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Idiosyncratic Volatility and Expected Stock Returns: Evidence from Thailand

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This paper demonstrates the finding that time-varying expected idiosyncratic volatility has a significant and positive effect on expected stock returns for individual stocks as well as stock sectors. The positive relation remains after controlling for liquidity variables. The second finding is that time-varying expected market volatility has a significant effect on expected stock returns for both individual stocks and stock sectors, which is consistent with the traditional capital asset pricing model. Although the models control for liquidity variables, the significantly positive relation still exists. In addition, expected idiosyncratic volatility plays a more important role than expected market volatility in determining expected stock returns in the case of individual stocks. In contrast, expected market volatility plays a more important role than expected idiosyncratic volatility in the case of stock sectors.

Keywords: idiosyncratic volatility, market volatility, liquidity, expected stock return

JEL Classification: C33, G12

Introduction

Idiosyncratic volatility or idiosyncratic risk which is defined as firm-specific risk does not figure in the traditional asset pricing model, the capital asset pricing model (CAPM). It is because systematic risk is only priced in equilibrium in such model. Indeed, systematic risk determines solely expected stock returns because idiosyncratic risk can be eliminated through diversification. In contrast, most studies document that only idiosyncratic risk plays an important role in determining expected stock returns.

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Previous studies have shown, however, that there are three different results: positive, negative, and mixed relationship between idiosyncratic risk and expected stock returns. The well-known study of Merton's (1987) paper states that idiosyncratic risk has predictive properties. Such theoretical work shows that idiosyncratic risk is positively related to expected stock returns because investors do not fully diversify their portfolios under an imperfect capital market. Later empirical papers still show that there is a positive relationship between idiosyncratic volatility and expected stock returns. In particular, Amihud and Mendelson (1989), Malkiel and Xu (2006), Goyal and Santa-Clara (2003), Spiegel and Wang (2005), Guo and Neely (2008), Boehme *et al*. (2009), Fu (2009), Ooi *et al*. (2009), and Bali and Cakici (2010) document that idiosyncratic volatility is positively and significantly correlated with expected stock returns. Although their explanations are slightly different, the main reason is that investors are able to diversify their portfolios well rather than the market portfolio. In other words, market volatility or beta has no ability to explain the expected stock returns.

Contrary to these assertions, some researchers have found that there is a negative relationship between idiosyncratic volatility and expected stock returns. The systematic risk, however, still does not matter. Guo and Savickas (2006), Ang *et al*. (2006; 2009), Angelidis (2010), and Guo and Savickas (2010) show that idiosyncratic volatility is negatively related to expected stock returns. Furthermore, Bali and Cakici (2008) state that there is a negative and significant cross-sectional relationship between idiosyncratic volatility and expected stock returns even though they use daily data to construct value-weighted portfolios based on the Center for Research on Security Prices (CRSP) breakpoint.

There are several explanations for a negative relationship between idiosyncratic volatility and expected stock returns. In particular, Guo and Savickas (2006) state that value-weighted idiosyncratic volatility and market volatility are jointly significant predictors of excess stock market returns by using quarterly data of the Center for Research on Security Prices. That is, it is consistent with CAPM that stock market volatility is positively related to expected stock return. On the contrary, value-weighted idiosyncratic volatility is negatively related to future stock return because of its negative co-movements with the consumption-wealth ratio. In fact, such negative relationship results from the liquidity premium.

Additionally, Guo and Savickas (2010) document that value-weighted average idiosyncratic volatility is negatively correlated with future stock returns because it is a proxy for conditional variance of discount-rate shocks when using monthly data from the United States and G7 countries. Ang *et al*. (2006) conclude that aggregate volatility risk is negatively priced because risk-averse agents reduce current consumption to increase precautionary saving in the presence of higher uncertainty about future market returns. In addition, Angelidis (2010) shows that idiosyncratic risk predicts the market return only in conjunction with stock market risk when he uses monthly and quarterly data from 25 emerging markets. Idiosyncratic risk is also the dominant component of tracking error volatility, and it might be a proxy for systematic risk omitted from the CAPM.

The relationship between idiosyncratic volatility and expected stock return is shown to be mixed by using daily and monthly data. Huang *et al.* (2010) demonstrate that there is a negative relationship between estimated conditional idiosyncratic volatility and expected stock return based on daily data. Still, it is no longer significant after return reversals are controlled. In contrast, there is a significantly positive relationship between estimated conditional idiosyncratic volatility and expected stock returns based on monthly data when the model controls for return reversal. In addition, return reversal can help to illustrate both the negative relationship between value-weighted portfolio returns and idiosyncratic volatility, and the insignificant relation between equal-weighted portfolio returns and idiosyncratic volatility

As a result, there is still no clear evidence to show whether idiosyncratic volatility is correlated with expected stock returns as well as market volatility, especially in the case of Thailand. The empirical research mentioned above shows relationships that reflect both positive and negative effects. Such results may lead to confusing implications, especially over how to construct the optimal portfolio. In addition, they do not show what exactly the role of liquidity should be in jointly determining expected stock returns. Therefore, this paper attempts to provide some evidence from the SET50 and stock sectors of the Stock Exchange of Thailand (SET) which show that expected stock returns are determined by conditional idiosyncratic volatility of individual stock as well as the conditional market volatility. The additional robustness is whether the relationship still exists after liquidity variables are included in the models.

This paper is closely similar to Fu's (2009) paper in adopting the conventional practice of using the realized return as an explained variable in both time-series and cross-section regression setting. Its main contribution, however, is that the time-varying idiosyncratic volatility and market volatility from CAPM are controlled to test the pooled panel data and fixed effect panel data models. This study shows that the appropriate model to estimate idiosyncratic volatility conditional on information set at time *t-1* is the "exponential generalized autoregressive conditional heteroskedasticity" (EGARCH) model from CAPM. It does not come from Fama-French three-factor model as in Fu (2009). Such model is proposed by Nelson (1991) which is extended from the GARCH model of Bollerslev's (1986) work. Furthermore, the GARCH model is employed to estimate expected market volatility or beta for stock *i* at time *t* conditional on the information set at time *t-1* from CAPM. Typically, the empirical test shows that the variance of idiosyncratic and market volatility is not constant. In addition, such variance does not follow random walk. It implies that the pooled and fixed effect panel data regressions are appropriate to examine the time-series and cross-section equations as used in Fama and MacBeth (1973).

The time-series and cross-sectional data for this study come from the daily data on the SET50 index and the Thai Bond Market Association (ThaiBMA) from April 2001 to December 2009 which are 2,142 days in total. They comprise 97 stocks traded in the SET50 index during that period. Data also come from daily data of 28 stock sectors traded in the Stock Exchange of Thailand from March 2001 to December 2011.

Next section presents the conceptual framework and methods. It is followed by the description of data used, analysis of stock characteristics, and time-series and cross-sectional effects from the pooled and fixed effect model. Conclusion is in the last section.

