Idiosyncratic Risk and Asset Returns

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This study shows the relationship between idiosyncratic risk and expected returns on stock regarding theoretical and empirical results. By introducing idiosyncratic stochastic productivity level in production function of heterogenous firms, the dynamic stochastic general equilibrium is derived to come up with a new asset pricing model. Given any state $s$, the main finding states that expected stock returns depends on the rate of time preference, depreciation rate, capital share, expected idiosyncratic productivity level at time $t+1$, the percentage deviation of capital from steady state at time $t+1$, and the percentage deviation of labor from steady state at time $t+1$. In fact, expected idiosyncratic productivity level, expected capital, and expected labor are the determinant factors that affect on expected stock returns. Eventually, expected idiosyncratic stochastic productivity level is positively related to expected stock returns similar to expected labor. In contrast, expected capital has a negative effect on expected stock returns.

The empirical evidence also demonstrates the findings 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 another 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 SET50 index. In contrast, the coefficients of expected market volatility are larger than those of expected idiosyncratic volatility in the case of individual stocks in SET and stock sectors.

In addition, the results imply that expected idiosyncratic volatility conditional on information set at time $t-1$ estimated by the EGARCH (1, 1) model and expected market volatility conditional on information set at time $t-1$ estimated by the GARCH (2, 2) model are the appropriate proxies for market and idiosyncratic volatility. It is because such volatilities have not constant variance.

In particular, stock value and turnover ratio have significantly positive effects on expected stock returns for individual stocks. In contrast, relative bid-ask spread is negatively related to expected stock returns for individual stocks in SET50 and SET. It implies that the higher the relative bid-ask spread is, the lower the expected stock return to investors. However, illiquidity ratio does not provide any clear evidence for empirical relation. That is, it has a positive effect for individual stocks in SET index, and a negative effect for individual stocks in SET50 index. Yet, such variable has no significant effect in case of stock sectors. Similarly, value of stock sector and turnover ratio of stock sector have significantly positive effects on expected stock returns. It implies that investors are able to earn the liquidity premium by investing in a frictionless stock market.
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CHAPTER 1:
INTRODUCTION

Chapter Summary

Significance of this study is first provided the important and purpose. According to the capital asset pricing model (CAPM), expected returns on any asset in equilibrium rely solely on systematic risk. Such result leads to several empirical tests of model which conclude that such risk has a positive effect on expected returns, especially the two parameter model. Although later papers take idiosyncratic risk into account for expected stock returns, a few studies develop asset pricing model to explore an effect of such risk. Therefore, there are three objectives in this study. The first one is that we attempt to derive asset pricing model from dynamic stochastic general equilibrium model. Empirical evidence also finds out the relationship between conditional expected idiosyncratic volatility and expected stock returns as well as the conditional expected market volatility.

Scope of the study is as follows. The real business cycle model applied to account for an effect of idiosyncratic risk on expected stock returns. Such model extended from Jermann and Quadrini (2009) is employed to derive the asset pricing model in order to find the effect of idiosyncratic risk on expected stock returns. Fama and MacBeth (1973) model is employed to test empirical evidence by using pooled and fixed effect panel data regressions.

Framework of theoretical study is based on dynamic stochastic general equilibrium model. That is, there are two sources of uncertainty. That is, production function consists of aggregate shock and idiosyncratic shock. The modeled economy consists of two types of agent: infinitely homogeneous households and infinitely heterogeneous firms. They differ in level of idiosyncratic productivity. All agents are in competitive market, and thus all prices are taken as given.

1.1 Significance of the study

The capital market theory built on the mean-variance framework of Markowitz (1959) and extended by Sharpe (1964) and Lintner (1965) describes the substantial relationship between risk expected returns. Still, there are several particular
assumptions of the capital asset pricing model (CAPM) under perfect capital market. That is, investors would optimally hold a mean-variance portfolio. This means that they prefer portfolio with higher expected return given two investments with equal level of variance. Similarly, investors prefer portfolio with the lower variance given those with equal expected returns. In addition, it is assumed that all investors have homogeneous expectation, unlimited risk-free lending and borrowing, price takers, and there are neither transaction costs nor information costs. Therefore, the implication of the mean-variance efficiency portfolio shows that expected return on risky asset derives from return on risk-free asset and beta-adjusted market risk premium. This implies that beta measures systematic risk. Indeed, expected returns on any asset in equilibrium rely solely on systematic risk.

Systematic risk cannot be diversified away. It is associated with overall movement in the general market or economy, and is always referred to as the market risk. Thus, such risk cannot be eliminated through portfolio diversification. This is a key fundamental of CAPM which states that systematic risk measures expected return of an individual stock. It seems useful implication for portfolio construction to invest in stock market because investors should consider only the sources of such risk, e.g., economic fluctuation, political turmoil, problem of public debts, oil shock. This means that most stocks should covary with market changes. The facts of stock value, however, indicate that some individual stocks move in the same direction with overall market but the others move in the opposite direction with one. It means that expected return on stock could not be explained by systematic risk alone. Consequently, there are other risks which are specific to an individual stock such as business risk or financial risk.

In other words, the risk associated with individual stocks is idiosyncratic risk. It can be diversified away by including a large number of stocks in portfolio. That is, a rational investor should take not only on systematic risk, but also on idiosyncratic risk in order to obtain compensates. Additionally, the CAPM considers only systematic risk relative to expected returns on stock, disregards another risk. Campbell et al. (2001) state that industry and idiosyncratic firm-level shocks are also important components of individual stock returns. It is because (1) investors may fail to diversify in manner recommended by financial theory, (2) some investors who do try to diversify do so by holding a portfolio of 20 or 30 stocks which all idiosyncratic risk is eliminated, but the adequacy of closely approximation depends on the level of
Idiosyncratic volatility in stocks, (3) arbitrageurs who trade to exploit the mispricing of an individual stock face risks that are related to idiosyncratic return volatility, not aggregate market volatility, (4) events affect individual stocks, and the statistical significance of abnormal event-related returns determined by the volatility of individual stock returns relative to the market, and (5) the price of an option on an individual stock depends on the total volatility, industry-level volatility, idiosyncratic volatility and market volatility.

It is surprisingly that there are a few studies on idiosyncratic risk especially the role idiosyncratic and market risk. Even though there is very useful for portfolio construction to invest in stock market, idiosyncratic risk does not consider as an important determining factor in expected stock returns. Almost all of the studies in the past assert on systematic risk, for instance, consumption, labor income, rate of inflation etc.

The purpose of this study is to provide a general equilibrium asset pricing model which shows the effect of idiosyncratic risk on expected stock returns in theoretical section. Moreover, an empirical research develops how a measurement of idiosyncratic risk has been done. It typically shows the empirical result that idiosyncratic risk has an effect on expected returns on stocks as well as market volatility. Therefore, it is beneficial to develop investment strategy and allocate the investor’s assets.

1.2 Statement of Problems

Idiosyncratic risk, defined as diversified risk, does not figure in the traditional asset pricing model, the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964) and Lintner (1965). It is because systematic risk is only priced in equilibrium. This particular characteristic is the same assertion as documented by consumption-based capital asset pricing model (CCAPM) as in Lucas (1978) and Breeden (1979) or production-based asset pricing model in Cochrane (1991). Consequently, expected stock returns are determined solely by systematic risk since idiosyncratic risk can be eliminated through portfolio diversification.

In terms of theoretical papers in financial economics, almost all the asset pricing literatures have less examined in the role of idiosyncratic risk. Such studies show the macroeconomic sources of risk that drive asset prices such as consumption, labor
income, money demand, inflation, habit formation, capital adjustment cost, output, debt and equity financing, etc. These variables are considered as the sources of systematic risk which affect expected returns.

Still, such risk plays important role in determining expected stock returns regarding empirical papers. There are different results and implication, however. More importantly, the explanations for these findings are also not the same. That is, previous studies have shown that there are three results: positive, negative, and mixed relationship between idiosyncratic risk and expected stock returns. This is why this study tries to explore whether idiosyncratic affect on expected returns on stock.

In the case of Thailand, the key facts about asset returns are given in Table 1. The data comes from the daily data on the SET index and Treasury-bill between March 2001 and December 2011, a total of 2,560 trading-days each. The net daily SET index returns over the past one month are calculated by daily-closed SET index on day \( t \) minus daily-closed SET index on day \( t-20 \), and divided by daily-closed SET index on day \( t-20 \). The mean of stock returns for this period is 1.0813 percent per month with standard deviation of 6.8508. It has maximum returns of 24.6049 percent per month, and minimum returns of -35.5669 percent per month.

On the contrary, the returns on one-month Treasury-bill during the same period have an average of 0.1927 percent per month with standard deviation of 0.0927. The maximum returns on one-month Treasury-bill equal 0.4051 percent per month, and the minimum returns equal 0.0646 percent per month. Consequently, there is an equity premium for Thai stock market of 0.8886 percent per month.

<table>
<thead>
<tr>
<th>Table 1 Stock Returns on SET Index and Treasury-bill</th>
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<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>SET index</td>
</tr>
<tr>
<td>1M T-bill</td>
</tr>
<tr>
<td>3M T-bill</td>
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</table>
Consistent with three-month Treasury-bill, it has average daily returns over the past one month of 0.1991 percent per month with standard deviation of 0.0915. It has maximum returns on three-month Treasury-bill of 0.4062 percent per month, and minimum returns of 0.0661 percent per month.

Figure 1 shows historical movement of SET index returns and one-month Treasury-bill returns. Indeed, the daily stock returns over the past one month are more highly volatile than the daily returns on one-month Treasury-bill during the same period. This implies that stocks are riskier than Treasury-bills. This study will use these facts to develop an asset pricing model for capturing volatility, especially idiosyncratic volatility. The model is developed from the stochastic general equilibrium model. Empirical study also shows that a particular determinant which causes the returns on stock move relatively more volatile than risk free asset is idiosyncratic risk. It is because investor rewarded a premium for bearing this additional risk.

Figure 1 Asset Returns Facts
1.3 Objectives of the Study
This study has three objectives as the followings.

