year past return.

He found that momentum factor could explain mutual fund's persistence well. Especially funds on the top and bottom performance decile, effects from momentum are stronger. Cahart reported that buying funds in top momentum decile and selling funds in bottom momentum decile could yield 8% average return.

In addition, he found that CAPM fails to explain the mutual fund returns persistence. His sorted momentum portfolios share similar beta. Ultimately, he could explain mutual fund returns using market, size, value and momentum factor. His 4-factor model explains most spreads and patterns in the portfolios.

In this study, Cahart's Four-Factor model can be written as follows:

$$R_{it} - R_{Ft} = a_i + b_i\left(R_{Mt} - R_f\right) + s_i(SMB_t) + h_i(HML_t) + w_i(WML_t) + e_{it}$$

Added to the three-factor model is the WML factor, it is a value-weighted return of winner stocks minus loser stocks. In Cahart's orginal work, WML is referred as $PR1YR_t$.

2.3.2) Empirical Evidence

There are several evidences that momentum factor works well in Asian emerging market. Cakici, Fabozzi, and Tan (2013) study effectiveness of Cahart's model in emerging markets across continents. In Asia, they include over 800 stocks from China, India, Indonesia, South

Korea, Malaysia, Philippines, Taiwan, and Thailand using data from 1990 to 2011. They found that momentum factor could explain stock returns in Asia; in addition, they reported that value factor is negatively correlated with momentum factor.

In Vietnam, trading stocks with momentum strategy could yield return as high as 6% from 2007 – 2015 (Vo & Truong, 2018). Vo and Truong form 16 portfolios by sorting stocks based on past returns. They found that momentum effect is significant in 10 out of 16 portfolios. However, in Thailand, the momentum effect is reported to be rare (Chancharat, Valadkhani, & Harvie, 2007). As this paper only focuses on the effectiveness of asset pricing models in Thailand, the author will not investigate why momentum factor works in outside Thailand.

2.3.3) Absolute momentum and Relative momentum

As momentum factor can poorly predict returns in Thailand, this paper explores alternatives to form momentum factor. Cahart's momentum factor is also known as relative momentum (Kolanovic & Wei, 2015). To classify winners and losers, stocks are relatively compared to each other. In literature on Cahart's four factor model, scholars usually sort stocks by one-year past performance excluding last month. Then, the momentum factor (WML) is the value-weighted return of top 30 percentile minus the return of bottom 30 percentile. By this classification, winner stocks are the ones that 'relatively' outperform others.

Absolute momentum is different. Stocks can be indicated as a winner alone by itself. If a stock's one-year past performance is positive, then it is a winner (Antonacci, 2013). By contrast, if its past return is negative, it is a loser. With this method, stocks can be identified as winners or losers without relative comparison to others.

Kolanovic and Wei (2015) shows that absolute momentum trading strategy is superior to relative momentum strategy. Long absolute winners and short absolute losers give higher returns and lower volatility. This implies that absolute momentum has stronger relationship with future returns. Ultimately, using absolute momentum to construct momentum factor should reduce four-factor model's intercepts.

2.3.4) Probabilistic Momentum

David Varadi (2014) improved absolute momentum by adding a probability element. He formed a trading strategy from the probability of stocks to outperform the market, which is determined by information ratio.

$$Information\ Ratio = \frac{\left(R_p - R_m\right)}{S_{p-m}}$$

$R_p - R_m$ is the spread of portfolio's return relative to the market and S_{p-m} is the standard deviation of portfolio's return minus market return. The information ratio is then used as t-value to obtain the probability of portfolio to outperform the market from the t-distribution.

2.4) Development of Fama-French Five Factor Model

2.4.1) Theory

Fama-French (2006) discuss dividend evaluation model and suggests profitability and investment could affect expected returns. They used empirical data to test their hypothesis adopting current earning as a simple proxy for profitability and found that firms with high profit generate higher expected rate of return. By contrast, using the valuation theory as the base, they argued that firms with high investment generally have lower expected rate of return. However, Fama and French thought that profitability and investment relationships to stock returns are already captured by the value factor.

Novy-Marx (2013) use gross profits instead of current earnings to measure profitability. He argued that gross profit is a better representation of profitability as current earnings might be affected activities unrelated to profit generation. The examples of those activities are R&D investment or interest expenses. He ran 3 factor model cross-sectional regressions on portfolios sorted on size and gross-profitability. The result suggested that profitability once controlled for size, value and market yields excess returns. Unlike Fama and French (2006), Marx proved that profitable firm is not the same as value firm. Furthermore, he argues that value premium in value strategy is not driven by unprofitable stocks because there is a difference of duration in profitability and value strategy. Hence, gross profit can explain other aspects of return.

Titman, Wei and Xie (2004) study abnormal returns related to capital investment. He noted that increase in investment could provide both favorable and unfavorable information. Investment could signal good opportunity for growth. On the other hand, it could also imply over investment. He found that firms with higher cash flows and debt ratios experience stronger negative effect from capital investment. Sorting portfolios by abnormal capital investment and running Cahart's four factor model regression, the negative relationship between abnormal investment and returns can be established after controlling for four factors in Cahart's model. This means that investment can explain return anomalies aside from size, value and market.

Fama and French (2015) revisited their conclusion on relations of profitability and investment on stock returns from valuation theory. Given more evidences pointed out that value factor is inadequate to capture profitability and investment effect, they constructed two more factors aiming to reduce anomaly in three-factor models. Fama and French reformed their theory and argued that investment and profitability are relevant for forecasting future cash flows. Looking at long-term rate of return, cash flows is a better proxy which captures horizon effects in the term structure of expected returns. Hence, investment and profitability factor could offer explanatory power differently from value factor.

Fama-French Five-Factor model can be written as follows:

$$R_{it} - R_{Ft} = a_i + b_i\left(R_{Mt} - R_f\right) + s_i(SMB_t) + h_i(HML_t) + r_i(RMA_t) + c_i(CMA_t) + e_{it}$$

where RMA_t represents profitability factor calculated by subtracting value-weighted returns of robust profit stocks by the returns of weak profit stocks (robust minus weak). $CMA_t$is investment factor calculated by the value-weighted returns of low investing stock minus high investing stock (conservative minus aggressive).

There are many interesting findings in the empirical test of five-factor model in the US. Firstly, the accuracy of the model improved significantly. This applies especially for the firms with strong investment or profitability. In general, the value of intercept is reduced comparatively to three-factor model. HML factor or value factor lost its significance in some portfolios meaning that the added factors can capture all effects of value factor.

Secondly, five-factor model has issues in predicting returns of small stocks and stocks in the highest investment quintile. For some small stock portfolios, they have a negative exposure to profitability and investment factor. By sorting Left Hand Side portfolios differently taking in account of both profitability and investment, Fama and French explain that these small firms are likely to invest a lot despite low profitability. As a result, small firms report negative coefficients. For big stocks in highest investment quintile, the model under-estimate the returns for these stocks.

2.4.2) Empirical Evidence

In addition to evidence in NYSE in Fama and French's "Five-factor asset pricing model" paper, they also do international empirical test in the same year, 2015. Fama and French formed continental portfolios from four regions which are North America, Europe, Japan and Asia Pacific (AP).

Firstly, they found that the profitability factor and investment factor fail to improve the model in Japan. This is because there is a strong value effect, but weak profitability and investment effect. Secondly, in North America, the five-factor model outperforms three-factor model; nevertheless, the model can still be improved further by dropping investment factor. In Europe and Asia Pacific, five-factor model also significantly lower intercepts. Thirdly, when looking at intercept dispersion throughout portfolios; five-factor model fails miserably in AP. The intercepts variation is as high as the variation of AP portfolios' return implying that the model cannot accurately predict the returns across various AP portfolios. The author suggests that selected countries in AP including Australia, Hong Kong, New Zealand, and Singapore are disintegrated creating model's poor performance.

As Thailand is geographically in Asia-Pacific region and close to Japan, it is possible that the five factor asset pricing model will perform poorly as well. Chancharat, Valadkhani and Harvie (2007) provided evidence that Thai stock market is positively influenced by the Singapore stock market return. However, they cannot find evidence that supports relationship between Australian and Thai stock market. This means that Thailand might be different, and the effectiveness of five-factor model in Thai stock market is still worth exploring.

Section 3: Research Methodology

The data used in this research is drawn from Bloomberg Terminal which contains historical data on total return index, market capitalization, market-to-book ratio, return on equity, capital expenditure, and total asset for listed stocks in the Stock Exchange of Thailand. The author analyzes SET100 stock data from February 2002 – December 2017. Instead of using the whole stock market data like Fama and French (2015) study, SET100 data could draw similar conclusion and remove liquidity issue which creates noises in returns. Also, stocks in SET100 data tend to have fewer missing data, facilitating analytical process in this research.

3.1) Econometric Methods

This study employs test on 8 asset pricing models including Fama-French three-factor asset pricing model, Cahart's four-factor asset pricing model and Fama-French five-factor asset pricing model. Three models are formed by dropping out value, investment, and profitability factor from Five-factor model respectively. The other two are created by replacement of WML with absolute momentum and probabilistic momentum respectively. Every model includes market factor.

The comparison of model is done by applying multivariate regression to 75 LHS portfolios. The intercept produced from the regression will be compared. The model that produce lowest average intercepts ($\mathrm{A}|a_i|$) means that they have the lowest value of unexplained returns. Hence, it would be considered a superior model.

In addition, two ratios are also used to compare models. First, average absolute intercept over absolute value of $\bar{r}$, which is average value of return on portfolio i minus the average of all portfolio returns (Fama & French, 2015). This can be written as $\frac{\mathrm{A}|a_i|}{A|\bar{r}|}$ and used to measure ability of model to explain return dispersion. Second, $\frac{\mathrm{A}|a_i{}^2|}{A(\bar{r^2})}$ or the average squared intercept over average squared $\bar{r}$ will be used to compare intercepts' dispersion with the return dispersion.

3.2) Risk Factors

3.2.1) Market Factor $(\boldsymbol{R_{Mt}} - \boldsymbol{R_f})$

The market factor is the return of market portfolio minus the risk-free rate. The SET Index is used as market portfolio. The return of market portfolio is based on total return index which assumes that dividends and rights offerings are reinvested into the market. For the risk-free rate, F12203M Index data from Bloomberg is used, which contains group of government's 3 month bill.

3.2.2) Size factor $(\boldsymbol{R_{Mt}} - \boldsymbol{R_f})$

Size is constructed by ranking firms on size measured by market capitalization at the end of December in the prior year. Small stocks (S) and big stocks (B) are indicated by the median size value among SET100 stocks. Size factor (SMB or Small Minus Big) is the subtraction of equal-weighted small stocks returns and equal-weigted big stocks retrun. Following approach in Kaewthammachai, et al. (2016), the size factor portfolio is rebalanced at the end of January every year. The lag of stock allocation is for the market to absorb firm's information. Conversely in Fama and French (2015), they rebalanced portfolios later which is in June.

3.2.3) Value factor (HML_t)

Similarly, to construct value factor, stocks are sorted according to the reverse of market-to-book ratio obtained from Bloomberg Terminal at the end of December in the prior year. Stocks are classified in three groups: low (L), neutral (N) and high (H) book-to-market ratio by using 30th and 70th SET100 value breakpoints respectively. Considering both division in size and value, 6 portfolios are formed and illustrated in diagram as follows.

Size (break by median)

		S(50)	B(50)
B/M (Book-to-Market Ratio)	H (30)	SH	BH
	N(40)	SN	BN
	L (30)	SL	BL

Value factor (HML or High Minus Low) is the difference in value-weighted return of value stocks (high B/M) and growth stocks(low B/M). The equation can be expressed as follows:

$$HML_t = \frac{1}{2}(r_{SH} + r_{BH}) - \frac{1}{2}(r_{SL} + r_{BL})$$

Similarly to size factor, the value factor portfolio is rebalanced at the end of every January.

3.2.4) Relative Momentum factor (WML_t)

For relative momentum, stocks are ranked based on their past cumulative one-year return excluding last month. For example, if current period is January year t, stocks are ranked based on sum of January to November returns in year t-1. Stocks are classified into three groups: losers (L), neutral (N) and winner (W) using 30th and 70th SET100 breakpoints of past return respectively. Considering both division in size and momentum, 6 portfolios are formed in the similar manner as value factor construction.

		S(50)	B(50)
WML (Relative Momentum)	W (30)	SW	BW
	N(40)	SN	BN
	L (30)	SL	BL

Momentum factor (WML or Winner Minus Loser) is the difference in value-weighted return of winner and loser stocks. The equation can be expressed as follows:

$$WML_t = \frac{1}{2}(r_{SW} + r_{BW}) - \frac{1}{2}(r_{SL} + r_{BL})$$

Following approach in Kaewthammachai, et al. (2016), the relative momentum factor portfolio is rebalanced every month.

