LOW BETA PORTFOLIOS AND STATISTICS OF CONSTITUENT STOCKS: EVIDENCE FROM THE STOCK EXCHANGE OF THAILAND

BY

MR. SUNCHAI ANUJARAWAT

AN INDEPENDENT STUDY SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE PROGRAM IN FINANCE (INTERNATIONAL PROGRAM)
FACULTY OF COMMERCE AND ACCOUNTANCY
THAMMASAT UNIVERSITY
ACADEMIC YEAR 2016

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ENTITLED

LOW BETA PORTFOLIOS AND STATISTICS OF CONSTITUENT STOCKS:
EVIDENCE FROM THE STOCK EXCHANGE OF THAILAND

was approved as partial fulfillment of the requirements for
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Independent Study Title	LOW BETA PORTFOLIOS AND STATISTICS OF CONSTITUENT STOCKS: EVIDENCE FROM THE STOCK EXCHANGE OF THAILAND
Author	Mr. Sunchai Anujarawat
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ABSTRACT

According to CAPM, higher expected return of any security only come with higher risk measured by its market beta, where market portfolio (β=1) has highest attainable Sharpe ratio among all risky-asset portfolio. Therefore, low-beta stocks (β<1) are predicted to generate lower rate of returns and to have no greater Sharpe ratio than the market portfolio. This study examines the existence of low-beta anomaly of stocks listed Thai stock market (SET and SET100) with the data covering from January 2006 to December 2015. Empirically, the prediction regarding to CAPM is not meet and the low-beta anomaly exists in Thai market where the low-beta portfolios achieve higher both rate of return and Sharpe ratio than the market portfolio.

This study also performs multiple regression extended from the standard CAPM to investigate effect of skewness and kurtosis on the excess returns of the low-beta portfolios since CAPM assume normal distribution and investors consider only mean and variance. The test results show significant effect of skewness and kurtosis only on the low-beta portfolio in SET but insignificant for that in SET100. The smaller numbers of observations and lower normality of stocks in SET100 leading to lower power of the test which could be possible explanations for difference in the test results.

Keywords: Low beta portfolio, Low beta anomaly, CAPM, Skewness, Kurtosis

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Mr. Sunchai Anujarawat

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CHAPTER 1
INTRODUCTION

In an investment world, most investors might be familiar with phrase 'high risks, high returns' where beta is used as one of important tools for measuring volatility which presents systematic risk of a security or a portfolio with respect to stock market. According to well-known Capital Asset Pricing Model (CAPM) developed by Treynor, Sharpe, and Linter in 1960s, returns of any assets or any portfolios are linearly related to its beta (market portfolio has its beta equal to one). In expected returns – beta space, the expected returns of any assets should lie on the Securities Market Line (SML) which its slope is the market excess returns. Hence, this implies that the higher beta, the higher expected rates of returns. In other word, any low-beta securities ($\beta<1$) will be predicted to earn lower rates of returns than the market portfolio ($\beta=1$) and high-beta securities ($\beta>1$).

In addition, CAPM suggest that all investors can improve their risk-reward tradeoff by investing in combination between the market portfolio and risk-free asset, where the proportion invested is determined by their risk preference. For example, given a low-beta portfolio which fully invest in risky asses with beta portfolio equal to 0.5, the investor can create a new portfolio by short selling the low-beta portfolio and investing half of proceeds in the market portfolio and lending the rest at risk-free rate. This new portfolio, called the de-levered market portfolio, will provide the investor the same expected rates of returns and has same beta of 0.5 as the original low-beta portfolio but now with lower standard deviation.

In expected rates of returns – standard deviation space, the market portfolio is found at a point on Capital Market Line (CML) which is tangent to the efficient frontier of risky assets. The slope of CML is equal to market Sharpe ratio which measure excess returns per unit of risks. Therefore, the market portfolio has the highest attainable Sharpe ratio and the de-levered market portfolio will also have the same Sharpe ratio as the market portfolio and will be a good nature benchmark for the low-beta portfolios.

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Therefore, based on CAPM, the low-beta portfolio is expected to have Sharpe ratio and earn returns no greater than the market portfolio and its de-levered market portfolio. However, there is a number of studies which empirically show that the low-beta portfolios have outperformed the market portfolio and their de-levered portfolio over long periods in term of both absolute returns and risk-adjusted returns. This phenomenon is commonly known as "The low-beta Anomaly" and first extensively documented in the works of Black, Jensen, and Scholes (1972) and Black (1972).

In addition to the studies of Black, Jensen, and Scholes (1972) and Black (1972), the studies by Fama and French (1992), Black (1993), Baker et al. (2011, 2012, and 2013), Ang et al. (2006 and 2009), Scherer (2011), Blitz et al. (2007 and 2013), Frazzini et al. (2014), and Bianchi (2014) also provide the empirical evidences of the low-beta anomaly consistent with the previous studies that the low-beta portfolios tend to outperform the market portfolio and high-beta portfolios over the long periods. For the explanation of the low-beta anomaly, there are various explanations but there are still no conclusive explanations for the existence of the low-beta anomaly. the possible explanations of the low-beta anomaly can be classified into three main types as;

Firstly, the behavioral explanation by Baker et al. (2001) which stated that three behavioral biases (preference for lotteries, representativeness, and overconfidence) causes higher demand, higher prices, and, consequently, lower expected returns for high-beta stocks. Secondly, the leverage restriction by Frazzini et al. (2014) which explains that since investors cannot use leverage, they tend to overweight high-beta securities which are associated with lower alpha. Lastly, the risk-based explanation by Bianchi (2014) which stated that the low-beta stocks are compensated extra returns by bearing extra risks in term or kurtosis risk.

Since traditional CAPM considers only the first two moments of the returns distribution which are mean and variance (standard deviation), there are numbers of researchers extend the traditional CAPM model by taking into account the third moment (Skewness) and the fourth moment (kurtosis) of the return distribution. Kraus and Litzenberger (1976) study the impact of skewness on asset pricing of NYSE (New York Stock Exchange) stocks during periods 1926 to 1935 by adding skewness as additional variable to the traditional CAPM and conclude that investors have preference

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for positive skewness, that higher expected returns are required when market portfolio has negative skewness, with a significantly negative relationship between returns and skewness. Fand and Lai (1997) perform a fourth-moment capital asset pricing model which add kurtosis as another to estimate risk premium for systematic variance, systematic skewness, and systematic kurtosis on stocks in NYSE from 1969 to 1988. They also find the negative relationship between skewness and asset returns. They further conclude that for bearing systematic kurtosis, investors require higher excess rates of returns.

This study is motivated by an interesting nature of the low-beta anomaly which deviate from the traditional CAPM. This leads to main objectives of the study which are, firstly, to detect whether the low-beta anomaly exists in Thailand and, secondly, to analyze impacts of skewness and kurtosis on returns of low-beta portfolios of stocks listed in The Stock Exchange of Thailand (SET) and SET100 covering periods of January 2006 to December 2015.

For research methodologies in this study, there are two main parts. First, beta estimation and low-beta portfolios construction to detect existence of the low-beta anomaly in Thailand. Second, multiple regressions are performed which extend traditional CAPM by adding skewness or kurtosis as another independent variable to reveal effect of skewness and kurtosis on excess returns of low-beta portfolios. The empirical results from this study find that there exists the low-beta anomaly in Thailand. In addition, there are significant effect of skewness and kurtosis only on the excess returns of low-beta portfolio in SET but find insignificant effect in SET100.

This study will provide insights and expand the financial literature regarding the low-beta anomaly in Thailand to the readers and will be useful for investors who aim to take advantage of the anomaly to create an investment strategy to outperform the market with knowledge of higher moments of return distribution that impact the returns of low-beta portfolios.

The remainder of this study consists of the following section: literature reviews and conceptual framework section reviews insights and literature regarding to the low-beta anomaly, research methodology section details about data selection, low-beta portfolio construction and statistics of return-distribution analysis, results section, and, lastly, conclusion, discussions, and recommendation section.

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CHAPTER 2
LITERATURE REVIEW AND CONCEPTUAL FRAMWORK

2.1 The Low-Beta Anomaly and its Explanations

The low-beta anomaly was first extensively documented in literature dating at least back to Black, Jensen, and Scholes (1972) and Black (1972). The CAPM implies the relation between excess returns on any risky assets and their systematic risk which measured by, β, is:

$$\mathrm{E}[\mathrm{r_i}] - \mathrm{r_f} = \beta_\mathrm{i}(\mathrm{E}[\mathrm{r_m}] - \mathrm{r_f}) \tag{1}$$

where $\mathrm{r_f}$ is the risk-free rate, $\mathrm{r_m}$ is the market portfolio's returns and

$$\beta_\mathrm{i} = \mathrm{Cov}(\mathrm{r_i}, \mathrm{r_m})/\mathrm{Var}(\mathrm{r_m}) \tag{2}$$

Hence, equation (1) implies that alpha of any risky assets, α_i, should be zero:

$$\alpha_i = (\mathrm{E}[\mathrm{r_i}] - \mathrm{r_f}) - \beta_\mathrm{i}(\mathrm{E}[\mathrm{r_m}] - \mathrm{r_f}) \tag{3}$$

However, Black, Jensen, and Scholes showed empirical evidence, based on U.S. stock data from 1926 to1966, that the stock's alphas actually depend on their beta which high-beta stocks tend to generate negative alphas while low-beta stocks tend to generate positive alphas. They introduced the two factor models in which add the beta factor to the traditional CAPM, single factor model:

$$\mathrm{E}[\mathrm{r_i}] = \beta_\mathrm{i}(\mathrm{E}[\mathrm{r_m}] - \mathrm{r_f}) + (1 - \beta_\mathrm{i})\mathrm{E}[\mathrm{r_z}] \tag{4}$$

where $\mathrm{E}[\mathrm{r_z}]$ is the expected returns on the beta factor which has a covariance of zero with the market returns, $\mathrm{r_m}$. Their result showed the significant existence of the beta factor which is significant positive for low-beta stocks and significant negative for high-beta stocks. Black (1972) gave a possible explanation might be an assumption, which state that investors can short or long any assets, and can borrow or lend with unlimited

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amount at risk-free rate, did not hold and he showed the derivation of borrowing restrictions were consistent with the empirical results in Black, Jensen, and Scholes.