1) To develop general equilibrium asset pricing model to capture idiosyncratic risk as a particular determinant of expected stock returns.

2) To show that the conditional expected idiosyncratic volatility is related to expected stock returns.

3) To examine that the conditional expected market volatility is related to expected stock returns.

1.4 Scope of the Study
1) The dynamic stochastic general equilibrium model will be employed to derive the asset pricing model in order to find the effect of idiosyncratic risk on expected stock returns.

2) There are two sources of uncertainty. That is, production function consists of aggregate shock and idiosyncratic shock.

3) The modeled economy comprises two types of agent: infinitely homogeneous households and infinitely heterogeneous firms.

4) Fama and MacBeth (1973) model is employed to test empirical research by using pooled and fixed effect panel data regressions.

5) The daily realized return over the past one month is the explained variable. The explanatory variables are conditional expected idiosyncratic volatility, expected market volatility, percentage bid-ask spread, illiquidity measure, turnover ratio, and stock value.

1.5 Benefits of the Study
This study provides the fact of being useful as follows:

1) To come up with a new asset pricing model that derives from the real business cycle model.

2) To find out the relationship between conditional expected idiosyncratic volatility and expected stock returns.

3) To find out the conditional expected market volatility and expected stock returns.
1.6 Study Framework

There are a few theoretical studies which consider the idiosyncratic risk. This fact motivates us to spell a decentralized economy out in order to explicitly explore asset pricing model.

The purpose of this study is to examine real business cycle model which tries to show the effect of idiosyncratic risk on expected stock returns in the dynamic stochastic general equilibrium. In addition, this study also examines the role of an aggregate risk in asset pricing model. Thus, the model designed to capture asset prices is an extension of Jermann and Quadrini (2009). It differs considerably from all asset pricing models in productivity shocks because such model is developed by introducing idiosyncratic shock into a production function.

This economy model is based mainly on real business cycle model. It consists of two types of agent: infinitely-lived homogenous households and infinitely-lived heterogeneous firms. There are also two types of assets traded in this economy: real bonds and equity stocks.

An infinitely representative household maximizes his expected lifetime utility subject to budget constraint at each time. The infinitely heterogeneous firms otherwise maximize the expected present value of cash flow subject to their budget constraints. They differ in level of idiosyncratic productivity. All agents are in competitive market, and thus all prices are taken as given.

The homogenous households have to decide on how much consumption they will consume, how many bonds and stocks they will purchase at the beginning of period when they earn money from labor wages, bonds sold, stocks sold, and dividend payments at the end of period. Apart from consumption side, heterogeneous firms have to decide on how much they pay their debts, how much they pay dividends to the stock owners, how much they invest, and how many labors they hire. The funds available for this spending come from their outputs and future debts. At the end of period, bonds will be mature, and they are in zero net supply. In addition, equity stocks are in positive net supply in this economy. Therefore, such model economy then presents as the following and define the general equilibrium.
Chapter Summary

There are two theoretical foundations of underlying researches. In fact, theoretical foundation of an asset pricing model with idiosyncratic risk is derived from a dynamic stochastic general equilibrium model. Another theoretical foundation is an empirical model for testing.


In empirical studies, CAPM is to be tested with data which in turn demonstrates a positive relationship between systematic risk and expected returns. As a result, idiosyncratic risk does not matter in determining expected returns. Still, later studies find out an influence of idiosyncratic risk. In fact, an effect of such risk on expected returns is still not clear.

2.1 Theoretical Foundations of Underlying Research Concept 1

Systematic risk does matter in the Capital Asset Pricing Model (CAPM). This particular characteristic is the same assertion as stated by other asset pricing models. The consumption-based capital asset pricing model (CCAPM) considers a consumption growth and an intertemporal marginal rate of substitution of consumptions as the important determinants, for example. Another, almost all of previous studies find the macroeconomic sources of risk that determine asset prices such as labor income, money demand, inflation, habit formation, capital adjustment cost, debt, equity financing, and output. Very few of asset pricing literatures have considered the role of idiosyncratic risk.
The well-known papers of Lucas (1978) and Breeden (1979) measure systematic risk in form of covariance of stock returns with stochastic discount factor, which is known as the Consumption-based Capital Asset Pricing Model. This implies that systematic risk can be explained by marginal rate of intertemporal substitution from utility function. Additionally, such model is developed further by Mehra and Prescott (1985) who document that expected returns depend solely on covariance of stock returns with consumption growth. That is, the systematic risk of expected returns can be described by consumption growth risk.

In addition to consumption-based capital asset pricing models, the asset pricing model are developed by taking the uncertainty into account of expected returns in the growth model. Storesletten et al. (2001, 2007) introduce idiosyncratic labor market risk in overlapping generation model. They state that idiosyncratic labor risk figures in determining expected returns, in turn, it can resolve the equity premium puzzle.

The aggregate productivity shock, on the other hand, is still considered as the main source of risky returns because it plays an important role in determining expected stock returns especially in Lettau (2003). This paper derives the solution for asset pricing in an real business cycle model which finds that technology shocks affect equity returns and real long-term bond returns through two channels: directly through the shock and indirectly through capital accumulation. The premiums of equity returns over the risk-free rate and real long-term bond are small and often negative when technology shock is permanent.

The aggregate technology shock is an only one particular factor in Balvers and Huang (2007). Such aggregate shock is a key macroeconomic source of production-based asset pricing model conditional on the state of the economy which affects on asset returns. In other words, a pricing kernel is derived from production function arguments.

In addition, production-based asset pricing is derived by introducing some variables to account for expected stock returns and equity premium, such as habit formation preferences and capital adjustment cost in Jermann (1998,), endogenous solvency constraints in Alvarez and Jermann (2000), capital adjustment cost and stochastic productivity in Jermann (2010). In particular, Cochrane (1993), Belo (2010) derives a stochastic discount factor in order to account for asset returns from
equilibrium marginal rate of transformation instead of marginal rate of substitution for consumption. Indeed, such stochastic discount factor depends on a growth rate in the price and a growth rate in the output of technology’s goods.

An alternative approach of production-based asset pricing is first purposed by Cochrane (1991) who shows that investment returns is the same as stock returns. Cochrane (1996) then test the investment-based asset pricing model. In fact, investment returns factors significantly price assets, and adjustment cost is useful in order to figure asset returns and investment returns. As a result, this model is able to explain a wide spread in expected returns. Essentially, investment model performs substantially better than the standard consumption-based factor model. Consistent with Liu et al. (2009), such paper shows that stocks returns equal leveraged investment returns, which can be constructed from firm characteristics.

To some extent, production-based asset pricing model include the consumption side in order to demonstrate the economic fundamental behind the expected returns of growth stock and value stock as in Gala (2005). Such paper constructs a general equilibrium production economy with heterogeneous firms and irreversible investment. He documents that the dynamics of investors’ demand for consumption insurance and irreversibility in firm investment play a key role in explaining value and size effects in stock returns.

In conclusion, most assertions as mentioned above focus on the effect of systematic risk on expected stock returns, which comes from the economic fundamental. Those conclusions are contrast with Merton (1987)’s paper which states that idiosyncratic risk has the predictive power within incomplete market. Such work shows that idiosyncratic risk is positively related to expected stock returns because of information cost and institutional factors. It is due to that investors do not fully diversify their portfolios under imperfect capital market, so idiosyncratic risk plays an important role. Still, later empirical studies document that idiosyncratic risk has a negative effect on expected stock returns.

As a result, there is a few studies of asset pricing model that provide the effect of idiosyncratic risk in determining stock returns in general equilibrium asset pricing model. In other words, a real business cycle model does not account for an influence of idiosyncratic risk on stock returns yet. This is why this study tries to explore whether or not idiosyncratic risk affect on expected stock returns in the dynamic stochastic general equilibrium model. In addition, both idiosyncratic
risk and aggregate productivity risk could be examined as the key determinants in determining expected stock returns similar to empirical research papers as performed before.

2.2 Theoretical Foundations of Underlying Research Concept 2

Systematic risk determines solely expected stock returns in CAPM because idiosyncratic risk can be eliminated through diversification. Such risk cannot be diversified through portfolio, so investors attempt to hold efficient portfolio for receiving market risk premium. Black et al. (1972) provide considerable evidence that risk-free risk seems to be an important determinant of security returns, in addition to systematic risk. It is consistent with two factor model. CAPM is also to be tested empirically provided strong evidence by Fama and MacBeth (1973). This paper finds that the market efficiency hypothesis is not rejected. This means that investors attempt to hold efficient portfolio which, in turn, there is a positive between average return and systematic risk. The other main contribution is that no measure of risk in addition to portfolio risk, systematically affects average returns. It implies that idiosyncratic risk does not figure in determining average returns. In contrast, earlier studies document that only idiosyncratic risk plays an important role in determining expected stock returns.

These 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 (2002), 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 (20010) 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.

This study 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. Still, such study does not consider expected market volatility as a particular determinant. 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 EGARCH (exponential generalized autoregressive conditional heteroskedasticity) 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).
CHAPTER 3: Conceptual Model

Chapter Summary

The conceptual model for our study is derived from the dynamic stochastic general equilibrium model by introducing idiosyncratic stochastic productivity level into production function. It is based mainly on real business cycle model which consists of two types of agent: infinitely-lived homogenous households and infinitely-lived heterogeneous firms. There are also two types of assets traded in this economy: real bonds and equity stocks. An infinitely representative household maximizes his expected life-time utility subject to budget constraint at each time. In addition, the infinitely heterogeneous firms maximize the expected present value of cash flow subject to their budget constraints. This leads to an equilibrium allocation. We also apply Lagrangian equation, Bellman equation, and log-linearization to solve for expected stock returns which come up with an effect of idiosyncratic productivity level.

3.1 Introduction

The purpose of our research is to explore an asset pricing model which tries to show the effect of idiosyncratic risk on expected stock returns in the dynamic stochastic general equilibrium model. In addition, this study also examines the role of an aggregate risk in asset pricing model. Thus, the model designed to capture asset prices is an extension of Jermann and Quadrini (2009). It differs considerably from all asset pricing models in productivity shocks because such model is developed by introducing idiosyncratic shock into a production function.