Concept and Method

This paper examines whether conditional idiosyncratic volatility has an effect on expected stock returns including the effect of conditional market volatility or beta. It seeks to determine whether investors are compensated for bearing conditional idiosyncratic volatility in the same period. In addition, conditional market volatility is expected to be positively related to expected returns, similar to CAPM. Therefore, the result of this paper is expected to observe a relation between expected return, expected idiosyncratic volatility, and expected market volatility. However, investors are not able to observe expected stock returns and expected idiosyncratic volatility. Following Fu (2009), the conventional methodology is to use the realized return as the explained variable in both time-series and cross-section regression setting. In other words, such return is assumed to be the sum of the expected return and a random error. Thus, the pooled and fixed effect panel data regressions are applied to examine the time-series and cross-section equations as used in Fama and MacBeth (1973), as follows:

$$R_{it} = \alpha_i + \sum_{l==1}^{L} \beta_l X_{lit} + u_{it}, i = 1,2,\ldots,N_t, t = 1,2,\ldots,T \quad (1)$$

where the explained variable, R_{it}, stands for the daily realized return for stock *i* at time *t* and is assumed to be the sum of the expected return and a random error. X_{lit} represents the explanatory variable *l* for stock *i* at time *t*. Hence, there are several explanatory variables. That is, the daily expected idiosyncratic volatility for stock *i* at time *t* conditional on the information set at time *t-1* is represented as $E_{t-1}(IV_{it})$. The daily expected market volatility or beta for stock *i* at time *t* conditional on the information set at time *t-1* is denoted as $E_{t-1}(BETA_{it})$. The daily percentage bid-ask spread, RS_{it}, is defined as the ratio of the difference between ask and bid price to the average of the sum of ask and bid price of stock *i* at time *t*. ILR_{it} is the daily illiquidity measure as discussed in Amihud (2002) which is defined as the daily absolute return over the trading volume in Thai baht (THB) of stock *i* at time *t*. $TURN_{it}$ is the daily turnover ratio which is defined as the percentage of the ratio of the trading volume in units of shares on all boards to the number of listed shares on the same day for stock *i* at time *t*. $VALUE_{it}$ represents the daily value of stock *i* at time *t* which is defined as the product of trading volume and stock price on the same day. N_t is the total number of stocks at time *t*. *T* is the total of time periods. α_i is the constant return on stock *i* which is the only one constant in the pooled panel data regression, but it is allowed to vary in the fixed effect panel data regression. The error term, u_{it}, captures the deviation of the realized returns on stock i from its expected value.

Equation (1) focuses on β_l, especially the coefficient on expected idiosyncratic volatility and other explanatory variables, which are expected to be not equal to zero. Thus, the null hypothesis is $\beta_l = 0$. In other words, expected idiosyncratic volatility is not priced if it equals zero as well as other explanatory variables.

In addition to more details of explained variables, R_{it} is the daily realized return for stock *i* on day *t*. It is calculated from the ratio of daily closing price, P_{it} , the daily closing price on day *t-20*, P_{it-20} , and dividend on the same day, D_{it} , to the daily closing price on day *t-20* , assuming that there are approximately 20 trading days in one month.[1] Therefore, this implies that it is the daily realized return over the past one month as stated in Ang *et al*. (2006; 2009) which is computed as:

$$R_{it} = \frac{P_{it} + D_{it} - P_{it-20}}{P_{it-20}} \tag{2}$$

The explanatory variables are then computed as the followings. $E_{t-1}(IV_{it})$ is the expected idiosyncratic volatility for stock *i* at time *t* conditional on the information set at time *t-1*. Following Bali *et al*. (2005), and Guo and Savickas (2008), such volatility can come from either the CAPM or the three-factor model of Fama and French (1993). It is due to the fact that both results are expressed similarly, as did Angelidis (2010). This study then applies the CAPM-base to calculate, $E_{t-1}(IV_{it})$ as in the following cross-sectional equation:

$$R_{it} - r_{ft} = a_i + b_i(R_{mt} - r_{ft}) + \varepsilon_{it}, \varepsilon_{it} \sim N(0, \sigma_{it}^2) \tag{3}$$

where r_{ft} stands for the risk-free rate on day *t* as measured by a daily one-month treasury-bill rate. R_{mt} represents the daily market return on day *t* as measured by the daily return on SET50 index of the Stock Exchange of Thailand, assuming to be the stock market return. That is, it is the daily market return over the past one month (20 trading days) which is similar to daily stock return. The parameter a_i is a constant showing excess return on stock *i*. The coefficient b_i is the average daily beta or market risk for stock *i* consistent with the security market line.

More importantly, the previous study measures the estimated idiosyncratic volatility of stock *i* at time *t* as the standard deviation of the regression residual, ε_{it} . It is also assumed to have normal distribution with zero mean and variance σ_{it}^2 . In other words, $IV_{it} = \sqrt{var(\varepsilon_{it})}$.

However, Fu (2009) suggests that it is not appropriate to describe a typical stock's idiosyncratic volatility process as random walk because of its time-varying volatility. In

[1] There are total trading days of 2,142 in 105 months for individual stocks. Thus, it is approximately 20.4 days in one month. It is consistent with sector data. A total of trading days is 2,650 in 130 months for sector of the Stock Exchange of Thailand. That is, it is approximately 20.38 days in one month.

addition, this study takes EGARCH into account as the appropriate model to estimate idiosyncratic volatility for stock *i* at time *t* conditional on the information set at time *t-1*. To make sure that conditional volatility exists, the regression residual ε_{it} from equation (3) should be tested with the ARCH LM test for autoregressive conditional heteroskedasticity (ARCH). The null hypothesis is that there is no ARCH up to *q* order in the residuals, and then the following regression analysis is performed:

$$\varepsilon_{it}^2 = \delta_0 + (\sum_{s=1}^{q} \delta_s \varepsilon_{it-s}^2) \tag{4}$$

where ε_{it} is the regression residual of equation (3). Equation (4) is a regression analysis of the squared residuals on a constant, δ_0, and lagged squared residuals up to order *q*. The null hypothesis is that $\delta_1, ..., \delta_q = 0$. If the null hypothesis is rejected, it means that there exists a significant ARCH effect in this model such that the idiosyncratic volatility is not constant. The test eventually shows a significant ARCH effect.