Later, Fama and French (1992) introduced three factor models, including market beta factor, size factor, and value factor, to study the variation of average stock's returns in NYSE, AMEX, and NASDAQ between 1963 to1990. The results showed that market beta factor did not help explain the variation in stock's returns while they found significantly explanatory power in size and value factor. In addition to, Fama-French three factor models, Carhart (1997) add another factor which is a momentum factor to the three factor models and found that the momentum factor help better explain the variation of stock returns for mutual funds data covering the periods from 1962 to 1993.

Despite the fact that size, value, and momentum factors were invented to capture the variation of the stock returns, however, those factors cannot be able to identify the source of risks represented by each factor. More recently, some researchers try to explain the low-beta anomaly in different ways and can be classified into three groups following by:

Firstly, the leverage restriction explanation introduced by Black (1972 and 1993), and Frazzini et al. (2014). One of the assumption of CAMP is that investors are freely to take short and long position in any asset and at any size with unlimited borrowing and lending at risk-free rate. However, this assumption does not hold in the real world. Black (1972 and 1993) explain that borrowing restriction including margin constraint, bankruptcy and tax rules could cause higher expected returns for low-beta stocks than CAPM prediction. Frazzini et al. (2014) introduced betting-against-beta factor to capture the low-beta anomaly with the explanation that margin and leverage constraint make investor demand high-beta stocks which associated to lower alpha.

Secondly, the behavioral biases explanation introduced by Baker et al. (2011 and 2012). According to the difficulty of direct test (Baker et al., 2011), they instead provide evidence and explanation that investors are irrational and the low-beta anomaly is caused by three behavioral biases which are preference for lotteries bias, representativeness bias and overconfidence bias (see Baker et al., 2011). As a result, these behavioral biases cause higher demand, higher prices, and, consequently, lower expected returns for high-beta stocks and vice versa for low-beta stocks.

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Lastly, the risk-based explanation introduced by Bianchi (2014). Since, in efficient market, the higher returns can be earned only by bearing higher risk, hence, there must be some missing risks that can explain the low-beta anomaly. Bianchi apply Quantile regression with Fama-Mecbeth two-step procedure and simulation to study U.S. data covering the period between 1990 and 2011. According to his results, he concludes that the low-beta stocks are actually riskier than high-beta stocks and earn extra return by bearing extra risks in the form of kurtosis risk.

The low-beta anomaly does not exist only in the U.S. but also occurs in international stock market. Baker et al. (2013) and Frazzini et al. (2014) use the data from international stock market in developed countries and find that the low-beta stocks have higher risk-adjusted returns than high-beta stocks. Blitz (2007) find similar evidence in Europe and Japan in the periods from 1986 to 2006.

2.2 Higher moments of distribution

According to Capital Asset Pricing Model (CAPM), one of its assumptions is that investors consider only mean and variance (standard deviation) of the returns distribution which is normally distributed. However, asset-return distributions do not empirically always follow normal distribution and higher moments (skewness and kurtosis) have effect on asset pricing, i.e. preference for higher moments are important for security pricing. In addition, ignoring effect of higher moments in term of skewness risk and kurtosis risk may lead a model to underestimate risk.

Skewness is the third moment of the distribution which measures asymmetry from normal distribution (skewness is zero) about its mean and can be positive or negative skewed which can be defined as:

$$Skewness(s) = \frac{E[(r_t-\mu)^3]}{\sigma^3} \tag{5}$$

where r_t is returns of any security or portfolio at time t, μ is the mean returns, and σ is the standard deviation of returns.

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Ingersoll (1975), Kraus and Litzenberger (1976), and Sears and Wei (1985) extend CAPM to investigate impact of skewness on asset pricing and find significantly negative relationship between skewness and asset returns with investor preference for positive skewness. When the distribution is negatively skewed, negative outcomes have a greater chance to occur. For positive skewness, investors can expect small negative outcomes or low extremely bad scenarios.

Kurtosis, the fourth moment of the distribution, measures degree of peak in distribution and equals three for normal distribution. Kurtosis is defined as:

$$Kurtosis(k) = \frac{E[(r_t - \mu)^4]}{\sigma^4} \tag{6}$$

where r_t is returns of any security or portfolio at time t, μ is the mean returns, and σ is the standard deviation of returns. The positive kurtosis or excess kurtosis risk is described as the situation when the model assumes normal distribution but, in fact, the results show higher kurtosis which have fatter tail than the normal distribution and implies there is higher chance of extreme value will be occur on either side of the mean.

For prior studies related to kurtosis, Fang and Lai (1997) extend the study of Kraus and Litzenberger (1976) by investigating the impact of kurtosis on asset valuation and empirically show the significant for both skewness and kurtosis risks, and conclude that investors require higher returns for bearing those risks, based on NYSE stock data from 1969 to 1988. Aggarwal et al. (1989) also find significantly persistent of skewness and kurtosis on stock returns distribution on Tokyo Stock Exchange from 1965 to 1984. Besides standard skewness and kurtosis, there are also co-skewness and co-kurtosis which measure how much two random variables change together as documented in the studies of Kraus and Litzenberger (1976), and Fang and Lai (1997), respectively, however, they are beyond the scope of this study.

Recently, Bianchi (2014) study U.S. equity from 1990 to 2011 and find significant excess kurtosis which is result in existence of the low-beta anomaly that low-beta stocks generate excess returns by bearing kurtosis risk, but find insignificant skewness.

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CHAPTER 3
RESEARCH METHODOLOGY

3.1 Data Selection

The data used in this study will cover daily and monthly stock data including adjusted-prices and market capitalizations covering periods from January 2006 to December 2015 of all stocks listed in the Stock Exchange of Thailand (SET) and SET100. In addition, the SET total return index (SETTRI) and SET100 total return index (SET100TRI) will be used as a proxy of the capital-weighted market portfolio. All data are collected from Bloomberg and Thai BMA data sources.

At the beginning of each month, one-month Thai treasury bill rates collected from Thai Bond Market Association (TBMA) database will be used as a proxy of risk-free rates.

Table 3.1 presents the summary statistics of variable used in the multiple regression (see section 3.3) to test the effect of skewness and kurtosis on the low-beta portfolio returns for both SET and SET100. Coefficient variations (CV) are also calculated to measure the extent of variability in relation to the mean which can affect the significant test of the multiple regression. The mean of the SET market kurtosis (K) of 3.6646 and skewness (S) of -0.0306 indicate more normality than SET100 as presented by the SET100 market kurtosis (Kh) of 0.7129 and skewness (Sh) of -0.1051.

Table 3.1 Summary statistic of variables in multiple regressions

	Obs	Mean	Std. Dev.	Min	Max	CV
Rm	114	0.00682	0.0647	-0.3612	0.14479	9.48
Ri	114	0.00968	0.04795	-0.2275	0.13261	4.95
K	114	3.66468	9.47193	-0.2253	356.515	2.58
S	114	-0.0306	0.59761	-1.6143	1.65045	-19.52
Rmh	114	0.00846	0.06657	-0.3172	0.17593	7.87
Rih	114	0.01097	0.05782	-0.302	0.16538	5.27
Kh	114	0.71291	1.02976	-1.3328	9.53041	1.44
Sh	114	-0.1051	0.57512	-1.9014	2.60097	-5.47

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3.2 Beta estimation and low-beta portfolio construction

To construct low-beta portfolio, first step is to estimate betas of each individual stock in both SET and SET100. Using daily stock data covering the period of January 2006 to December 2015, the betas are estimated at the end of each month using prior six months from daily data in the sample periods from June 2006 to November 2015 and standard time-series ordinary least square (OLS) regression will be performed to obtain the estimated betas as:

$$R_i = \propto_i + \beta_i R_m + \varepsilon_i \tag{7}$$

where R_i is daily excess returns $(r_i - r_f)$ of daily total returns of individual stock i over daily one-month risk-free rate, R_m is daily excess returns $(r_m - r_f)$ of total return of market portfolio (SETTRI and SET100TRI) over daily one-month risk-free rate.

Each estimation is performed for each individual stock at the end of each month based on prior six-months daily data and the estimated individual stock betas change from month to month. Next, sorting the betas of each stock from lowest to highest beta and creating capitalization-weighted low-beta portfolio[1] which contain the first tercile of the sorted stock in both SET and SET100. At the end of each month, there are two low-beta portfolios. The first low-beta portfolio consists of the first tercile sorted stock from SET and the second low-beta portfolio consists of the first tercile sorted stock from SET100.

Then, the one-month-ahead returns of the low-beta stocks will be compared to the one-month-ahead returns of the market portfolio and de-levered market portfolio which will be constructed in each month to match the capitalization-weighted low-beta portfolios. Statistical results for monthly time-series excess return of these portfolios are illustrated in table 4.1 for SET and in table 4.2 for SET100. The cumulative returns of the low-beta portfolios over the sample period from SET is presented in figure 4.1 and from SET100 is presented in figure 4.2.