This economy model is based mainly on real business cycle model. It consists of two types of agent: infinitely-lived homogenous households and infinitely-lived heterogeneous firms. There are also two types of assets traded in this economy: real bonds and equity stocks. An infinitely representative household maximizes his expected life-time utility subject to budget constraint at each time. The infinitely heterogeneous firms otherwise maximize the expected present value of cash flow subject to their budget constraints. They differ in level of
idiosyncratic productivity. All agents are in competitive market, and thus all prices are taken as given.

The homogenous households have to decide on how much consumption they will consume, how many bonds and stocks they will purchase at the beginning of period when they earn money from labor wages, bonds sold, stocks sold, and dividend payments at the end of period. Apart from consumption side, heterogeneous firms have to decide on how much they pay their debts, how much they pay dividends to the stock owners, how much they invest, and how many labors they hire. The funds available for this spending come from their outputs and future debts. At the end of period, bonds will be mature, and they are in zero net supply. In addition, equity stocks are in positive net supply in this economy. Therefore, such model economy then presents as the following and define the general equilibrium.

3.2 Process of Developing the Model

This section will account for process of developing the model. There are three subsections: households, firms, and equilibrium. The agents in each sector are optimizations together with the existence of markets. It leads to the equilibrium allocation in this economy.

3.2.1 Households

There are infinitely homogeneous households that will exist forever in this economy, so the economic behavior of the entire population can be modeled as a single representative household. An agent’s endowment of time for each period has to divide into leisure, \( l_t \) and work \( h_t \). For simplicity, such endowment is normalized to one, such that \( l_t + h_t = 1 \). Thus, household’s preference is defined over stochastic sequences of consumption and leisure:

\[
E \left( \sum_{t=0}^{\infty} \beta^t U(c_t, 1-h_t) \right); \quad 0 < \beta < 1 \tag{1}
\]
where $E_t(\bullet)$ is the expectation operator conditional on information available at time $t$. The time $t$ refers to time period from time $t-1$ to $t$. $c_t$ stands for consumption at time $t$. $h_t$ stands for hours worked at time $t$. $\beta$ is the subjective discount factor. The utility function is assumed to be twice continuously differentiable and strictly concave in both consumption and hours worked. This means that the first and second partial derivatives of utility function with respect to both arguments as follows: $U_t > 0, U_h > 0, U_{cc} < 0, U_{hh} < 0$ and $U_{cc}U_{hh} - (U_{ch})^2 > 0$. In addition, household gets income from labor wage, bonds holding, equity stocks and dividend payments at time $t$ to allocate for consumption, investment and lump-sum taxes financing on debt. There are two types of investment: holding bond issued by firms at time $t+1$ and investing in equity stocks at time $t+1$. Thus, household’s budget constraint can be written as

$$w_t h_t + \sum_{i} b_{it} + \sum_{i} s_{it} (d_{it} + q_{it}) = \sum_{i} \frac{b_{it+1}}{1 + r_t} + \sum_{i} s_{it+1} q_{it} + c_t + T_t$$  \hspace{1cm} (2)

where $i$ represents firm $i$. $w_t$ and $r_t$ are wage rate and interest rate at time $t$. $q_{it}$ is the price of equity stock $i$ at time $t$. $d_{it}$ represents the dividend payment received from firm $i$ at time $t$. $s_{it}$ represents the equity stocks for firm $i$ at time $t$. $b_{it}$ represents one-period bonds issued by firm $i$ at time $t$. $T_t$ are lump-sum taxes financing the tax benefits received by firms on debts, then $T_t = \frac{B_{t+1}}{1 + r_t (1 - \pi)} - \frac{B_{t+1}}{1 + r_t}$, where $\pi$ represents the tax benefit.

Taking all prices as given, a representative household will choose consumption, hours of work, investing in the next period bond, and investing in the next period equity stock to maximize expected discounted utility function (1) subject to a sequential budget constraint (2). This results in the optimality choices of the first-order conditions. However, the more details of computation of the first
order conditions are given in Appendix. The solutions for household’s optimization problem are the Euler equations as follows:

\[
\begin{align*}
\frac{U_i(c_i,1-h_i)}{U_i(c_i,1-h_i)} &= w_i \\
\beta E_t \left\{ U_t(c_{t+1},1-h_{t+1})(1+r_f) \right\} &= U_t(c_t,1-h_t) \\
\beta E_t \left\{ U_t(c_{t+1},1-h_{t+1}) \left( \frac{d_{t+1} + q_{t+1}}{q_t} \right) \right\} &= U_t(c_t,1-h_t)
\end{align*}
\]  

Equation 3 states that wage rate is equal to the expectation of ratio of marginal utility of hours of work to marginal utility of consumption. In other words, the wage rate is equivalent to the marginal rate of substitution between hours worked and consumption at the same time. Equation 4 shows that the risk-free asset returns equals to the marginal rate of intertemporal substitution between consumption at time \( t+1 \) and consumption at time \( t \). Additionally, the last Euler equation determines a stock price and a risky asset returns.

### 3.2.2 Firms

This economy is also populated by infinitely heterogenous firms which produce consumption goods. The outputs come from constant returns to scale of production functions that take labor \( h_i \) and capitals \( k_{it} \) as inputs. Capital depreciates at rate \( \delta \). In particular, all firms face the uncertainties which consist of two types: aggregate stochastic productivity level \( z_i \) and idiosyncratic stochastic productivity level \( \varepsilon_i \). Such idiosyncratic productivity makes all firms different in their levels of risk, so it becomes idiosyncratic stochastic risk. Thus, the production function of each firm has the following form:
\[ F(z_t, \epsilon_t, k_{it}, h_{it}) = (e^{\epsilon_t})^{k_{it}^\theta} h_{it}^{1-\theta} \]  

(6)

where \( k_{it} \) is capital for firm \( i \) at time \( t \), \( h_{it} \) is labor for firm \( i \) at time \( t \). \( z_t \) is aggregate stochastic risk of all firms at time \( t \). \( \epsilon_t \) is idiosyncratic stochastic risk of firm \( i \) at time \( t \). \( \theta \) is a capital share. Such aggregate stochastic risk is assumed further to follow a first-order autoregressive Markov process.

\[ z_t = \tilde{z} + \psi z_{t-1} + \nu_t \]  

(7)  

: \( \nu_t \sim N(0, \sigma_\nu^2) \)  

: \( 0 < \psi < 1 \)

where \( \nu_t \) is normally distributed with mean zero and constant variance, i.e. \( \nu_t \sim N(0, \sigma_\nu^2) \). In addition, idiosyncratic stochastic risk also evolves according to a first-order autoregressive Markov process as the following.

\[ \epsilon_t = \tilde{\epsilon} + \tau \epsilon_{t-1} + \mu_{it} \]  

(8)  

: \( \mu_{it} \sim N(0, \sigma_\mu^2) \)  

: \( 0 < \tau < 1 \)

where \( \mu_{it} \) is independently and identically distributed for firm \( i \) at time \( t \) with mean zero and constant variance, i.e. \( \mu_{it} \sim N(0, \sigma_\mu^2) \).

More importantly, each firm can use debt in conjunction with output for investment, dividend payment, labor wage, and debt payment. Accordingly, the firm’s budget constraint can be written as the following:
(1 - \delta)k_t + F(z_t, e_t, k_t, h_t) + \frac{b_{t+1}}{1 + r_t} = b_t + d_t + k_{t+1} + w_t h_t \quad (9)

where \( b_t \) and \( b_{t+1} \) denotes debt in terms of bond issuing of firm \( i \) at time \( t \) and time \( t+1 \), respectively. \( d_t \) denotes dividend payment of firm \( i \) at time \( t \) to the ownership of equity stock. Furthermore, each firm operates business by maximizing his value of firm which equals to the present discounted value of cash flows. Consequently, the optimization problem can be written as recursive equation. That is, state variables for each firm are \( k_t, e_t, z_t, b_t, H_t \), and control variables are \( h_t, k_{t+1}, b_{t+1}, d_t \). Let’s denote \( H_t \) as the summary of the next period information. Define the vector of state variables as \( X_t = (k_t, e_t, z_t, b_t, H_t) \). Thus, Bellman equation for optimal value of each firm is

\[
V(X_t) = \max_{\{h_t, k_{t+1}, b_{t+1}, d_t\}} \left\{ d_t + E_t \left( M_{t+1} V(X_{t+1}) \right) \right\} \quad (10)
\]

subject to

\[
(1 - \delta)k_t + (e_t, e_t)k_t, k_{t+1} + \frac{b_{t+1}}{1 + r_t} = b_t + d_t + k_{t+1} + w_t h_t \quad (11)
\]

where \( M_{t+1} \) denotes the stochastic discount factor. In a competitive market, all prices are taken as given, and then each firm chooses current labor, the next capital, the next debt, and current dividend payment to maximize the present value of cash flow. Eventually, the efficiency conditions of firm come from the first-order conditions and Envelope conditions that are shown in Appendix. Such conditions take account of optimal choices of Euler equations as follows:
\[ \begin{align*}
E_t \left[ M_{t+1} \left[ (1-\delta) + \theta (e^{\bar{c}_{i,t}} \epsilon_{i,t+1} k_{i,t+1}^\theta h_{i,t+1}^{1-\theta}) \right] \right] &= 1 \quad (12) \\
E_t [M_{t+1}] &= \frac{1}{1+r_t} \quad (13)
\end{align*} \]

### 3.2.3 Equilibrium

A solution for household and firm maximization problem as before must satisfy a recursive general equilibrium that defines as the following. The aggregate state variables in this economy are given by the aggregate capital \( K \), aggregate stochastic productivity level \( z \), aggregate bond \( B \), and aggregate information \( H \). That is, \( X = (K, z, B, H) \) and \( X_i = (k_i, \epsilon_i, z, b_i, H) \) for firm \( i \).