As a result, the appropriate model to estimate conditional idiosyncratic volatility is the EGARCH model proposed by Nelson (1991) which is extended from GARCH model of Bollerslev's (1986) work. The exponential GARCH model parameterized the conditional variance in terms of a natural logarithm as follows:

$$ln\sigma_{it}^2 = \omega_i + \sum_{j=1}^{p} \varphi_{i,j} ln\sigma_{i,t-j}^2 + \sum_{k=1}^{q} \psi_{i,k} \left\{ \theta\left(\frac{\varepsilon_{i,t-k}}{\sigma_{i,t-k}}\right) + \gamma\left[\left|\frac{\varepsilon_{i,t-k}}{\sigma_{i,t-k}}\right| - \left(2/\pi\right)^{1/2}\right]\right\} \tag{5}$$

This explicit equation (5) is employed to estimate the conditional variance, σ_{it}^2. It yields the expected idiosyncratic volatility for stock *i* at time *t* conditional on information set at time *t-1* such that $E_{t-1}(IV_{it}) = \sqrt{\sigma_{it}^2}$. Indeed, the expected idiosyncratic volatility is composed of the past p-period of forecast conditional variance, $\sigma_{i,t-j}^2$, and the past q-period of return shocks or unexpected news, $\varepsilon_{i,t-k}$. In addition to specification, each of nine different EGRACH models, EGARCH (1, 1-3; 2, 1-3; 3, 1-3), is employed to estimate the conditional idiosyncratic volatility. After that, the best one with the lowest Akaike information criterion (AIC) or Schwarz information criterion (SIC) will be selected. Accordingly, EGARCH (1, 1) is the best model and denoted as $E_{t-1}(IV_{it})$ in this study.

Apart from expected idiosyncratic volatility, there is an amount of market volatility of stock *i*. In fact, it is a proxy for market risk that cannot be diversified away relative to the market risk. Such market volatility is computed as follows:

$$b_{it} = \frac{cov((R_{it}, R_{mt}) \mid \Omega_{t-20})}{var(R_{mt} \mid \Omega_{t-20})} \qquad (6)$$

where b_{it} represents market volatility of stock *i* on day *t*. $cov((R_{it}, R_{mt}) \mid \Omega_{t-20})$ is the covariance between returns on stock *i* on day *t* and market returns on the same day conditional on returns on 20-trading days. $var(R_{mt} \mid \Omega_{t-20})$ is the variance of market returns on day t conditional on returns on 20-trading days. Still, this study shows that the variance of market volatility changes over time. This is why the GARCH model of Bollerslev (1986) is employed to estimate expected market volatility or beta for stock *i* at time *t* conditional on the information set at time *t-1*, $E_{t-1}(BETA_{it})$.

This paper illustrates further that market volatility does not have a constant variance. Equation (7) is the time-series regression that is performed before the residual of regression, ν_{it} , can be tested with ARCH LM test for autoregressive conditional heteroskedasticity. The following regression is performed:

$$b_{it} = c_i + \nu_{it}, \nu_{it} \sim N(0, \vartheta_{it}^2) \qquad (7)$$

where equation (7) is the market volatility's mean equation. The null hypothesis is that there is no ARCH up to q order in the residuals, similar to the form of equation (4). That is,

$$\nu_{it}^2 = \zeta_0 + (\sum_{s=1}^{q} \zeta_s \nu_{i,t-s}^2) \qquad (8)$$

If the null hypothesis $(\zeta_1, ..., \zeta_q = 0)$ is rejected, it means that there exists a significant ARCH effect. Hence, the GARCH model is the appropriate model to estimate expected market volatility, as notated by Ooi, *et al.* (2009).

As expected, the ARCH LM test shows that the autoregressive conditional heteroskedasticity exists. Thus, equation (9) is used to estimate expected conditional variance of market volatility or beta, which is composed of the last period expected conditional variance of market volatility, $\vartheta_{i,t-1}^2$, and the last period of unexpected news or information shocks, $\nu_{i,t-1}^2$, as follows:

$$\vartheta_{it}^2 = \omega_i + \varphi_i \vartheta_{i,t-1}^2 + \psi_i \nu_{i,t-1}^2 \qquad (9)$$

Each of four GARCH models, GARCH (1, 1-2; 2, 1-2), is used for estimating the expected conditional market volatility, and the one with the lowest AIC or SIC is selected. Thus, GARCH (2, 2) was determined to be the best model and is represented as $E_{t-1}(Beta_{it})$ in this work.

To check robustness of the relation between expected idiosyncratic volatility, expected market volatility and expected stock returns, liquidity variables are controlled for each model. In other words, liquidity variables can be interpreted as the demand-side in the stock market while idiosyncratic and market volatility can be considered as supply-side of the stock market. Such variables are employed to test whether both types of volatility still significantly determine expected stock returns. The first well-known market microstructure factor is the relative bid-ask spread, RS_{it} . It is defined as the ratio of the difference between ask price and bid price to the average of the sum of ask price and bid price of stock *i* on day *t* as follows:

$$RS_{it} = \frac{(ask - bid)}{\left(\frac{ask + bid}{2}\right)} \times 100 \tag{10}$$

The other liquidity variable is an illiquidity measure as discussed in Amihud (2002), which is called "Amihud measure", ILR_{it} . It is defined as the daily absolute return over the trading volume in Thai baht of stock *i* on day *t*. That is,

$$ILR_{it} = \frac{\left|R_{it}\right|}{VOL_{it}} \tag{11}$$

where $\left|R_{it}\right|$ stands for the daily absolute return on stock *i* on day *t*, and VOL_{it} denotes the trading volume in Thai baht (trading value) of stock *i* on day *t*. As in Amihud (2002), the value of illiquidity measure, ILR_{it} , is multiplied by 10^6.

Moreover, the simplest liquidity variable is the turnover ratio, $TURN_{it}$. It is defined as the percentage of the ratio of the trading volume in units of shares on all boards in the Stock Exchange of Thailand to the number of listed shares on the same day for stock *i* on day *t*. In addition, the value of each stock, $VALUE_{it}$, that is traded on day *t* is an additional variable. It is defined as the product of trading volume and stock price on the same day. These liquidity variables are employed to test whether expected idiosyncratic and expected market volatility still significantly affect on expected stock returns.

To summarize, the testable implications of Fama and macBeth model for expected stock returns as in equation (1) are:

1) The relationship between expected stock returns and volatility should not be zero. That is, the estimated coefficients on $BETA_{it}(\beta_1)$, $E_{t-1}(IV_{it})(\beta_2)$ and $E_{t-1}(BETA_{it})(\beta_3)$ in all of the models should not be zero. The null hypotheses are $\beta_1 = 0$, $\beta_2 = 0$, and $\beta_3 = 0$. That is, idiosyncratic risk and systematic risk are not priced

2) The relationship between the relative bid-ask spread, RS_{it} , and expected stock returns should be negative because the lower the relative bid-ask spread the higher the expected stock returns. It means that there are several investors who buy and sell stocks at time *t*. Thus, the null hypothesis is $\beta_4 \geq 0$.

3) The estimated coefficient on $VALUE_{it}$ should be positive. In fact, the null hypothesis is $\beta_5 \leq 0$. This means that there are many stocks traded in stock market which might, in turn, increase expected stock returns.

4) The estimated coefficient on ILR_{it} should be negative. Thus, the null hypothesis is $\beta_6 \geq 0$. In fact, the higher the value of illiquidity the lower the expected stock returns.

