Characteristic Approach to High Risk Low Return Puzzle in SET

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ลักษณะเฉพาะที่นำไปสู่สาเหตุของหุ้นความเสี่ยงสูงจ่ายผลตอบแทนต่ำในตลาดหลักทรัพย์แห่งประเทศไทย

นายพัชร พุ่มกุมาร

สารนิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
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Thesis Advisor	Associate Professor Kanis Saengchote, Ph.D.

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พัชร พุ่มกุมาร : ลักษณะเฉพาะที่นำไปสู่สาเหตุของหุ้นความเสี่ยงสูงจ่ายผลตอบแทนต่ำในตลาดหลักทรัพย์แห่งประเทศไทย. (Characteristic Approach to High Risk Low Return Puzzle in SET) อ.ที่ปรึกษาหลัก : รศ. ดร.คณิสร์ แสงโชติ

Theoretically investing in high risk asset generates high return. However, actual payoff in market is in the opposite side. In several empirical studies documented high risk stocks paid low return even lower than the portfolio of the lowest volatile stocks. I examine whether the cause of this anomaly is the lottery stocks. Lottery stocks which are low price, high skewness and high kurtosis might be desired by many investors even institutional investors. The assumption is that this high demand of lottery stocks might push the price up and cause low average return finally. Therefore, I set up the hypothesis these risky stocks are lottery stocks. I collect monthly total return, market value, book to market and price of SET listed and delisted stocks in 2002 to 2019 to construct asset pricing model by mimicking portfolio as Carhart 4 factors. I calculate excess return, market risk premium, smb, hml, umd and lottery factors similar to Carhart 4 factors but used skewness, kurtosis and price to form mimicking portfolio factors instead. I classify SET stocks into 5 portfolios sorting by volatility focusing on the highest volatile whether lottery factors affect their return. Nevertheless, there is no evidence enhancing the hypothesis that they are lottery stocks. However, although not all lottery factors can explain the return of high risk stocks, but skewness factor can. I can imply that high risk stocks in Thai stocks market is partially lottery stocks. In additional, I found this asset pricing model is fitter to explain return and generate less alpha after GRS testing which can be implied that this lottery factor model is informative or meaningful to the return.

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Putchara Poomgumarn : Characteristic Approach to High Risk Low Return Puzzle in SET. Advisor: Assoc. Prof. Kanis Saengchote, Ph.D.

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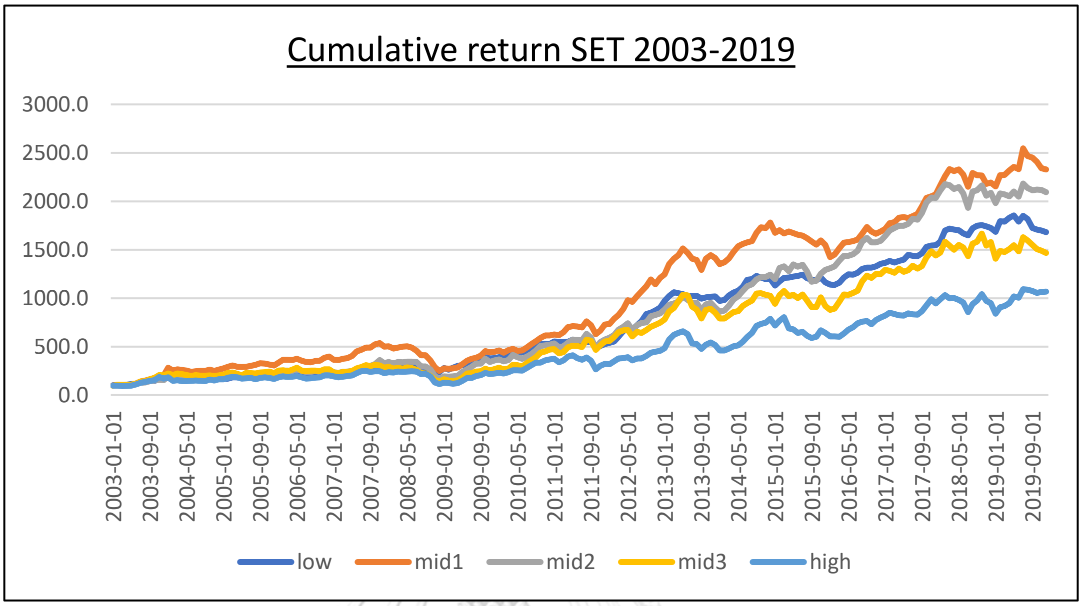
INTRODUCTION

The anomaly outcomes which low volatile stock generates high return is called low volatility anomaly. This anomaly is even shown that low volatile stocks outperforms high volatility stocks in any periods persistently. Hence this attracted several studies to learn and they reveal that stocks with low volatility have greater performance than high-volatility stocks in real situations. The capital asset pricing model called CAPM is challenged by this event, it stated generally high risks asset has high return or risk and return has a positive relationship. Black (1972) stated low risk stocks empirically outperform high risk stocks in term of beta as risk. However, in the opposite side, high risk low return stocks puzzled how this occurred and who invest in.

The object of this research is to study the cause of high risk low return in the Stock Exchange of Thailand between 2003 and 2019. Firstly, I provide the evidence of high risk low return stocks and low risk high return stocks through low-volatility anomaly model as graph demonstrated in Figure 1. Then I investigate why high risk (volatility) stock has low return.

Figure 1 **Accumulated monthly return graph classified by volatility from 2003 to 2019 of SET stocks**



LITERATURE REVIEW

A linear equation stands for CAPM to compute the expected return from market risk premium coefficient or beta. By its linear relationship, higher beta means higher return. As states before, not only Black (1972), several studies dig down informative data and documented indeed the relationship of the return and risk can be explained as flat or in some cases negative graph.

An evidence in American stocks market shew that low volatility stocks win high volatility stocks in the same way as low-volatility anomaly phenomenon when Baker, Bradley and Wurgler (2011) studied stocks data over a period of 41 years between 1968 and 2008. In data construction, they allocate quintile portfolios sorted by volatility value which is monthly rebalanced. They found that a portfolio of low volatile stocks (quintile of stocks with the lowest volatility) outperformed persistently a portfolio of high volatile stocks. Blitz and Van Vliet (2007) and Ang et al. (2009) also found likely same result.

From these studies and the others concerned low-volatility anomaly, there tend to be overvaluation on high volatile stocks and vice versa on low volatile stocks. And surprisingly the event stands across countries and over periods. Several studies also attempted to find reasons behind this outcome as will be explained in next section.

Managers' behavioral as compensation

Fund managers manage the funds which could generate high payoff as their assignment of their career. The compensation or bonus can be paid to them if the outcomes of their funds return is better than the benchmark. In order to beat the benchmark, managers try to find stocks those could outperform the others. For this concept, they are attracted to high volatile stocks which would make extreme return by their big swing magnitude of return or high SD. They tend to seek for risky assets to increase their compensation or bonus as the study from Blitz, Falkenstein and Van Vliet (2014). As their job to create wealth for customers, in the conflict of interest, they might focus to make high reward by investing in riskier stocks instead of concentrating to make value of customers' portfolio.