**Definition 2.1** A recursive general equilibrium for this decentralized economy is defined as a set of functions for (i) household’s decision rules, \( c(X), h(X), b(X), \) and \( s(X) \); (ii) firm’s decision rules, \( h(X_i), k(X_i), b(X_i) \) and \( d(X_i) \); (iii) a value function of firm \( V(X_i) \); (iv) price functions, \( w(X), r(X), q(X), M(X') \) such that household’s decision rules satisfy the optimal conditions of equation 3, 4 and 5, and firm’s decision rules satisfy the optimal conditions of equation 10 and 11. The resource constraints are also satisfied so that, at each time, all markets clear:

(i) The goods market:

\[ C_t + I_t = Y_t \]

\[ C_t + \sum_i (k_{i,t+1}^{\theta} - (1-\delta) k_i) = \sum_i (e^{\bar{c}_i} \epsilon_i k_i^\theta h_i^{1-\theta}) \]

where
\[ \sum_{i} k_{it} = k_{i} \]

\[ \sum_{i} h_{it} = h_{i} \]

(ii) The bond market:
\[ \sum_{i} b_{it} = 0 \quad (15) \]

(iii) The stock market:
\[ \sum_{i} s_{it} = 1 \quad (16) \]

In competitive market, all prices are taken as given. Therefore, the stochastic discount factor equals the intertemporal marginal rate of substitution between consumption at time \( t+1 \) and consumption at time \( t \). This means that the rate at which agent is willing to substitute consumptions at time \( t+1 \) for consumptions at time \( t \) equals the stochastic discount factor as follows:

\[ M_{t+1} = \beta \frac{U_{c}(c_{t+1}, 1-h_{t+1})}{U_{c}(c_{t}, 1-h_{t})} \quad (17) \]

### 3.3 Development of the Model

Asset price implication of this economy can be derived from Euler equation 5. This equation shows that the price of equity stocks at time \( t \) comes from the expected intertemporal marginal rate of substitution between consumption at time \( t+1 \) and consumption at time \( t \) as well as the next
period dividend payout. This price can be rearranged in general form using forward iteration, so the price of equity stock \( i \) is

\[
q_{it} = E_t \left\{ \sum_{j=1}^{\infty} \beta^j U_t \left( c_{t+j+1} \frac{1-h_{t+j}}{1-h_t} \right) d_{it+j} \right\} \tag{20}
\]

Denote \( R_{it+1}^t \) as the returns on stock \( i \) at time \( t+1 \); that is, returns on stock \( i \) at time \( t+1 \) can be defined as

\[
R_{it+1}^t = \frac{q_{it+1} + d_{it+1}}{q_{it}} \tag{21}
\]

Dividing both side of equation 5 by \( U_t \left( c_t, 1-h_t \right) \), and substituting equation 21 into equation 5, Euler equation 5 then becomes

\[
\beta E_t \left\{ \frac{U_t \left( c_{t+1}, 1-h_{t+1} \right)}{U_t \left( c_t, 1-h_t \right)} R_{it+1}^t \right\} = 1 \tag{22}
\]

Thus, by using equation 19 in Definition 2.1, such asset pricing equation can be written as

\[
E_t \left[ M_{t+1} R_{it+1}^t \right] = 1 \tag{23}
\]

Equation 23 implies that the expectation of the multiplication of stochastic discount factor and returns on stock is equal to one, which is the same standard asset pricing.
In addition, equation 12 can be rewritten as an asset pricing equation which shows the relationship between expected stock returns and idiosyncratic stochastic risk as the following.

Let’s define
\[
\Omega_{t+1} = \left[ (1-\delta) + \theta \left( e^{\gamma_{t+1}} \gamma_{t+1} l^{\gamma_{t+1}} \right) \right]
\]

Substituting \( \Omega_{t+1} \) into equation 12, then such Euler equation becomes

\[
E_t \left[ M_{t+1} \Omega_{t+1} \right] = 1
\]  

(24)

In other words, equation 24 can be written in form of probability on state \( s \) as

\[
\sum_s \pi_s M_{t+1} (s) \Omega_{t+1} (s) = 1
\]  

(25)

Define the right hand-side of equation 25 as the following.

\[
\sum_s \pi_s M_{t+1} (s) \Omega_{t+1} (s) \equiv \sum_s P_s
\]

Then, equation 25 becomes

\[
\sum_s P_s = 1
\]  

(26)
From the left hand-side of equation 23, \( E_i\left[M_{t+1}R_{t+1}^i\right] \) can be transformed into the probability on state \( s \) as

\[
\sum_s \pi_s M_{t+1}(s) R_{t+1}^s(s) = 1
\] (27)

Rearranging equation 27 by dividing and multiplying by \( \Omega_{t+1}(s) \), so this equation can be written as

\[
\sum_s \pi_s M_{t+1}(s) \frac{R_{t+1}^s(s)}{\Omega_{t+1}(s)} = 1
\] (28)

\[
\sum_s \pi_s \frac{R_{t+1}^s(s)}{\Omega_{t+1}(s)} = 1
\] (29)

\[
E_p \left[R_{t+1}^{s} \Omega_{t+1}^{-1}\right] = 1
\] (30)

As a result, equation 30 is the particular contribution of this study which shows that idiosyncratic stochastic risk has an effect on expected stock returns. In more detail, equation 30 can be instead solved in a way of an approximate analytical solution. Therefore, the method of log-linearization which first proposed by Cambel (1994) will apply to find the log-linear equation as the followings.

Let’s define: \( \ln X_{t+1} = x_{t+1} \), and \( x_i \) stands for a steady state value of \( x \). In particular, equation 22 at steady state can be rewritten as follows:

\[
\beta R^s_i = 1
\] (31)

\[
\ln R^s_i = \rho
\] (32)
where $\rho$ is the rate of time preference.

At steady state, $e^\ast = 1$, then equation 12 also becomes

$$1 - \delta + \theta e_k \theta^{-1}h_i^{1-\theta} = \frac{1}{\beta}$$ (33)

$$\theta e_k \theta^{-1}h_i^{1-\theta} = \rho + \delta$$ (34)

Let $\hat{x}_i$ be a deviation from steady state at time $t$, and we assume that $e_i = 1$.

Consider $R^r_{t+1} \Omega^{-1}_{t+1}$ in equation 30, it can be rearranged and approximated in exponential term as follows:

$$\frac{R^r_{t+1}}{(1-\delta)+\theta(e_i \hat{e}_{t+1})k_i^{\theta-1}h_i^{1-\theta}} = e^{e_i \hat{e}_{t+1} - \ln[(1-\delta)+\theta(e_i \hat{e}_{t+1})k_i^{\theta-1}h_i^{1-\theta}]}$$

$$\approx 1 + (r_{t+1} - \rho) - \frac{1}{1 - \delta + \theta e_k \theta^{-1}h_i^{1-\theta}} \left\{ \theta k_i^{\theta-1}h_i^{1-\theta} (e_{t+1} - e_i) + \theta(1-\theta) e_i k_i^{\theta-2}h_i^{1-\theta} (k_{t+1} - k_i) + \theta(1-\theta) e_i k_i^{\theta-1}h_i (h_{t+1} - h_i) \right\}$$

$$\approx 1 + (r_{t+1} - \rho) - \frac{\theta e_k \theta^{-1}h_i^{1-\theta}}{1 + \rho} e_{t+1} + \frac{\theta k_i^{\theta-1}h_i^{1-\theta}}{1 + \rho} e_i - \frac{(\theta-1)(\rho + \delta)}{1 + \rho} k_{t+1} - \frac{k_i}{1 + \rho} (1-\theta)(\rho + \delta) h_{t+1} - h_i$$

$$\approx 1 + r_{t+1} - \rho - \frac{\rho + \delta}{1 + \rho} e_{t+1} + \frac{\rho + \delta}{1 + \rho} e_i - \frac{(\theta-1)(\rho + \delta)}{1 + \rho} \hat{k}_{t+1} = (1-\theta)(\rho + \delta) \hat{h}_{t+1}$$ (35)
Substituting result from equation 35 into equation 30, then we will obtain

\[ 1 + E_p r_{it+1}^{s} - \rho - \frac{\rho + \delta}{1 + \rho} E_p \epsilon_{it+1} + \frac{\rho + \delta}{1 + \rho} (\theta - 1)(\rho + \delta) E_p \hat{\kappa}_{it+1} - \frac{(1 - \theta)(\rho + \delta)}{1 + \rho} E_p \hat{h}_{it+1} = 1 \]  

(36)

Rearranging equation 36, we obtain the log-linearized equation of expected stock returns as

\[ E_p r_{it+1}^{s} = \frac{\rho}{1 + \rho} \left[ E_p \epsilon_{it+1} + (\theta - 1) E_p \hat{\kappa}_{it+1} + (1 - \theta) E_p \hat{h}_{it+1} - 1 \right] \]  

(37)

Equation 37 is the main contribution in conjunction with equation 30 which show the relationship between expected returns on stock and idiosyncratic stochastic productivity level.

### 3.4 Description of the Components on the Model

Equation 30 and 37 show the relationship between idiosyncratic productivity level and expected returns on stock in forms of nonlinearity and linearity, respectively. This is the main finding we come up with new asset pricing model. Equation 37 states that expected stock returns depends on the rate of time preference, depreciation rate, capital share, expected idiosyncratic productivity shock at time $t$, the percentage deviation of capital from steady state at time $t$, and the percentage deviation of labor from steady state at time $t$. In other words, expected idiosyncratic productivity shock, expected capital, and expected labor affect on expected returns on stock since all the parameters are very small value. In addition, expected idiosyncratic productivity shock is positively related to expected stock returns similar to expected labor. Contrary to expected capital, it has a negative effect.
on expected stock returns since capital share $\theta$ less than one. It is interestingly that the more capital used the less expected stock returns obtained. As a result, such equation takes idiosyncratic risk into account of expected stock returns as well as fundamental factors in production of firms.

3.5 Discussion

Equation 23, 24, 30 and 37 are the asset pricing models which derive from the dynamic stochastic general equilibrium model with idiosyncratic productivity shock. It is quite similar contingent claims prices in complete market as stated in standard asset pricing model. That is, equation 23 and 24 show that the price of asset rely substantially on the stochastic discount factor. Once we carry out asset pricing to show expected returns on stock, idiosyncratic risk is an important determinant of expected stock returns in equation 30 and 37.