3.2.5) Absolute Momentum factor $(\boldsymbol{Abs\_MOM_t})$

For absolute momentum, the mothod used in this study is different from Gary Antonacci's. Stocks are put in winner portfolio when the prediction of return is greater than the current risk free rate. The prediction is done by using simple auto-regressive model.

$$r_t = a + b(r_{t-1}) + e_t$$

r_t stands for current period return and r_{t-1} refers to the past period return. After running time-series regression on past 12 month return data, the coefficient and intercept value will be produced. To predict the next month return, the current period return can be plugged into the equation at the end of every month.

$$E(r_{t+1}) = \hat{a} + \hat{b}(r_t)$$

If $E(r_t)$ is greater than current risk-free rate, then it is a winner stock. If $E(r_t) < 0$, it is considered as loser. Absolute momentum factor (Abs_MOM) is the difference in value-weighted return of winner and loser stocks. The equation can be expressed as follows:

$$Abs\_MOM_t = \frac{1}{2}(r_{SW} + r_{BW}) - \frac{1}{2}(r_{SL} + r_{BL})$$

The factor portfolio is rebalanced at the end of every month from the updated prediction and new risk-free rate. Monthly value-weighted returns of the portfolio is the Abs_MOM factor.

3.2.6) Probabilistic Momentum $(\boldsymbol{ProbMOM_t})$

Probabilistic momentum factor is the monthly value-weighted returns of ProbMOM portfolio. Using Varadi (2014) method, each stock's monthly information ratio (IR) is derived. At the end of each month, ProbMOM factor portfolio is adjusted. It adds new stocks with IR more than 0.26, which is the t-value of 10% confidence level that the stocks will outperform the market. For stocks that is already in the portfolio, they will be sold off once the IR falls below -0.26. This gives at least 10% confidence level that their performances are below the market.

3.2.7) Investment factor $(\boldsymbol{CMA_t})$

Forming investment factor, stocks are ranked based on abnormal captial investment. Following Titman, Wie and Xie (2004) equation, abnormal investment is calculated as:

$$CI_{t-1} = \frac{CE_{t-1}}{(CE_{t-2} + CE_{t-3} + CE_{t-4})/3} - 1$$

CE_{t-1} is firm's captial expenditure divided by total asset in year t-1. CI_{t-1} is the abnormal investment in year t-1. Stocks are then classified into three groups: conservative (C), neutral (N) and aggressive (A) using 30th and 70th SET100 breakpoints of abnormal investment respectively. Considering both division in size and investment, 6 portfolios are formed.

Investment factor (CMA or Conservative Minus Aggressive) is the difference in value-weighted return of conservative and aggressive stocks. The equation can be expressed as follows:

$$CMA_t = \frac{1}{2}(r_{SC} + r_{BC}) - \frac{1}{2}(r_{SA} + r_{BA})$$

Follwing approach in Kaewthammachai, et al. (2016), the investment factor portfolio is rebalanced at yearly at the end of January.

3.2.8) Profitability factor (RMW_t)

As discussed in section 2, it is ideal to use gross profit to form profitability factor. However, due to missing data in Bloomberg Terminal, the author decided to substitute gross profit with net profit. In Fama and French (2015), they used operating profit scaled by total equity. In other words, return on total equity ratio (ROE) is used to allocate stocks.

Similarly, stocks are classified into three groups: robust (R), neutral (N) and weak (W) using 30th and 70th SET100 breakpoints of ROE. Dividing further by size, 6 portfolios are then formed. The profitabilty factor portfolio is rebalanced at the end of January.

Profitability factor equation can be expressed as follows:

$$RMW_t = \frac{1}{2}(r_{SR} + r_{SR}) - \frac{1}{2}(r_{SW} + r_{BW})$$

3.3) Testing portfolio formation

Following Fama and French (2015), the left hand side portfolio is formed by constructing 25-Size-B/M, 25-Size-OP and 25-Size-Inv portfolios. Adding them up, the models are tested on 75 portfolios. To form each 25 portfolio, the SET100 stocks are ranked by two factors. They are then split by SET100 quintile breakpoints. Consider diagram below:

25-Size-B/M testing portfolios

	Low	2	3	4	High → B/M
Small	SBM11	SBM12	SBM13	SBM14	SBM15
2	SBM21	SBM22	SBM23	SBM24	SBM25
3	SBM31	SBM32	SBM33	SBM34	SBM35
4	SBM41	SBM42	SBM43	SBM44	SBM45
Big	SBM51	SBM52	SBM53	SBM54	SBM55

The diagram above illustrates 25 testing portfolios formed by classifying each stock on size and book-to-market value. They are split by size and B/M quintile. SBM11 stands for Size-B/M portfolio with size in 1st quintile and B/M in 1st quintile. SBM 21 stands for Size-B/M portfolio with size in 2nd quintile and B/M in 1st quintile. Additionally, SBM12 stands for Size-B/M portfolio 1st size quintile and 2nd B/M quintile.

Reading vertically, Stocks in SBM11 are ones that have smallest size as well as has lowest book-to-market ratio. Moving down, stocks in SBM21 are ones that are in 2nd size quintile and 1st B/M quintile. Portfolio's size increases as the SBM portfolio has higher first digit number.

Reading this diagram horizontally, stocks in SBM12 are ones that its size falls in smallest quintile similarly to SBM11; however, these stocks have B/M ratio in 2nd quintile. The stock B/M ratio increases as the portfolio has higher second digit number. 25-Size-OP and 25-Size-Inv portfolios are constructed and interpreted similarly.

25-Size-OP testing portfolios

	Weak	2	3	4	Robust → OP
Small	SOP11	SOP12	SOP13	SOP14	SOP15
2	SOP21	SOP22	SOP23	SOP24	SOP25
3	SOP31	SOP32	SOP33	SOP34	SOP35
4	SOP41	SOP42	SOP43	SOP44	SOP45
Big	SOP51	SOP52	SOP53	SOP54	SOP55

25-Size-Inv testing portfolios

	Conservative	2	3	4	Aggressive → Inv
Small	SInv11	Sinv12	Sinv13	Sinv14	Sinv15
2	Sinv21	Sinv22	Sinv23	Sinv24	Sinv25
3	Sinv31	Sinv32	Sinv33	Sinv34	Sinv35
4	Sinv41	Sinv42	Sinv43	Sinv44	Sinv45
Big	Sinv51	Sinv52	Sinv53	Sinv54	Sinv55

Section 4: Results

This section discusses the results obtained from the data and portfolio testing. First, the descriptive statistics as well as the returns behavior in each factor portfolios are shown. Second, the method to form 75 testing portfolios is discussed and the statistics on those portfolios are presented. Third, the author investigates the effectiveness of 8 factor models tested in this study. Lastly, we go into the details of regression coefficients, statistical significance, and effects of different factors on portfolios.

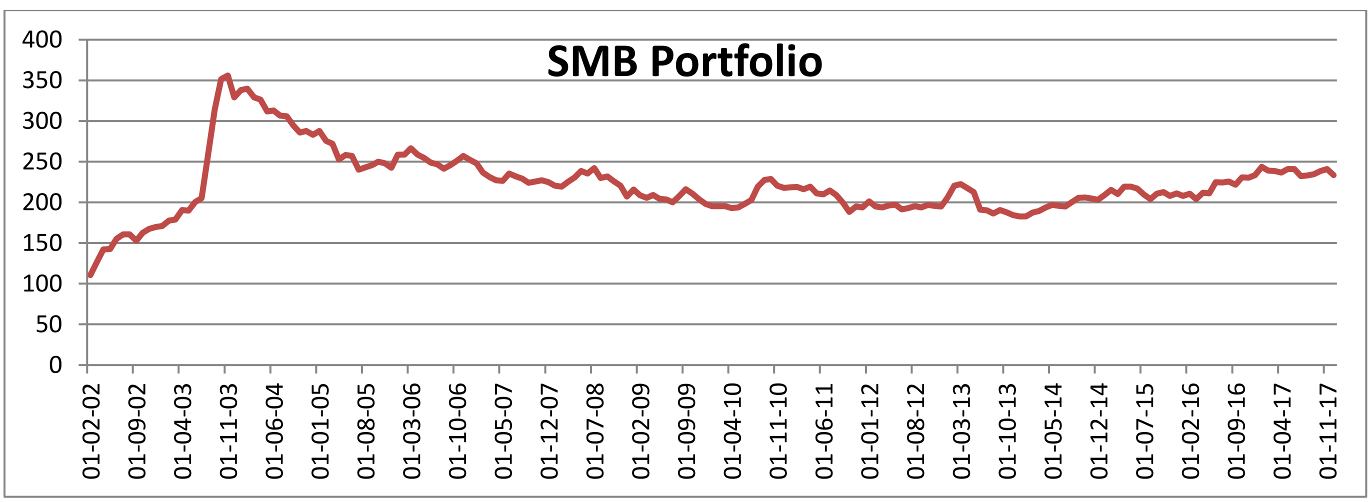
4.1) Factor Descriptive Statistic

4.1.1) SMB Factor

The table below shows average monthly excess returns, standard deviation and Sharpe ratio of Small and Big stock portfolio from 2002-2017. Small stocks report small investment premiums which support Fama and French (2015) thesis in the US. However, the result contradicts with the existing evidence in Thai stock market. In Kaewthammachai et al. (2016) work, big stock has investment premium over small stocks in 2003-2012.

SMB (2002-2017)	**Small**	**Big**
Average Return	1.59%	1.06%
SD	8.12%	6.12%
Sharpe	0.20	0.17

As expected, the bigger stocks have lower risk measured by standard deviation. This result is consistent with what is reported in NYSE study as well as Thai stock exchange.



Consider the graph above, which assumes that 100 Baht is invested in SMB strategy on 1st of February 2002, the portfolio value always exceed 100 Baht later-on. This implies that during 2003-2012, there is always a premium for small and big stocks contradicting with what is found before. The author believes that this is caused by missing stocks return data in some months from Bloomberg Terminal.

4.1.2) HML Factor

The table below shows average monthly excess return, standard deviation and Sharpe ratio of value factor from 2002-2017. Value stocks have higher rate of return than growth stocks (1.51% and 1.17% respectively). The table implies that sorting stocks according to B/M can reduce size premium. The premium here is 0.41% whereas the last section premium is 0.53%.

On average, value stocks have lower standard deviation in excess return comparing to growth stocks (7.33% and 7.45%). Looking BN and BL portfolios, the standard deviation is interestingly lower than SN and SL respectively.

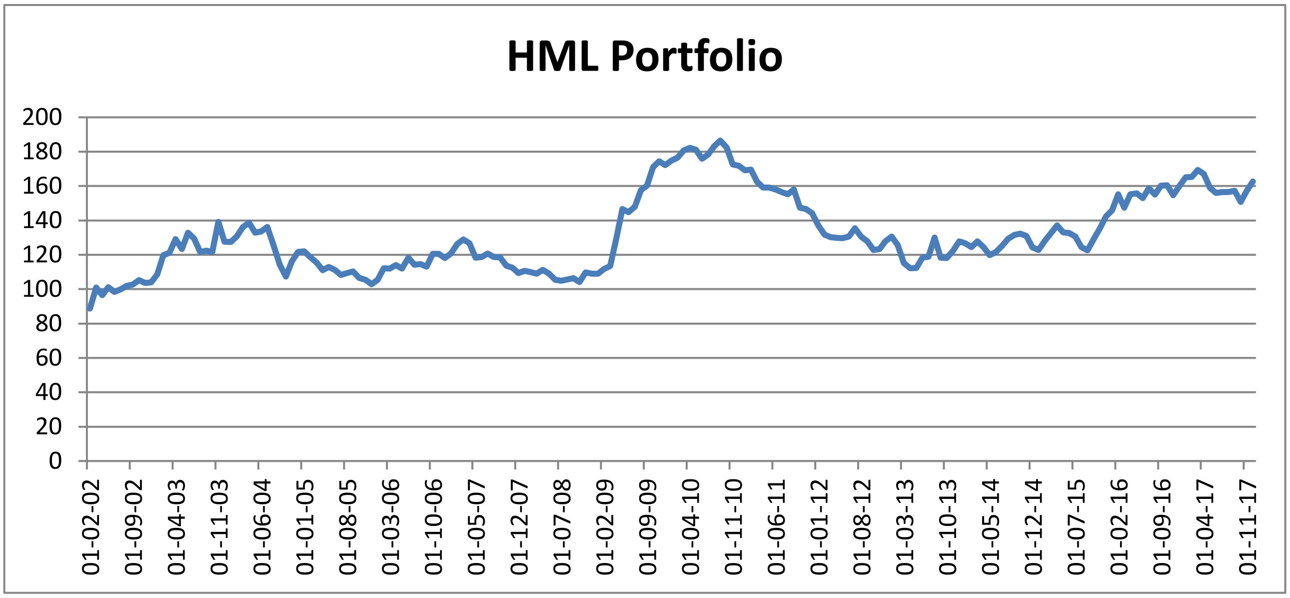
Comparing to the report by Kaewthammachai, et al. (2016), the returns for growth stock is significantly higher than the statistics below. Monthly excess returns in Kaewthammachai, et al. for SL and BL are greater than 3.3%. As a result, their work found that HML factor grants negative average excess returns as growth stocks perform amazingly well. Here, the HML factor grants positive average excess return of 0.34%. The author hypothesizes that the difference in statistics is caused by missing data or the difference in treatment of the missing data.