Behavioral finance

The most general explanation of low-volatility phenomenon by many researchers and academics is Behavioral finance. "The analysis of various psychological traits of individuals and how those traits affect how they act as investors, analysts and portfolio managers" is defined by Reilly & Brown (2011). There are many explanations involving bias and irrational actions from individuals and investors can be used to declare why low-volatility anomaly occurs. It looks to be driven by high volatility demand from irrational desire from Baker, Bradley and Wurgler (2011). Investors have the optimistic mind would tend to invest disproportionately to high risk stocks with inappropriate or not reasonable sense. By this action, high volatile stocks are overvalued and cause them produce low average payoff later on.

Representativeness bias

An assumption of CAPM is the market is efficient. Information are distributed to everyone in the same speed and same acknowledgement. In this case, all investors have the same logic in investing strategy in additional. This is not compatible with real world market which reflected into this low-volatility anomaly.

Representativeness is the concept of brands. We might see stocks with high past return in the perspective that this would happen again in the likelihood stocks. Tversky and Kahneman (1983) documented in their study that investors see the image of high volatile stocks as the high payoff stocks. Therefore, investors focus in this type of stocks and invest more in them. For example, people may invest in any others IT stocks following Apple or Facebook those have high success in price before.

Overconfidence bias

Investors may prefer high volatility stocks as they can show off their future forecast and skill over other investors because they could generate positive alpha as the theory. Blitz, Falkenstein and Van Vliet (2014) found that investing in high volatile assets can be implied that person is skillful. Hence this thinking method leads investors to be overconfident to invest in high risk stocks. Willingness to bear high risk to find alpha is the cause of overconfidence bias which make them feel beating the others or better than low-risk investors.

Not only retail investors think in this way, this occurs in managers' as well. Fund managers or professional investors seem prefer to implementing concept of overconfidence bias. Gort (2009) study found fund managers have high confidence towards the ending performance of their funds. By this optimistic thinking way, they tend to overinvest in risky stocks to receive their hoping high performance. The higher they are confident in their skill, the higher they tend to invest in risky assets. This concerned compensation or bonus they would get in the future. Finally, high risk stocks are overpriced and the drawback is low average return in the future.

Mental aspiration

Most investors allocate their investing asset into 2 portions. The first portion is a safety asset which maintains their wealth, not making them poorer than they are currently. Another portion is more aggressive asset which would possibly make them richer or gain extreme wealth by an amount of possibility. The style of prior portion is likely to be diversify portfolio and not high volatile. The second portion is riskier but low price which has a bit of possibility to win extreme payoff. This later portfolio is a kind of lottery stocks concerned preference of skewness. This concept is a combination between Shefrin and Statman (2000) and Blitz and Van Vliet (2007).

This mental aspiration indicates why investors invest mainly in diversify portfolio but leave a few portions to be lottery stocks with hoping to make them wealthier but when lose they would not pay that much.

Preference for lottery-like stock, higher moments of return

An assumption restricted in CAPM which may different from actual is that investors are risk-averse. They are interested in only mean and volatility. Skewness and kurtosis or other moments of return are not accounted in investors' mind. This concept is made simply because to assume return distribution is normal. In actual data we acknowledged, the distribution is not likely to be normal. Skewness and kurtosis can tell us that they skewed and deviated from normal. And the other fact studied is that investors are not only risk-averse but loss-averse. They count how much amount they will lose, Galagedera (2007). The other moments than mean and varience play roles because they can evaluate how much they will lose in some certain payoff with their intrinsic possibility tolerance. Lambert and Hubner (2013) and Post et al. (2008) documented that reducing skewness of portfolio increase the expected return in compensation or generate abnormal return. Friend and Westerfield (1980) indicated skewness can drive return in asset pricing model. In additional, they summarized high volatile stocks drive low-volatility anomaly by their higher skewness and lower kurtosis than the low volatile stocks.

There is supporting study enhancing lottery stock characteristic. Jacqmin, Rémy (2016) found stocks type which is a kind of gamble. This can be called lottery-like distribution, high chance to lose money but low chance to win extreme return. These stocks are cheap with high volatility. And their upside return could be double or triple of their value, Kumar (2009). In conclusion, lottery stocks are low-price, relatively high volatility, high skewness and likely to have high kurtosis.

From unclear conclusion whether lottery stock is the reason behind high risk low return anomaly or not. This paper tries to find further explanation through Thai stock market (SET) following the assumption below.

Research Question: Are high risk low return stocks lottery stocks?

Research Objective: To examine high risk low return stocks explained by the price, skewness and kurtosis of stock returns in previous period.

Contribution

As the goal of this thesis is to find cause of high risk low return, several papers has written low-volatility anomaly explanation and some explain skewness and kurtosis play no role in that volatility effect, in foreign country. This paper tries to focus further more in type of investors and their characteristic that could affect high risk low return in Thai stock market. This paper adds price factor to examine deeper whether high risk stocks are lottery type stocks in Thai stock market in sample by

SET which is different from previous research paper that studied for only skewness or kurtosis.

Hypothesis Development

Hypothesis 1: High risk low return stocks are lottery stocks. Lottery factors have been priced for return on average.

The characteristic of lottery type stock is low price, high skewness and high kurtosis Kumar (2009). I will use Fama-MacBeth regression method to regress these factors and expect to see coefficients are far away from 0 and statistically significant leading to the first hypothesis to conclude that lottery type stocks exist in average.

Hypothesis 2: High risk low return puzzle is explained by price, skewness and kurtosis factors

The second hypothesis is these high volatility stocks in SET are explained by lottery stocks. I can grasp conclusion that they are lottery type stocks if monthly return regression result on these factors get the coefficients different from 0 as negative skewness coefficient, negative kurtosis coefficient and positive price coefficient and statistically significant as detail explained further in “Data and Methodology”.

DATA

For the object of my investigation, I construct sets of the dependent and independent data. It’s consisted of SET stocks (634 stocks) monthly total return index, market value, book to market and price in Thai Baht from January 2002 to December 2019, 18 years period which searched via Thomson Reuters Datastream software with

Microsoft Excel. This dataset came from both listed and delisted stocks over 216 months. And I use Thai government one-month risk free in the same period via Bloomberg. I use data of year 2002 to calculate for SD, skewness and kurtosis for 2003 data sets and do repeat this calculation cycles until 2019 data sets. This means I use past 12 months data to calculate for statistical value in current month. For both hypothesis I provide monthly total return as equation below for dependent variable for Fama-Macbeth and time series regression. When t in the equation denotes for month.

$$monthly\ total\ return_t = \frac{total\ return\ index_t}{total\ return\ index_{t-1}} - 1$$

Then I provide 7 independent variables in each month from 2003 to 2019; mrp (market risk premium), smb (return of small market capitalization stocks minus big market capitalization stocks), hml (return of high book to market ratio stocks minus low book to market ratio stocks), umd (return of winner stocks minus loser stocks; allocate by averaging past 12 monthly return), sk (return of high skewness stocks minus low skewness stocks), ku (return of high kurtosis stocks minus low kurtosis stocks) and pr (return of high price stocks minus low price stocks). I calculate mrp by monthly return of weighting all stocks by value minus monthly one-month risk free following below equation.

$$monthly\ market\ return = \frac{\sum_{i=1}^{k} monthly\ market\ value\ x\ monthly\ return}{\sum_{i=1}^{k} monthly\ market\ value}$$

$$mrp = monthly\ market\ return - monthly\ one\ month\ risk\ free\ rate$$

When i^{th} denotes for stock and k is total number of stocks.