5) The estimated coefficient on $TURN_{it}$ should be positive. Hence, the null hypothesis is $\beta_7 \leq 0$. This means that the higher the turnover ratio the higher the expected stock returns.

Data

Data for studying the relationship between expected idiosyncratic volatility, expected market volatility, expected stock returns and other factors come from the daily data on the SET50 index and the Thai Bond Market Association (ThaiBMA) between April 2001 and December 2009, a total of 2,142 days. They also come from daily data of 28 stock sectors traded in the Stock Exchange of Thailand from March 2001 to December 2011. Data comprise 97 common stocks which are traded in SET50 during that period. For more detail, SET50 index is calculated and composed of the top 50 listed companies in the Stock Exchange of Thailand. The criteria of such companies are the large market capitalization, high liquidity, and compliance with the requirement regarding the distribution of shares to minor shareholders. This index was launched on August 16, 1995, so this is the base date, set at 1000.

For the variables of individual stocks, *R* stands for the daily realized stock returns over the past one month (20 trading days) reported in percentage, and representing expected stock returns. *EIV* is the daily expected idiosyncratic volatility conditional on the information set at time *t-1* for stock *i* at time *t* which is estimated by using the EGARCH (1, 1) model. *EBETA* is the daily expected market volatility or beta for stock *i* at time *t* conditional on the information set at time *t-1* which is estimated by using GARCH (2, 2) model. RS is the daily relative bid-ask spread which is defined as the ratio of the difference between ask price and bid price to the average of sum of ask price and bid price of stock *i* at time *t.* *VALUE* is the daily value of stock *i* at time *t*, which is defined as the product of trading volume and stock price on the same day reported in Thai baht. *ILR* represents the daily illiquidity ratio as discussed in Amihud (2002), which is defined as the daily absolute return over the trading volume in Thai baht of stock *i* at time *t*, and multiplied by 10^6. *TURN* is the daily turnover ratio which is defined as the percentage ratio of the trading volume in units of shares on all boards to the number of listed shares on the same day for stock *i*.

For the variables of stock sectors, R_S stands for the daily realized stock returns over the past one month (20 trading days) reported in percentage, and representing expected stock returns. EIV_S is the daily expected idiosyncratic volatility conditional on the information set at time *t-1* for stock *i* at time *t* which is estimated by using the EGARCH (1, 1) model. $EBETA_S$ is the daily expected market volatility or beta for stock *i* at time *t* conditional on the information set at time *t-1* which is estimated by using GARCH (2,2) model. $VALUE_S$ is the daily value of stock *i* at time *t*, which is defined as the product of trading volume and stock price on the same day reported in Thai baht. ILR_S represents the daily illiquidity ratio as discussed in Amihud (2002), which is defined as the daily absolute return over the trading volume in Thai baht of stock *i* at time *t*. $TURN_S$ is the daily turnover ratio which is defined as the percentage ratio of the trading volume in units of shares on all boards to the number of listed shares on the same day for stock *i*.

Results

This paper explores the mutual influences of expected idiosyncratic volatility and expected market volatility on expected stock returns. The mean risk-free rate as measured by the one-month Treasury-bill is equal to 0.198 percent per month while the average market return (average SET50 return) is equal to 1.094 percent per month. It is not interesting that the average market return is much higher than the average risk-free rate. That is, the average equity premium is equal to 0.895 percent per month. This is also the same when comparing individual stock returns with the risk-free rate. Indeed, almost all average stock returns are much higher than the risk-free rate; in other words, there exists a positive equity premium in the case of Thailand. These results imply that there is an equity premium in the SET50 index similar to those in the UK (6.1%), the US (6.1%), and Japan (8.8%) during the period 1946-2006 as shown by Corte *et al.* (2010).

Table 1 presents the descriptive statistics of the pooled sample's variables. The average expected stock returns *(R)* between April 2001 and December 2009 are 1.736 percent per month. The average expected conditional idiosyncratic volatility *(EIV)* which comes from the EGARCH (1, 1) model is equal to 11.423 percent per month. Surprisingly, it is quite similar to results shown by Fu (2009) which is equal to 12.67 percent per month because there are considerable uncertainties about stock returns in SET50. Equally important, the average expected conditional market volatility *(EBETA)* which is calculated from the GARCH (2, 2) model is equal to 12.740 percent per month. Such amount of volatility is slightly higher than the average expected conditional idiosyncratic volatility. More importantly, after using ARCH test, two regression residual tests of risk measure, i.e. equations (4) and (8), have a significant ARCH effect in the model with a 0.05 significance level. It is also to be noted that the average expected stock returns are higher than expected conditional idiosyncratic volatility and market volatility during this time period. It implies that the idiosyncratic risk and systematic risk are very high because there are several uncertainties after the economic crisis in 1997 such as the unremunerated reserve requirement in 2006.

Table 1 Summary statistics for the pooled sample of individual stocks

	R	*BETA*	*EBETA*	*EIV*	*RS*	*VALUE*	*ILR*	*TURN*
Mean	1.736	0.800	12.741	11.423	0.781	1.48×10^{8}	0.674	0.472
Median	0.000	0.713	6.862	5.620	0.710	42371200	0.100	0.190
Maximum	4947.170	185.370	17481.77	17458.99	25.170	7.10×10^{9}	1978.020	50.730
Minimum	-96.140	-2587.986	0.023	0.000	-11.970	0.000	0.000	0.000
Std. Dev.	51.069	7.783	173.631	172.716	0.538	3.08×10^{8}	10.548	1.144
Skewness	72.745	-304.521	82.254	82.641	6.504	5.540	160.362	12.490
Kurtosis	5806.528	101208.3	6936.700	6986.180	129.956	52.783	28402.15	291.720
Jarque-Bera	1.70×10^{11}	5.16×10^{13}	2.42×10^{11}	2.46×10^{11}	82104910	13112317	4.07×10^{12}	4.23×10^{8}
Probability	0.000	0.000	0.000	0.000	0.000	0.0000	0.000	0.000
Sum	210086.3	96804.59	1541435.	1382041.	94464.54	1.80×10^{13}	81484.93	57133.77
SumSq. Dev.	3.16×10^{8}	7328956.	3.65×10^{9}	3.61×10^{9}	34979.70	1.15×10^{22}	13461447	158318.5
Observations	120987	120987	120987	120987	120987	120987	120987	120987
Cross sections	97	97	97	97	97	97	97	97

Note: This table reports the pooled descriptive statistics from 114,790 observations of 97stocks traded in the SET50 index from April 2001 to December 2009.

Liquidity variables have little average magnitude except on the stock value. The daily average percentage of relative spread *(RS)* is 0.781 percent. The daily mean value of the illiquidity ratio *(ILR)* is 0.674. The daily average turnover ratio *(TURN)* equals 0.472 percent, and the mean of stock value equals 1.48×10^{8} Thai baht. In addition, all the calculated p-values of Jarque-Bera test statistic are lower than a 0.01 significance level. This implies that all the residuals of variables are not normally distributed. However, it does not affect the results. That is, the estimators from the pooled and fixed panel data regressions are still minimum-variance unbiased.