Such findings change the key determinants of asset price from consumption to production factor and idiosyncratic productivity shock. In terms of consumption, stochastic discount factor considerably determines stock returns which mean that the rate at which investor can give up consumption in time $t+1$ in return for consumption in time $t$ through buying and selling of stocks. This results in expected returns on stock for delay consumption.

Once we transform asset price model to expected stock returns model, idiosyncratic productivity level and production’s factors affect expected returns on state $s$. It has positively predictive power. Even though it has similar procedure of consumption-based asset pricing model with contingent claims, the determined factors are very different. This result leads to the effect of idiosyncratic risk on expected stock return on state $s$ contrary to Lucas (1978), Beeden (1979), Mehra and Prescott (1985), Storesletten et al. (2001, 2007), Lettua (2003), Balvers and Huang (2007), Jerman (1988, 2010), Cochrane (1991, 1993, 1996), Alvarez and Jermann (2000), Gala (2005), Liu et al. (2009), and Belo (2010). It might be because almost all studies believe that idiosyncratic component of expected returns is uncorrelated with the stochastic discount factor.
CHAPTER 4:
Method Selection and Development of Measurements

Chapter Summary

Empirical evidence examine to show whether idiosyncratic volatility is correlated with expected stock returns as well as market volatility, especially in the case of Thailand. It is because previous researches find that relationship between idiosyncratic volatility and expected stock returns is not clear evidence. That is, there are positive and negative effects.

For measurement of effect of idiosyncratic risk, 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). The daily realized return for stock \( i \) at time \( t \) is used for explained variable. There are six 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 calculated from EGARCH (1,1). The daily expected market volatility for stock \( i \) at time \( t \) conditional on the information set at time \( t-1 \) is calculated from GARCH(2,2). The liquidity variables which used for robust check consist of the daily percentage bid-ask spread, the daily illiquidity measure as discussed in Amihud (2002), the daily turnover ratio, and the daily value of stock \( i \) at time \( t \).

4.1 Introduction

The empirical studies does not consider idiosyncratic risk, which is defined as diversified risk, as figuring in determining stock returns, especially empirical test of 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 idiosyncratic risk plays an important role in determining expected stock returns. 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 a positive effect on expected
stock returns because investors do not fully diversify their portfolios under an imperfect capital market. Consistent with Amihud and Mendelson (1989), Malkeil and Xu (2002), 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), they show that idiosyncratic volatility is positively and significantly correlated with expected stock returns.

In contrast to these assertions, some researchers have found that there is a negative relationship between idiosyncratic volatility and expected stock returns. Guo and Savickas (2006), Ang et al. (2006; 2009), Bali and Cakici (2008), Angelidis (2010), and Guo and Savickas (2010) state that idiosyncratic volatility is negatively related to expected stock returns. The relationship between idiosyncratic volatility and expected stock return, however, is shown to be mixed by using daily and monthly data. Huang et al. (2010) find that there is a negative relationship between estimated conditional idiosyncratic volatility and expected stock return based on daily data. Still, 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 fact, 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 index, and 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.

4.2 Selection of Measurements

This study 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:

\[ R_{it} = \alpha_i + \sum_{l=1}^{L} \beta_l X_{itl} + u_{it}, i = 1,2,\ldots,N_i, t = 1,2,\ldots,T \] (38)

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. \( X_{itl} \) represents the explanatory variables \( l \) 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 \( E_{t,i}(\text{VOL}_{it}) \). 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 \( E_{t,i}(\text{MVOL}_{it}) \). 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) or Amihud measure 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. \( N_i \)
is the total number of stocks at time $t$. $T$ is the total of time periods. $\alpha_i$ 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, $u_i$, captures the deviation of the realized returns on stock $i$ from its expected value.

Equation 38 focuses on $\beta_i$, 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 $\beta_i = 0$. In other words, expected idiosyncratic volatility is not priced if it equals zero as well as other explanatory variables.

4.3 Development of Measurements

Each variable is measured with different methods. In fact, explained variables, $R_i$, is the daily realized return for stock $i$ on day $t$. It is calculated from the ratio of daily closing price, $P_i$, the daily closing price on day $t-20$, $P_{it-20}$, and dividend during the 20-trading day, $D_{it-20}$, to the daily closing price on day $t - 20$, assuming that there are approximately 20 trading days in one month\(^1\). Such returns are also eliminated the effect of stock split by deleting the data. 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:

$$R_i = \frac{P_i + D_{it-20} - P_{it-20}}{P_{it-20}}$$ (39)

The explanatory variables are then computed as the followings. $E_{t-1}(\text{VOL}_{it})$ 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

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\(^1\) 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.
Angelidis (2010). This study then applies the CAPM-base to calculate, $E_{t-i}(VOL_{it})$ as in the following cross-sectional equation:

$$R_{it} - r_{it} = a_i + b_i (R_{mt} - r_{it}) + \varepsilon_{it}, \quad \varepsilon_{it} \sim N(0, \sigma^2_{it})$$

(40)

Where $r_{it}$ 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 in SET50 index and SET 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 daily beta or market risk for stock $i$ on day $t$ consistent with the security market line. That is, it comes from the ratio of covariance between returns on stock $i$ and market returns to variance of market returns as in equation 43.

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

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 addition, this study takes EGARCH (exponential generalized autoregressive conditional heteroskedasticity) 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 $\varepsilon_{it}$ from equation 40 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:

$$\varepsilon^2_{it} = \delta_0 + (\sum_{s=1}^{q} \delta_s \varepsilon^2_{it-s})$$

(41)
where $\varepsilon_i$ is the regression residual of equation 40. Equation 41 is a regression analysis of the squared residuals on a constant, $\delta_0$, 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:

$$
\ln \sigma_i^2 = \omega + \sum_{j=1}^{p} \varphi_j \ln \sigma_{i,t-j}^2 + \sum_{k=1}^{q} \psi_k \varepsilon_{i,t-k} \left\{ \theta \left( \frac{\varepsilon_{i,t-k}}{\sigma_{i,t-k}} \right) + \sqrt{\frac{2}{\pi}} \right\} \left( 2 \right)^{1/2} \right\} \right\} \right\} \right\}
$$

This explicit equation 42 is employed to estimate the conditional variance, $\sigma_i^2$. It yields the expected idiosyncratic volatility for stock $i$ at time $t$ conditional on information set at time $t-1$, such that $E_{t-1}(\text{VOL}_i) = \sqrt{\sigma_i^2}$. 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 EGARCH 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 $E_{t-1}(\text{VOL}_i)$ 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:

$$
b_{it} = \frac{\text{cov}(\left( R_{it}, R_{mt} \right) | \Omega_{it-20})}{\text{var}(R_{mt} | \Omega_{it-20})}
$$

- 43 -
where \( b_{it} \) represents market volatility of stock \( i \) on day \( t \). \( \text{cov}((R_{it}, R_{mt}) | \Omega_{t-20}) \) 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. \( \text{var}(R_{mt} | \Omega_{t-20}) \) 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 \( t-1 \), \( E_{t-1}(\text{MVOL}_t) \).

This paper illustrates further that market volatility does not have a constant variance. Equation 44 is the time-series regression that is performed before the residual of regression, \( \nu_{it} \), can be tested with ARCH LM test for autoregressive conditional heteroskedasticity (ARCH). The following regression is performed:

\[
b_{it} = c_i + \nu_{it} \cdot \nu_{it} \sim N(0, \sigma_{\nu}^2)
\]  \hspace{1cm} (44)

where equation 44 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,

\[
\nu_{it}^2 = \xi_0 + (\sum_{s=1}^{q} \sigma_{\nu}^2 \nu_{it-s}^2)
\]  \hspace{1cm} (45)

If the null hypothesis \((\xi_1, ..., \xi_q = 0)\) 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 46 is used to estimate expected conditional variance of market volatility or beta, which is composed of the \( j \) period expected conditional variance of market volatility, \( \sigma_{ij}^2 \), and the last period of unexpected news or information shocks, \( \nu_{it-k}^2 \), as follows:

\[
\sigma_{it}^2 = \omega_0 + \sum_{j=1}^{q} \varphi_{ij} \sigma_{ij}^2 + \sum_{k=1}^{a} \psi_{ik} \nu_{it-k}^2
\]  \hspace{1cm} (44)
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 Akaike Information Criterion (AIC) or Schwarz Information Criterion (SIC) is selected. Thus, GARCH (2, 2) was determined to be the best model and is represented as $E_{t-1}(MVOL_t)$ 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:

$$RS_{it} = \frac{(ask - bid)}{(ask + bid)} \times 100$$

(46)

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,

$$ILR_{it} = \frac{|R_t|}{TVOL_{it}}$$

(47)

where $|R_t|$ stands for the daily absolute return on stock $i$ on day $t$, and $TVOL_{it}$ 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, \( \text{Value}_i \), 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.

### 4.4 Discussion

The methodology of this study is appropriate to find the predictive power of idiosyncratic risk and market risk. It is because we apply CAPM to estimate such volatility which stands for idiosyncratic and market risk. More importantly, variance of residual estimated from CAPM does not follow random similar to variance of market volatility. This is why the previous studies fail to test the risk, in addition to market risk, which affects expected stock returns. Furthermore, this study measures the conditional expected idiosyncratic volatility and market volatility after testing. The residual estimated from CAPM and conditional expected market volatility are the main difference from Fu’s (2009) work.

Another important difference is the return on stock which is calculated in terms of the return over the past one month. It is useful to find the relationship to market risk premium since one month treasury-bill return stands for risk-free rate. In addition, our study controls for liquidity variables to check the robustness of the relation between conditional expected volatility and expected returns. That implies that the significant predictions still exist.
Chapter Summary

Chapter 5 is an important part of empirical study since it should come up with expected results. The coefficients on explanatory variables are estimated by using the pooled and fixed effect panel data regressions. Redundant fixed effect test and Hausman test, however, display the fixed effect model is a suitable model for this study.