For the other factors, I sort data into two dimensions; size or market value and each factor value themselves replicating Fama-French and Carhart factors concept but including skewness, kurtosis and price in further more. For smb and umd, I sort stocks into 2 groups separated by the 50th percentile. And For each individual factor of hml, sk, ku and pr, I sort stocks into three groups by using 30th and 70th percentiles to distinguish between low, natural and high value. Hench I summarily calculate the dependent factors as shown in below equation.

$$smb = \frac{1}{2}(small\ value + small\ natural + small\ growth) - \frac{1}{2}(big\ value + big\ natural + big\ growth)$$

$$hml = \frac{1}{2}(small\ value + big\ value) - \frac{1}{2}(small\ growth + big\ growth)$$

$$umd = \frac{1}{2}(small\ upturn + big\ upturn) - \frac{1}{2}(small\ downturn + big\ downturn)$$

$$sk = \frac{1}{2}(small\ skewed + big\ skewed) - \frac{1}{2}(small\ normal + big\ normal)$$

$$ku = \frac{1}{2}(small\ fat\ tail + big\ fat\ tail) - \frac{1}{2}(small\ normal + big\ normal)$$

$$pr = \frac{1}{2}(small\ expensive + big\ expensive) - \frac{1}{2}(small\ cheap + big\ cheap)$$

In order to regress for the second hypothesis, I do sort stocks into 5 portfolios by volatility which will be explained in the next section. But before that, I filter stocks with price less than 1 Baht/share and also stocks which has no transactions in previous 12 months out to eliminate noise or inappropriate SD caused from very low-price fluctuation which affect stock selection for volatility portfolio sorting. For additional explanation, one tick movement of less than 1 Baht stocks causes high SD even it is not substantial or significant change in magnitude.

METHODOLOGY

I regress the returns of each stocks on factors as below equation. I utilize Carhart 4 factors model as core equation plus factor I'm interested.

$$R_{i,t} = \propto_{i,t} + B_1 MRP_{i,t} + B_2 SMB_{i,t} + B_3 HML_{i,t} + B_4 UMD_{i,t} + B_5 SK_{i,t} + B_6 KU_{i,t} + B_7 PR_{i,t}$$

Where Ri,t is the return of portfolio or asset i (n total) at time t, MRPi,t is the market risk premium at time t, SMBi,t is the size premium at time t, HMLi,t is the market value premium at time t, UMDi,t is the momentum premium at time t, SKi,t is long high skewness the rolling 12 month short low skewness in same rolling period as stocks premium at time t, KUi,t is the rolling 12 month kurtosis premium at time t, PRi,t is the price premium at time t, βi are the factor exposures, or loadings, that describe how returns are exposed to the factors, and t begins from 1 through T.

Hypothesis 1: High risk low return stocks are lottery stocks. Lottery factors have been priced for return on average.

Since the first hypothesis is to clarify whether high risk low return stocks are lottery stocks or not. I will regress in the same way as Fama-MacBeth (1973) regression method. Firstly, to see exposure of each factors, I will regress return of each stocks over all time-series on factors said earlier and get coefficient Beta (B) of each factors. Secondly, to see each premium from exposure to each factors, I will cross-sectional regress return of each stocks again on previous coefficient Beta and get coefficient Gamma (γ) of each periods as below equation.

$$R_{i,1} = \propto_{i,1} + B_{i,MRP}\gamma_{1,1} + B_{i,SMB}\gamma_{1,2} + B_{i,HML}\gamma_{1,3} + B_{i,UMD}\gamma_{1,4} + B_{i,SK}\gamma_{1,5} + B_{i,KU}\gamma_{1,6} + B_{i,PR}\gamma_{1,7} + \varepsilon_{i,1}$$

$$R_{i,2} = \propto_{i,2} + B_{i,MRP}\gamma_{2,1} + B_{i,SMB}\gamma_{2,2} + B_{i,HML}\gamma_{2,3} + B_{i,UMD}\gamma_{2,4} + B_{i,SK}\gamma_{2,5} + B_{i,KU}\gamma_{2,6} + B_{i,PR}\gamma_{2,7} + \varepsilon_{i,2}$$

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$$R_{i,T} = \propto_{i,T} + B_{i,MRP}\gamma_{T,1} + B_{i,SMB}\gamma_{T,2} + B_{i,HML}\gamma_{T,3} + B_{i,UMD}\gamma_{T,4} + B_{i,SK}\gamma_{T,5} + B_{i,KU}\gamma_{T,6} + B_{i,PR}\gamma_{T,7} + \varepsilon_{i,T}$$

The denote R is the same as the first equation, γ are regression coefficients that would be used to calculate the risk premium for each factor, and in regressions of the hypothesis analysis I start from 1 to n. In the end there are m + 1 series of γ (including the constant in the second step) for every factor, each of length T. The ε are assumed to be iid, I compute the risk premia for factors by taking average all γ over T. Each regression uses the same factors F, in order to estimate the factor loading of each portfolio's return for given assigned factors.

To conclude, I will take average of coefficient Gamma of each stocks and calculate t-stat.

$$t - stat = \frac{\gamma_m}{\sigma_{\gamma m}/\sqrt{T}}$$

This will demonstrate how much impact of premium of each factors. I would like to see that there are high skewness, kurtosis and price premium and statistically significant to conclude that in average these factors play roles.

Hypothesis 2: High risk low return puzzle is explained by price, skewness and kurtosis factors

In order to regress in high volatile stocks, I separate data into 5 quintiles sorting by volatility (SD of return), beginning quintile1 (portfolio 1) with the lowest volatility stocks group ending at quintile5 (portfolio 5) with the highest volatility using past 12 month SD of total return data in order to sort. Each portfolio is monthly rebalanced to compute monthly return. I would like to note that the return calculated as value weighted return which I sum product of each portfolio monthly return and monthly market value.

Then, I check several explanations for high risk low return; low price, high skewness, high kurtosis. Then I created 3 mimicking portfolios: prior one has a long in stocks with high skewness and selling short stocks with low skewness which used median to separate high and low value each month, next is a portfolio which long high kurtosis stocks and short low kurtosis with the same separation method as before and the last portfolio of stocks is long high price and short low-priced stocks. The portfolios are rebalanced monthly as well as the return construction method informed and the skewness, kurtosis are computed by exploiting 12 past monthly total returns.

Therefore, I obtain three mimicking portfolio factors for skewness, kurtosis and price factor.