Table 2 presents the descriptive statistics of the pooled sample's variables for sectors of stock in the Stock Exchange of Thailand. The mean risk-free rate as measured by the one-month Treasury-bill is equal to 0.1980 percent per month; in contrast, the average market return (average return of stock sector) is equal to 1.1377 percent per month. In other words, the equity premium is equal to 0.9397 percent per month. It is consistent with individual stocks; therefore, it has an equity premium in the Stock Exchange of Thailand.

Table 2 Summary statistics for the pooled sample of stock sectors

	R_S	EIV_S	$EBETA_S$	$VALUE_S$	ILR_S	$TURN_S$
Mean	1.245	4.760	0.466	6.50×10^{8}	8.24×10^{-5}	0.522
Median	0.828	3.689	0.349	95168138	0.000	0.250
Maximum	221.529	509.861	10.143	7.80×10^{10}	0.985	33.430
Minimum	-52.619	0.000	0.000	0.000	0.000	0.000
Std. Dev.	8.794	5.417	0.481	1.48×10^{9}	0.007	1.016
Skewness	1.256	26.177	3.984	6.733	117.618	8.910
Kurtosis	23.066	1754.630	32.053	154.185	14468.73	148.303
Jarque-Bera	1140927	8.57×10^{9}	2532119	64274765	5.84×10^{11}	59789256
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Sum	83364.220	318720.7	31208.93	4.35×10^{13}	5.520	34932.49
Sum Sq. Dev.	5178063	1964799	15491.68	1.47×10^{23}	3.197	69078.14
Observations	66958	66958	66958	66958	66958	66958
Cross sections	28	28	28	28	28	28

Note: This table reports the pooled descriptive statistics of stock sectors from 66,958 observations of 28 sectors of stocks traded in the Stock Exchange of Thailand from March 2001 to December 2011.

The average expected stock returns *(R_S)* between March 2001 and December 2011 are 1.245 percent per month. The average expected conditional idiosyncratic volatility *(EIV_S)* which comes from the EGARCH (1,1) model is equal to 4.760 percent per month. It is not a large amount compared with one of individual stocks. Similar to the average expected conditional market volatility *($EBETA_S$)*, which is calculated from the GARCH (2,2) model, it is equal to 0.466 percent per month. Such amount of volatility is also lower than the average expected conditional idiosyncratic volatility. It is to be noted that both volatilities for stock sectors are lower than ones for individual stocks. In addition, the means of liquidity variables are lower than those of the individual stocks. In fact, the daily average value of stock sector *($VALUE_S$)* equals $6.50X10^{8}$ Thai baht. The daily mean value of the illiquidity ratio *(ILR_S)* is $8.24X10^{-5}$. The daily average turnover ratio *($TURN_S$)* equals 0.5217 percent each.

Following the Fama and MacBeth model, equation (1) is used to examine the relationship between expected conditional idiosyncratic volatility, expected conditional market volatility and expected individual stock returns by using time-series and cross-sectional daily data. The estimation results are summarized in Table 3 under models 1, 2, 3, 4, 5, and 6. Such models can be shown explicitly as follows:

Model 1: $R_{it} = \alpha_{1i} + \beta_1 Beta_{it} + \beta_2 E_{t-1}(IV_{it}) - u_{1it}$ (12)

Model 2: $R_{it} = \alpha_{2i} + \beta_2 E_{t-1}(IV_{it}) + \beta_3 E_{t-1}(Beta_{it}) - u_{2it}$ (13)

Model 3: $R_{it} = \alpha_{3i} + \beta_2 E_{t-1}(IV_{it}) + \beta_3 E_{t-1}(Beta_{it}) + \beta_4 RS_{it} - u_{3it}$ (14)

Model 4: $R_{it} = \alpha_{4i} + \beta_2 E_{t-1}(IV_{it}) + \beta_3 E_{t-1}(Beta_{it}) + \beta_4 RS_{it} + \beta_5 Value_{it} - u_{4it}$ (15)

Model 5: $R_{it} = \alpha_{5i} + \beta_2 E_{t-1}(IV_{it}) + \beta_3 E_{t-1}(Beta_{it}) + \beta_4 RS_{it} + \beta_5 Value_{it} + \beta_6 ILR_{it} - u_{5it}$ (16)

Model 6: $R_{it} = \alpha_{6i} + \beta_2 E_{t-1}(IV_{it}) + \beta_3 E_{t-1}(Beta_{it}) + \beta_4 RS_{it} + \beta_5 Value_{it} + \beta_6 ILR_{it} + \beta_7 TURN_{it} - u_{6it}$ (17)

All the models show that expected conditional idiosyncratic volatility displays a strongly positive relationship to expected stock returns at a 0.01 significance level, and the size of coefficient is approximately 0.245. The t-statistics are larger than 30. In addition, an average of adjusted R-squared is about 0.75. The positive relation is similar to Merton (1987), Amihud and Mendelson (1989), Malkiel and Xu (2006), Goyal and Santa-Clara (2003), Spiegel and Wang (2005), Guo and Neely (2008), Boehme *et al*. (2009), Fu (2009), Ooi *et al*. (2009), and Bali and Cakici (2010). However, it is contrary to the results of Guo and Savickas (2006), Ang *et al*. (2006; 2009), Angelidis (2010), and Guo and Savickas (2010). In addition, the coefficients on expected conditional idiosyncratic volatility gradually increase in models 3, 4, 5 and 6 after controlling for liquidity variables. This implies that liquidity variables make coefficients of idiosyncratic volatility slightly go up.

The other finding states that expected conditional market volatility is positively and significantly related to expected stock return other than model 6. This relationship is weakly significant in the pooled panel regressions. Contrary to Goyal and Santa-Clara (2003), Fu (2009), Ooi *et al.* (2009), and Bali and Cakici (2010), expected market volatility is economically significantly positive in models 2, 3, 4, and 5, even though the models control for liquidity variables. Furthermore, the coefficients on conditional market volatility vary little after the explanatory liquidity variables are included in the regression models. This implies that liquidity variable does not influence its relationship. Still, unconditional market volatility does not play important role as stated in model 1.

Additionally, comparing *EIV* with *EBETA*, the coefficients on conditional idiosyncratic volatility are quite the same size in all the models and larger than those of conditional market volatility. Therefore, conditional idiosyncratic volatility plays a more important role than conditional market volatility in case of individual stocks. In fact, an average coefficient on *EIV* equals 0.245 and an average coefficient on *EBETA* equals 0.013. This means that a change in 0.245% of *EIV* results in a change in 1% of stock returns in the next period, and a change in 0.013% of *EBETA* results in a change in 1% of stock returns in the next period.