Returns	S	B	Avg.
R	1.74%	1.27%	1.51%
N	0.82%	1.02%	0.92%
W	1.65%	0.69%	1.17%
Avg.	1.40%	0.99%	

STD	S	B	Avg.
R	7.55%	7.11%	7.33%
N	8.28%	5.98%	7.13%
W	9.03%	5.87%	7.45%
Avg.	8.29%	6.32%	

Sharpe	S	B	Avg.
R	0.23	0.18	0.21
N	0.10	0.17	0.13
W	0.18	0.12	0.16
Avg.	0.17	0.16	

In addition, standard deviations shown above are significantly lower than Kaewthammachai, et al. (2016). Especially for BN and BL portfolios, the standard deviation was no less than 9.51% in Kaewthamachai, et al. study.



The graph above shows portfolio performance by using HML strategy assuming initial investment of 100 Baht on 1st February 2002.

4.1.3) CMA Factor

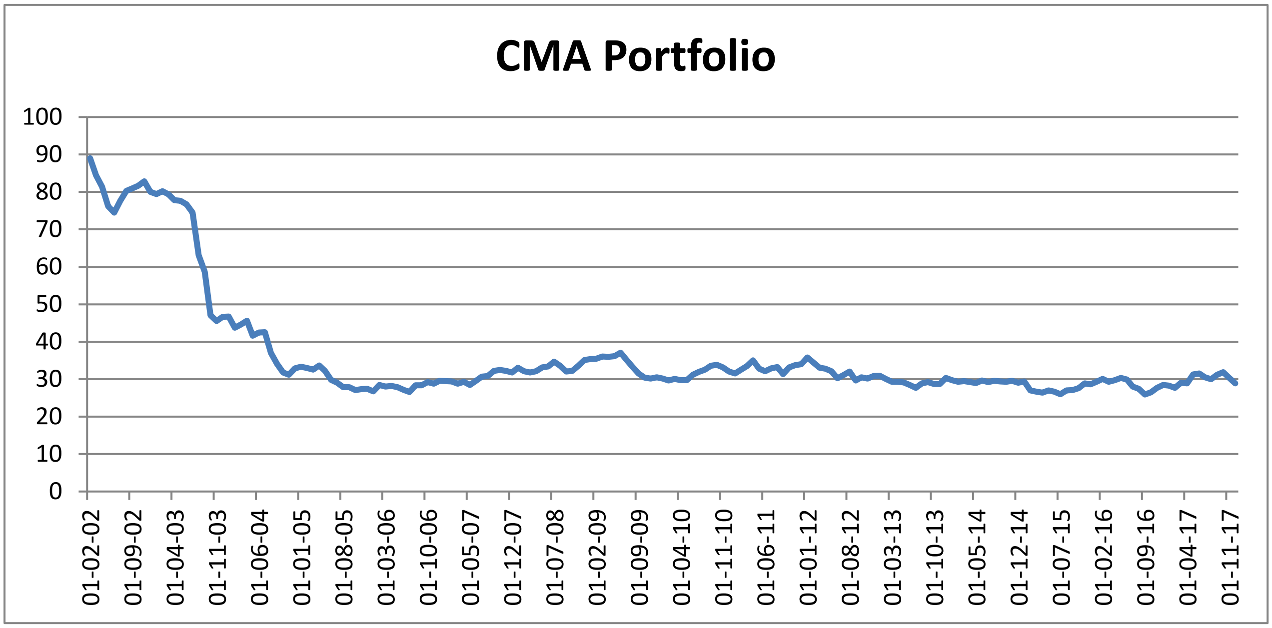
The table below shows average monthly excess return, standard deviation and Sharpe ratio of investment factor portfolios. While this study finds that SMB and HML factors behave similarly to the US factors. This does not apply to CMA factor. Conservative stocks have lower returns than aggressive stocks giving -0.57% monthly average excess return for CMA. Sharpe ratios for small and big stocks are the same as B/M allocation. This means that the change of stock allocation from B/M to investment does not affect the size premium.

Returns	S	B	Avg.
A	2.11%	1.04%	1.57%
N	1.59%	0.99%	1.29%
C	0.93%	1.08%	1.00%
Avg.	1.54%	1.04%	

STD	S	B	Avg.
A	8.83%	6.76%	7.80%
N	8.12%	5.78%	6.95%
C	7.92%	6.07%	6.99%
Avg.	8.29%	6.20%	

Sharpe	S	B	Avg.
H	0.24	0.15	0.2
N	0.2	0.17	0.19
L	0.12	0.18	0.14
Avg.	0.19	0.17	

The graph below shows portfolio performance by using CMA strategy assuming initial investment of 100 Baht on 1st February 2002. In this study, the portfolio experience huge drop in value during 2002 to 2005. Then, the return remains constant later-on.



4.1.4) RMW Factor

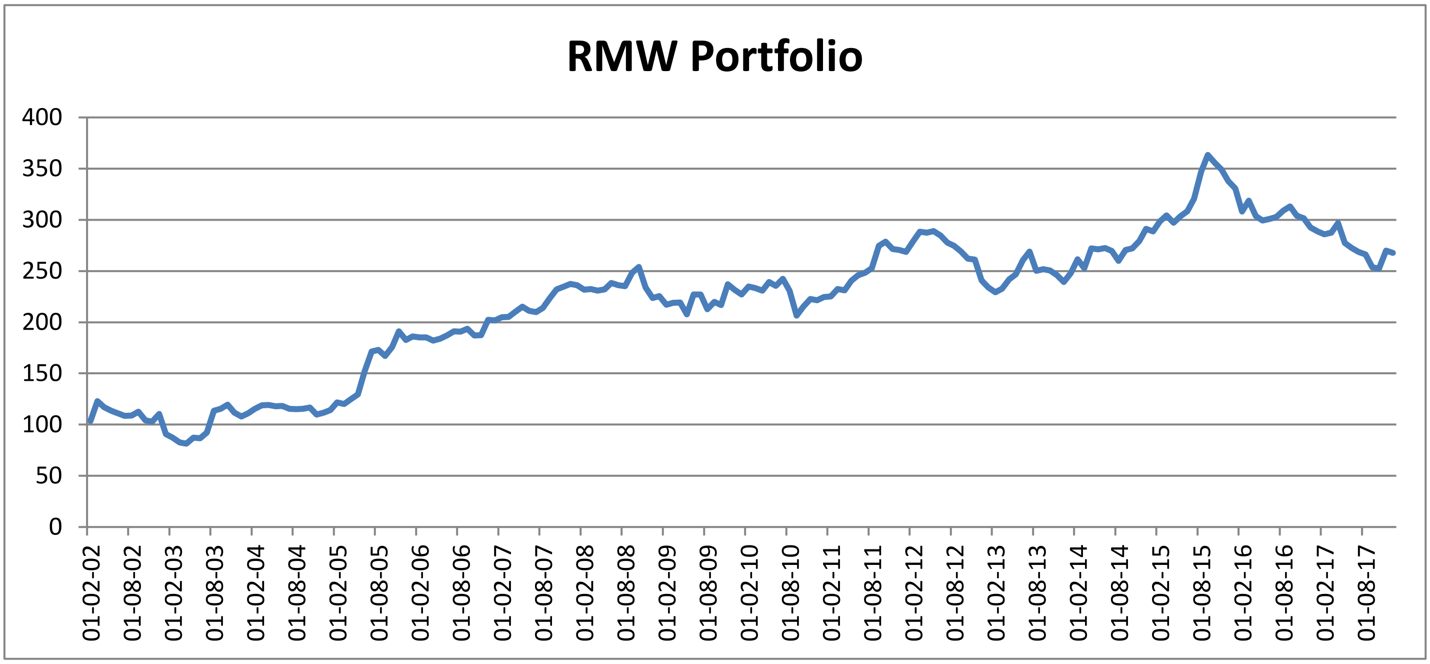
The table below shows average monthly excess return, standard deviation and Sharpe ratio of profitability factor portfolio from 2002-2017. There is evidence of robust profit stocks outperforming weak profit stocks. In addition, weak stocks also have higher risks making their Sharpe ratio far worse than robust stocks.

Considering size premium by profitability allocation, the small and big premium rises to 0.64%. The change in size premium caused by different portfolios allocations is also reported in Fama and French (2015). This means trading SMB strategy by profitability allocation creates bigger gains than trading by B/M allocation. However, the standard deviation also increases by 0.2% for small stocks and 0.66% for big stocks from the reallocation.

Returns	S	B	Avg.
R	1.95%	1.13%	1.54%
N	1.27%	1.06%	1.16%
W	1.38%	0.47%	0.92%
Avg.	1.53%	0.89%	

STD	S	B	Avg.
R	8.68%	6.31%	7.50%
N	8.60%	5.40%	7.00%
W	7.93%	8.87%	8.40%
Avg.	8.40%	6.86%	

Sharpe	S	B	Avg.
R	0.22	0.18	0.21
N	0.15	0.20	0.17
W	0.17	0.05	0.11
Avg.	0.18	0.13	



The graph above shows portfolio performance of RMW strategy assuming initial 100 Baht investment on 1st February 2002. The portfolio value increases consistently over the long run. The performance tails off at the end of 2015 giving reasonable doubt on the persistence of increasing trends in the future.

4.1.5) WML factor

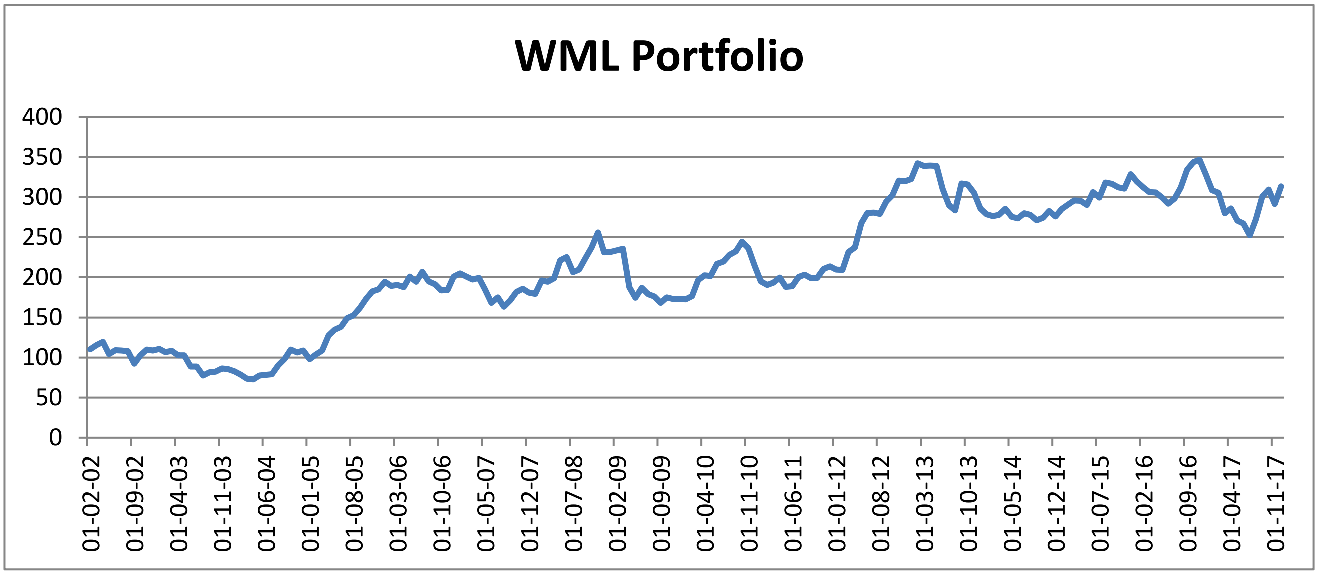
The table below shows average monthly excess return, standard deviation and Sharpe ratio of relative momentum factor portfolios from 2002-2017. Winner stocks have both higher return and lower risk comparing to loser stocks. This supports Cahart's evidence that there is a persistence in stock returns.

Returns	S	B	Avg.
W	2.40%	0.92%	1.66%
N	0.97%	1.10%	1.04%
L	1.32%	0.48%	0.90%
Avg.	1.56%	0.83%	

STD	S	B	Avg.
W	8.51%	7.19%	7.85%
N	8.19%	6.37%	7.28%
L	10.37%	7.44%	8.91%
Avg.	9.02%	7.00%	

Sharpe	S	B	Avg.
W	0.28	0.13	0.21
N	0.12	0.17	0.14
L	0.13	0.06	0.10
Avg.	0.17	0.12	

Comparing the reported statistic to Kaewthamachai, et al. (2016), the returns of both winners and losers are approximately 1% lower than their report in 2003-2012. From the graph below, the portfolio grows substantially after February 2012.