The hypothesis is skewness has positive correlation with return, kurtosis has positive correlation with return and price has negative correlation with return; to reflect lottery type stocks. I will add these 3 factors to Carhart 4 factors model as below equation.

$$R_{1,t} = \propto_{1,t} + B_1 MRP_{1,t} + B_2 SMB_{1,t} + B_3 HML_{1,t} + B_4 UMD_{1,t} + B_5 SK_{1,t} + B_6 KU_{1,t} + B_7 PR_{1,t}$$

$$R_{2,t} = \propto_{2,t} + B_1 MRP_{2,t} + B_2 SMB_{2,t} + B_3 HML_{2,t} + B_4 UMD_{2,t} + B_5 SK_{2,t} + B_6 KU_{2,t} + B_7 PR_{2,t}$$

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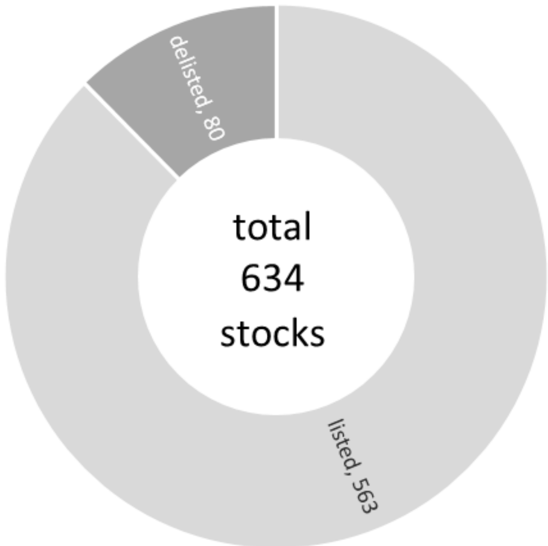
$$R_{n,t} = \propto_{n,t} + B_1 MRP_{n,t} + B_2 SMB_{n,t} + B_3 HML_{n,t} + B_4 UMD_{n,t} + B_5 SK_{n,t} + B_6 KU_{n,t} + B_7 PR_{n,t}$$

Where variables denoted the same as the first equation. Each regression uses the same factors F, in order to estimate the factor loading of each portfolio's return for given assigned factors. As hypothesis set up, I would like to see that portfolio 5 have statistically significant positiveB_5, positive B_6 and negative B_7 to conclude that portfolio 5 has lottery stocks characteristic.

Finally, after investigation and interpret of regression result, If results are not statistically compatible by the hypothesis, I will conclude there is no lottery stocks characteristic in SET high risk stocks but overconfidence or representative characteristic bias take in charge of root cause because this phenomenon concerned solely on demand for high risk characteristic.

DESCRIPTIVE STATISTIC

Figure 2 **Pie chart demonstrates stocks data category of SET between 2003 and 2019**



Stocks selected after filtered as described in "Data" section, there are totally 634 stocks of SET between 2003 and 2019 as Figure 2. 80 delisted stocks and 563 listed stocks in informed criteria to be constructed as portfolio sorted by volatility. I utilize percentile method to classify stocks into 5 portfolios sorted by past 12 months volatility. In additional, these portfolios are rebalanced monthly along periods of 2003-2019. From the hypothesis and the main question why high risk stocks has low return, I focus to investigate the data of portfolio 5 which has the highest volatility.

The average of monthly return in the highest volatile portfolio is the lowest at 1.442% and the second portfolio generates return above the others at 1.708% shown in Table 1. As sorting method, portfolio 5 has the highest SD at 7.297% double of portfolio 1. Skewness of portfolio 5 is on the high side but not the highest in magnitude because portfolio 2 is leading at value 0.926. Kurtosis of portfolio 5 is at 2.590 following the lead, portfolio 2, at 9.066. The average price of portfolio 5 is the lowest comparing to the others at 25.337 Baht per share and it is only a quarter of portfolio 1 which has the highest average price at 87.324 Baht per share. From statistical data, portfolio 5 has the most likely image of lottery stocks as the lowest price, among the highest skewness and kurtosis which is follow the noticed point that this might cause portfolio 5 has the lowest average return and as well as cumulative return shown in Introduction section. Lastly, Sharp ratio of portfolio 5 is not surprisingly the lowest and the data are monotonic as shown that ratio are leading by portfolio 1 and following by portfolio 2-5 accordingly.

For independent variable side as data shown in Table 2, which replicated from Carhart 4 factors and I added 3 lottery factors, I focus on the last 3 factors. For sk, the average is 0.128% which reflect not high value implying that high skewness portfolio produces slightly higher return than the low skewness. As the t-stat data at 0.720 meaning it is not significantly different from zero, this can be implied there is no different between those two portfolios. The result is the same for ku in term of t-stat. However, t-stat of pr is more than 2 indicating that the mean value is significantly different from zero and it is positive. This can be implied that the low price portfolio pay the lower return than the high price portfolio. This can be matched along with lottery characteristic which I will analyze further more in the next section.

Table 1 **Statistical data of quintile volatility sorted 5 portfolios**

	Portfolio Return (Dependent Variable)				
	1	2	3	4	5
	lowest SD		mid SD		highest SD
mean	1.459	1.708	1.681	1.554	1.442
min	-8.398	-19.625	-26.319	-22.710	-32.121
max	18.641	38.568	24.518	25.418	21.867
SD	3.701	5.657	5.968	6.797	7.297
skewness	0.680	0.926	0.407	0.018	0.677
kurtosis	2.385	9.066	3.486	0.898	2.590
Sharp ratio	0.394	0.302	0.282	0.229	0.198
Price	87.324	86.664	65.710	45.516	25.337

Table 2 **Statistical data of independent variable (Carhart 4 factors and lottery 3 factors)**

	Factors (Independent Variable)						
	mrp	smb	hml	umd	sk	ku	pr
mean	1.725	0.288	-2.604	2.878	0.128	-0.035	1.286
min	-20.332	-35.701	-43.513	-40.504	-9.659	-12.344	-21.603
max	44.988	24.687	9.128	148.446	14.838	5.993	59.264
SD	6.152	5.088	5.830	15.468	2.545	2.323	5.269
skewness	1.643	-0.296	-4.050	4.279	0.575	-0.823	6.597
kurtosis	12.561	17.078	22.440	38.974	6.579	3.535	75.459
T-stat	4.005	0.807	-6.380	2.657	0.720	-0.212	3.485
Obs#	204	204	204	204	204	204	204

EMPIRICAL RESULT AND DISCUSSION

This section demonstrates empirical result and discussion corresponding to each questions and hypothesis. Result from Fama-Macbeth regression of Carhart 4 factors adding 3 lottery factors and time series regression of Carhart 4 factors but with any combination of lottery factors on each 5 groups of stocks sorted by past 12 months volatility are presented in ordered subsection with discussion. Statistical data of regressions mainly show coefficients, standard error, p-value and adjusted R squared. Each row inform each variable statistical data. For 5 groups volatility sorted part, each column show each models implemented and each groups subjected. Additional materials are shown as each factors correlation which are found not likely to correlated each other except for sk and ku and GRS test shown to clarify whether each new constructed models can be contributed in explaining returns more than Carhart 4 factors or not.