Liquidity variables do not have a significant effect on the relationship between expected conditional idiosyncratic volatility and expected stock returns. It is interesting that the relative bid-ask spread has a strong negative correlation with the expected stock returns. It implies that the larger the relative bid-ask spread is, the lower the expected stock returns will be. Similarly, the illiquidity ratio has a significantly negative effect on the expected stock returns in model 6. In contrast, the turnover ratio and the stock value have positive effects on expected stock returns. More importantly, the magnitude of the turnover ratio is larger than the other variables. This implies that the higher the stock value and the turnover ratio, the higher the expected stock returns should be. In other words, investors can obtain greater stock returns when stocks are more liquid in the stock market. Therefore, it is very useful to account for a frictionless stock market.

Table 3 Pooled panel data regressions of Fama and MacBeth model for individual stocks

Model	Intercept	BETA	*EIV*	*EBETA*	*RS*	*VALUE*	*ILR*	*TURN*	$\overline{R}^2$
1	-1.194***	-0.008	0.257***						0.75
2	-1.219***		0.242***	0.015*					0.75
3	0.069		0.241***	0.015*	-1.632***				0.75
4	-0.983***		0.243***	0.013*	-1.448***	(6.18×10^{-9})***			0.76
5	-0.989***		0.243***	0.013*	-1.437***	(6.17×10^{-9})***	-0.002		0.76
6	-1.330***		0.246***	0.011	-1.606***	(4.10×10^{-9})***	-0.018***	1.652***	0.76

Note: This table reports the coefficients of the pooled panel data regressions using Fama and MacBeth (1973) model. The sample is the daily data from April 2001 to December 2009. Intercept is the constant stock return in each model. * ** *** denote 0.10, 0.05 and 0.01 significance levels.

The results of pooled panel data regressions for stock sectors are shown in Table 4. The main findings are the same as results from individual stocks. That is, expected conditional idiosyncratic volatility is positively related to expected stock returns in all five models. Model 1 is a univariate pooled panel regression of expected stock return on *EIV,* Model 2 controls for *EBETA,* Model 3 controls for *EBETA* and *VALUE*, and Model 4 controls for *EBETA, VALUE* and *ILR*. Model 5, in addition, controls for *EBETA* and three liquidity variables. The estimated coefficients on *EIV* are positive and statistically significant at the 0.01 level. The average slope on *EIV* is 0.3761, and t-statistics are larger than 54. Moreover, the mean of adjusted R-squared is about 0.073. The coefficients on expected conditional idiosyncratic volatility gradually go down after controlling for liquidity variables. In fact, liquidity variables make its effects on expected stock returns decrease. However, these findings indicate that stock sectors with higher expected conditional idiosyncratic volatility deliver higher expected returns, and are robust after controlling for liquidity variables.

Models 2-5 in Table 4 also yield surprising evidence that expected conditional market volatility is positively related to expected stock returns in cross-section. This positive relationship is statistically significant at 0.01 level. The average slope on *EBETA* is 0.9709, and t-statistics are larger than 12. The estimated coefficients change very little from 0.9181 to 1.0247 after the explanatory liquidity variables are included in the regression models. This evidence indicates that liquidity variable does not influence considerably its relationship.

Table 4 Pooled panel data regressions of Fama and MacBeth model for stock sectors.

Model	*EIV*	*EBETA*	*VALUE*	*ILR*	*TURN*	$\overline{R}^2$
1	0.4057^{***}					
2	0.3734^{***}	0.9181^{***}				0.064
3	0.3716^{***}	1.0246^{***}	$(6.73\times10^{-10})^{***}$			0.077
4	0.3716^{***}	1.0247^{***}	$(6.73\times10^{-10})^{***}$	-1.7564		0.077
5	0.3582^{***}	0.9142^{***}	$(5.60\times10^{-10})^{***}$	-0.8136	0.8425^{***}	0.087

Note: This table reports the coefficients of the pooled panel data regressions using Fama and MacBeth (1973) model. The sample is the daily data of stock sectors from March 2001 to December 2011. * ** *** denote 0.10, 0.05 and 0.01 significance levels.

In contrast with findings from individual stock, conditional idiosyncratic volatility plays less important role than conditional market volatility in determining expected stock returns in case of stock sectors. Indeed, an average slope coefficient on conditional market volatility is larger than one on conditional idiosyncratic volatility. It implies that investors are able to diversify idiosyncratic risk through stock sectors. Even though both types of risks have positive effects on expected stock returns, systematic risk has a higher effect than idiosyncratic risk. Specifically, stock sector with higher systematic risk delivers higher expected stock returns.

As a robustness check, liquidity variables are controlled for. Models 3-6 demonstrate that they do not change considerably the relationship between expected conditional idiosyncratic volatility and expected stock returns. It is similar to expected conditional market volatility. Although the estimated coefficients change very little in models 1-5, there is still a significantly positive relation. Compared with individual stocks, similar results show that the average coefficients on stock value and turnover ratio are positive and statistically significant in all specifications. Moreover, the magnitude of average slope on turnover ratio is larger than the other variables. It implies that investors should construct portfolios with more liquidity to obtain higher expected returns in the stock market. More importantly, the estimated coefficients on illiquidity ratio are negative but statistically insignificant in model 5 and model 6. Specifically, there is no significant relationship between illiquidity ratio and expected stock returns.   There is an important point in equation (1) that could lead to a biased and inconsistent estimation because of an omitted-variable problem. Such omitted variables might result in a change of the intercept, α_i , in equation (1). The fixed effect panel data model is used to remedy this problem and allow the constant term to vary over time and over cross-section units. The coefficient estimators, β_l , then become unbiased and consistent. Importantly, after using the F-test and Chi-squares test to choose the model, the results show that the null hypothesis, $\alpha_i = 0$, is rejected at a 0.01 significance level. This indicates that fixed effect panel data regression is the appropriate model to estimate expected stock returns.

Table 5 shows the estimated coefficients on explanatory variables which are also the same as the results from the pooled panel data regressions. The fixed effect panel data regressions come up with statistically positive effects of expected conditional idiosyncratic volatility on expected stock returns. In fact, it is significantly related to expected stock returns in all the models. The estimated coefficients on *EIV* are quite similar, i.e. they vary little from 0.240 to 0.257, and are statistically significant at a 0.01 significance level. The t-statistics are larger than 29.37, and an average adjusted R-squared is 0.755. Furthermore, the models which control for liquidity variables do not give a substantial change in the expected conditional idiosyncratic volatility. It implies that liquidity variables do not have much effect on the relationship between expected conditional idiosyncratic volatility and expected stock returns.

Table 5 Fixed effect panel data regressions of Fama and MacBeth model for individual stocks.