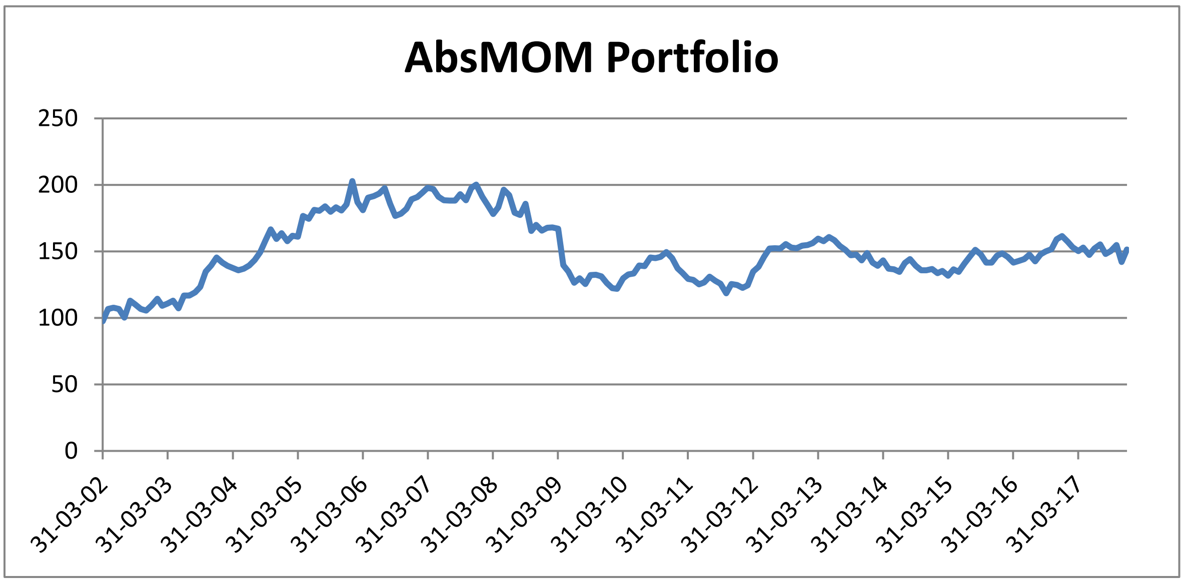


We can conclude that the data on excess returns shown in the table above is significantly lower. Furthermore, winner stocks in this study also have lower risk than Kaewthamachai, et al evidence. Again, the author believes that this is caused by difference in treatment of missing data or the missing data by itself.

4.1.6) AbsMOM factor

	Winners	Losers	**AbsMOM**
Avg. Return	1.08%	0.79%	0.29%
SD	6.37%	6.15%	3.87%
Sharpe	0.17	0.19	0.08

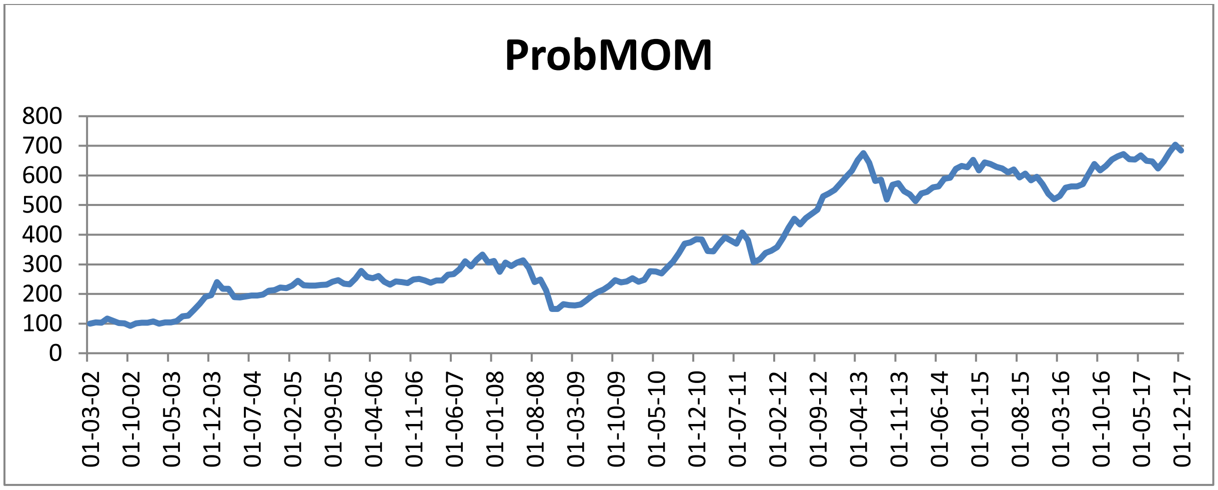
The table above shows average monthly excess return, standard deviation and Sharpe ratio of absolute momentum factor portfolios from 2002-2017. Buying winners with predicted positive return and selling losers with negative predicted returns yields 0.29% gains. However, excess returns and Sharpe ratio of AbsMOM strategy deteriorates greatly comparing to buying winners alone. This happens unexpectedly as loser portfolio generates positive returns. Looking at historical return, there is also a huge drop in return during 2008 – 2010 shown by the graph below.



4.1.7) ProbMOM factor

	ProbsMOM
Return	1.36%
STD	9.37%
Sharpe	0.15

The table above shows average monthly excess return, standard deviation and Sharpe ratio of probabilistic momentum factor portfolios from 2002-2017. Buying winning stock with past positive return yields positive return in the long run as the graph illustrated below.



4.1.8) Factor Summary

Ultimately, factors descriptive statistics can be shown as following:

Variable	Mean	Std. Dev.	Min	Max
RmRf	-8.81%	6.81%	-43.10%	12.62%
SMB	0.53%	4.19%	-10.21%	27.21%
HML	0.34%	4.09%	-11.31%	14.39%
WML	0.76%	5.61%	-20.34%	17.25%
RMW	0.62%	4.57%	-18.03%	22.83%
CMA	-0.57%	3.85%	-19.75%	8.10%
AbsMOM	0.29%	3.88%	-16.39%	12.71%
ProbMOM	1.06%	6.38%	-30.12%	22.66%

Factors correlation matrix is shown below. Similar to Fama and French (2015), size correlates with market factor as small stocks tends to have higher beta granting higher return. The fact that RMW factor negatively correlates with HML fits with value theory discussed by Fama and French. They argued that firms with high book-to-market value tend to have low profitability. However, the investment factor should also correlate with HML factor as well. Instead, investment negatively correlates with size factor and profitability implying that big firms and profitable firms tend to invest more. Lastly, it is interesting that probabilistic momentum shares positive correlation to size. It is possible that small firms tend to have long period of positive return.

	RmRf	SMB	HML	WML	RMW	CMA	AbsMOM	ProbMOM
RmRf	100.00%							
SMB	31.19%	100.00%						
HML	9.77%	7.49%	100.00%					
WML	-8.16%	-3.67%	-29.33%	100.00%				
RMW	6.94%	8.67%	-26.97%	-0.19%	100.00%			
CMA	-19.33%	-25.18%	7.07%	-6.67%	-33.94%	100.00%		
AbsMOM	7.26%	9.42%	-14.10%	38.71%	-4.98%	-21.62%	100.00%	
ProbMOM	17.67%	25.84%	-8.25%	9.95%	-8.80%	-12.36%	28.86%	100.00%

4.2) Testing Portfolio statistics

Here, there are no clear trends of increasing returns from conservative to aggressive stocks. This matches with the graph shown earlier that CMA factor portfolio value is flat in the long run. In all investment quintiles, there is a trend of decreasing risk as stock size got bigger. The difference in size premiums can only be seen clearly by comparing smallest and biggest.

The table below show average monthly returns, standard deviation and Sharpe ratio of each LHS portfolio. On the left panel, it represents 25 Size-B/M portfolios (SBM) while on the right, 25 Size-OP portfolios (SOP) are shown.

	SBM11	**SBM12**	**SBM13**	**SBM14**	**SBM15**	**SOP11**	**SOP12**	**SOP13**	**SOP14**	**SOP15**
AVERAGE	**1.78%**	**2.21%**	**1.38%**	**2.04%**	**2.09%**	**2.39%**	**1.21%**	**0.90%**	**3.21%**	**2.33%**
STD	13.52%	12.60%	12.00%	11.70%	10.28%	12.52%	10.41%	10.78%	11.32%	11.56%
SHARPE	0.13	0.18	0.11	0.17	0.20	0.19	0.12	0.08	0.28	0.20
	SBM21	**SBM22**	**SBM23**	**SBM24**	**SBM25**	**SOP21**	**SOP22**	**SOP23**	**SOP24**	**SOP25**
AVERAGE	**1.85%**	**0.97%**	**0.70%**	**2.21%**	**1.03%**	**0.44%**	**1.22%**	**0.76%**	**1.85%**	**1.63%**
STD	8.75%	10.05%	9.84%	11.71%	9.62%	11.78%	9.23%	9.07%	11.29%	10.31%
SHARPE	0.21	0.10	0.07	0.19	0.11	0.04	0.13	0.08	0.16	0.16
	SBM31	**SBM32**	**SBM33**	**SBM34**	**SBM35**	**SOP31**	**SOP32**	**SOP33**	**SOP34**	**SOP35**
AVERAGE	**1.06%**	**0.49%**	**1.49%**	**1.74%**	**1.96%**	**1.36%**	**1.25%**	**0.87%**	**1.37%**	**1.66%**
STD	11.07%	7.60%	8.84%	9.24%	9.49%	10.81%	8.10%	8.80%	8.17%	11.21%
SHARPE	0.10	0.06	0.17	0.19	0.21	0.13	0.15	0.10	0.17	0.15
	SBM41	**SBM42**	**SBM43**	**SBM44**	**SBM45**	**SOP41**	**SOP42**	**SOP43**	**SOP44**	**SOP45**
AVERAGE	**0.29%**	**0.37%**	**1.03%**	**1.36%**	**0.91%**	**0.55%**	**0.88%**	**0.99%**	**0.71%**	**0.68%**
STD	7.88%	8.04%	7.26%	7.24%	9.18%	12.08%	8.90%	8.32%	6.84%	8.53%
SHARPE	0.04	0.05	0.14	0.19	0.10	0.05	0.10	0.12	0.10	0.08
	SBM51	**SBM52**	**SBM53**	**SBM54**	**SBM55**	**SOP51**	**SOP52**	**SOP53**	**SOP54**	**SOP55**
AVERAGE	**0.57%**	**1.61%**	**0.71%**	**1.75%**	**0.71%**	**0.19%**	**1.10%**	**1.23%**	**1.21%**	**1.37%**
STD	6.10%	7.30%	6.88%	8.15%	6.17%	10.49%	8.10%	6.30%	5.78%	7.86%
SHARPE	0.09	0.22	0.10	0.21	0.11	0.02	0.14	0.20	0.21	0.17

There is a trend of increasing returns as stock has higher book-to-market. This can be seen clearly when reading average return horizontally in the first, third and fourth size quintile. Fama and French (2015) refer this as value effect. In Size-OP portfolios, the trend of increasing return following profitability quintile is only clear in second and fifth size quintile. Nevertheless, except for the fourth quintile, returns of stocks in fourth and fifth profitability quintiles are always higher than returns of stocks in the second and first profitability quintile.

The table below show average monthly returns, standard deviation and Sharpe ratio of each LHS portfolio in 25 Size-Investment allocations. Again, the two-digit numbers after portfolio name represent size quintile and investment quintile respectively.

	SInv11	**SInv12**	**SInv13**	**SInv14**	**SInv15**
AVERAGE	**2.28%**	**2.04%**	**3.40%**	**1.17%**	**1.96%**
STD	13.82%	11.05%	12.63%	11.21%	12.83%
SHARPE	0.16	0.18	0.27	0.10	0.15
	SInv21	**SInv22**	**SInv23**	**SInv24**	**SInv25**
AVERAGE	**0.67%**	**1.70%**	**1.30%**	**1.56%**	**1.99%**
STD	9.75%	11.07%	10.57%	9.99%	10.38%
SHARPE	0.07	0.15	0.12	0.16	0.19
	SInv31	**SInv32**	**SInv33**	**SInv34**	**SInv35**
AVERAGE	**1.49%**	**0.84%**	**1.89%**	**2.07%**	**0.45%**
STD	11.25%	9.33%	9.13%	10.13%	8.74%
SHARPE	0.13	0.09	0.21	0.20	0.05
	SInv41	**SInv42**	**SInv43**	**SInv44**	**SInv45**
AVERAGE	**1.48%**	**1.01%**	**1.03%**	**0.63%**	**0.74%**
STD	9.71%	8.48%	9.57%	6.97%	8.44%
SHARPE	0.15	0.12	0.11	0.09	0.09
	SInv51	**SInv52**	**SInv53**	**SInv54**	**SInv55**
AVERAGE	**0.76%**	**0.97%**	**0.92%**	**0.96%**	**1.05%**
STD	8.10%	7.61%	6.47%	6.83%	9.54%
SHARPE	0.09	0.13	0.14	0.14	0.11

Here, there are no clear trends of increasing returns from conservative to aggressive stocks. This matches with the graph shown earlier that CMA factor portfolio value is flat in the long run. In all investment quintiles, there is a trend of decreasing risk as stock size got bigger. The difference in size premiums can only be seen clearly by comparing smallest and biggest.