1. Lottery factors have been priced for return on average? – they have not been priced

From result after Fama-Macbeth regression on listed and delisted SET stocks return between 2003-2019 totally 634 stocks (554 listed stocks, 80 delisted stocks), lottery factors as a bunch those are sk, ku and pr do not affect to return in average as the t-stat are shown 0.843, 1.150 and 4.319 accordingly since all factors should be significantly positive. For the remaining factors, Carhart 4 factors, their coefficients are statistically significant as the t-stat are 3.282, 10.505, -15.658 and 8.458 for mrp, smb, hml and umd accordingly shown in Table 3. This means skewness, kurtosis have not been priced on average except for price factor. Additionally, the coefficients or risk premia of mrp, smb, hml and umd which are 0.35, 0.93, -1.62 and 2.69 orderly are much higher in magnitude at least 5 times of sk and ku which are 0.04 and 0.07 except for price that coefficient is close to value of mrp. Therefore, this can be implied that the loading factors of sk, ku and pr cannot explain returns cross-sectionally on average comparing to those Carhart 4 factors. This does not follow the first hypothesis that the lottery loading factors can be priced on average or affect the return.

Table 3 **Fama-MacBeth regression result**

Independent Variable	Average Coefficient	Average SE	Test-Statistic	10% Confidence Significant Result
mrp	0.355	1.397	3.628	Significant
smb	0.934	1.210	11.023	Significant
hml	-1.619	1.241	-18.630	Significant
umd	2.687	4.231	9.071	Significant
sk	0.043	0.722	0.843	Not significant
ku	0.073	0.905	1.150	Not significant
pr	0.350	1.159	4.319	Significant
Constant	1.129	1.500	10.746	Significant
Observations	204			

2. Stock returns can be explained by lottery factors? – lottery factors cannot explain the return either

As time series regression on each 5 groups of stocks classifies by past 12 months SD shown in Table 4, start from portfolio 1 which has the least SD to portfolio 5 which has the highest SD, sk is statistically significant in 2 portfolios. The coefficient is negative in portfolio 2 and is positive in portfolio 5. The ku is only statistically significant in portfolio 2 and the coefficient is positive. The pr is not statistically significant in any portfolios. This result is not followed by the 2nd hypothesis that sk, ku and pr are statistically significant persistently. This can be concluded that lottery factors do not affect stocks return on average in actual outcomes of SET between 2003-2019. For portfolio 5 which is the most volatile in return, coefficient of sk is significantly impact as positive value. This can be implied that this portfolio has components of high skewness and nearly high kurtosis and low price (as the last 2 factors are positive and negative but t-stat not high enough to effect significantly) which affect the return as incomplete manner of lottery stock. The adjusted R squared of this asset pricing model is the highest in all tested groups comparing to Fama-French 3 factors and Carhart 4 factors model. In additional, the GRS test on average shown in Figure 3 found t-stat value is the lowest. This means that model is fitter and can reduce the alpha, can explain the return deeper than Fama-French 3 factors and Carhart 4 factors. Then I construct model consisting of Carhart 4 factors and adding in all combination of sk, ku and pr. For adding each factor combinations, GRS test shown t-stat are all lower than Carhart 4 factors model as well as constant or intercept which is all reduced with the adjusted R squared higher than Carhart 4 factors. Therefore, this means Carhart 4 factors model adding lottery factors can explains return more because of the higher adjusted R squared and lower t-stat value illustrated. However, from correlation of each factors as shown in Table 5, sk and ku are in highly correlated. Hence, I utilize another checking method to evaluate whether the factors adding in the model are effective or not.

To evaluate the effectiveness of the model, I use spanning regressions of each factors on remaining factors after as results shown in Table 6. Similar to coefficient concept to check relevance of each factors, the factors should not be relevant or should not be a linear combination of other factors. In regression side, constant should remain significantly different from 0 so that can imply it cannot be explained completely by the rest factors. The factor pr is not spannable as result shown in Table 6 because after regressed with Carhart 4 factors it remains constant significantly away from 0 as well as when regressed with sk and ku. But when regressed sk or ku with Carhart 4 factors, constant are not significantly different from zero. This means they can be explained by other factor which is smb whose coefficients are significantly different from zero. The factors sk and ku are spanned by smb, however, sk is still substantial for portfolio 5 because it is significantly impact. The lottery factor should be useful is pr which is not spanned by the others despite its result that is insignificant, but ku can be neglected because it is not significant and it is spanned. The lottery factors those are high skewness, high kurtosis and low price adding to Carhart 4 factors nearly explain the stock return from great result in GRS test. But from regression result, they are not simultaneously significant in portfolio 5 which reflect that they cannot explain the return. However, kurtosis is not a substantial moment compared to skewness in Thai stocks market. I would like to propose that low price and high skewness are meaningful enough to be lottery stocks. By this concept, this highest volatile portfolio is a kind of lottery stock which significantly has high skewness character but not completely because it is significantly not that cheap.

Table 4a **Regression result in each volatility sorted groups in Fama French 3 factors model**

	FF 3 Factors				
Independent Variable	1	2	3	4	5
mrp	0.510***	0.909***	0.975***	1.167***	1.281***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
smb	0.252***	0.121**	0.211***	0.479***	0.676***
	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)
hml	0.134**	0.0884**	0.171***	0.346***	0.471***
	(0.002)	(0.008)	(0.000)	(0.000)	(0.000)
umd					
sk					
ku					
pr					
Alpha	0.854***	0.335*	0.384	0.305	0.265
	(0.000)	(0.044)	(0.053)	(0.220)	(0.339)
Observations	204	204	204	204	204
Adjusted R-squared	0.482	0.861	0.822	0.784	0.766

noted: p-values in parentheses "* p<0.05   ** p<0.01 *** p<0.001". Denoted 1-5 mean portfolio 1-5 sorting by past 12 months volatility. Portfolio 1 is the lowest volatile portfolio and portfolio 5 is the highest volatile portfolio. The dependent variable is monthly total return between 2003 – 2019 of SET listed and delisted stocks. Independent variables are factor constructed as the same method indicated in Methodology section.

Table 4b **Regression result in each volatility sorted groups in Carhart 4 factors model**

	Carhart 4 Factors				
Independent Variable	1	2	3	4	5
mrp	0.519***	0.909***	0.983***	1.183***	1.295***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
smb	0.174**	0.125**	0.133*	0.322***	0.543***
	(0.004)	(0.009)	(0.018)	(0.000)	(0.000)
hml	0.0628	0.0921*	0.100*	0.203***	0.351***
	(0.189)	(0.018)	(0.027)	(0.000)	(0.000)
umd	-0.0452**	0.00229	-0.0450**	-0.0909***	-0.0764***
	(0.004)	(0.853)	(0.002)	(0.000)	(0.000)
sk					
ku					
pr					
Alpha	0.808***	0.337*	0.338	0.211	0.186
	(0.000)	(0.044)	(0.083)	(0.367)	(0.489)
Observations	204	204	204	204	204
Adjusted R-squared	0.501	0.861	0.830	0.809	0.780

noted: p-values in parentheses "* p<0.05 ** p<0.01 *** p<0.001". Denoted 1-5 mean portfolio 1-5 sorting by past 12 months volatility. Portfolio 1 is the lowest volatile portfolio and portfolio 5 is the highest volatile portfolio. The dependent variable is monthly total return between 2003 – 2019 of SET listed and delisted stocks. Independent variables are factor constructed as the same method indicated in Methodology section.