Data collection comes from the daily data on the SET50 index and the Thai Bond Market Association (ThaiBMA) between April 2001 and December 2009. They also come from daily data of the SET index and daily data of stock sectors traded in the Stock Exchange of Thailand from March 2001 to December 2011.

Importantly, the main findings show that conditional expected idiosyncratic volatility has a positive effect on expected stock returns. Consistent with previous papers, conditional expected market volatility is positively related to expected stock returns. In addition, the estimated coefficients on expected idiosyncratic volatility are larger than those of expected market volatility in the case of STE50. In contrast with SET and stock sector, the average coefficients on expected market volatility play a more important role than those of expected idiosyncratic volatility.

5.1 Research Overview

Models for testing pooled and fixed effect panel data regressions comprise many variables: expected stock returns, conditional expected idiosyncratic volatility, conditional expected market volatility, relative bid-ask spread, stock value, illiquidity measure, and turnover ratio. However, conditional expected idiosyncratic volatility, conditional expected market volatility are the key determinant factors to explore the effects. This is why this study employs pooled and fixed effect panel to estimate the coefficients on explanatory variables. Moreover, Redundant fixed effect test and Hausman test are applied to perform for choosing the appropriate model.
5.2 Research Design

Following the Fama and MacBeth model, equation 38 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 of individual stocks in SET50 index are summarized in Table 5-11 under models 1, 2, 3, 4, 5, and 6. In addition, Model 1 will change when data from stock sectors use to test. Thus, such models can be shown explicitly as the followings.

Model 1: \[ R_{it} = \alpha_{it} + \beta_{1}E_{it1}(VOL_{it}) + \beta_{2}E_{it2}(VOL_{it}) - u_{it} \]

(48)

Model 2: \[ R_{it} = \alpha_{it} + \beta_{2}E_{it1}(VOL_{it}) + \beta_{3}E_{it2}(MVO_{it}) - u_{it} \]

(49)

Model 3: \[ R_{it} = \alpha_{it} + \beta_{2}E_{it1}(VOL_{it}) + \beta_{3}E_{it2}(MVO_{it}) + \beta_{4}RS_{it} - u_{it} \]

(50)

Model 4: \[ R_{it} = \alpha_{it} + \beta_{2}E_{it1}(VOL_{it}) + \beta_{3}E_{it2}(MVO_{it}) + \beta_{4}RS_{it} + \beta_{5}Value_{it} - u_{it} \]

(51)

Model 5: \[ R_{it} = \alpha_{it} + \beta_{2}E_{it1}(VOL_{it}) + \beta_{3}E_{it2}(MVO_{it}) + \beta_{4}RS_{it} + \beta_{5}Value_{it} + \beta_{6}LR_{it} - u_{it} \]

(52)

Model 6: \[ R_{it} = \alpha_{it} + \beta_{2}E_{it1}(VOL_{it}) + \beta_{3}E_{it2}(MVO_{it}) + \beta_{4}RS_{it} + \beta_{5}Value_{it} + \beta_{6}LR_{it} + \beta_{7}TURN_{it} - u_{it} \]

(53)

To summarize, the testable implications of Fama and MacBeth model for expected stock returns as in equation 38 are:

1) The relationship between expected stock returns and volatility should not be zero. That is, the estimated coefficients on \( Beta_{it} \) (\( \beta_{1} \)), \( E_{it1}(VOL_{it}) \) (\( \beta_{2} \)) and \( E_{it2}(MVO_{it}) \) (\( \beta_{3} \)) 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 $\text{ILR}_i$ should be positive. Thus, the null hypothesis is $\beta_{\text{ILR}} \leq 0$. In fact, the higher the value of illiquidity the higher the expected stock returns.

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

5.3 Research Tools

The pooled and fixed effect panel data regressions are applied to estimate the coefficients on explanatory variables. Such econometric methods are very useful to eliminate a biased and inconsistent estimation. Pooled panel data regression first uses to estimate the average slope on variables. It, however, might omit some variables which make the estimated coefficients seem to be biased and inconsistent. This is why our study use fixed effect panel regression model to remedy such problem. Such method allows the constant term to vary over time and over cross section.

In addition, Redundant fixed effect test is applied to perform for choosing the appropriate model between pooled and fixed effect panel regression model. The result demonstrates that fixed effect panel model is the true model. Moreover, random effect model is performed to estimate the average coefficients which come up with different findings from fixed effect model. This is why this study use Hausman test to choose the appropriate model. The evidence still confirms that fixed effect model is the true model.

5.4 Data Collection

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 the SET index and daily data of stock sectors traded in the Stock Exchange of Thailand from March 2001 to December 2011. There are 496 stocks and 28 stock sectors in total. In addition, data comprise 97 common stocks which are
traded in SET50 index 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. \( EVOL \) 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. \( EMVOL \) 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. \( EVOL_s \) 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. \( EMVOL_s \) 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 $i$.

5.5 Data Measurement and Analysis

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 index 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 0.896 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).

5.5.1 Descriptive Analysis

Table 2 presents the descriptive statistics of the pooled sample’s variables, a total of 120,987 observations. The average expected stock returns ($R$) between April 2001 and December 2009 are 1.736 percent per month. The average expected conditional idiosyncratic volatility ($EVOL$) 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 index. Equally important, the average expected conditional market volatility ($EMVOL$) 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. equation (4) and (8), have a significant ARCH effect in the model with a 0.01 significance level. It is also to be noted that the average expected stock returns are lower 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>
<thead>
<tr>
<th>Table 2 Summary Statistics for the Pooled Sample of Individual Stocks in the SET50 Index.</th>
</tr>
</thead>
<tbody>
<tr>
<td>R</td>
</tr>
<tr>
<td>-----</td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>Median</td>
</tr>
<tr>
<td>Minimum</td>
</tr>
<tr>
<td>Std. Dev.</td>
</tr>
<tr>
<td>Skewness</td>
</tr>
<tr>
<td>Kurtosis</td>
</tr>
<tr>
<td>Jarque-Bera</td>
</tr>
<tr>
<td>Probability</td>
</tr>
<tr>
<td>Sum</td>
</tr>
<tr>
<td>SumSq. Dev.</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>Cross sections</td>
</tr>
</tbody>
</table>

Note: This table reports the pooled descriptive statistics from 120,987 observations of 97 stocks 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 1.48×10⁸ 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 3 also shows the descriptive statistics of the pooled sample’s variables for all the stocks traded in the Stock Exchange of Thailand (SET) between March 2001 and December 2011, a total of 496 stocks. There are total observations of 983,160. The mean risk-free rate as measured by the one-month Treasury-bill is equal.
to 0.193 percent per month; in contrast, the average market return (average return of SET index) is equal to 1.081 percent per month. That is, the equity premium is equal to 0.888 percent per month. It is consistent with equity premium of SET50 index; therefore, it has a positive equity premium in the Stock Exchange of Thailand.

Table 3 Summary Statistics for the Pooled Sample of Individual Stocks in the SET.

<table>
<thead>
<tr>
<th></th>
<th>R</th>
<th>BETA</th>
<th>EMVOL</th>
<th>EVOL</th>
<th>RS</th>
<th>VALUE</th>
<th>ILR</th>
<th>TURN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1.344</td>
<td>0.523</td>
<td>1.195</td>
<td>$3.89 \times 10^{29}$</td>
<td>1.188313</td>
<td>36910439</td>
<td>14.145</td>
<td>0.535</td>
</tr>
<tr>
<td>Median</td>
<td>0.000</td>
<td>0.192</td>
<td>1.210</td>
<td>5.900</td>
<td>0.700</td>
<td>946725.0</td>
<td>0.288</td>
<td>0.060</td>
</tr>
<tr>
<td>Maximum</td>
<td>1790.910</td>
<td>182.480</td>
<td>116.000</td>
<td>3.82$ \times 10^{35}$</td>
<td>147.830</td>
<td>1.30$ \times 10^{10}$</td>
<td>52014.31</td>
<td>229.390</td>
</tr>
<tr>
<td>Minimum</td>
<td>-94.550</td>
<td>-159.037</td>
<td>0.0079</td>
<td>0.0002</td>
<td>-196.260</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
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<tr>
<td>Std. Dev.</td>
<td>14.977</td>
<td>1.837</td>
<td>1.219</td>
<td>3.85$ \times 10^{32}$</td>
<td>2.831</td>
<td>1.66$ \times 10^{9}$</td>
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<td>1.636.636</td>
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<td>231.505</td>
<td>253.513</td>
<td>36345.80</td>
<td>19.502</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>6.60$ \times 10^{10}$</td>
<td>1.14$ \times 10^{11}$</td>
<td>1.09$ \times 10^{11}$</td>
<td>3.96$ \times 10^{16}$</td>
<td>2.16$ \times 10^{9}$</td>
<td>2.59$ \times 10^{9}$</td>
<td>5.41$ \times 10^{13}$</td>
<td>2.73$ \times 10^{10}$</td>
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<td>0.000</td>
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<td>0.000</td>
<td>0.000</td>
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<tr>
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<td>231.505</td>
<td>253.513</td>
<td>36345.80</td>
<td>19.502</td>
</tr>
<tr>
<td>SumSq.Dev.</td>
<td>2.21$ \times 10^{18}$</td>
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<td>Observations</td>
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<tr>
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<td>496</td>
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</tr>
</tbody>
</table>

Note: This table reports the pooled descriptive statistics from 983,160 observations of 496 stocks traded in the SET from March 2001 to December 2011.

In particular, the average expected stock returns ($R$) during that period 1.344 percent per month. The average expected conditional idiosyncratic volatility ($EVOL$) which comes from the EGARCH (1,1) model is equal to $3.89 \times 10^{29}$ percent per month. Such amount is very higher than $EVOL$ from stock returns in the SET50 index. In contrast, the average expected conditional market volatility ($EMVOL$) which is calculated from the GARCH (2,2) model, is equal to 1.195 percent per month. More importantly, it has lower amount than the average expected conditional idiosyncratic volatility from the SET and the average expected conditional market volatility from the SET50 index. It implies that the large amounts of uncertainties in the Stock Exchange of Thailand usually come from stocks which are not traded in SET50 index.
In addition, it is also to be noted that two regression residual tests of risk measure have a significant ARCH effect in the model with a 0.01 significance level. This means that idiosyncratic volatility and market volatility are not constant in the case of stocks on the SET index.