4.3) Model Comparison

There are 8 models tested with 75 LHS portfolios. There are three classic models: Fama-French Three-factor (3FF), Five-factor (5FF), and Cahart's 4 factor model.

Five adjusted models are created to test if there are improvements. Three models are formed by dropping out, value, investment and profitability factor from Five-factor model respectively. Another two are created by replacement of WML with absolute momentum and probabilistic momentum respectively. Every model includes market factor.

The results shown below are sorted based on average absolute intercept produced by the model where its value is reported in the second column. Apparently, the model with probabilistic momentum produces lowest average intercepts. Hence, it is the dominant model in all portfolio sorts. For Size-OP and Size-Inv, the adjusted model that dropped out profitability from 5FF followed by absolute momentum model are the runner ups in performance.

We found that profitability is already explained by value factor in Thailand. From the table, 5FF never dominates its derivative that omits either profitability or value factor. This means that there is a redundancy in these two factors and they decrease 5FF effectiveness. Furthermore, dropping out profitability factor is always better than dropping value factor. In conclusion, omitting profitability factor improves models' efficiency. This is different from Fama and French evidence discussed in section 2 where HML is totally explained by RMW and CMA.

Comparing classic models, 3FF dominates both 5FF and Cahart's 4 factor model in most of the time. In Size-Inv, 5FF dominates 3FF, but only removes 0.08% of average intercepts. Comparing to the adjusted model, 3FF performs well only in Size-B/M allocation. In other allocation, adding investment factor or alternatives of momentum could improve effectiveness to 3FF.

Looking at momentum models, Cahart's four factor model is always inferior to 3FF model. This result gets along with Kaewthammachai et al (2016) evidence suggesting that WML factor is not significant. Nevertheless, 3FF cannot match with four factor probabilistic momentum and absolute momentum model. To conclude, value factor in 3FF cannot capture all aspect of investment and momentum in Thailand.

To conclude, four-factor model is likely to work best in Thailand. Four-factor probabilistic momentum model is the most effective. Four factor model that augment investment factor to Fama-French 3 factor model could also reduce average intercept in most cases. In some cases, four-factor absolute momentum model is more preferable to investment augmented model.

As a final twist, the reported statistic and ratios suggest the accuracy of predictions formed by factor models is still inadequate. In the third column, the average intercept over average $\bar{r}$ determines how much intercept explain anomalies in returns. As the value exceeds 1, it means the model is not efficient enough to predict returns unexplained by simple average. In other words, using simple average can predict portfolios' returns better in long run. The same goes for ratio in the fourth column, which measure dispersion of intercepts over dispersion of returns. If the value is more than 1, model should be rejected as the variance of intercept's error is higher than that of simple average. The reason that ratios turn out to be more than one is LHS portfolios deviation from average returns or $\bar{r}$ are low. 25-Size-OP has the highest $\bar{r}$ only at 0.54%.

Overall, this means factor models are not a good predictor of returns in Thailand unless their average intercepts fall below 0.54%. However, the models can still be used to analyze factor effects on portfolios which will be discussed in next session. In appendix, the author also demonstrates how investor could use the models to analyze investment strategy.

25 Size-Inv Portfolios	$A\lvert a_i\rvert$	$A\lvert a_i\rvert / A\lvert\bar{r}\rvert$	$A({a_i}^2) / A(\lvert\bar{r}\rvert^2)$
SMB HML ProbMOM	**1.19%**	2.25	6.4
SMB HML CMA	**2.54%**	4.80	18.2
SMB HML AbsMOM	**2.66%**	5.04	20.6
SMB CMA RMW	**2.71%**	5.14	20.7
5FF - (SMB HML CMA RMW)	**2.73%**	5.18	20.7
3FF - (SMB HML)	**2.81%**	5.33	22.7
SMB HML RMW	**2.86%**	5.41	22.7
Cahart's 4	**2.89%**	5.48	23.7

25 Size-OP Portfolios	$A\lvert a_i\rvert$	$A\lvert a_i\rvert / A\lvert\bar{r}\rvert$	$A({a_i}^2) / A(\lvert\bar{r}\rvert^2)$
SMB HML ProbMOM	**0.66%**	1.40	1.8
SMB HML CMA	**2.17%**	4.63	13.0
SMB HML AbsMOM	**2.18%**	4.63	12.5
3FF - (SMB HML)	**2.29%**	4.88	14.1
Cahart's 4	**2.36%**	5.02	14.8
SMB CMA RMW	**2.37%**	5.05	15.1
5FF - (SMB HML CMA RMW)	**2.40%**	5.10	15.6
SMB HML RMW	**2.57%**	5.46	17.9

25 Size-B/M Portfolios	$A\lvert a_i\rvert$	$A\lvert a_i\rvert / A\lvert\bar{r}\rvert$	$A({a_i}^2) / A(\lvert\bar{r}\rvert^2)$
SMB HML ProbMOM	**0.74%**	1.37	2.3
SMB HML AbsMOM	**2.13%**	3.98	14.5
3FF - (SMB HML)	**2.19%**	4.10	15.5
Cahart's 4	**2.28%**	4.25	16.6
SMB HML CMA	**2.36%**	4.41	18.0
SMB CMA RMW	**2.46%**	4.60	20.4
5FF - (SMB HML CMA RMW)	**2.55%**	4.77	20.9
SMB HML RMW	**2.65%**	4.95	22.3

4.4) Regression Details and Risk Exposure Analysis

In this section, the coefficient produced by regression of probabilistic four factor model, Fama-French five-factor and three-factor model are analyzed. Furthermore, the t-value and significance of the factors will also be discussed to describe the effects of factors on returns.

First, for all portfolios sorts, small stock portfolios are exposed to size factor risk more. The coefficients are usually around 1 in small size quintiles. In big stock quintiles, the coefficients are below one and some report no statistical significance. This is similar to what is found by Kaewthammachai, et al. (2016) as well as Fama and Frech (2015).

Second, to further prove redundancy in HML and RMA, HML factor in five-factor model lost its significance in all portfolios sorts. Unreported in this paper, this also happens in Cahart's four factor model when adding WML factor to Fama-French three factor models. The result is not surprising as correlation matrix in the section 4 reports around 30% of correlation between HML and WML. However, in Kaewthammachai et al. (2016), HML factor does not lose significance in the analysis of four-factor model.

Third, five-factor models produce lower intercepts when analyzing small stocks in high investment and profitability quintile. Fama and French (2015) argue that small stocks behave like high investment firms despite low profitability. Hence, adding profitability factor and investment factor can help explain their returns better. In addition, they found that CMA and RMW works better in stocks with extreme investment or high profit. These seems to hold true in Thailand as well in small stocks. CMA factor reports negative coefficient, but low statistical significance suggesting slight positive relationship between firm's investment and stock returns.

Fourth, adding probabilistic momentum to three-factor model, coefficients for market and size factor are lowered when compared to three-factor model. This means momentum can explain some of the size and market factor movements. Interestingly, stocks in 4^{th} and 5^{th} quintiles usually report negative exposure to size factor after adding momentum factor. As big stocks pay lower returns, this makes the size coefficient matches well with empirical data.

25 Size-Inv Portfolios

As discussed earlier, investment factor can work well in stocks with high investment and profitability. Here, profitability factor tends to be significant in big stocks. Adding these two effects together, HML factor lost its significance in almost all portfolios.

In Fama-French three factor model, value factor reports negative coefficient in small and aggressive stocks. This may suggest that small and high investment stocks are usually growth stock, which matches with the value theory (Fama and French, 2006). In Size-Inv portfolios, adding profitability and investment factor in five factor model reduces intercepts in small stocks of 4^{th} and 5^{th} investment quintile. Furthermore, HML factor also lost its significance in these portfolios strengthening our evidence that profitability and investment is needed to explain extreme stocks.

25-Size-OP Portfolios

Here, Fama-French five factor model works better than three factor model in robust stocks. In 4^{th} and 5^{th} profitability quintile portfolios, five-factor model reports lower intercepts. HML factor of five-factor model is statistical insignificant in most of 4^{th} profitability quintile. This means investment and profitability factor can absorb inaccuracies caused by size and value factor especially in high profit stocks.

Interestingly, investment and profitability factor reports negative coefficient and low statistical significance in most Size-OP portfolios. While these factors improve the intercepts for high profit stocks, results are not statistically robust. Probabilistic momentum augmented model can resolve this issue. In this model, ProbMOM factor removes HML factor significance in 5^{th} quintile of profitability factor. In 4^{th} profitability quintile, HML still have statistical significance, but the intercepts are dramatically lower to less than 1% in most cases. Hence we can conclude that high-profit stocks are exposed to momentum risk and can be explained by momentum factor rather than profitability and investment factor.

25-Size-B/M Portfolios

There is one interesting output from Fama-French three-factor model in this portfolio sort. Almost all portfolios show positive exposure to size factor. However, in smallest and biggest size quintile, they have negative HML coefficient. Given that value factor is already controlled by portfolio sort. This means three factor cannot adequately explain returns in these portfolios.

Furthermore, HML factor is not robust in terms of statistical significance for small stocks and growth stock. In five factor model, HML lost significance in most portfolios in the 2^{nd} size and value quintile. In probabilistic augmented momentum model, HML lost significance in 50% of portfolios that contain small and low B/M stock.

In this portfolio sort, it seems that five factor model can explain the negative coefficient. Firstly, after augmenting new factors to three-factor model, the size factor coefficient becomes statistically insignificant in big stocks. This means big stock is not exposed to positive size return anymore. Secondly, it makes negative HML coefficient in growth stocks portfolios more robust. This goes along with theory that growth stock should have negative exposure to value factor. Thirdly, it makes negative coefficients in value portfolio becomes statistically insignificant. This implies that value stocks are not exposed to positive correlation with value factor.

Momentum augmented portfolio can also make coefficients go along with theory better. Firstly, size coefficients become negative for big stocks implying big stock has lower return due to size. Secondly, for big stock with high B/M ratio, HML coefficient becomes positive and fits with theory better. In other words, after controlling momentum effect, negative returns can be explained better by size risk rather than value. Lastly, momentum factor makes most negative HML coefficient insignificant including the small stocks with negative coefficients. This might imply that growth stock returns are more influenced by momentum factor more than B/M. By contrast, in five factor model, growth stock has strong negative relationship with value factor.

25 Size-Inv Portfolios

(Note that size is shown in columns unlike other tables shown earlier where size is in rows)

The left panel shows the coefficient of factors per portfolio while the right side shows the p-values. Box colored light green, dark green and dark green with bold show 10%, 5% and 1% level of significance respectively.

For intercepts, box colored in yellow means the portfolio intercept is dominated by 3FF model.

3 FACTOR	Intercept									
	Small	2	3	4	Big					
Conservative	0.027	0.054	0.051	0.019	0.009	0.06	0.27	**0.00**	0.15	**0.00**
2	0.032	0.034	0.025	0.028	0.016	0.01	**0.01**	0.03	**0.01**	**0.00**
3	0.054	0.036	0.019	0.018	0.017	0.27	**0.01**	0.15	0.15	**0.00**
4	0.054	0.017	0.019	0.023	0.017	0.27	0.13	0.15	**0.01**	**0.00**
Aggressive	0.053	0.030	0.012	0.015	0.025	**0.00**	**0.01**	0.26	0.15	**0.00**
	Rm-Rf									
	Small	2	3	4	Big					
Conservative	0.16	0.28	0.44	0.07	0.01	0.21	0.20	**0.00**	0.57	**0.00**
2	0.21	0.27	0.22	0.22	0.10	0.06	0.01	0.03	0.02	**0.00**
3	0.28	0.26	0.07	0.09	0.10	0.20	0.03	0.57	0.40	**0.00**
4	0.28	0.09	0.07	0.20	0.10	0.20	0.37	0.57	0.01	**0.00**
Aggressive	0.45	0.18	0.10	0.11	0.16	**0.00**	0.07	0.28	0.25	**0.00**
	SMB									
	Small	2	3	4	Big					
Conservative	1.78	1.16	0.30	1.14	0.03	**0.00**	**0.00**	0.12	0.38	**0.00**
2	0.85	1.15	0.51	0.01	0.32	**0.00**	**0.00**	**0.00**	0.95	**0.00**
3	1.16	1.38	1.14	0.20	0.14	**0.00**	**0.00**	0.38	0.30	**0.00**
4	1.16	1.24	1.14	0.09	0.14	**0.00**	**0.00**	0.38	0.49	**0.00**
Aggressive	1.25	1.22	0.40	0.24	-0.01	**0.00**	**0.00**	0.01	0.12	**0.00**
	HML									
	Small	2	3	4	Big					
Conservative	0.06	-0.30	0.36	-0.10	-0.12	0.06	0.27	**0.00**	0.15	**0.00**
2	0.65	0.30	0.15	0.24	0.15	0.01	**0.01**	0.03	**0.01**	**0.00**
3	-0.30	-0.08	-0.10	0.06	0.05	0.27	**0.01**	0.15	0.15	**0.00**
4	-0.30	0.02	-0.10	0.13	0.05	0.27	0.13	0.15	**0.01**	**0.00**
Aggressive	-0.04	-0.08	-0.15	0.11	-0.16	**0.00**	**0.01**	0.26	0.15	**0.00**