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[1] The estimated betas are, then, used to estimate risk-premium or empirical quantile by using Fama-Mecbth with quantile regression for analyzing relationship between beta and cross-section of stock returns. For more details, please see appendix A.

3.3 Multiple regression analysis

The standard CAPM is a single factor model which suggest that investors consider only mean and variance, i.e. the higher expected return of any asset is required for bearing higher risks which is measured by the market beta (β) as shown in equation (1). According to prior literature regarding to higher moments, skewness and kurtosis are found significant effect on asset returns besides variance from standard CAPM.

Hence, the standard CAPM is extend by adding another variable which is skewness, called three-moment CAPM, and kurtosis, called four-moment CAPM as presented in studies of Ingersoll (1975), Kraus and Litzenberger (1976), Sears and Wei (1985), Fang and Lai (1997), and Aggarwal et al. (1989) to examine impact of skewness and kurtosis on asset valuation.

In this study, multiple regression[2], which has one dependent variable and more than one independent variable, is used to investigate whether skewness and kurtosis have effect on excess returns of low-beta stocks by the following models with Prais-Winsten and Cochrane-Orcutt method used to correct for autocorrelation:

$$R_{i,t} = \alpha + b_m R_m + b_s S_t + \varepsilon_i \tag{8}$$

where:

$R_{i,t}$ is excess returns of capital-weighted low-beta portfolio from SET at month t

R_m is excess returns of market portfolio (SET total return index) at month t

S_t is skewness of market portfolio at month t calculated as shown in equation (5)

$$R_{i,t} = \alpha + b_m R_m + b_k K_t + \varepsilon_i \tag{9}$$

where:

$R_{i,t}$ is excess returns of capital-weighted low-beta portfolio from SET at month t

R_m is excess returns of market portfolio (SET total return index) at month t

K_t is kurtosis of market portfolio at month t calculated as shown in equation (6)

[2] All regression in this study is performed by STATA, a data analysis and statistical software, where the commands used and tables of regression results are displays in appendix B.

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Multiple regression from model (8) and model (9) use input data of stocks listed in SET to investigate the effect of skewness and kurtosis on excess return of capitalization-weighted low-beta stock from SET. The obtained results from the regression are b_s in model (8) which is slope coefficient for skewness variable which indicate skewness impact on returns of low-beta portfolio, and b_k in model (9) which is slope coefficient for kurtosis variable which indicate kurtosis impact on returns of low-beta portfolio. The statistical results and significant test are reported in table 4.5.

To examine the effect of higher moments on excess returns of capitalization-weighted low-beta portfolio form SET100, the multiple regression with Prais-Winsten and Cochrane-Orcutt method used to correct for autocorrelation are performed as following models:

$$Rh_{i,t} = \alpha + b_{mh}Rh_m + b_{sh}Sh_t + \varepsilon_i \tag{10}$$

where:

$Rh_{i,t}$ is excess returns of capital-weighted low-beta portfolio from SET100 at month t

Rh_m is excess returns of market portfolio (SET100 total return index) at month t

Sh_t is skewness of market portfolio at month t calculated as shown in equation (5)

$$Rh_{i,t} = \alpha + b_{mh}Rh_m + b_{kh}Kh_t + \varepsilon_i \tag{11}$$

where:

$Rh_{i,t}$ is excess returns of capital-weighted low-beta portfolio from SET100 at month t

Rh_m is excess returns of market portfolio (SET100 total return index) at month t

Kh_t is kurtosis of market portfolio at month t calculated as shown in equation (6)

The statistical results and significant test from model (10) and model (11) are reported in table 4.6.

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CHAPTER 4
EMPIRICAL RESULTS

4.1 Empirical observations

In this section, the first research objective of whether there exists low-beta anomaly in Thailand is answered by the empirical results reported in table 4.1 and table 4.2. The statistical results of the capitalization-weighted low beta portfolio formed from the first tercile of beta sorted stocks in SET is showed in table 4.1 by comparing with that of de-levered market portfolio and SET market portfolio.

Table 4.1 Statistical results: Market portfolio Vs. Low-Beta portfolio (SET)

Sample Period Jul 2006 - Dec 2015	Average Beta	Average Returns	Average Excess Returns	Excess Returns Volatility	Sharpe Ratio
Market portfolio	1	10.70%	8.19%	22.31%	0.37
Capitalization-Weighted					
Low-Beta portfolio	0.07	14.13%	11.62%	16.54%	0.70
De-levered portfolio	0.07	3.51%	1.00%	3.25%	0.31
Equal-Weighted					
Low-Beta portfolio	0.06	17.34%	14.82%	15.03%	0.99
De-levered portfolio	0.06	2.97%	0.45%	3.09%	0.15

Note. The statistical results of equal-weighted portfolios are calculated for illustration only. The main focus in this study is on capitalization-weight portfolios. For illustration purpose, returns, excess returns, volatilities, and Sharpe ratios are all computed on monthly basis and then annualized by multiplying by 12, 12, $\sqrt{12}$, and $\sqrt{12}$, respectively.

The benchmark market portfolio has average excess returns of 8.19% with volatility of 22.31%, and Sharpe ratio of 0.37. average beta over 114 months of the capitalization-weighted low beta portfolio is 0.07, the average returns, the average excess returns, the excess returns volatility, and the Sharpe ratio are 14.13%, 11.62%, 16.54%, and 0.70 respectively. The de-levered market portfolios are constructed to match capitalization-weighted low beta portfolio's beta of 0.07 and have average returns, average excess returns, excess returns volatility, and Sharpe ratio of 3.51%, 1.00%, 3.25%, and 0.31 respectively.

Table 4.2 Statistical results: Market portfolio Vs. Low-Beta portfolio (SET100)

Sample Period Jul 2006 - Dec 2015	Average Beta	Average Returns	Average Excess Returns	Excess Returns Volatility	Sharpe Ratio
Market portfolio	1	10.70%	8.19%	22.31%	0.37
Capitalization-Weighted					
Low-Beta portfolio	0.56	16.40%	13.89%	19.97%	0.70
De-levered portfolio	0.56	7.43%	4.91%	11.14%	0.44
Equal-Weighted					
Low-Beta portfolio	0.53	15.96%	13.44%	20.37%	0.66
De-levered portfolio	0.53	7.41%	4.89%	10.72%	0.46

Note. The statistical results of equal-weighted portfolios are calculated for illustration only. The main focus in this study is on capitalization-weight portfolios. For illustration purpose, returns, excess returns, volatilities, and Sharpe ratios are all computed on monthly basis and then annualized by multiplying by 12, 12, $\sqrt{12}$, and $\sqrt{12}$, respectively.

Table 4.2 reports statistical results of the low beta portfolio constructed from the first tercile of beta sorted stock in SET100 to illustrate low-beta anomaly in SET100. The capitalization-weighted low beta portfolio has the average beta over 114 months of 0.56, average returns, average excess returns, excess returns volatility, and Sharpe ratio of 16.40%, 13.89%, 19.97%, and 0.70 respectively which are all higher than that of its de-levered market portfolio.

For illustration for the existence of low-beta anomaly in Thai stock market, according to the results, in both SET and SET100, the low beta portfolios perform better than the market portfolio and its de-levered market portfolio in term of both absolute return (higher excess returns) and risk-adjusted returns (higher Sharpe ratio). According to CAPM, the higher returns are compensated by bearing higher risk, i.e. portfolio with lower risks (lower beta) should earn no greater returns than portfolio with higher risks. However, the low beta portfolio which have betas lower than the market portfolio turn out to generate higher returns. Especially, the low beta portfolio in both SET and SET100 can generate higher returns than the market with lower standard deviation. Therefore, the low-beta anomaly can be concluded to exist in Thailand.

For further illustration of low-beta anomaly, the last tercile of the sorted betas of stocks in SET and SET100 are also used to construct high-beta portfolios and their performance are compared to the low-beta portfolios and the market portfolio as

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presented in table 4.3 for SET and table 4.4 for SET100. The results still confirm the existence of the low-beta anomaly since low-beta portfolios are outperform high-beta portfolio for both SET and SET100. For low-beta portfolios, the cumulative total returns over the sample period of all 114 months are represented for SET in figure 4.1 and for SET100 in figure 4.2. Figure 4.3 and figure 4.4 illustrate the cumulative total returns of low-beta portfolios comparing to high-beta portfolios in SET and SET100.

Table 4.3 Statistical results: High-Beta Vs. Low-Beta portfolio (SET)

Sample Period Jul 2006 - Dec 2015	Average Beta	Average Returns	Average Excess Returns	Excess Returns Volatility	Sharpe Ratio
Market portfolio	1	10.70%	8.19%	22.31%	0.37
Capitalization-Weighted					
Low-Beta portfolio	0.07	14.13%	11.62%	16.54%	0.70
High-Beta portfolio	1.41	13.06%	10.54%	31.64%	0.33
Equal-Weighted					
Low-Beta portfolio	0.06	17.34%	14.82%	15.03%	0.99
High-Beta portfolio	1.45	14.88%	12.37%	31.49%	0.39

Note. The statistical results of equal-weighted portfolios are calculated for illustration only. The main focus in this study is on capitalization-weight portfolios. For illustration purpose, returns, excess returns, volatilities, and Sharpe ratios are all computed on monthly basis and then annualized by multiplying by 12, 12, $\sqrt{12}$, and $\sqrt{12}$, respectively.