Table 4c **Regression result in each volatility sorted groups in Carhart 4 factors and Lottery 3 factors model**

	Carhart 4 Factors and Lottery 3 Factors				
Independent Variable	1	2	3	4	5
mrp	0.519***	0.908***	0.983***	1.183***	1.302***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
smb	0.170**	0.123*	0.140*	0.304***	0.467***
	(0.006)	(0.011)	(0.015)	(0.000)	(0.000)
hml	0.0638	0.0842*	0.103*	0.202***	0.351***
	(0.193)	(0.029)	(0.026)	(0.000)	(0.000)
umd	-0.0457**	0.00579	-0.0450**	-0.0909***	-0.0667***
	(0.006)	(0.651)	(0.004)	(0.000)	(0.001)
sk	0.0683	-0.240**	-0.0191	0.149	0.344**
	(0.461)	(0.001)	(0.827)	(0.154)	(0.003)
ku	-0.0371	0.224**	-0.0398	-0.00972	0.203
	(0.730)	(0.008)	(0.694)	(0.936)	(0.123)
pr	-0.00648	0.0273	-0.00649	-0.0118	-0.0714
	(0.870)	(0.382)	(0.862)	(0.792)	(0.142)
Alpha	0.811***	0.312	0.352	0.209	0.221
	(0.000)	(0.064)	(0.082)	(0.388)	(0.398)
Observations	204	204	204	204	204
Adjusted R-squared	0.495	0.867	0.828	0.809	0.806

noted: p-values in parentheses "* p<0.05 ** p<0.01 *** p<0.001". Denoted 1-5 mean portfolio 1-5 sorting by past 12 months volatility. Portfolio 1 is the lowest volatile portfolio and portfolio 5 is the highest volatile portfolio. The dependent variable is monthly total return between 2003 – 2019 of SET listed and delisted stocks. Independent variables are factor constructed as the same method indicated in Methodology section.

Table 4d **Regression result in each volatility sorted groups in Carhart 4 factors model adding sk factor**

	Carhart 4 Factors adding sk factors				
Independent Variable	1	2	3	4	5
mrp	0.518***	0.910***	0.983***	1.182***	1.292***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
smb	0.168**	0.140**	0.138*	0.304***	0.489***
	(0.006)	(0.004)	(0.015)	(0.000)	(0.000)
hml	0.0615	0.0952*	0.101*	0.200***	0.340***
	(0.199)	(0.013)	(0.026)	(0.000)	(0.000)
umd	-0.0455**	0.00319	-0.0447**	-0.0919***	-0.0796***
	(0.003)	(0.795)	(0.002)	(0.000)	(0.000)
sk	0.0498	-0.127*	-0.0389	0.145	0.455***
	(0.499)	(0.032)	(0.575)	(0.081)	(0.000)
ku					
pr					
Alpha	0.801***	0.353*	0.343	0.192	0.128
	(0.000)	(0.033)	(0.079)	(0.409)	(0.614)
Observations	204	204	204	204	204
Adjusted R-squared	0.499	0.863	0.829	0.811	0.804

noted: p-values in parentheses "* p<0.05 ** p<0.01 *** p<0.001". Denoted 1-5 mean portfolio 1-5 sorting by past 12 months volatility. Portfolio 1 is the lowest volatile portfolio and portfolio 5 is the highest volatile portfolio. The dependent variable is monthly total return between 2003 – 2019 of SET listed and delisted stocks. Independent variables are factor constructed as the same method indicated in Methodology section.

Table 4e **Regression result in each volatility sorted groups in Carhart 4 factors model adding ku factor**

	Carhart 4 Factors adding ku factors				
Independent Variable	1	2	3	4	5
mrp	0.519***	0.909***	0.982***	1.183***	1.297***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
smb	0.172**	0.116*	0.141*	0.308***	0.479***
	(0.005)	(0.018)	(0.014)	(0.000)	(0.000)
hml	0.0624	0.0900*	0.102*	0.200***	0.336***
	(0.194)	(0.021)	(0.025)	(0.000)	(0.000)
umd	-0.0450**	0.00354	-0.0461**	-0.0889***	-0.0670***
	(0.004)	(0.777)	(0.002)	(0.000)	(0.001)
sk					
ku	0.0102	0.0584	-0.0533	0.0936	0.439***
	(0.906)	(0.398)	(0.509)	(0.336)	(0.000)
pr					
Alpha	0.807***	0.332*	0.342	0.203	0.149
	(0.000)	(0.047)	(0.079)	(0.386)	(0.565)
Observations	204	204	204	204	204
Adjusted R-squared	0.498	0.860	0.829	0.809	0.796

noted: p-values in parentheses "* p<0.05 ** p<0.01 *** p<0.001". Denoted 1-5 mean portfolio 1-5 sorting by past 12 months volatility. Portfolio 1 is the lowest volatile portfolio and portfolio 5 is the highest volatile portfolio. The dependent variable is monthly total return between 2003 – 2019 of SET listed and delisted stocks. Independent variables are factor constructed as the same method indicated in Methodology section.

Table 4f **Regression result in each volatility sorted groups in Carhart 4 factors model adding pr factor**

	Carhart 4 Factors adding pr factors				
Independent Variable	1	2	3	4	5
mrp	0.520***	0.905***	0.983***	1.185***	1.305***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
smb	0.173**	0.128**	0.132*	0.320***	0.537***
	(0.004)	(0.008)	(0.019)	(0.000)	(0.000)
hml	0.0646	0.0844*	0.101*	0.207***	0.368***
	(0.184)	(0.032)	(0.028)	(0.000)	(0.000)
umd	-0.0442**	-0.00161	-0.0443**	-0.0891***	-0.0677**
	(0.006)	(0.901)	(0.004)	(0.000)	(0.001)
sk					
ku					
pr	-0.00866	0.0356	-0.00626	-0.0161	-0.0795
	(0.826)	(0.263)	(0.866)	(0.720)	(0.123)
Alpha	0.819***	0.290	0.346	0.232	0.293
	(0.000)	(0.092)	(0.086)	(0.337)	(0.291)
Observations	204	204	204	204	204
Adjusted R-squared	0.498	0.861	0.829	0.808	0.782

noted: p-values in parentheses "* p<0.05 ** p<0.01 *** p<0.001". Denoted 1-5 mean portfolio 1-5 sorting by past 12 months volatility. Portfolio 1 is the lowest volatile portfolio and portfolio 5 is the highest volatile portfolio. The dependent variable is monthly total return between 2003 – 2019 of SET listed and delisted stocks. Independent variables are factor constructed as the same method indicated in Methodology section.