4 FACTOR	Intercept									
	Small	2	3	4	Big					
Conservative	0.012	0.036	0.025	0.004	-0.009	0.37	0.49	0.01	0.70	0.31
2	0.018	0.016	0.005	0.010	0.000	0.13	0.12	0.59	0.23	0.98
3	0.036	0.016	0.004	-0.003	0.000	**0.01**	0.12	0.63	0.78	0.96
4	0.036	-0.001	0.004	0.008	0.000	0.49	0.93	0.70	0.25	**0.00**
Aggressive	0.032	0.009	-0.008	-0.001	0.004	**0.01**	0.28	0.32	0.94	0.68

	Rm-Rf									
	Small	2	3	4	Big					
Conservative	0.08	0.19	0.31	-0.01	-0.10	0.47	0.63	**0.00**	0.48	0.21
2	0.14	0.18	0.12	0.13	0.02	0.18	0.05	0.11	0.08	0.79
3	0.19	0.15	-0.01	-0.01	0.01	0.09	0.10	0.90	0.91	0.81
4	0.19	0.00	-0.01	0.12	0.01	0.63	0.99	0.48	0.05	**0.00**
Aggressive	0.34	0.08	0.00	0.03	0.05	**0.00**	0.28	0.98	0.72	0.52

	SMB									
	Small	2	3	4	Big					
Conservative	1.53	0.85	-0.17	0.87	-0.24	**0.00**	**0.00**	0.27	0.04	0.07
2	0.59	0.84	0.16	-0.32	0.04	**0.00**	**0.00**	0.20	**0.01**	0.72
3	0.85	0.85	0.87	-0.19	-0.17	**0.00**	**0.00**	**0.00**	0.26	0.04
4	0.85	0.93	0.87	-0.17	-0.17	**0.00**	**0.00**	0.04	0.10	**0.00**
Aggressive	0.86	0.85	0.02	-0.06	-0.37	**0.00**	**0.00**	0.86	0.68	**0.01**

	HML									
	Small	2	3	4	Big					
Conservative	0.16	-0.14	0.64	0.05	0.02	0.40	0.22	**0.00**	**0.00**	0.87
2	0.81	0.46	0.33	0.41	0.30	**0.00**	**0.00**	**0.01**	**0.00**	**0.01**
3	-0.14	0.25	0.05	0.25	0.23	0.46	0.09	0.69	0.11	**0.00**
4	-0.14	0.20	0.05	0.28	0.23	0.22	0.12	**0.00**	**0.01**	**0.00**
Aggressive	0.21	0.13	0.08	0.29	0.02	0.23	0.29	0.52	0.03	0.88

	ProbMOM									
	Small	2	3	4	Big					
Conservative	0.82	0.86	1.16	0.71	0.76	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
2	0.64	0.86	0.96	0.90	0.76	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
3	0.86	0.77	0.71	0.91	0.79	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
4	0.86	0.81	0.71	0.68	0.79	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Aggressive	0.90	0.98	0.92	0.73	1.05	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**

5 FACTOR	**Intercept**									
	Small	2	3	4	Big					
Conservative	0.029	0.017	0.054	0.022	0.009	0.05	0.13	**0.00**	0.10	0.39
2	0.035	0.034	0.026	0.030	0.014	**0.01**	**0.01**	0.02	**0.01**	0.14
3	0.053	0.032	0.016	0.020	0.018	**0.00**	0.02	0.11	0.11	0.03
4	0.012	0.018	0.043	0.025	0.026	0.13	0.10	0.10	**0.00**	**0.00**
Aggressive	0.055	0.027	0.019	0.020	0.026	**0.00**	0.02	0.07	0.05	0.04

	Rm-Rf									
	Small	2	3	4	Big					
Conservative	0.17	0.15	0.45	0.07	0.01	0.20	0.13	**0.00**	0.53	0.91
2	0.22	0.28	0.22	0.22	0.09	0.05	0.01	0.03	0.02	0.30
3	0.28	0.22	0.04	0.09	0.10	0.03	0.06	0.62	0.40	0.17
4	0.03	0.09	0.29	0.20	0.15	0.13	0.37	0.53	**0.01**	**0.00**
Aggressive	0.45	0.16	0.13	0.13	0.16	**0.00**	0.11	0.15	0.17	0.15

	SMB									
	Small	2	3	4	Big					
Conservative	1.80	1.12	0.29	0.17	0.03	**0.00**	**0.00**	0.13	0.36	0.82
2	0.86	1.17	0.49	0.02	0.30	**0.00**	**0.00**	**0.00**	0.92	0.03
3	1.15	1.34	1.07	0.19	0.14	**0.00**	**0.00**	**0.00**	0.32	0.24
4	1.17	1.22	0.78	0.09	0.10	**0.00**	**0.00**	0.36	0.49	**0.00**
Aggressive	1.24	1.14	0.45	0.27	-0.02	**0.00**	**0.00**	**0.00**	0.08	0.91

	HML									
	Small	2.00	3.00	4.00	Big					
Conservative	0.00	-0.10	0.21	0.17	-0.14	0.99	0.51	0.29	0.36	0.36
2	0.54	0.33	0.02	0.18	0.20	**0.00**	0.06	0.91	0.26	0.16
3	-0.30	-0.05	-0.10	-0.07	-0.02	0.16	0.78	0.49	0.72	0.89
4	-0.21	-0.07	0.01	0.03	-0.27	0.51	0.67	0.36	0.80	**0.00**
Aggressive	-0.19	-0.09	-0.35	-0.05	-0.22	0.35	0.56	0.02	0.76	0.22

	CMA									
	Small	2.00	3.00	4.00	Big					
Conservative	-0.01	0.09	-0.27	-0.07	0.00	0.96	0.60	0.21	0.76	0.98
2	-0.13	0.18	-0.34	-0.07	-0.03	0.52	0.37	0.06	0.69	0.85
3	-0.05	-0.56	-0.36	-0.14	-0.10	0.83	0.01	0.03	0.49	0.45
4	0.23	-0.20	-0.36	-0.14	-0.02	0.60	0.25	0.76	0.31	**0.00**
Aggressive	-0.32	-0.45	0.01	-0.07	-0.16	0.16	0.01	0.96	0.67	0.44

	RMW									
	Small	2.00	3.00	4.00	Big					
Conservative	-0.19	-0.34	-0.59	-0.29	-0.08	0.33	0.02	**0.00**	0.10	0.57
2	-0.40	0.15	-0.54	-0.25	0.15	0.02	0.35	**0.00**	0.09	0.27
3	-0.02	-0.16	-0.12	-0.39	-0.25	0.94	0.35	0.38	0.05	0.03
4	-0.34	-0.37	-0.56	-0.37	-0.40	0.02	0.01	0.10	**0.00**	**0.00**
Aggressive	-0.58	-0.21	-0.62	-0.54	-0.26	**0.00**	0.17	**0.00**	**0.00**	0.13

25 Size-OP Portfolios

(Note that size is shown in columns unlike other tables shown earlier where size is in rows)

The left panel shows the coefficient of factors per portfolio while the right side shows the p-value. Box colored light green, dark green and dark green with bold show 10%, 5% and 1% level of significance respectively.

For intercepts, box colored in yellow means the portfolio intercept is dominated by 3FF model.

3 FACTOR	**Intercept**									
	Small	2	3	4	Big					
Weak	0.040	0.020	0.036	0.022	0.016	**0.00**	0.92	**0.01**	0.14	**0.00**
2	0.005	0.019	0.015	0.038	0.019	0.65	0.07	0.14	**0.00**	**0.00**
3	0.020	0.022	0.022	0.019	0.025	0.92	0.02	0.14	0.08	**0.00**
4	0.020	0.031	0.022	0.014	0.025	0.92	0.01	0.14	0.11	**0.00**
Robust	0.014	0.033	0.030	0.013	0.034	0.29	**0.00**	**0.01**	0.21	**0.00**

	Rm-Rf									
	Small	2	3	4	Big					
Weak	0.26	0.17	0.29	0.17	0.20	0.03	0.69	0.01	0.13	**0.00**
2	0.01	0.14	0.07	0.34	0.10	0.92	0.14	0.44	**0.00**	**0.00**
3	0.17	0.23	0.17	0.11	0.15	0.69	**0.01**	0.13	0.23	**0.00**
4	0.17	0.20	0.17	0.08	0.15	0.69	0.08	0.13	0.29	**0.00**
Robust	0.04	0.26	0.24	0.10	0.22	0.73	**0.01**	0.02	0.30	**0.00**

	SMB									
	Small	2	3	4	Big					
Weak	1.42	1.44	0.57	0.22	0.08	**0.00**	**0.00**	**0.00**	0.42	**0.00**
2	1.29	0.86	0.60	0.07	0.28	**0.00**	**0.00**	**0.00**	0.65	**0.00**
3	1.44	0.91	0.22	0.09	0.10	**0.00**	**0.00**	0.42	0.57	**0.00**
4	1.44	1.17	0.22	0.12	0.10	**0.00**	**0.00**	0.42	0.34	**0.00**
Robust	1.82	1.18	1.47	0.38	-0.07	**0.00**	**0.00**	**0.00**	0.01	**0.00**

	HML									
	Small	2	3	4	Big					
Weak	-0.14	0.28	0.08	0.31	0.30	**0.00**	0.92	**0.01**	0.14	**0.00**
2	0.30	0.23	0.21	0.05	-0.07	0.65	0.07	0.14	**0.00**	**0.00**
3	0.28	0.28	0.31	0.27	0.04	0.92	0.02	0.14	0.08	**0.00**
4	0.28	-0.45	0.31	-0.08	0.04	0.92	0.01	0.14	0.11	**0.00**
Robust	-0.38	-0.18	-0.16	0.03	-0.25	0.29	**0.00**	**0.01**	0.21	**0.00**

4 FACTOR Intercept

	Small	2	3	4	Big					
Weak	0.016	0.000	0.011	0.003	-0.008	0.13	0.06	0.24	0.97	0.42
2	-0.009	0.001	-0.004	0.019	-0.001	0.38	0.88	0.57	0.03	0.85
3	0.000	0.004	0.003	0.002	0.009	0.99	0.62	0.72	0.80	0.10
4	0.000	0.009	0.003	0.000	0.009	0.06	0.36	0.97	0.98	**0.00**
Robust	0.003	0.017	0.011	-0.006	0.014	0.80	0.07	0.22	0.44	0.03

Rm-Rf

	Small	2	3	4	Big					
Weak	0.14	0.07	0.17	0.08	0.06	0.13	0.53	0.05	0.44	0.55
2	-0.06	0.05	-0.03	0.24	0.00	0.50	0.49	0.67	**0.00**	0.96
3	0.07	0.14	0.08	0.03	0.07	0.41	0.04	0.29	0.67	0.14
4	0.07	0.09	0.08	0.01	0.07	0.53	0.34	0.44	0.86	**0.00**
Robust	0.04	0.18	0.14	0.00	0.12	0.67	0.04	0.08	0.98	0.03

SMB

	Small	2	3	4	Big					
Weak	1.00	1.09	0.13	-0.11	-0.33	**0.00**	**0.00**	0.34	0.29	0.03
2	1.07	0.56	0.26	-0.28	-0.08	**0.00**	**0.00**	0.02	0.04	0.45
3	1.09	0.57	-0.11	-0.19	-0.19	**0.00**	**0.00**	0.39	0.13	0.02
4	1.09	0.73	-0.11	-0.14	-0.19	**0.00**	**0.00**	0.29	0.19	**0.00**
Robust	1.43	0.89	1.14	0.05	-0.43	**0.00**	**0.00**	**0.00**	0.68	**0.00**

HML

	Small	2	3	4	Big					
Weak	0.10	0.45	0.32	0.49	0.56	0.51	**0.01**	0.02	**0.01**	**0.00**
2	0.38	0.38	0.42	0.27	0.12	**0.01**	**0.00**	**0.00**	0.03	0.24
3	0.45	0.49	0.49	0.40	0.20	**0.00**	**0.00**	**0.00**	**0.00**	**0.01**
4	0.45	-0.12	0.49	0.06	0.20	**0.01**	0.40	**0.01**	0.53	**0.00**
Robust	-0.08	0.01	0.01	0.20	-0.07	0.59	0.94	0.94	0.08	0.44