Table 4.4 Statistical results: High-Beta Vs. Low-Beta portfolio (SET100)

Sample Period Jul 2006 - Dec 2015	Average Beta	Average Returns	Average Excess Returns	Excess Returns Volatility	Sharpe Ratio
Market portfolio	1	10.70%	8.19%	22.31%	0.37
Capitalization-Weighted					
Low-Beta portfolio	0.56	16.40%	13.89%	19.97%	0.70
High-Beta portfolio	1.65	13.40%	10.88%	35.57%	0.31
Equal-Weighted					
Low-Beta portfolio	0.53	15.96%	13.44%	20.37%	0.66
High-Beta portfolio	1.70	14.92%	12.41%	36.72%	0.46

Note. The statistical results of equal-weighted portfolios are calculated for illustration only. The main focus in this study is on capitalization-weight portfolios. For illustration purpose, returns, excess returns, volatilities, and Sharpe ratios are all computed on monthly basis and then annualized by multiplying by 12, 12, $\sqrt{12}$, and $\sqrt{12}$, respectively.

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Figure 4.1 Cumulative total returns of Market Portfolio Vs. Low-Beta portfolios (SET)

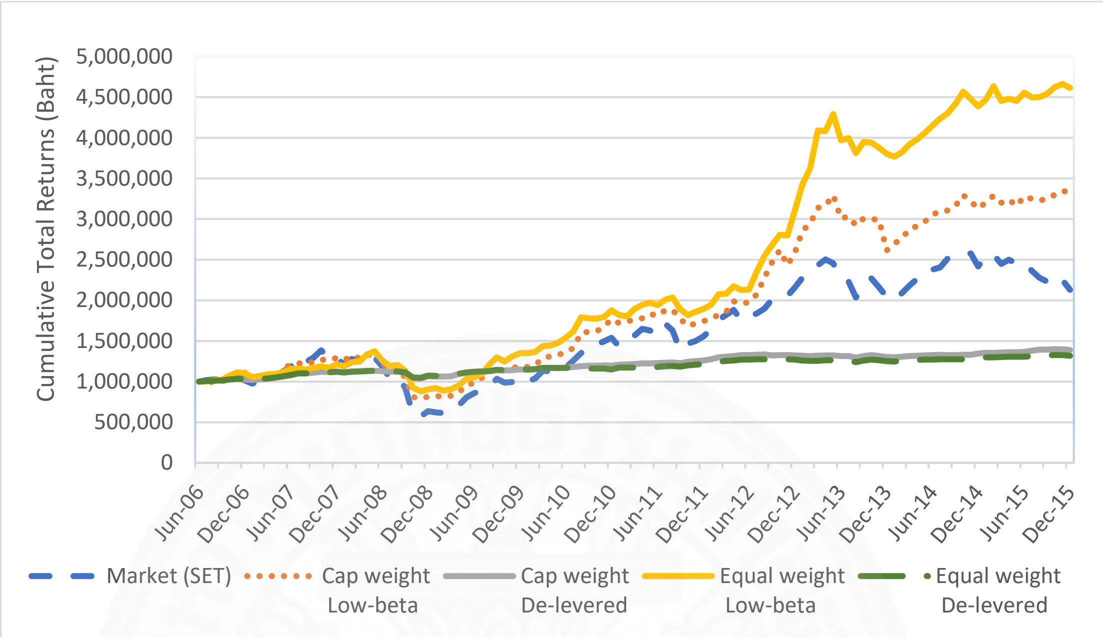


Figure 4.2 Cumulative total returns of Market Portfolio Vs. Low-Beta portfolio (SET100)

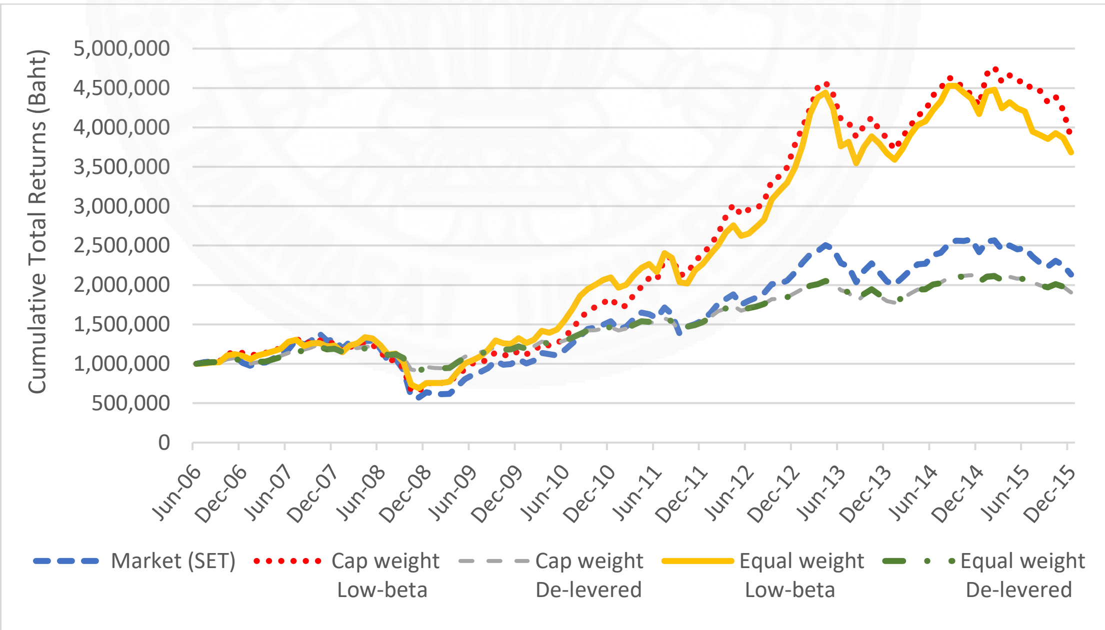


Figure 4.3 Cumulative total returns of High-Beta Vs. Low-Beta portfolios (SET)

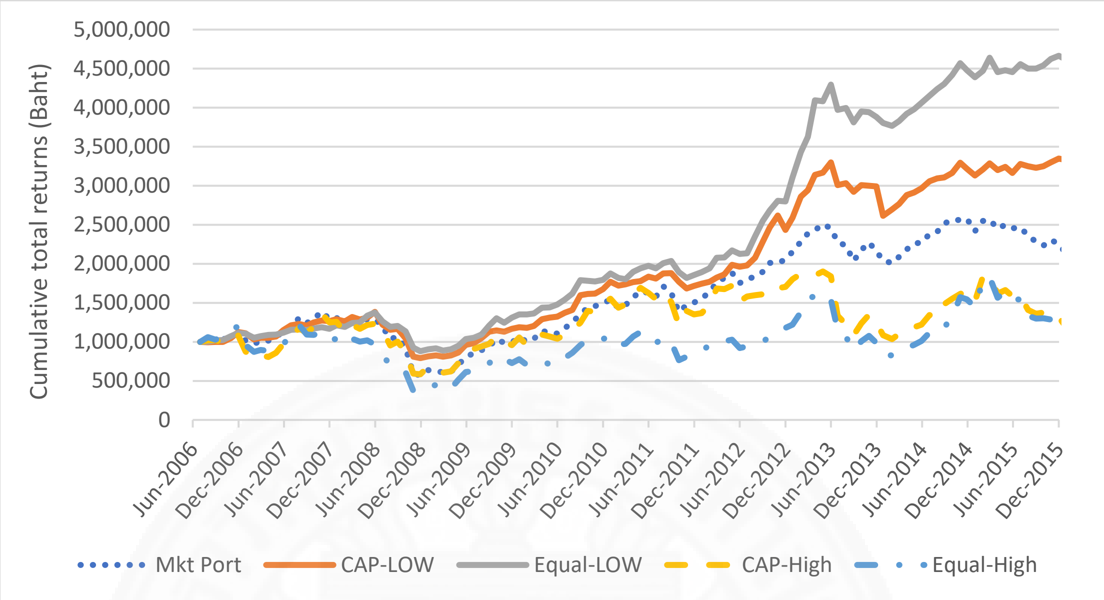
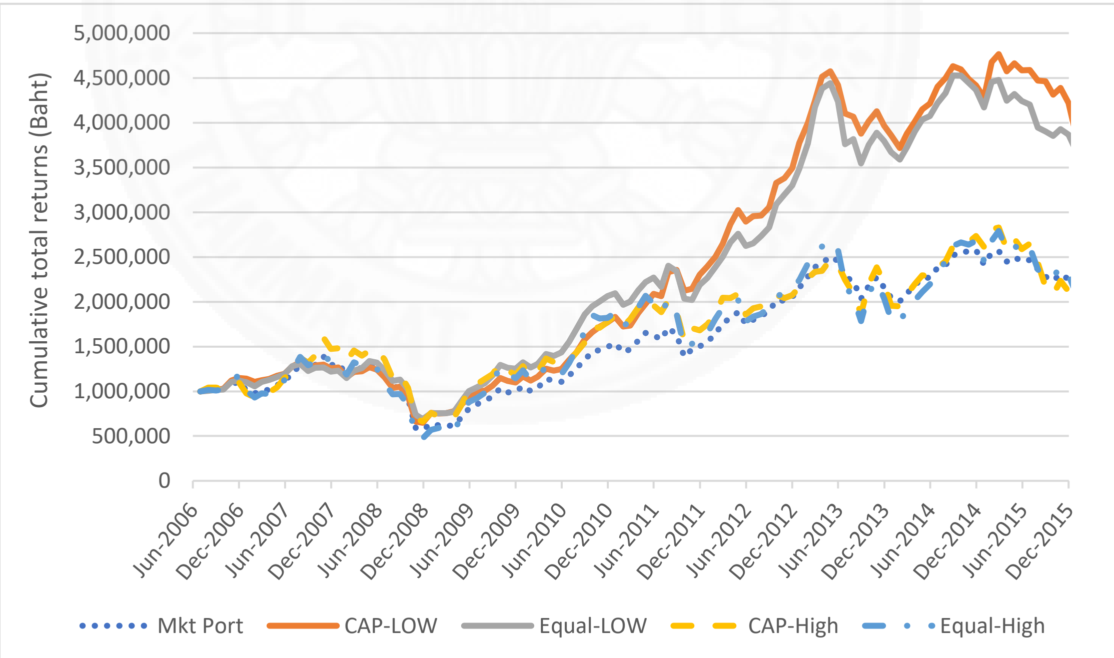


Figure 4.4 Cumulative total returns of High-Beta Vs. Low-Beta portfolios (SET100)



4.2 Testing statistical characteristics of low-beta portfolios

In this section, the statistical results from the multiple regression which extend the standard CAPM by adding another variable, skewness or kurtosis, are represented in table 4.5 and table 4.6 to reveal the impact of skewness and kurtosis on the returns of low-beta portfolio in both SET and SET100, respectively. Each model is improved and corrected for autocorrelation by Prais-Winsten and Cochrane-Orcutt method.