Almost all the means of liquidity variables for individual stocks in SET are higher than ones for individual stocks in SET50 index other than stock value. That is, the daily average percentage of relative spread \((RS)\) is 1.188 percent. The daily average value of the illiquidity ratio \((ILR)\) is 14.145. The daily average turnover ratio \((TURN)\) equals 0.535 percent each. The daily average value of stock sector \((VALUE)\) equals 36,910,439 Thai baht.

Table 4 presents the descriptive statistics of the pooled sample’s variables for sectors of stock in the Stock Exchange of Thailand between March 2001 and December 2011, a total of 28 stock sectors. That period consists of 66,958 observations. The mean risk-free rate as measured by the one-month Treasury-bill is equal to 0.193 percent per month; in contrast, the average market return (average return of stock sector) is equal to 1.245 percent per month. In other words, the equity premium is equal to 1.052 percent per month. This magnitude is larger than one for SET50 index and SET index. It is consistent with individual stocks in SET 50 index and SET index; therefore, it has an equity premium in the Stock Exchange of Thailand.
Table 4 Summary Statistics for the Pooled Sample of Stock Sectors.

<table>
<thead>
<tr>
<th></th>
<th>$R_s$</th>
<th>$EMVOL_s$</th>
<th>$EVOL_s$</th>
<th>$VALUE_s$</th>
<th>$ILR_s$</th>
<th>$TURN_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1.245</td>
<td>0.466</td>
<td>4.760</td>
<td>$6.50 \times 10^8$</td>
<td>$8.24 \times 10^5$</td>
<td>0.522</td>
</tr>
<tr>
<td>Median</td>
<td>0.828</td>
<td>0.349</td>
<td>3.689</td>
<td>95168138</td>
<td>0.000</td>
<td>0.250</td>
</tr>
<tr>
<td>Maximum</td>
<td>221.529</td>
<td>10.143</td>
<td>509.861</td>
<td>$7.80 \times 10^8$</td>
<td>0.985</td>
<td>33.430</td>
</tr>
<tr>
<td>Minimum</td>
<td>-52.619</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>8.794</td>
<td>0.481</td>
<td>5.417</td>
<td>$1.48 \times 10^8$</td>
<td>0.007</td>
<td>1.016</td>
</tr>
<tr>
<td>Skewness</td>
<td>1.256</td>
<td>3.984</td>
<td>26.177</td>
<td>6.733</td>
<td>117.618</td>
<td>8.910</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>23.066</td>
<td>32.053</td>
<td>1754.630</td>
<td>154.185</td>
<td>14468.73</td>
<td>148.303</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>1140927</td>
<td>2532119</td>
<td>$8.57 \times 10^8$</td>
<td>64274765</td>
<td>$5.84 \times 10^{11}$</td>
<td>59789256</td>
</tr>
<tr>
<td>Probability</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Sum</td>
<td>83364.220</td>
<td>31208.93</td>
<td>318720.7</td>
<td>$4.35 \times 10^{13}$</td>
<td>5.520</td>
<td>34932.49</td>
</tr>
<tr>
<td>Sum Sq. Dev.</td>
<td>5178063</td>
<td>15491.68</td>
<td>1964799</td>
<td>$1.47 \times 10^{23}$</td>
<td>3.197</td>
<td>69078.14</td>
</tr>
<tr>
<td>Observations</td>
<td>66958</td>
<td>66958</td>
<td>66958</td>
<td>66958</td>
<td>66958</td>
<td>66958</td>
</tr>
<tr>
<td>Cross sections</td>
<td>28</td>
<td>28</td>
<td>28</td>
<td>28</td>
<td>28</td>
<td>28</td>
</tr>
</tbody>
</table>

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 ($EVOL_s$) which comes from the EGARCH (1,1) model is equal to 4.760 percent per month. It is not a large amount compared with ones of individual stocks. Similar to the average expected conditional market volatility ($EMVOL_s$), 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 consistent with one of characteristic of stocks in SET index. 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 except value of stock. In fact, the daily average value of stock sector ($VALUE_s$) equals $6.50 \times 10^8$ Thai baht. The daily mean value of the illiquidity ratio ($ILR_s$) is $8.24 \times 10^{-5}$. The daily average turnover ratio ($TURN_s$) equals 0.5217 percent each.

5.5.2 Time-series and Cross-sectional Effects

In Table 5, 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. Moreover, an average of adjusted R-squared is about 0.75. The
A positive relation is similar to Merton (1987), Amihud and Mendelson (1989), Malkeil and Xu (2002), 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 EVOL with EMVOL, 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 EVOL equals 0.245 and an average coefficient on EMVOL equals 0.013. This means that a change in 0.245% of EVOL results in a change in 1% of stock returns in the next period, and a change in 0.013% of EMVOL 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 5** Pooled Panel Data Regressions of Fama and MacBeth Model for Individual Stocks in SET50 Index.

<table>
<thead>
<tr>
<th>Model</th>
<th>Intercept</th>
<th>BETA</th>
<th>EVOL</th>
<th>EMVOL</th>
<th>RS</th>
<th>VALUE</th>
<th>ILR</th>
<th>TURN</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-1.194***</td>
<td>-0.008</td>
<td>0.257***</td>
<td>0.015</td>
<td>-1.632***</td>
<td>0.002</td>
<td>1.632***</td>
<td>0.75</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-1.219***</td>
<td>0.242***</td>
<td>0.013</td>
<td>-1.448***</td>
<td>(6.18x10^9)**</td>
<td>0.002</td>
<td>1.652***</td>
<td>0.76</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.069</td>
<td>0.241***</td>
<td>0.015</td>
<td>-1.437***</td>
<td>(6.17x10^9)**</td>
<td>0.002</td>
<td>1.652***</td>
<td>0.76</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>-0.983***</td>
<td>0.243***</td>
<td>0.013</td>
<td>-1.437***</td>
<td>(6.17x10^9)**</td>
<td>-0.002</td>
<td>1.652***</td>
<td>0.76</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>-0.989***</td>
<td>0.243***</td>
<td>0.013</td>
<td>-1.437***</td>
<td>(6.17x10^9)**</td>
<td>-0.002</td>
<td>1.652***</td>
<td>0.76</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>-1.330***</td>
<td>0.246***</td>
<td>0.011</td>
<td>-1.606***</td>
<td>(4.10x10^9)**</td>
<td>-0.018***</td>
<td>1.652***</td>
<td>0.76</td>
<td></td>
</tr>
</tbody>
</table>

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.
* Denotes a 0.10 significance level.
** Denotes a 0.05 significance level.
*** Denotes a 0.01 significance level.

The results of pooled panel data regressions for individual stocks traded in SET are shown in Table 6. The main findings are the same as results from individual stocks in SET50 index. In fact, expected conditional idiosyncratic volatility is positively related to expected stock returns in all six models. Model 1 is a univariate pooled panel regression of expected stock return on $E_{VOL}$ which take out $BETA$ from the model because of its time-varying volatility. Model 2 controls for $E_{VOL}$ and $E_{MVL}$, Model 3 controls for $E_{VOL}$, $E_{MVL}$ and $RS$, Model 4 controls for $E_{VOL}$, $E_{MVL}$, $RS$ and $VALUE$, Model 5 controls for $E_{VOL}$, $E_{MVL}$, $RS$ and $VALUE$, and $ILR$. Model 6, in addition, controls for $E_{VOL}$, $EBETA$ and four liquidity variables.

The estimated coefficients on $E_{VOL}$ are positive and statistically significant at the 0.01 level, yet their sizes of effect are close to zero. The average slope on $E_{VOL}$ is $1.50 \times 10^{-33}$, and t-statistics are larger than 31. Furthermore, the mean of adjusted R-squared is about 0.038. The coefficients on expected conditional idiosyncratic
volatility remain significant effect after controlling for liquidity variables. In fact, liquidity variables do not change the effects of $\text{EVOL}$ on expected stock returns.

Models 2-6 in Table 6 also yield contrary evidence to individual stocks in SET50 index. In fact, expected conditional market volatility play a more important role than expected conditional idiosyncratic volatility. Such volatility is positively related to expected stock returns in cross-section. This positive relationship is also statistically significant at a 0.01 significant level. The average slope on $\text{EMVOL}$ is 2.461, and t-statistics are larger than 199. Typically, the estimated coefficients of $\text{EMVOL}$ are very larger than those of $\text{EVOL}$. They are still significant effects after the explanatory liquidity variables are included in the regression models. The coefficients change very little from 2.292 to 2.549; however, liquidity variable does not influence considerably on its relationship.

Table 6 Pooled Panel Data Regressions of Fama and MacBeth Model for Individual Stocks in SET Index

<table>
<thead>
<tr>
<th>Model</th>
<th>Intercept</th>
<th>$\text{EVOL}$</th>
<th>$\text{EMVOL}$</th>
<th>$\text{RS}$</th>
<th>$\text{VALUE}$</th>
<th>$\text{ILR}$</th>
<th>$\text{TURN}$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.005</td>
<td>(1.43×10^{-3})</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.001</td>
</tr>
<tr>
<td>2</td>
<td>-1.727</td>
<td>(1.42×10^{-3})</td>
<td>2.462</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.045</td>
</tr>
<tr>
<td>3</td>
<td>-1.658</td>
<td>(1.42×10^{-3})</td>
<td>2.455</td>
<td>-0.022</td>
<td></td>
<td></td>
<td></td>
<td>0.046</td>
</tr>
<tr>
<td>4</td>
<td>-1.931</td>
<td>(1.41×10^{-3})</td>
<td>2.549</td>
<td>-0.060</td>
<td>(7.36×10^{-3})</td>
<td></td>
<td>0.054</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>-1.931</td>
<td>(1.44×10^{-3})</td>
<td>2.549</td>
<td>-0.060</td>
<td>(7.36×10^{-3})</td>
<td>3.72×10^{-6}</td>
<td>0.054</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>-2.088</td>
<td>(1.19×10^{-3})</td>
<td>2.292</td>
<td>-0.131</td>
<td>(4.16×10^{-3})</td>
<td>0.006</td>
<td>1.130</td>
<td>0.087</td>
</tr>
</tbody>
</table>

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 March 2001 to December 2011. Intercept is the constant stock return in each model.