ProbMOM

	Small	2	3	4	Big					
Weak	1.09	0.86	1.17	0.88	1.09	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
2	0.73	0.88	0.83	0.84	0.97	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
3	0.86	0.85	0.88	0.82	0.76	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
4	0.86	0.87	0.88	0.66	0.76	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Robust	0.82	0.69	0.90	0.95	0.99	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**

5 FACTOR	Intercept									
	Small	2	3	4	Big					
Weak	0.042	0.006	0.042	0.035	0.017	**0.00**	0.67	**0.00**	0.02	0.23
2	0.012	0.026	0.016	0.040	0.021	0.29	0.01	0.10	**0.00**	0.04
3	0.021	0.025	0.025	0.018	0.028	0.07	0.01	0.02	0.10	**0.00**
4	0.032	0.029	0.021	0.014	0.022	0.67	0.02	0.02	0.12	**0.00**
Robust	0.013	0.025	0.023	0.013	0.034	0.32	0.02	0.05	0.22	**0.00**

	Rm-Rf									
	Small	2	3	4	Big					
Weak	0.26	0.06	0.31	0.23	0.19	0.03	0.59	**0.01**	0.07	0.16
2	0.04	0.18	0.07	0.34	0.11	0.70	0.05	0.43	**0.00**	0.24
3	0.17	0.24	0.19	0.10	0.16	0.10	**0.01**	0.05	0.27	0.02
4	0.05	0.18	0.11	0.08	0.11	0.59	0.11	0.07	0.33	**0.00**
Robust	0.04	0.21	0.19	0.10	0.21	0.74	0.03	0.06	0.32	0.02

	SMB									
	Small	2	3	4	Big					
Weak	1.3985	1.2733	0.5886	0.2644	0.0318	**1.7E-11**	**7.4E-10**	**0.00142**	0.2382	0.8771
2	1.3477	0.9828	0.5855	0.0480	0.2628	**1E-14**	**1E-09**	**5.2E-05**	0.75987	0.0748
3	1.4613	0.9123	0.2460	0.0543	0.1226	**2.5E-13**	**1.8E-09**	0.12497	0.72742	0.29147
4	1.6474	1.1045	0.5749	0.0952	0.1365	**7.4E-10**	**1.2E-08**	0.2382	0.45969	**0**
Robust	1.7993	1.0754	1.3444	0.3767	-0.0923	**9.7E-20**	**9.8E-11**	**4.6E-14**	0.01849	0.52938

	HML									
	Small	2	3	4	Big					
Weak	-0.30	0.07	-0.16	-0.17	0.16	0.12	0.73	0.37	0.45	0.44
2	0.11	0.13	0.11	-0.09	-0.19	0.49	0.38	0.43	0.58	0.19
3	0.25	0.18	0.19	0.25	-0.04	0.19	0.21	0.22	0.10	0.71
4	-0.51	-0.45	-0.28	-0.12	-0.01	0.73	0.02	0.45	0.35	**0.00**
Robust	-0.33	-0.01	-0.08	0.01	-0.25	0.06	0.95	0.64	0.95	0.08

	CMA									
	Small	2	3	4	Big					
Weak	-0.38	-0.07	-0.29	-0.22	-0.57	0.08	0.74	0.16	0.35	0.02
2	0.00	0.50	-0.22	-0.34	-0.27	0.98	0.00	0.16	0.05	0.11
3	0.06	-0.15	-0.05	-0.21	-0.01	0.77	0.36	0.79	0.23	0.93
4	-0.65	-0.33	-0.19	-0.18	0.00	0.74	0.11	0.35	0.20	**0.00**
Robust	0.04	-0.32	-0.57	-0.07	-0.11	0.82	0.07	**0.00**	0.67	0.49

	RMW									
	Small	2	3	4	Big					
Weak	-0.64	-0.48	-0.88	-1.39	-0.65	**0.00**	**0.01**	**0.00**	**0.00**	**0.00**
2	-0.59	-0.12	-0.40	-0.56	-0.49	**0.00**	0.41	**0.00**	**0.00**	**0.00**
3	-0.06	-0.39	-0.39	-0.15	-0.26	0.74	**0.00**	**0.01**	0.30	0.02
4	-0.48	-0.13	-0.13	-0.18	-0.13	**0.01**	0.46	**0.00**	0.12	**0.00**
Robust	0.20	0.41	0.05	-0.10	-0.06	0.25	**0.00**	0.75	0.49	0.66

25 Size-B/M Portfolios

(Note that size is shown in columns unlike other tables shown earlier where size is in rows)

The left panel shows the coefficient of factors per portfolio while the right side shows the p-value. Box colored light green, dark green and dark green with bold show 10%, 5% and 1% level of significance respectively.

For intercepts, box colored in yellow means the portfolio intercept is dominated by 3FF model.

3 FACTOR	Intercept										
	Small	2	3	4	Big						
Low	0.015	0.011	0.032	0.023	0.013		0.32	**0.00**	0.02	0.39	**0.00**
2	0.030	0.022	0.024	0.030	0.031		0.03	0.06	**0.01**	**0.00**	**0.00**
3	0.011	0.013	0.023	0.018	0.019		**0.00**	0.22	0.39	0.05	**0.00**
4	0.011	0.040	0.023	0.031	0.019		**0.00**	**0.00**	0.39	**0.00**	**0.00**
High	0.027	0.021	0.033	0.025	-0.002		0.02	0.05	**0.00**	0.03	**0.00**
	Rm-Rf										
	Small	2	3	4	Big						
Low	0.09	0.09	0.25	0.14	0.07		0.54	0.07	0.04	0.41	**0.00**
2	0.17	0.19	0.23	0.28	0.17		0.15	0.06	**0.00**	**0.00**	**0.00**
3	0.09	0.14	0.14	0.10	0.14		0.07	0.15	0.41	0.24	**0.00**
4	0.09	0.27	0.14	0.21	0.14		0.07	0.02	0.41	**0.01**	**0.00**
High	0.14	0.19	0.24	0.21	-0.10		0.17	0.06	**0.00**	0.03	**0.00**
	SMB										
	Small	2	3	4	Big						
Low	1.68	1.71	0.49	0.63	-0.02		**0.00**	**0.00**	0.01	0.09	**0.00**
2	1.57	0.93	0.46	-0.14	0.10		**0.00**	**0.00**	**0.00**	0.36	**0.00**
3	1.71	1.08	0.63	0.14	0.13		**0.00**	**0.00**	0.09	0.28	**0.00**
4	1.71	1.02	0.63	0.03	0.13		**0.00**	**0.00**	0.09	0.82	**0.00**
High	1.05	0.90	1.15	0.24	0.23		**0.00**	**0.00**	**0.00**	0.15	**0.00**
	HML										
	Small	2	3	4	Big						
Low	-0.83	-0.28	-0.40	0.02	-0.19		0.32	**0.00**	0.02	0.39	**0.00**
2	-0.26	-0.09	-0.26	0.08	-0.05		0.03	0.06	**0.01**	**0.00**	**0.00**
3	-0.28	0.06	0.02	0.07	-0.14		**0.00**	0.22	0.39	0.05	**0.00**
4	-0.28	0.22	0.02	0.29	-0.14		**0.00**	**0.00**	0.39	**0.00**	**0.00**
High	0.21	0.25	0.43	0.56	-0.01		0.02	0.05	**0.00**	0.03	**0.00**

4 FACTOR	Intercept									
	Small	2	3	4	Big					
Low	-0.003	-0.004	0.006	0.007	-0.002	0.83	0.04	0.57	0.16	0.69
2	0.013	0.004	0.009	0.011	0.011	0.28	0.70	0.21	0.15	0.05
3	-0.004	-0.004	0.007	0.002	0.001	0.72	0.67	0.43	0.75	0.92
4	-0.004	0.021	0.007	0.014	0.001	0.04	0.08	0.16	0.04	**0.00**
High	0.011	0.001	0.017	0.009	-0.011	0.28	0.92	0.02	0.33	0.38
	Rm-Rf									
	Small	2	3	4	Big					
Low	-0.04	0.03	0.12	0.05	0.00	0.78	0.23	0.16	0.73	0.99
2	0.09	0.10	0.16	0.19	0.07	0.42	0.23	0.01	**0.00**	0.13
3	0.03	0.06	0.05	0.02	0.04	0.81	0.47	0.50	0.77	0.36
4	0.03	0.18	0.05	0.12	0.04	0.23	0.09	0.73	0.04	**0.00**
High	0.06	0.08	0.16	0.13	-0.14	0.49	0.24	0.02	0.10	0.31
	SMB									
	Small	2	3	4	Big					
Low	1.47	1.41	0.02	0.34	-0.28	**0.00**	**0.00**	0.91	0.33	**0.00**
2	1.26	0.61	0.20	-0.46	-0.25	**0.00**	**0.00**	0.05	**0.00**	**0.00**
3	1.41	0.79	0.34	-0.13	-0.20	**0.00**	**0.00**	0.01	0.23	0.02
4	1.41	0.69	0.34	-0.30	-0.20	**0.00**	**0.00**	0.33	**0.00**	**0.00**
High	0.77	0.55	0.87	-0.06	0.00	**0.00**	**0.00**	**0.00**	0.68	0.99
	HML									
	Small	2	3	4	Big					
Low	-0.71	-0.08	-0.13	0.20	-0.07	**0.00**	0.02	0.37	0.45	0.38
2	-0.06	0.06	-0.13	0.23	0.14	0.72	0.63	0.18	0.04	0.08
3	-0.08	0.19	0.20	0.22	0.04	0.63	0.13	0.13	0.04	0.65
4	-0.08	0.43	0.20	0.51	0.04	0.02	0.01	0.45	**0.00**	**0.00**
High	0.33	0.44	0.58	0.69	0.21	0.02	**0.00**	**0.00**	**0.00**	0.19
	ProbMOM									
	Small	2	3	4	Big					
Low	0.65	0.65	1.20	0.73	0.74	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
2	0.71	0.91	0.76	0.89	0.96	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
3	0.65	0.87	0.73	0.74	0.87	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
4	0.65	0.83	0.73	0.74	0.87	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
High	0.84	0.96	0.76	0.81	0.50	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**

5 FACTOR	Intercept									
	Small	2	3	4	Big					
Low	0.018	0.036	0.037	0.013	0.014	0.24	**0.00**	**0.01**	0.17	0.08
2	0.026	0.023	0.026	0.031	0.032	0.05	0.05	**0.00**	**0.00**	**0.00**
3	0.012	0.015	0.023	0.021	0.021	0.38	0.18	0.03	0.02	0.02
4	0.020	0.045	0.034	0.032	0.037	**0.00**	**0.00**	0.17	**0.00**	**0.00**
High	0.037	0.025	0.031	0.026	-0.003	**0.00**	0.02	**0.00**	0.03	0.82

	Rm-Rf									
	Small	2	3	4	Big					
Low	0.11	0.17	0.27	0.08	0.07	0.44	0.06	0.02	0.31	0.29
2	0.14	0.19	0.24	0.29	0.18	0.23	0.07	**0.00**	**0.00**	0.03
3	0.09	0.15	0.13	0.11	0.14	0.47	0.13	0.17	0.17	0.07
4	0.10	0.30	0.22	0.21	0.22	0.06	0.01	0.31	**0.01**	**0.00**
High	0.18	0.20	0.22	0.21	-0.11	0.05	0.04	**0.01**	0.04	0.46

	SMB									
	Small	2	3	4	Big					
Low	1.74	0.85	0.52	0.25	-0.03	**0.00**	**0.00**	**0.01**	0.07	0.79
2	1.49	0.91	0.47	-0.13	0.12	**0.00**	**0.00**	**0.00**	0.39	0.38
3	1.71	1.10	0.62	0.18	0.13	**0.00**	**0.00**	**0.00**	0.19	0.32
4	1.58	1.10	0.38	0.02	0.19	**0.00**	**0.00**	0.07	0.89	**0.00**
High	1.14	0.94	1.08	0.20	0.19	**0.00**	**0.00**	**0.00**	0.23	0.25

	HML									
	Small	2	3	4	Big					
Low	-0.89	-0.63	-0.59	-0.33	-0.23	**0.00**	**0.00**	**0.00**	0.02	0.04
2	-0.25	-0.18	-0.34	0.02	-0.08	0.19	0.27	**0.01**	0.91	0.58
3	-0.31	0.02	0.02	0.00	-0.21	0.09	0.92	0.90	0.98	0.09
4	0.22	0.12	0.25	0.23	0.38	**0.00**	0.52	0.02	0.08	**0.00**
High	-0.07	0.14	0.39	0.51	0.06	0.67	0.39	**0.00**	**0.00**	0.75

	CMA									
	Small	2	3	4	Big					
Low	0.13	-0.17	-0.12	-0.27	-0.10	0.60	0.31	0.59	0.08	0.41
2	-0.42	-0.25	-0.07	-0.07	0.06	0.06	0.19	0.62	0.72	0.71
3	-0.05	0.01	-0.04	0.08	-0.11	0.80	0.95	0.81	0.60	0.44
4	-0.28	0.26	-0.34	-0.16	-0.11	0.31	0.23	0.08	0.28	**0.00**
High	0.07	0.04	-0.48	-0.28	0.04	0.69	0.83	**0.00**	0.13	0.85

	RMW									
	Small	2	3	4	Big					
Low	-0.16	-0.51	-0.65	-0.71	-0.18	0.46	**0.00**	**0.00**	**0.00**	0.09
2	-0.14	-0.40	-0.31	-0.21	-0.04	0.45	0.01	0.01	0.15	0.73
3	-0.13	-0.13	-0.02	-0.21	-0.29	0.44	0.38	0.90	0.10	0.02
4	-0.27	-0.21	-0.36	-0.27	-0.37	**0.00**	0.26	**0.00**	0.03	**0.00**
High	-0.84	-0.36	-0.31	-0.29	0.18	**0.00**	0.02	0.02	0.06	0.37

Section 5: Discussion

In this section, we discuss investment strategy inspired by factor portfolio construction, which is a practical aspect of this study. In the last section, there is an empirical evidence that holding small, robust, aggressive or winning stocks can generate higher positive returns. Furthermore, Kolanovic and Wei (2015) showed that holding stocks which pass various good criteria can create consistent high return.