Table 4.5 presents the multiple regression results of model (8) and model (9) to test significant effect of skewness and kurtosis, respectively, on the low-beta portfolio formed from the first tercile sorted beta of stocks listed in SET. For model (8), the monthly market skewness coefficient (b_s) is significantly negative at one percent significant level. In addition, for model (9), the monthly market kurtosis coefficient (b_k) is significantly positive at ten percent significant level.

Table 4.5 Testing multiple regression for statistical of low-beta portfolio (SET)

Model (8) $R_{i,t} = \alpha + b_m R_m + b_s S_t + \varepsilon_i$			**Model (9)** $R_{i,t} = \alpha + b_m R_m + b_k K_t + \varepsilon_i$		
Variable	Standard method	Prais-Winsten and Cochrane-Orcutt method	Variable	Standard method	Prais-Winsten and Cochrane-Orcutt method
α	0.0056* (0.0030)	0.0056** (0.0024)	α	0.0053 (0.0034)	0.0042 (0.00289)
b_m	0.5502*** (0.0462)	0.5820*** (0.0442)	b_m	0.5511*** (0.0471)	0.5934*** (0.4268)
b_s	-0.0106** (0.0050)	-0.0096*** (0.0036)	b_k	0.000018 (0.00048)	0.000052* (0.000029)
N	114	113	N	114	113
RSS	0.1121	0.1066	RSS	0.1164	0.1096
F	73.1314	89.5104	F	68.3401	96.8457
R2	0.5685	0.6426	R2	0.5518	0.6393
Adj.R2	0.5608	0.6361	Adj.R2	0.5438	0.6328
DW	2.3787	2.024	DW	2.3949	2.0356

Note. The standard methods are improved by using Prais-Winsten and Cochrane-Orcutt method for autocorrelation correction. *, **, *** show significant at 10%, 5%, and 1% level where standard errors are reported in brackets.

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Where N is the number of observations, RSS is the regression sum of squared, F is F-statistic indicating how well independent variables explains the variation in the dependent variable, R2 or r-square is coefficient of determination, Adj. R2 is adjusted R-square, and DW is Durbin-Watson statistic used to detect the presence of autocorrelation.

The Adjusted-R^2 in model (8) and in model (9) are qualitatively similar at about 63% which means that skewness or kurtosis with excess returns of market can approximately explain 63% of the excess returns of low beta portfolio of stocks in SET. The significantly negative sign of risk premium for skewness is consistent to the prior study of Kraus and Litzenberger (1976) which implies that investors require higher rate of returns when skewness of market decrease, i.e. investor have preference for positive skewness. The significantly positive sign of risk premium for kurtosis is also consistent to Fang and Lai (1997) which implies that when kurtosis of market increase, the higher rates of returns are required from investors.

Table 4.6 Testing multiple regression for statistical of low-beta portfolio (SET100)

model (10) $Rh_{i,t} = \alpha + b_{mh}Rh_m + b_{sh}Sh_t + \varepsilon_i$			**Model (11)** $Rh_{i,t} = \alpha + b_{mh}Rh_m + b_{kh}Kh_t + \varepsilon_i$		
Variable	Standard method	Prais-Winsten and Cochrane-Orcutt method	Variable	Standard method	Prais-Winsten and Cochrane-Orcutt method
α	0.00394 (0.00245)	0.00401 (0.00249)	α	0.00341 (0.0034)	0.00350 (0.0027)
b_{mh}	0.78489*** (0.03616)	0.78131*** (0.05447)	b_{mh}	0.78624*** (0.03598)	0.78068*** (0.05325)
b_{sh}	-0.00378 (0.0050)	-0.00342 (0.0037)	b_{kh}	0.00219 (0.0017)	0.00194 (0.0019)
N	114	113	N	114	113
RSS	0.07169	0.07145	RSS	0.07114	0.07079
F	236.924	104.2905	F	239.2912	109.0181
R2	0.8102	0.8065	R2	0.8117	0.8071
Adj.R2	0.8068	0.8030	Adj.R2	0.8083	0.8036
DW	1.8811	1.9846	DW	1.8527	1.989

Note. The standard methods are improved by using Prais-Winsten and Cochrane-Orcutt method for autocorrelation correction. *, **, *** show significant at 10%, 5%, and 1% level where standard errors are reported in brackets.

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Table 4.6 presents the multiple regression results of model (10) and model (11) which take into account additional independent variable of the market skewness and the market kurtosis of SET100, respectively. Both model (10) and model (11) have significantly positive risk premium for market at 1% significant level of 0.7813 and 0.7806, respectively.

The risk premium for the market skewness or the market kurtosis of SET100 is not statistically significant in either cases. This may be explained by the numbers of stocks used to form the low-beta portfolio of SET100 since there are 100 stocks in SET100 and the first tercile of low beta stocks contain about 30 stocks which is relatively smaller numbers comparing to the first tercile of low beta stocks in SET. Hence, the smaller number of observation can lead to lower variation of skewness and kurtosis and consequently reduce the power of the test. Table 3.1 shows lower CV of SET100 market skewness (Sh) and kurtosis (Kh) comparing to CV of SET market skewness (S) and kurtosis (K) which implies lower variation of skewness and kurtosis for SET100. Another possible explanation for the insignificant regression results for skewness and kurtosis in SET100 is that mean of SET100 market skewness and kurtosis indicate more normality of the distribution than that of SET. Hence, when the distribution is closer to be normally distributed, this lead to the regression result to be insignificant.

The adjusted-R^2 of model (10) and model (11) are almost the same at 80% which mean that independent variable in the models can explain about 80% of the excess return of the low-beta portfolio formed from the first tercile sorted beta stocks in SET100. In Summary, skewness and kurtosis factor have significant impact for low-beta stocks listed in SET but may not be important factor for low-beta stocks listed in SET100, i.e. skewness and kurtosis are priced by investors and can explain the returns of the low-beta portfolio in SET but not in SET100.

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CHAPTER 5
CONCLUSIONS, DISCUSSIONS, AND RECOMMENDATIONS

5.1 Conclusions

The first objective of this study aims to detect whether the low-beta anomaly exists in Thai stock market during the period from January 2006 to December 2015. The low-beta portfolios ($\beta<1$) are formed by the first tercile sorted beta of stocks estimated by using the 6-month prior of daily data at the end of each month. The empirical results show that the low-beta portfolios from both SET and SET100 can outperform the market portfolio ($\beta=1$), de-levered portfolio (β equals to beta of the low-beta portfolio), and high-beta portfolios ($\beta>1$) in both absolute returns (average excess returns), and risk-adjusted returns (Sharpe ratio) over the sample period which contrast with CAPM that lower-risky asset should generate return no greater than equal or higher-risky asset. This can confirm the existence of the low-beta anomaly in Thailand.

The second objective is to test the effect of higher moments of the distribution, which are skewness and kurtosis, on the excess returns of the low-beta portfolios. The standard single factor model of CAPM is extend by adding another market skewness or market kurtosis variable to the standard CAPM. The test results of the multiple regression with Prais-Winsten and Cochrane-Orcutt method show the negatively significant effect of the market skewness and positively significant effect of the market kurtosis on the excess returns of low-beta portfolio for stocks in SET as expected. However, there is no significant effect either for the market skewness and kurtosis on the excess returns of the low-beta portfolio of stocks in SET100. The possible explanations are that the smaller numbers of observation for the low-beta portfolio in SET100 and lower normality of distribution in SET 100 lead to lower variation of the higher moments to the excess returns and, consequently, lower power of the test which cause insignificantly tested results.

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5.2 Discussions

According to the well-known Capital Asset Pricing Model (CAPM), the expected returns of any security is linearly related to its market beta (β), which is a systematic risk measurement. Further, the higher returns are required by bearing higher risk (higher β) which means that the securities with lower risk could generate returns greater than the security with equal or higher risk as measured by beta. However, the empirical results of this study show that the low-beta portfolios ($\beta<1$) can generate greater not only absolute returns (average returns) but also risk-adjusted returns (Share ratio) than the market portfolio and their de-levered market portfolios, which is another benchmark for low-beta portfolio with the same beta (same risk) as the low-beta portfolios. This phenomenon refers to the low-beta anomaly and is consistent to the prior literature of Black, Jensen, and Scholes (1972), Black (1993), Baker et al. (2011, 2012, and 2013), Ang et al. (2006 and 2009), and Frazzini et al. (2014) which discover the low-beta anomaly in other international stock markets. This anomaly could be explained by behavioral explanation, leverage restriction explanation, and risk-based explanation.