Table 4g **Regression result in each volatility sorted groups in Carhart 4 factors model adding sk, ku factor**s

	Carhart 4 Factors adding sk, ku factors				
Independent Variable	1	2	3	4	5
mrp	0.518***	0.912***	0.983***	1.182***	1.293***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
smb	0.171**	0.121*	0.141*	0.305***	0.473***
	(0.005)	(0.012)	(0.014)	(0.000)	(0.000)
hml	0.0624	0.0900*	0.102*	0.200***	0.336***
	(0.194)	(0.018)	(0.025)	(0.000)	(0.000)
umd	-0.0465**	0.00890	-0.0458**	-0.0922***	-0.0748***
	(0.003)	(0.469)	(0.002)	(0.000)	(0.000)
sk	0.0694	-0.244***	-0.0179	0.151	0.357**
	(0.451)	(0.001)	(0.836)	(0.146)	(0.002)
ku	-0.0381	0.228**	-0.0409	-0.0116	0.191
	(0.722)	(0.007)	(0.685)	(0.923)	(0.146)
pr					
Alpha	0.802***	0.349*	0.343	0.193	0.125
	(0.000)	(0.032)	(0.079)	(0.410)	(0.623)
Observations	204	204	204	204	204
Adjusted R-squared	0.497	0.867	0.828	0.810	0.805

noted: p-values in parentheses "* p<0.05 ** p<0.01 *** p<0.001". Denoted 1-5 mean portfolio 1-5 sorting by past 12 months volatility. Portfolio 1 is the lowest volatile portfolio and portfolio 5 is the highest volatile portfolio. The dependent variable is monthly total return between 2003 – 2019 of SET listed and delisted stocks. Independent variables are factor constructed as the same method indicated in Methodology section.

Table 4h **Regression result in each volatility sorted groups in Carhart 4 factors model adding sk, pr factor**s

	Carhart 4 Factors adding sk, pr factors				
Independent Variable	1	2	3	4	5
mrp	0.519***	0.906***	0.984***	1.184***	1.300***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
smb	0.167**	0.142**	0.137*	0.303***	0.484***
	(0.006)	(0.003)	(0.016)	(0.000)	(0.000)
hml	0.0631	0.0882*	0.103*	0.202***	0.355***
	(0.196)	(0.024)	(0.026)	(0.000)	(0.000)
umd	-0.0447**	-0.000353	-0.0439**	-0.0906***	-0.0723***
	(0.006)	(0.978)	(0.004)	(0.000)	(0.000)
sk	0.0491	-0.124*	-0.0397	0.144	0.449***
	(0.507)	(0.037)	(0.569)	(0.085)	(0.000)
ku					
pr	-0.00729	0.0322	-0.00736	-0.0121	-0.0670
	(0.854)	(0.309)	(0.844)	(0.787)	(0.169)
Alpha	0.811***	0.310	0.353	0.209	0.219
	(0.000)	(0.070)	(0.081)	(0.387)	(0.404)
Observations	204	204	204	204	204
Adjusted R-squared	0.497	0.863	0.828	0.810	0.805

noted: p-values in parentheses "* p<0.05 ** p<0.01 *** p<0.001". Denoted 1-5 mean portfolio 1-5 sorting by past 12 months volatility. Portfolio 1 is the lowest volatile portfolio and portfolio 5 is the highest volatile portfolio. The dependent variable is monthly total return between 2003 – 2019 of SET listed and delisted stocks. Independent variables are factor constructed as the same method indicated in Methodology section.

Table 4i **Regression result in each volatility sorted groups in Carhart 4 factors model adding ku, pr factor**s

	Carhart 4 Factors adding ku, pr factors				
Independent Variable	1	2	3	4	5
mrp	0.520***	0.905***	0.983***	1.185***	1.307***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
smb	0.171**	0.120*	0.140*	0.306***	0.472***
	(0.005)	(0.015)	(0.015)	(0.000)	(0.000)
hml	0.0643	0.0825*	0.103*	0.203***	0.353***
	(0.189)	(0.037)	(0.025)	(0.000)	(0.000)
umd	-0.0440**	-0.000336	-0.0455**	-0.0870***	-0.0579**
	(0.007)	(0.979)	(0.003)	(0.000)	(0.004)
sk					
ku	0.0105	0.0572	-0.0531	0.0942	0.442***
	(0.903)	(0.408)	(0.512)	(0.334)	(0.000)
pr	-0.00874	0.0352	-0.00586	-0.0168	-0.0828
	(0.825)	(0.269)	(0.875)	(0.708)	(0.095)
Alpha	0.819***	0.285	0.350	0.225	0.260
	(0.000)	(0.098)	(0.083)	(0.352)	(0.330)
Observations	204	204	204	204	204
Adjusted R-squared	0.496	0.861	0.828	0.808	0.798

noted: p-values in parentheses "* p<0.05 ** p<0.01 *** p<0.001". Denoted 1-5 mean portfolio 1-5 sorting by past 12 months volatility. Portfolio 1 is the lowest volatile portfolio and portfolio 5 is the highest volatile portfolio. The dependent variable is monthly total return between 2003 – 2019 of SET listed and delisted stocks. Independent variables are factor constructed as the same method indicated in Methodology section.

Figure 3 **GRS tests on each combinations of factors**

Asset Pricing Model	Model Equation	GRS Test Statistic	P-Value
FF 3 Factors	$R_{i,t} = \propto_{1,t} + B_i RP_{i,t} + B_2 SMB_{i,t} + B_3 HML_{i,t}$	4.698	0.000448
Carhart 4 Factors	$R_{i,t} = \propto_{1,t} + B_i RP_{i,t} + B_2 SMB_{i,t} + B_3 HML_{i,t} + B_4 MOM_{i,t}$	4.452	0.000729
Carhart 4 Factors including			
- Lottery 3 Factors (sk ku and pr)	$R_{i,t} = \propto_{1,t} + B_i RP_{i,t} + B_2 SMB_{i,t} + B_3 HML_{i,t} + B_4 MOM_{i,t} + B_5 SK_{i,t} + B_6 KU_{i,t} + B_7 PR_{i,t}$	4.080	0.001526
- sk	$R_{i,t} = \propto_{1,t} + B_i RP_{i,t} + B_2 SMB_{i,t} + B_3 HML_{i,t} + B_4 MOM_{i,t} + B_5 SK_{i,t}$	4.444	0.000743
- ku	$R_{i,t} = \propto_{1,t} + B_i RP_{i,t} + B_2 SMB_{i,t} + B_3 HML_{i,t} + B_4 MOM_{i,t} + B_6 KU_{i,t}$	4.400	0.000811
- pr	$R_{i,t} = \propto_{1,t} + B_i RP_{i,t} + B_2 SMB_{i,t} + B_3 HML_{i,t} + B_4 MOM_{i,t} + B_7 PR_{i,t}$	4.138	0.001356
- sk and ku	$R_{i,t} = \propto_{1,t} + B_i RP_{i,t} + B_2 SMB_{i,t} + B_3 HML_{i,t} + B_4 MOM_{i,t} + B_5 SK_{i,t} + B_6 KU_{i,t}$	4.418	0.000784
- sk and pr	$R_{i,t} = \propto_{1,t} + B_i RP_{i,t} + B_2 SMB_{i,t} + B_3 HML_{i,t} + B_4 MOM_{i,t} + B_5 SK_{i,t} + B_7 PR_{i,t}$	4.086	0.001506
- ku and pr	$R_{i,t} = \propto_{1,t} + B_i RP_{i,t} + B_2 SMB_{i,t} + B_3 HML_{i,t} + B_4 MOM_{i,t} + B_6 KU_{i,t} + B_7 PR_{i,t}$	4.086	0.001505

noted: Denoted 1-5 mean portfolio 1-5 sorting by past 12 months volatility. Portfolio 1 is the lowest volatile portfolio and portfolio 5 is the highest volatile portfolio. The dependent variable is monthly total return between 2003 – 2019 of SET listed and delisted stocks. Independent variables are factor constructed as the same method indicated in Methodology section.