As a result, the author forms two trading strategies which use size, investment and profitability as criteria to include stocks into the portfolios. Small stocks that fall in the top 30th percentile of profitability and investment will be selected. Another trading strategy uses different momentum measurements as a criteria to include stocks into the portfolio.

After setting up portfolios, following Kolanovic and Wei (2015), two risk management methods are applied:

1) Stop Loss: once the portfolio experience more than 5% loss, the position will be closed and trading will begin again in the next quarter
2) Switch: once the portfolio experience more than 5% loss, we turn to hold a safer portfolio which consists of big stocks mainly.

5.1) Trading small, aggressive and robust stocks

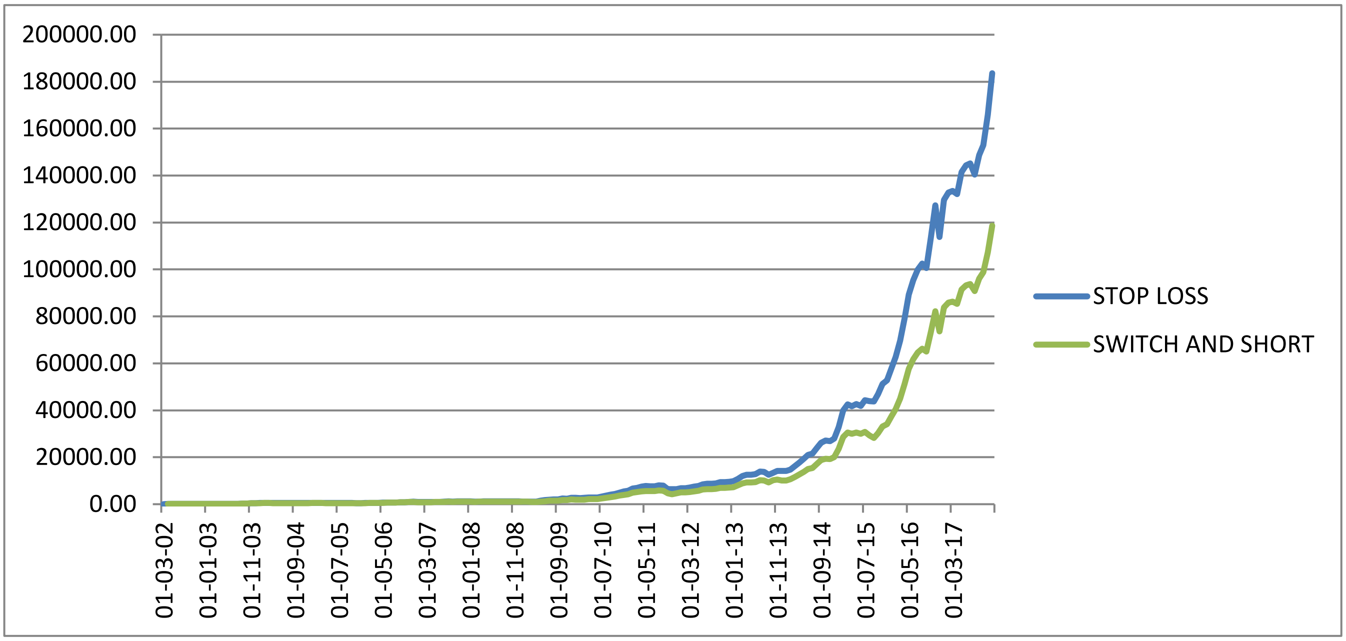
The table below shows descriptive statistic on trading strategy which buys small stocks with high investment and profit. Clearly, managing risks by stop loss yields highest returns and the Sharpe ratio. Switching also improves Sharpe ratio, but not as much as stop loss.

	Long Small high inv & OP	Big, neutral inv & OP	STOP LOSS	SWITCH
RETURN	4.39%	2.51%	4.35%	4.10%
STD	8.64%	5.48%	7.94%	7.88%
SHARPE	0.50	0.45	0.54	0.52

Source	SS	df	MS		
				Number of obs =	190
				F(6, 183) =	20.88
Model	.573726625	6	.095621104	Prob > F =	0.0000
Residual	.838240959	183	.004580552	R-squared =	0.4063
				Adj R-squared =	0.3869
Total	1.41196758	189	.007470728	Root MSE =	.06768

Long_AR	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
SMB	.8015744	.1314658	6.10	0.000	.5421908	1.060958
RmRf	.0576743	.0777026	0.74	0.459	-.095634	.2109825
HML	.2411023	.130273	1.85	0.066	-.0159279	.4981325
CMA	-.0875573	.1439853	-0.61	0.544	-.371642	.1965273
RMW	.1025534	.1205146	0.85	0.396	-.1352233	.34033
ProbMOM	.504337	.0820687	6.15	0.000	.3424145	.6662595
_cons	.0376911	.0089018	4.23	0.000	.0201277	.0552545

The information above shows regression including size, market, value investment, profitability and probabilistic momentum factors. This combination yields the lowest intercepts. To analyze this portfolio roughly, it is mostly exposed to size and value factor. The _cons indicates model's intercept which means that after controlling for all risks, the portfolio still generates 3.7% extra monthly returns. Suppose we assume probabilistic momentum can adequately explain portfolios for stocks with high investment and profitability, higher excess returns mean higher gains for controlled risk. This means that it is preferable for investors.



The graph above compares risk management in buying small profitable and high investing stocks. Stop loss clearly dominate switch to big neutral portfolio over the long run.

5.2) Trading stocks with positive probabilistic and absolute momentum

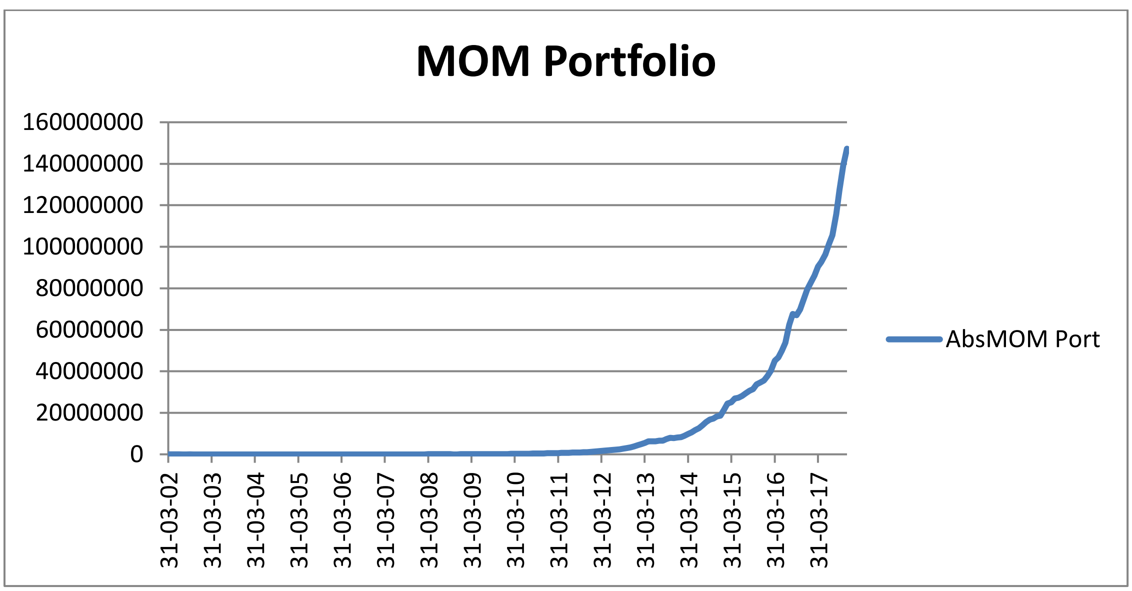
The table below shows descriptive statistic on second trading strategy, which buys stocks that both meet positive absolute momentum and probabilistic momentum criteria. In other words, we choose stocks that are predicted to outperform the market by information ratio as well as the risk-free rate by the autoregressive model.

	Long Prob+Abs MOM	STOP LOSS
RETURN	8.04%	7.34%
STD	7.26%	7.36%
SHARPE	1.11	0.99

Here, we can see that stop loss does not increase returns nor reduce standard deviation. This is because momentum effect has already been included in trading strategy and cutting loss is an action based on momentum. Hence, this distorts overall strategy and deteriorates Sharpe ratio.

MOMTrade	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
SMB	.0841886	.0687708	1.22	0.222	-.0515019	.2198792
RmRf	.070002	.0404614	1.73	0.085	-.0098318	.1498358
HML	.2609775	.0679689	3.84	0.000	.1268692	.3950859
CMA	-.0274617	.075394	-0.36	0.716	-.1762205	.121297
RMW	.0948363	.0627795	1.51	0.133	-.0290329	.2187055
ProbMOM	.9597768	.0427711	22.44	0.000	.8753857	1.044168
_cons	.0744815	.0046379	16.06	0.000	.0653306	.0836325

The information above shows regression including size, market, value investment, profitability and probabilistic momentum factors. This combination yields the lowest intercepts. To analyze this portfolio roughly, it is exposed to mostly momentum and value factor. This is expected because it is a momentum trading strategy. The _cons indicates model's intercept which means that after controlling for all risks, the portfolio still generates 7.45% extra monthly returns.



The graph above shows portfolio performance over the long run. It has a nice exponential growth. From the data, it rarely experiences negative returns and standard deviations of 8% are mostly contributed to upside risks. The portfolio experience one big loss of 14% at October of 2008 only. For the rest, no losses were bigger than 5%.

Section 6: Conclusion

Based on the ratios that compare average absolute intercepts and portfolio returns dispersion, market, size, value, investment, and momentum factor are still inadequate for explaining stocks return in the Stock Exchange of Thailand. It turns out that using simple returns average of all stocks in SET100 can produce lower variance in errors comparing to using factor asset pricing models. Thus, more development and experiments on new risk factors are needed to create a model that fits for Thailand. However, this study also found that better model does not necessarily mean more factors. Improvements in factor construction such as using absolute momentum instead of relative momentum can also bring a huge impact on the model accuracy.

We found that probabilistic momentum model is the dominant model. This provides a good direction for future researches. From the model, momentum factor already plays a huge role in determining stock returns. Hence, more study on factors with low correlation to momentum is needed to reduce unexplained returns. Factors' coefficients also fit the theories better after controlling for momentum effects. This makes the model even more helpful for identifying relevant risk factors in the future.

Besides, this research has shown that asset pricing models can still work well in some portfolios. In previous sections, there is evidence that investment and probabilistic momentum factor can greatly reduce intercepts for portfolios with robust profit and/or aggressive investment stocks. For neutral or mid-size portfolios, the model can still be used for risk management. For example, this study found that small stocks are exposed more to size risk by looking at SMB coefficient. Investors can measure risks or identify new risk factor exposed to their portfolios by including mixed factors into the asset pricing models. This study implies that investor should include major risk factors into the model which are market, size, value, investment, and momentum risks.

As discussed in earlier sections, the biggest drawback in this research is that reported results are different from existing evidences mainly by Kaewthammachai et al. (2016). This could be caused by missing data from Bloomberg Terminal and different choice of risk-free rates. Another challenge is that while probabilistic momentum could dramatically reduce intercepts, the author cannot explain the specific reasons behind that. It is doubtful why relative momentum and absolute momentum do not work as effectively as probabilistic momentum. Hence, more investigation is still needed to explain the relationships of stocks in probabilistic momentum portfolios and overall SET100 stocks.

Lastly, this research only focuses on SET100 stocks. The results could be different when applying the model to the whole Stock Exchange of Thailand. In the light of missing data, bigger samples could also bring more accurate and robust results. The test of the models in different time periods prior to 2002 might yield different outcome. The difference in risk exposures to stock found in the past comparatively to the present could contribute greatly in explaining the change of the structure in the Stock Exchange of Thailand.

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