In addition, one of assumptions of CAPM is that the asset returns are assumed normal distribution which only mean and variance are relevant, i.e. investors decide to invest by considering only mean and variance. However, some prior studies by Kraus and Litzenberger (1976), Aggarwal et al. (1989), and Fang and Lai (1997) find importance of skewness and kurtosis on the asset valuation. In this study, skewness and kurtosis are added into the standard CAPM as another independent variable. The regression results show negatively significant effect of skewness on the low-beta portfolio in SET, which implies that investor require higher returns for bearing negative skewness, i.e. investors have preference for positive skewness, and positively significant effect of kurtosis on the low-beta portfolio in SET which higher returns are required when kurtosis increase consistent to the stated prior studies. However, the results for SET100 find no significant effect which might be the smaller number of observations in SET100 leading skewness and kurtosis to less vary and, finally, lower power of the test.

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5.3 Recommendations

The study aims to make valuable contributions to all readers and market participants. Firstly, to investors and fund managers, the investment in low-beta stocks can be an alternative investment strategy to outperform the market with knowing factor that have effects on the low-beta stock returns which are skewness and kurtosis. Secondly, the found results of low-beta anomaly and effect of skewness and kurtosis for stocks in SET could help policy makers and regulators in order to increase efficiency of Thai stock market.

Lastly to researchers and further study, the study of low-beta anomaly can extend the literature about low-beta anomaly in financial field and can go beyond with other models or different approach to determine existence and explanation of the low-beta anomaly. Moreover, the limitation of this study is ignoring transaction cost which could lead to different results, and the sample period can be extend to be tested in longer than 10 years.

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APPENDICES

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APPENDIX A
FAMA-MACBETH WITH QUANTILE REGRESSION

In the study of Bianchi (2014), Quantile regression is applied to Fama-Macbth procedure[3] to analyze relationship between beta and cross-section of stock returns. Further, Quantile regression allow the study to examine entire conditional dimension of stock returns, rather than just conditional mean. The outcomes are empirical quantiles which are, then, used in simulation process to create the excess returns distribution of portfolios for studying higher moments of conditional distribution of stock returns. However, this study show only empirical quantiles for SET and SET100 in various methods.

Figure A.1 to figureA.8 illustrate empirical quantile or estimated risk premium for specified conditional quantile[4] of stock returns distribution in SET and SET100 in 4 different methods. For figure A.1 and Figure A.5, the empirical quantiles are obtained by taking time-series average across all of the cross-sections. Figure A.2 and figure A.6 perform quantile regression based on panel data with time fixed effect. Figure A.3 and figure A.7 show empirical quantile estimated by quantile regression based on panel data with grid-search optimization procedure (Grid). Lastly, figure A.4 and figure A.8 estimate risk premium by based on panel data with Markov Chain Monte Carlo technique (MCMC) sampling from distribution.

Figure A.1 to figure A.8 all show the negatively estimated risk-premium for the conditional median which is consistent to prior literature of Bianchi (2014) that show negative relationship between beta and returns. According to the results from each quantile regressions in figureA.1 to figureA.4, the shape of empirical quantiles for stocks in SET are smoother than that for stocks in SET100 as showed in figureA.5 to figureA.8 which might be explained by the smaller numbers of stocks in SET100 comparing with SET.

[3] For more details about Fama-Mecbth with quantile regression. Please see Bianchi (2014) “Looking under the hood: what does quantile regression tell us about the low-beta anomaly”.
[4] In this study, quantile regressions are run for each specified conditional quantile $q^{th} \in \ominus$, where $\ominus = \{0.05, 0.06, 0.07, 0.08, 0.09, \ldots, 0.50, \ldots, 0.91, 0.92, 0.93, 0.94, 0.95\}$

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Figure A.1 Average empirical quantile for stock returns in SET

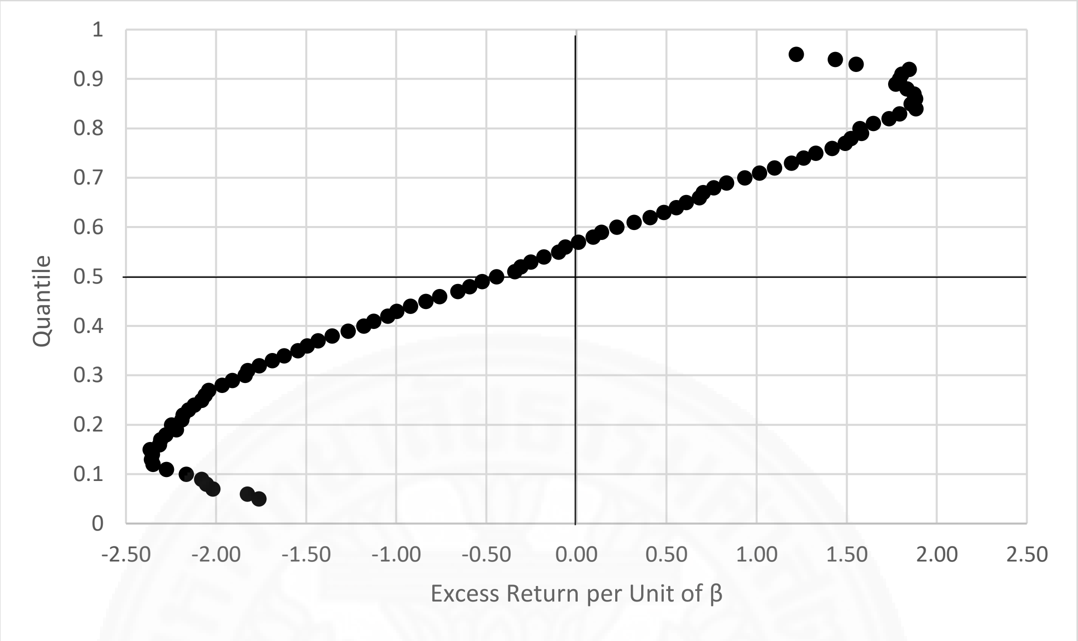


Figure A.2 Empirical quantile for stock returns in SET (time fixed effect)

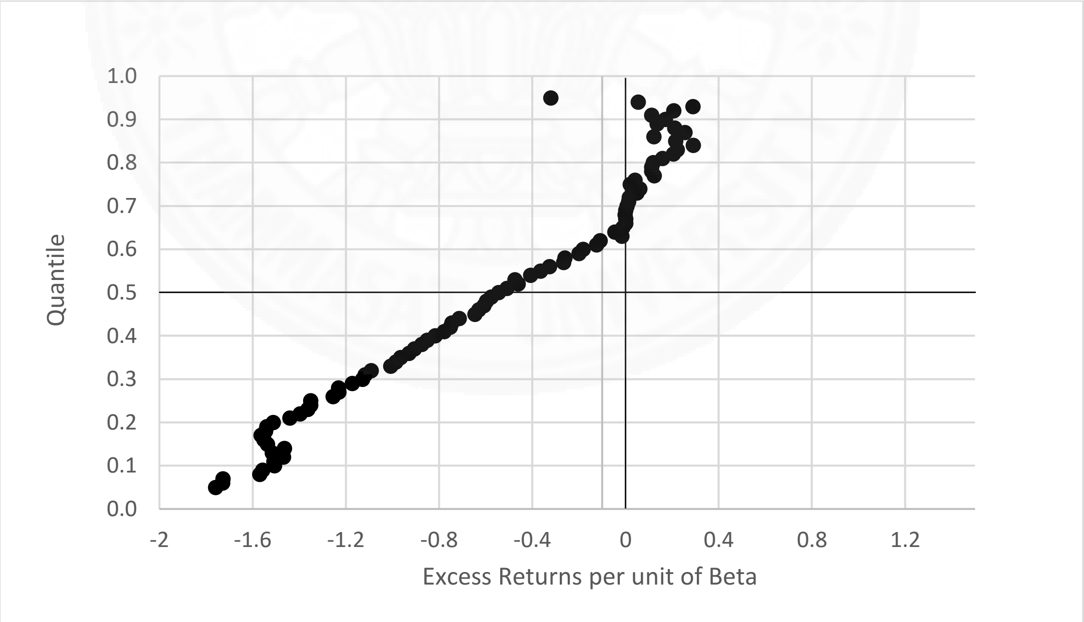


Figure A.3 Empirical quantile for stock returns in SET (Grid)

Figure A.4 Empirical quantile for stock returns in SET (MCMC)