Model	BETA	*EIV*	*EBETA*	*RS*	*VALUE*	*ILR*	*TURN*	$\overline{R}^2$
1	-0.006	0.257***						
2		0.241***	0.016**					0.75
3		0.240***	0.017**	-1.653***				0.75
4		0.242***	0.016*	-1.464***	(8.15×10^{-9})***			0.76
5		0.242***	0.016*	-1.449***	(8.15×10^{-9})***	-0.004***		0.76
6		0.243***	0.015*	-1.644***	(4.53×10^{-9})***	-0.020***	2.110***	0.76

Note: This table reports the coefficients of the fixed effect panel data regressions using Fama and MacBeth (1973) model. The sample is the daily data from April 2001 to December 2009. Intercepts are not presented here due to an excess of data. * ** *** denote 0.10, 0.05 and 0.01 significance levels.

Consistent with the pooled panel data regressions, Models 2-5 also show that expected conditional market volatility is positively and significantly related to expected stock returns in all the models. However, the estimated coefficients are statistically significant at a 0.10 significance level, and 0.05 significance level. They are smaller than those of expected conditional idiosyncratic volatility as well. That is, an average slope on *EBETA* is 0.016, and t-statistics are larger than 1.78. Liquidity variables, however, do not change the significant effect of expected market volatility. Therefore, not only are the coefficients on expected idiosyncratic volatility from the fixed panel data regressions similar to those from the pooled panel data regressions, the coefficients on expected market volatility from the fixed panel data regressions are also similar to the ones from pooled panel data regressions.

Another important finding is that all the explanatory liquidity variables have strong predictive power: stock value and turnover ratio are positive and significantly related to expected stock returns. In contrast, there is a significantly negative relation between relative bid-ask spread, illiquidity ratio and expected stock returns. In the SET50, the estimated coefficients on relative bid-ask spread and turnover ratio are very large, so liquidity premium plays an important role.

Table 6 shows the estimated coefficients on explanatory variables of models in equation (1) for stock sectors by using fixed effect panel data regressions. The results of such regressions come up with strongly positive effects of expected conditional idiosyncratic volatility on expected stock returns. The average slope coefficients on *EIV* vary from 0.3822 to 0.4330, and are statistically significant at a 0.01 significance level. The t-statistics are larger than 56.36, and an average adjusted R-squared is 8.85. Consistent with results of individual stocks, it is positively related, significantly, to expected stock returns in all the models. In addition, expected conditional market volatility is positively and significantly related to expected stock returns in models 1-5, which is similar to results of individual stock. The average slope coefficients on *EBETA* change very little from 1.3094 to 1.4438. The t-statistics are larger than 16.19. In particular, expected conditional market volatility plays a more important role than expected conditional idiosyncratic volatility, as indicated in average slopes on *EBETA* being larger than the ones on *EIV*.

Table 6 Fixed effect panel data regressions of Fama and MacBeth model for stock sectors.

Model	*EIV*	*EBETA*	*VALUE*	*ILR*	*TURN*	$\overline{R}^2$
1	0.4330***					6.24
2	0.3935***	1.3094***				7.57
3	0.3980***	1.4438***	(1.12×10^{-9})***			9.79
4	0.3980***	1.4438***	(1.12×10^{-9})***	-1.8972		9.79
5	0.3822***	1.3530***	(1.02×10^{-9})***	-1.3543	0.9596***	10.88

Note: This table reports the coefficients of the fixed effect panel data regressions using Fama and MacBeth (1973) model. The sample is the daily data of stock sectors from March 2001 to December 2011. Intercepts are not presented here due to an excess of data. * ** *** denote 0.10, 0.05 and 0.01 significance levels.

Furthermore, models 3-5 which control liquidity variables have significant effects on expected conditional idiosyncratic volatility and expected conditional market volatility. It implies that liquidity variables do not change the considerable effects of expected conditional idiosyncratic volatility and expected conditional market volatility on expected stock returns. The estimated coefficients, however, go down after explanatory liquidity variables are controlled for. Otherwise, illiquidity ratio is not significantly related to expected stock returns contrary to individual stocks.

Models 1-5 in Table 7 demonstrate the estimated coefficients on explanatory variables in equation (1) for stock sectors by using random effect panel data regressions. All the findings are similar to the estimated coefficients from pooled panel data regressions for stock sectors. In other words, the results of such regressions come up with significantly positive effects of expected conditional idiosyncratic volatility on expected stock returns. The average slope coefficients on *EIV* change very little from 0.3803 to 0.4314. The t-statistics are larger than 57.81, and an average adjusted R-squared is 0.084. Consistent with results from pooled panel data regressions for stock sectors, these coefficients are statistically significant at a 0.01 significance level in all the models. Additionally, expected conditional market volatility is positively and significantly related to expected stock returns in models 2-5. The estimated coefficients on *EBETA* change very little from 1.2841 to 1.4163. The t-statistics are larger than 16.89. Specifically, expected conditional market volatility plays more important role than expected conditional idiosyncratic volatility.

Table 7 Random effect panel data regressions of Fama and MacBeth model for stock sectors

Model	*EIV*	*EBETA*	*VALUE*	*ILR*	*TURN*	$\overline{R}^2$
1	0.4314***					0.066
2	0.3920***	1.2841***				0.070
3	0.3960***	1.4160***	(1.16×10^{-9})***			0.091
4	0.3960***	1.4163***	(1.16×10^{-9})***	-1.8689		0.091
5	0.3803***	1.3234***	(9.77×10^{-10})***	-1.3026	0.9553***	0.102

Note: This table reports the coefficients of the random effect panel data regressions using Fama and MacBeth (1973) model. The sample is the daily data of stock sectors from March 2001 to December 2011. Intercepts are not presented here due to an excess of data. * ** *** denote 0.10, 0.05 and 0.01 significance levels.

In addition, models 3-5 show that liquidity variables do not change the considerable effects of expected conditional idiosyncratic volatility and expected conditional market volatility on expected stock returns. The idiosyncratic coefficients reduce after models control for explanatory liquidity variables. In particular, illiquidity ratio is still not significantly related to expected stock returns. More importantly, this study tests whether random-effect model or fixed-effect model is more appropriate. Thus, Hausman test should be performed. The null hypothesis is that random-effect model is the true model, $cov(u_i, X_i) = 0$. The test shows that the null hypothesis is rejected at a 0.01 significance level for both stock sectors and individual stocks. Therefore, it implies that the appropriate model is fixed panel data regression.

Conclusions

Previous empirical studies show that there is a statistically significant relation between idiosyncratic volatility and expected stock returns, especially on the NYSE, Amex, and Nasdaq. Similarly, the findings of this paper document that expected idiosyncratic volatility for individual stocks has a significant effect on expected stock returns. Even though models control for liquidity variables, it still has a significant effect on expected stock returns for stock sector. The daily data for testing come from SET50 and stock sector of the Stock Exchange of Thailand. In contrast with Guo and Savickas (2006), Ang *et al*. (2006; 2009), Bali and Cakici (2008), Angelidis (2010), and Guo and Savickas (2010), such volatility is positive and significantly related to expected stock returns. The magnitude of coefficients for individual stocks is larger than one for stock sectors. Besides, the estimated coefficients of idiosyncratic volatility are quite equivalent magnitudes in all the models for both individual stock and stock sector. More importantly, liquidity variables do not change a significant effect of expected idiosyncratic volatility. This evidence supports the assumption of under-diversification which states that idiosyncratic volatility is positively related to expected stock returns because the investor might not hold perfectly diversified portfolio.