Table 5 **Correlations between each factors**

	mrp	smb	hml	umd	sk	ku	pr
mrp	1.0000						
smb	-0.4655	1.0000					
hml	-0.1392	-0.4909	1.0000				
umd	0.4202	-0.3135	-0.3226	1.0000			
sk	-0.0847	0.1885	-0.0757	-0.0432	1.0000		
ku	-0.2325	0.3269	-0.0211	-0.2763	0.6033	1.0000	
pr	0.2873	-0.3686	0.1547	0.3320	-0.1051	-0.1416	1.0000

CONCLUSION

Theoretically high risk assets generate high return. However, portfolio with the highest risk stocks produced the lowest return compared other portfolios in many empirical researches. This special project provides historical data of listed and delisted stocks in SET from 2003 to 2019 which were examined whether high risk low return anomaly exists or not and what reasons supported. I collected total return, price, market value and book-to-market value of SET stocks between 2002-2019 from Thomson Reuters Datastream software. Then, I sorted stocks into 5 portfolios by their volatility or SD value which is monthly balanced. The highest volatility portfolio (portfolio 5) has the lowest return as Table 1 shown. I observed skewness(sk), kurtosis(ku) and price(pr) and found it may have lottery characteristic because portfolio 5 has the lowest price and is among the highest skewness portfolios. Therefore, this special project aims to find whether the highest volatility portfolio stocks have lottery characteristic or not. The main hypothesis of this project is that they are lottery stocks; very volatile which means high SD with low price, high skewness and high kurtosis characteristic.

The first hypothesis is the lottery factors significantly effect to stock return in average to initiate the lottery characteristic assumption. The result was shown that they are not significantly impact even at 10% significant confidence except for price factor. However, this can imply that the lottery factors have not been priced for return meanwhile the rest factors which is Carhart 4 factors significantly effect but still cannot explain return theoretically completely because constant term or alpha is still not zero. This means there are unrevealed factors those can be added to in order to price the return.

The second hypothesis is skewness, kurtosis and price factors can explain the return of the highest volatile portfolio. The result of regression cooperating with Carhart 4 factors was shown that skewness is significantly impact but kurtosis and price are not. The adjusted R squared is better compared to modeled with Carhart 4 factors alone up to 81% from 78%. The constant terms remain not significantly different from zero for both models even on Fama-French 3 factors model. GRS tests are implemented to clarify whether the model with lottery factors can explain return better or not. Statistical method demonstrates t-stat is less than Carhart 4 factors which means it reduces the constant down implying lottery factors can explain better than Carhart 4 factors model along with better adjusted R squared but the factor significantly effect is only sk, not all lottery factors do. This is likely to be concluded as Jacqmin, Remy (2015) which skewness and kurtosis value have no effect to return in order to explain low anomaly when adding them to Carhart 4 factors model. But the different is this special project found relation between skewness factor and return and also found weak relation between price factor and return. In conclusion, portfolio 5 is not but nearly to be lottery stocks as it has the positive coefficient of skewness factor significantly and the price is on the same way to be lottery stocks by generating negative price factor but it has not enough t-stat value to be significant.

After calculating cumulative return between 2003 to 2019, highest volatile portfolio did generate lower return than lowest volatile portfolio. And there are some periods such as between 2004 to 2019 which low volatility anomaly existed and GRS test shown Carhart 4 factors model incorporating with skewness factors explains return better as shown in Figure 4. The anomaly effect is likely to be persist over time but the high risk low return anomaly still does not reveal the reason behind it or show up the impacting factors as this paper test for lottery factors found no strong relevance of them and the return. But there is evidence that high risk stocks in Thai stocks market has partially lottery character because skewness factor can explain their return. Further researches might focus on factors concerning price which this special project found price factor significantly effect in Fama-MacBeth regression and price factor is not spanned by other factors, different from skewness and kurtosis which are spanned each other. Furthermore, skewness and kurtosis are even can be explained by smb as regression results in Table 6. However, skewness can still be implied to be substantial for future research because it is significantly impact to return of the high risk stocks.

Table 6 **Span testing for lottery factors**

	Dependent Variable					
Independent Variable	pr	sk	ku	pr	sk	ku
mrp	0.126	0.00642	-0.00415			
	(0.071)	(0.863)	(0.897)			
smb	-0.0856	0.119*	0.146**			
	(0.422)	(0.039)	(0.003)			
hml	0.215*	0.0248	0.0354			
	(0.013)	(0.591)	(0.372)			
umd	0.109***	0.00706	-0.0214			
	(0.000)	(0.633)	(0.094)			
sk				-0.0640		0.543***
				(0.724)		(0.000)
ku				-0.279	0.658***	
				(0.162)	(0.000)	
pr					-0.00970	-0.0349
					(0.724)	(0.162)
Constant	1.339***	0.127	0.0843	1.284***	0.164	-0.0594
	(0.000)	(0.522)	(0.622)	(0.001)	(0.267)	(0.658)
Observations	204	204	204	204	204	204
Adjusted R-squared	0.200	0.018	0.128	0.011	0.358	0.364

noted: p-values in parentheses "* p<0.05 ** p<0.01 *** p<0.001". All independent variable are data constructed between 2003 – 2019 of SET listed and delisted stocks. The factors constructed as the same method indicated in Methodology section.

Figure 4 **GRS test of each regression models on return in period 2004-2019**

Asset Pricing Model	Model Equation	GRS Test Statistic	P-Value
FF 3 Factors	$R_{i,t} = \propto_{1,t} + B_i RP_{i,t} + B_2 SMB_{i,t} + B_3 HML_{i,t}$	8.012	0.00000073
Carhart 4 Factors	$R_{i,t} = \propto_{1,t} + B_i RP_{i,t} + B_2 SMB_{i,t} + B_3 HML_{i,t} + B_4 MOM_{i,t}$	8.153	0.00000057
Carhart 4 Factors including			
- Lottery 3 Factors (sk ku and pr)	$R_{i,t} = \propto_{1,t} + B_i RP_{i,t} + B_2 SMB_{i,t} + B_3 HML_{i,t} + B_4 MOM_{i,t} + B_5 SK_{i,t} + B_6 KU_{i,t} + B_7 PR_{i,t}$	8.855	0.00000015
- sk	$R_{i,t} = \propto_{1,t} + B_i RP_{i,t} + B_2 SMB_{i,t} + B_3 HML_{i,t} + B_4 MOM_{i,t} + B_5 SK_{i,t}$	7.674	0.00000143

noted: Denoted 1-5 mean portfolio 1-5 sorting by past 12 months volatility. Portfolio 1 is the lowest volatile portfolio and portfolio 5 is the highest volatile portfolio. The dependent variable is monthly total return between 2004 – 2019 of SET listed and delisted stocks. Independent variables are factor constructed as the same method indicated in Methodology section.

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