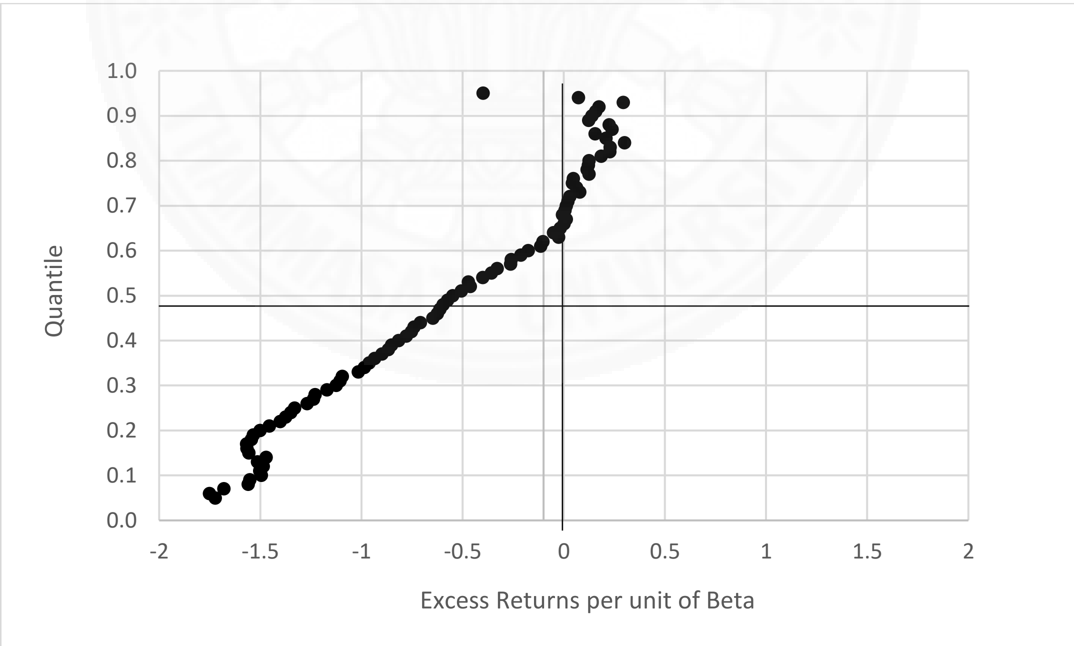


Figure A.5 Average empirical quantile for stock returns in SET100

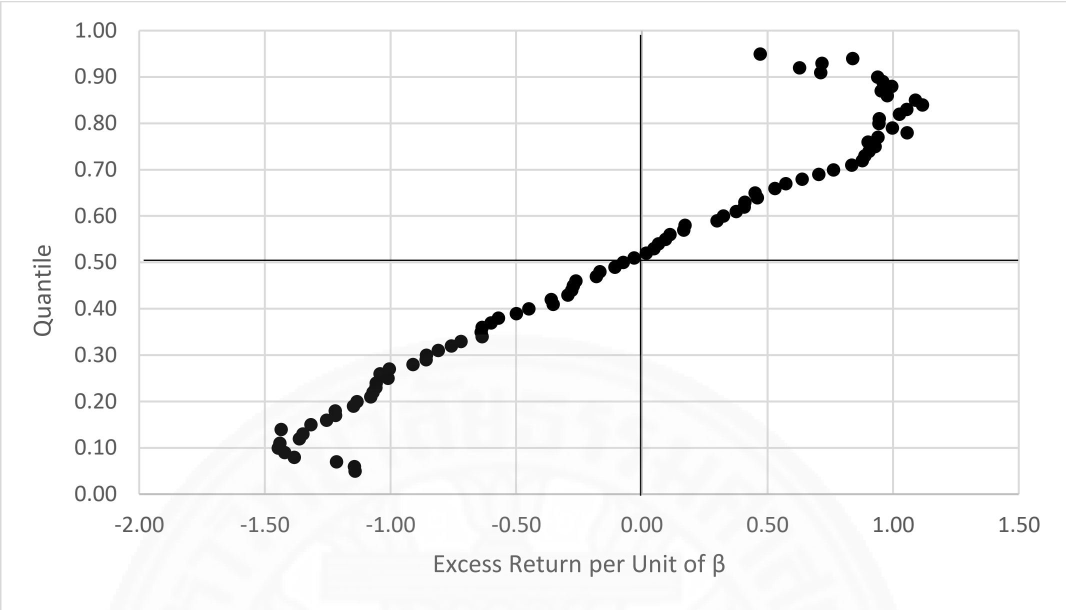


Figure A.6 Empirical quantile for stock returns in SET100 (time fixed effect)

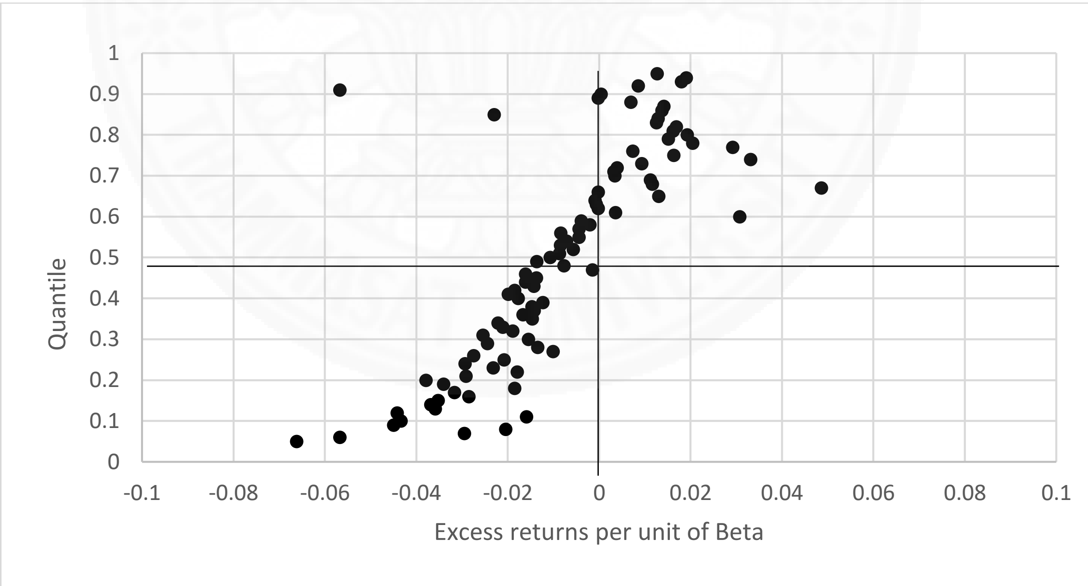
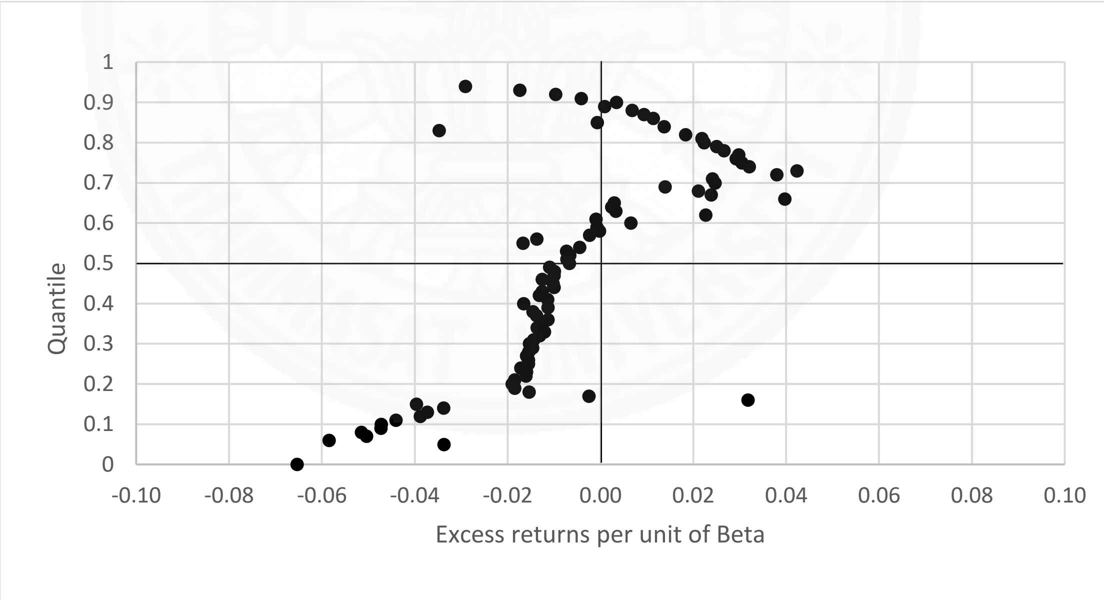


Figure A.7 Empirical quantile for stock returns in SET100 (Grid)

Figure A.8 Empirical quantile for stock returns in SET100 (MCMC)