Another contribution is that expected market volatility or beta plays an important role in determining expected stock returns contrary to the findings of the papers cited above for both individual stock and stock sector. Consistent with the traditional CAPM, there is a significantly positive relation between expected market volatility and expected stock returns. Although models control for liquidity variables, a positive relation remains. As a result, liquidity variables do not change its significant effect on expected stock returns for the stock sector. However, the coefficients of market volatility are larger than the ones of idiosyncratic volatility. This means that systematic risk is more important than idiosyncratic risk in the stock sectors. That is, investors can reduce the effect of idiosyncratic risk through portfolio diversification. In contrast, idiosyncratic risk plays a more important role in individual stocks. More importantly, the results imply that expected market volatility conditional on information set at time *t-1* estimated by the GARCH (2, 2) model and expected idiosyncratic volatility conditional on information set at time *t-1* estimated by the EGARCH (1, 1) model are the appropriate proxies for market and idiosyncratic volatility. It means that such volatilities are very volatile over time.

In addition, stock value and turnover ratio have significantly positive effects on expected stock returns for individual stock. In contrast, relative bid-ask spread and illiquidity ratio are negatively related to expected stock returns. Indeed, the higher the relative bid-ask spread is, the lower the expected stock return to investors. Similarly, value of stock sector and turnover ratio of stock sector have significantly positive effects on expected stock returns. Yet, illiquidity ratio has no significant effect in case of stock sectors. However, investors are able to earn the liquidity premium by investing in a frictionless stock market.

In the Stock Exchange of Thailand, the time-varying idiosyncratic volatility plays a less important role than the time-varying market volatility in case of stock sector, especially if the sizes of coefficients in both cases are compared. In other words, investors should always consider the sources of market volatility before they decide to construct portfolios to invest in the stock market. This volatility might come from an economic downturn, the fluctuation of foreign exchange rates or political crises, etc. Furthermore, investors should construct their portfolios by selecting common stocks with high idiosyncratic volatility. This could increase in their expected stock returns. Consequently, risky common stocks should be the first investment priority because they have high idiosyncratic volatility that results in high expected stock returns. Similarly, portfolios with high idiosyncratic volatility will deliver high expected stock returns. This investment strategy is also useful for the Stock Exchange of Thailand and Securities Exchange and Commission in selecting companies to list on the stock market. That is, the first priority of stock selection is idiosyncratic volatility. However, the different implication from this study might be due partly to the efficiency of the market. This should be examined in a future research, especially the role of idiosyncratic volatility.

References

Amihud, Y. 2002. "Illiquidity and stock return: Cross section and time series effects." **Journal of Financial Markets** 5 (1): 31-56.

__________ and H. Mendelson. 1989. "The effects of beta, bid-ask spread, residual risk, and size on stock returns." **Journal of Finance** 44 (2): 479-486.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang. 2006. "The cross-section of volatility and expected returns." **Journal of Finance** 61 (3): 259-299.

__________. 2009. "High idiosyncratic volatility and low returns: International and further U. S. evidence." **Journal of Financial Economics** 91 (1): 1-23.

Angelidis, T. 2010. "Idiosyncratic risk in emerging markets." **The Financial Review** 45 (4): 1053-1078.

Bali, T. G. and N. Cakici. 2008. "Idiosyncratic volatility and the cross-section of expected return." **Journal of Financial and Quantitative Analysis** 43 (1): 29-58.

__________. 2010. "World market risk, country-specific risk and expected returns in international stock markets." **Journal of Banking & Finance** 34 (6): 1152-1165.

__________, X. Yan, and Z. Zhang. 2005. "Does idiosyncratic risk really matter?" **Journal of Finance** 60 (2): 905-929.

Boehme, R. D., B. R. Danielsen, P. Kumar, and S. M. Sorescu. 2009. "Idiosyncratic risk and the cross-section of stock returns: Merton (1978) meets Miller (1977)." **Journal of Financial Markets** 12 (3): 438-468.

Bollerslev, T. 1986. "Generalized autoregressive conditional heteroskedasticity." **Journal of Econometrics** 31 (3): 307-328.

Corte, P. D., L. Sarno, and G. Valente. 2010. "A century of equity premium predictability and the consumption-wealth ratio: An international perspectives." **Journal of Empirical Finance** 17 (3): 313-331.

Fama, E. F. and J. D. MacBeth. 1973. "Risk and return: Some empirical tests." **Journal of Political Economy** 81 (3): 607-636.

__________ and K. French. 1993. "Common risk factors in the returns on stocks and bonds." **Journal of Financial Economics** 33 (1): 3-56.

Fu, F. 2009. "Idiosyncratic risk and the cross-section of expected stock returns." **Journal of Financial Economics** 91 (1): 24-37.

Goyal, A. and P. Santa-Clara. 2003. "Idiosyncratic risk matters!" **Journal of Finance** 58 (3): 975-1007.

Guo, H. and C. J. Neely. 2008. "Investigating the intertemporal risk-return relation in international stock markets with the component GARCH model." **Economics Letters** 99 (2): 371-374.

__________ and R. Savickas. 2006. "Idiosyncratic volatility, stock market volatility, and expected stock returns." **Journal of Business & Economic Statistics** 24 (1): 43-56.

__________. 2008. "Average idiosyncratic volatility in G7 countries." **Review of Financial Studies** 21 (3): 1259-1296.

__________. 2010. "Relation between time-series and cross-sectional effects of idiosyncratic variance on stock returns." **Journal of Banking & Finance** 34 (7): 1637-1649.

Huang, W., Q. Liu, S. G. Rhee, and L. Zhang. 2010. "Return reversals, idiosyncratic risk, and expected returns." **Review of Financial Studies** 23 (1): 147-168.

Malkiel, B. G. and Y. Xu. 2006. **Idiosyncratic Risk and Security Returns** (Online). www.utdallas.edu/~yexiaoxu/IVOT_H.PDF, June 10, 2011.

Merton, R. C. 1987. "A simple model of capital market equilibrium with incomplete information." **Journal of Finance** 42 (3): 483-510.

Nelson, D. 1991. "Conditional heteroskedasticity in asset returns: A new approach." **Econometrica** 59 (2): 347-370.

Ooi, J. T. L., J. Wang, and J. R. Webb. 2009. "Idiosyncratic risk and REIT returns." **The Journal of Real Estate Finance and Economics** 38 (4): 420-442.

Spiegel, M. and X. Wang. 2005. **Cross-sectional Variation in Stock Returns: Liquidity and Idiosyncratic Risk.** Research Paper Series No. 05-13. International Center for Finance, Yale School of Management.