APPENDIX B
REGRESSION RESULTS FROM STATA

All of the regression results in this study are performed in STATA, a data analysis and statistical software, where all commands and displayed results are shown below:

```
. tsset Month
        time variable:  Month, 1 to 114
                delta:  1 unit

. reg Ri Rm K

      Source |       SS       df       MS              Number of obs =     114
-------------+------------------------------           F(  2,   111) =   68.34
       Model |  .143374161     2  .071687081           Prob > F      =  0.0000
    Residual |  .116436214   111  .001048975           R-squared     =  0.5518
-------------+------------------------------           Adj R-squared =  0.5438
       Total |  .259810375   113  .002299207           Root MSE      =  .03239

------------------------------------------------------------------------------
          Ri |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          Rm |   .5510597   .0471385    11.69   0.000     .4576517    .6444678
           K |   .0000188   .0000488     0.38   0.701     -.000078    .0001155
       _cons |   .0053244   .0034262     1.55   0.123    -.0014648    .0121137
------------------------------------------------------------------------------

. estat dwatson

Durbin-Watson d-statistic(  3,   114) =   2.39491

. est store M1

. prais Ri Rm K, corc rho(reg) vce(r)

Iteration 0:  rho = 0.0000
Iteration 1:  rho = -0.2028
Iteration 2:  rho = -0.2359
Iteration 3:  rho = -0.2393
Iteration 4:  rho = -0.2396
Iteration 5:  rho = -0.2396
Iteration 6:  rho = -0.2396
Iteration 7:  rho = -0.2396

Cochrane-Orcutt AR(1) regression -- iterated estimates

Linear regression                                      Number of obs =     113
                                                       F(  2,   110) =   96.85
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.6393
                                                       Root MSE      =  .03156

------------------------------------------------------------------------------
             |             Semirobust
          Ri |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          Rm |   .5934281   .0426776    13.90   0.000     .5088511    .6780051
           K |   .0000525   .0000292     1.80   0.075    -5.39e-06    .0001104
       _cons |   .0041986    .002893     1.45   0.150    -.0015346    .0099318
-------------+----------------------------------------------------------------
         rho |   -.239611
------------------------------------------------------------------------------
```

```
Durbin-Watson statistic (original)    2.394910
Durbin-Watson statistic (transformed) 2.035598

. est store M2

. est table M1 M2, star(.1 .05 .01) stat(N rss F r2 r2_a dw)

----------------------------------------------
    Variable |      M1              M2        
-------------+--------------------------------
          Rm |  .55105975***    .59342813***  
           K |  .00001877       .00005251*    
       _cons |  .00532445       .00419859     
-------------+--------------------------------
           N |       114             113      
         rss |  .11643621       .10957847     
           F |   68.34013       96.845673     
          r2 |  .55184155       .63934796     
        r2_a |  .54376663       .63279065     
          dw |                  2.0355985     
----------------------------------------------
           legend: * p<.1; ** p<.05; *** p<.01

. tsset Month
        time variable:  Month, 1 to 114
                delta:  1 unit

. reg Ri Rm S

      Source |       SS       df       MS              Number of obs =     114
-------------+------------------------------           F(  2,   111) =   73.13
       Model |  .147711159     2  .073855579           Prob > F      =  0.0000
    Residual |  .112099216   111  .001009903           R-squared     =  0.5685
-------------+------------------------------           Adj R-squared =  0.5608
       Total |  .259810375   113  .002299207           Root MSE      =  .03178

------------------------------------------------------------------------------
          Ri |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          Rm |   .5502232   .0462062    11.91   0.000     .4586625     .641784
           S |  -.0105502   .0050024    -2.11   0.037    -.0204628   -.0006376
       _cons |   .0056014   .0029969     1.87   0.064    -.0003372      .01154
------------------------------------------------------------------------------

. estat dwatson

Durbin-Watson d-statistic(  3,   114) =  2.378707

. est store M1

. prais Ri Rm S, corc rho(reg) vce(r)

Iteration 0:  rho = 0.0000
Iteration 1:  rho = -0.1955
Iteration 2:  rho = -0.2153
Iteration 3:  rho = -0.2170
Iteration 4:  rho = -0.2171
Iteration 5:  rho = -0.2171
Iteration 6:  rho = -0.2171
```

```
Cochrane-Orcutt AR(1) regression -- iterated estimates

Linear regression                                      Number of obs =     113
                                                       F(  2,   110) =   89.51
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.6426
                                                       Root MSE      =  .03114

------------------------------------------------------------------------------
             |             Semirobust
          Ri |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          Rm |    .581997   .0442297    13.16   0.000     .4943441    .6696498
           S |   -.009611   .0036189    -2.66   0.009    -.0167828   -.0024393
       _cons |   .0055661   .0023808     2.34   0.021     .0008478    .0102843
-------------+----------------------------------------------------------------
         rho |  -.2171031
------------------------------------------------------------------------------
Durbin-Watson statistic (original)    2.378707
Durbin-Watson statistic (transformed) 2.023963

. est store M2

. est table M1 M2, star(.1 .05 .01) stat(N rss F r2 r2_a dw)

----------------------------------------------
    Variable |      M1              M2
-------------+--------------------------------
          Rm |  .55022324***    .58199696***
           S | -.01055019**    -.00961104***
       _cons |   .0056014*      .00556607**
-------------+--------------------------------
           N |        114             113
         rss |  .11209922       .10663884
           F |  73.131371       89.510418
          r2 |  .56853449       .64262492
        r2_a |  .56076034        .6361272
          dw |                  2.0239633
----------------------------------------------
           legend: * p<.1; ** p<.05; *** p<.01

. tsset Month
        time variable:  Month, 1 to 114
                delta:  1 unit

. reg Rih Rmh K

      Source |       SS       df       MS              Number of obs =     114
-------------+------------------------------           F(  2,   111) =  235.49
       Model |  .305685947     2  .152842973           Prob > F      =  0.0000
    Residual |  .072043449   111   .00064904           R-squared     =  0.8093
-------------+------------------------------           Adj R-squared =  0.8058
       Total |  .377729396   113  .003342738           Root MSE      =  .02548

------------------------------------------------------------------------------
         Rih |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         Rmh |   .7820586   .0360501    21.69   0.000     .7106229    .8534943
           K |   .0000198   .0000384     0.52   0.607    -.0000563    .0000959
       _cons |   .0037287   .0027026     1.38   0.170    -.0016268    .0090842
------------------------------------------------------------------------------

. estat dwatson

Durbin-Watson d-statistic(  3,   114) =  1.863332
```

Ref. code: 25595802042027OXQ

```
. est store M1

. prais Rih Rmh K, corc rho(reg) vce(r)

Iteration 0:  rho = 0.0000
Iteration 1:  rho = 0.0580
Iteration 2:  rho = 0.0586
Iteration 3:  rho = 0.0586
Iteration 4:  rho = 0.0586
Iteration 5:  rho = 0.0586

Cochrane-Orcutt AR(1) regression -- iterated estimates

Linear regression                                      Number of obs =     113
                                                       F(  2,   110) =  102.32
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.8054
                                                       Root MSE      =  .02552

------------------------------------------------------------------------------
             |              Semirobust
         Rih |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         Rmh |    .778389   .0545585    14.27   0.000     .6702668    .8865113
           K |    .000025   .0000232     1.08   0.284     -.000021    .0000709
       _cons |    .003703   .0029252     1.27   0.208    -.0020941       .0095
-------------+----------------------------------------------------------------
         rho |   .0586083
------------------------------------------------------------------------------
Durbin-Watson statistic (original)    1.863332
Durbin-Watson statistic (transformed) 1.992575

. est store M2

. est table M1 M2, star(.1 .05 .01) stat(N rss F r2 r2_a dw)

----------------------------------------------
    Variable |      M1               M2
-------------+--------------------------------
         Rmh |  .78205859***    .77838903***
           K |  .00001982       .00002498
       _cons |  .00372871       .00370295
-------------+--------------------------------
           N |        114             113
         rss |  .07204345       .07163334
           F |  235.49081       102.31687
          r2 |  .80927233       .80539748
        r2_a |  .80583579       .80185925
          dw |                  1.9925752
----------------------------------------------
           legend: * p<.1; ** p<.05; *** p<.01

. tsset Month
        time variable:  Month, 1 to 114
                delta:  1 unit

. reg Rih Rmh S

      Source |       SS       df       MS              Number of obs =     114
-------------+------------------------------           F(  2,   111) =  235.21
       Model |  .305617058     2  .152808529           Prob > F      =  0.0000
    Residual |  .072112338   111  .000649661           R-squared     =  0.8091
-------------+------------------------------           Adj R-squared =  0.8057
       Total |  .377729396   113  .003342738           Root MSE      =  .02549

------------------------------------------------------------------------------
         Rih |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         Rmh |   .7812028   .0360201    21.69   0.000     .7098265    .8525791
           S |   .0016047   .0040123     0.40   0.690    -.0063459    .0095554
       _cons |   .0044127   .0024096     1.83   0.070    -.0003621    .0091875
------------------------------------------------------------------------------
```

```
. estat dwatson

Durbin-Watson d-statistic(  3,   114) =  1.861554

. est store M1

. prais Rih Rmh S, corc rho(reg) vce(r)

Iteration 0:  rho = 0.0000
Iteration 1:  rho = 0.0589
Iteration 2:  rho = 0.0620
Iteration 3:  rho = 0.0622
Iteration 4:  rho = 0.0622
Iteration 5:  rho = 0.0622

Cochrane-Orcutt AR(1) regression -- iterated estimates

Linear regression                                      Number of obs =     113
                                                       F(  2,   110) =  105.41
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.8047
                                                       Root MSE      =  .02555

------------------------------------------------------------------------------
             |             Semirobust
         Rih |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         Rmh |   .7764002   .0547456    14.18   0.000     .6679073    .8848932
           S |   .0013285   .0041785     0.32   0.751    -.0069522    .0096092
       _cons |     .00449   .0025516     1.76   0.081    -.0005666    .0095466
-------------+----------------------------------------------------------------
         rho |   .0621602
------------------------------------------------------------------------------
Durbin-Watson statistic (original)    1.861554
Durbin-Watson statistic (transformed) 1.989995

. est store M2

. est table M1 M2, star(.1 .05 .01) stat(N rss F r2 r2_a dw)

----------------------------------------------
    Variable |      M1              M2        
-------------+--------------------------------
         Rmh |  .78120279***    .77640024***  
           S |  .00160474       .00132848     
       _cons |  .00441273*         .00449*    
-------------+--------------------------------
           N |        114             113     
         rss |  .07211234       .07180081     
           F |  235.21283       105.41394     
          r2 |  .80908995        .8046761     
        r2_a |  .80565013       .80112476     
          dw |                   1.989995     
----------------------------------------------
           legend: * p<.1; ** p<.05; *** p<.01
```

BIOGRAPHY

Name	Mr. Sunchai Anujarawat
Date of Birth	October 4, 1990
Educational Attainment	2009: Bachelor of Business Administration (Finance)

Ref. code: 25595802042027OXQ