* Denotes a 0.10 significance level.

** Denotes a 0.05 significance level.

*** Denotes a 0.01 significance level.

The findings of pooled panel data regressions for stock sectors are shown in Table 7. The main results are the same as what both volatilities of individual stocks show especially in the case of SET. 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 $\text{EVOL}$, Model 2 controls for $\text{EMVOL}$, Model 3 controls for $\text{EMVOL}$ and $\text{VALUE}$, and Model 4 controls for
Moreover, Model 5 controls for \( EMVOL \) and three liquidity variables. The estimated coefficients on \( EVOL \) are positive and statistically significant at the 0.01 significant level. The average slope on \( EVOL \) is 0.3761, and t-statistics are larger than 54. In addition, 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 7 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 significant level. The average slope on \( EMVOL \) is 0.9709, and t-statistics are larger than 12. The estimated coefficients on \( EMVOL \) change very little from 0.9181 to 1.0247 after models control for the explanatory liquidity variables. This evidence indicates that liquidity variable does not influence considerably its relationship.

<table>
<thead>
<tr>
<th>MODEL</th>
<th>( EVOL )</th>
<th>( EMVOL )</th>
<th>( VALUE )</th>
<th>( ILR )</th>
<th>( TURN )</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.4057***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.062</td>
</tr>
<tr>
<td>2</td>
<td>0.3734***</td>
<td>0.9181***</td>
<td></td>
<td></td>
<td></td>
<td>0.064</td>
</tr>
<tr>
<td>3</td>
<td>0.3716***</td>
<td>1.0246***</td>
<td>(6.73\times10^{-10})***</td>
<td></td>
<td></td>
<td>0.077</td>
</tr>
<tr>
<td>4</td>
<td>0.3716***</td>
<td>1.0247***</td>
<td>(6.73\times10^{-10})***</td>
<td>-1.7564</td>
<td></td>
<td>0.077</td>
</tr>
<tr>
<td>5</td>
<td>0.3582***</td>
<td>0.9142***</td>
<td>(5.60\times10^{-10})***</td>
<td>-0.8136</td>
<td>0.8425***</td>
<td>0.087</td>
</tr>
</tbody>
</table>

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.

* Denotes a 0.10 significance level.

** Denotes a 0.05 significance level.

*** Denotes a 0.01 significance level.

In contrast with findings from individual stock in SET50 index, conditional idiosyncratic volatility plays less important role than conditional market volatility in determining expected stock returns in case of stock sectors. Still, such relationship is similar to that of individual stocks from SET. 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 model 1-5, there is still a significantly positive relation. Compared with individual stocks in SET50 and SET, 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. In contrast, such variable is statistically significant for individual stocks at a 0.01 level.

There is an important point in equation 38 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, $\alpha_i$, in equation 38. 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, $\beta_i$, 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 8 shows the estimated coefficients on explanatory variables for individual stocks in SET50 index 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 0.258, and are statistically significant at a 0.01 significant 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 8 Fixed Effect Panel Data Regressions of Fama and MacBeth Model for Individual Stocks in SET50 Index.

<table>
<thead>
<tr>
<th>Model</th>
<th>$BETA$</th>
<th>$EVOL$</th>
<th>$EMVOL$</th>
<th>$RS$</th>
<th>$VALUE$</th>
<th>$ILR$</th>
<th>$TURN$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.006</td>
<td>0.258***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.75</td>
</tr>
<tr>
<td>2</td>
<td>0.241***</td>
<td>0.016**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.75</td>
</tr>
<tr>
<td>3</td>
<td>0.240***</td>
<td>0.017***</td>
<td>-1.653***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.75</td>
</tr>
<tr>
<td>4</td>
<td>0.242***</td>
<td>0.016*</td>
<td>-1.464*** $(8.15\times10^{-9})$***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.76</td>
</tr>
<tr>
<td>5</td>
<td>0.242***</td>
<td>0.016*</td>
<td>-1.449*** $(8.15\times10^{-9})$***</td>
<td>-0.004***</td>
<td></td>
<td></td>
<td></td>
<td>0.76</td>
</tr>
<tr>
<td>6</td>
<td>0.243***</td>
<td>0.015***</td>
<td>-1.644*** $(4.53\times10^{-9})$***</td>
<td>-0.020***</td>
<td>2.110***</td>
<td></td>
<td></td>
<td>0.76</td>
</tr>
</tbody>
</table>

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.

* Denotes a 0.10 significance level.
** Denotes a 0.05 significance level.
*** Denotes a 0.01 significance level.

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 0.05 significance level, and a 0.10 significance level. They are smaller than those of expected conditional idiosyncratic volatility as well. That is, an average slope on $EMVOL$ 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 index, the estimated coefficients on relative bid-ask spread and turnover ratio are very large, so liquidity premium plays an important role.

Table 9 shows the estimated coefficients on explanatory variables from fixed effect panel data regressions for individual stocks in SET index which are also similar to the results from the pooled panel data regressions. That is, the fixed effect panel data regressions come up with statistically positive effects of expected conditional idiosyncratic volatility on expected stock returns. It is significantly related to expected stock returns in all the models. All the estimated coefficients on EVOL are close to zero, i.e. they vary little from $1.18 \times 10^{-33}$ to $1.43 \times 10^{-33}$, and are statistically significant at a 0.01 significant level. The t-statistics are larger than 31, and an average adjusted R-squared is 0.064. Additionally, liquidity variables do not affect on the relationship between expected conditional idiosyncratic volatility and expected stock returns. It is because the significant effects still exist after controlling liquidity variables.

<table>
<thead>
<tr>
<th>Model</th>
<th>EVOL</th>
<th>EMVOL</th>
<th>RS VALUE</th>
<th>ILR</th>
<th>TURN</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(1.43×10^{-33})***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.011</td>
</tr>
<tr>
<td>2</td>
<td>(1.41×10^{-33})***</td>
<td>2.908***</td>
<td></td>
<td></td>
<td></td>
<td>0.061</td>
</tr>
<tr>
<td>3</td>
<td>(1.41×10^{-33})***</td>
<td>2.906***</td>
<td>-0.049***</td>
<td></td>
<td></td>
<td>0.061</td>
</tr>
<tr>
<td>4</td>
<td>(1.40×10^{-33})***</td>
<td>2.956***</td>
<td>-0.119***</td>
<td>(1.09×10^{-3})***</td>
<td></td>
<td>0.072</td>
</tr>
<tr>
<td>5</td>
<td>(1.40×10^{-33})***</td>
<td>2.956***</td>
<td>-0.119***</td>
<td>(1.09×10^{-3})***</td>
<td>-1.49×10^{-6}</td>
<td>0.072</td>
</tr>
<tr>
<td>6</td>
<td>(1.18×10^{-33})***</td>
<td>2.722***</td>
<td>-0.153***</td>
<td>(5.59×10^{-5})***</td>
<td>0.006***</td>
<td>1.23***</td>
</tr>
</tbody>
</table>

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 March 2001 to December 2011. Intercepts are not presented here due to an excess of data.

* Denotes a 0.10 significance level.
** Denotes a 0.05 significance level.
*** Denotes a 0.01 significance level.

Similarly, Models 2-5 also show that expected conditional market volatility is positively and significantly related to expected stock returns in all the models. Still, the estimated coefficients are statistically significant at a 0.01 significance level. It is
consistent with pool panel regression that such coefficients are also larger than those of expected conditional idiosyncratic volatility. That is, an average slope on $EMVOL$ is 2.8896, and t-statistics are larger than 109. Conversely, liquidity variables do not change the significant effect of expected market volatility. For this reason, the relationship between expected market volatility and expected stock returns is similar to one between expected idiosyncratic volatility and expected stock returns for both pooled and fixed panel data regressions. Yet, $EMVOL$ play a more important role than $EVOL$ in this case, like stock sectors.

In addition, Table 9 demonstrates that all the explanatory liquidity variables have significant effects. That is, stock value, turnover ratio, and illiquidity ratio are positive and significantly related to expected stock returns. On the contrary, bid-ask spread has a negative effect on expected stock returns. In this case, the estimated coefficient on turnover ratio are largest consistent with result from individual stocks in SET50 index. However, illiquidity ratio has a positive effect similar to earlier studies, especially Amihud(2002).

Table 10 shows the estimated coefficients on explanatory variables of models in equation 38 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 $EVOL$ 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 2-5, which is similar to results of individual stock. The average slope coefficients on $EMVOL$ 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 $EMVOL$ being larger than the ones on $EVOL$. 

- 63 -
### Table 10 Fixed Effect Panel Data Regressions of Fama and MacBeth Model for Stock Sectors.

<table>
<thead>
<tr>
<th>MODEL</th>
<th>EVOL</th>
<th>EMVOL</th>
<th>VALUE</th>
<th>ILR</th>
<th>TURN</th>
<th>$\bar{R}^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.4330***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.072</td>
</tr>
<tr>
<td>2</td>
<td>0.3935***</td>
<td>1.3094***</td>
<td></td>
<td></td>
<td></td>
<td>0.076</td>
</tr>
<tr>
<td>3</td>
<td>0.3980***</td>
<td>1.4438***</td>
<td>(1.12×10^9)***</td>
<td>-1.8972</td>
<td>0.098</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.3980***</td>
<td>1.4438***</td>
<td>(1.12×10^9)***</td>
<td>0.9596***</td>
<td>0.109</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.3822***</td>
<td>1.3530***</td>
<td>(1.02×10^9)***</td>
<td>-1.3543</td>
<td>0.9596***</td>
<td></td>
</tr>
</tbody>
</table>

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.

* Denotes a 0.10 significance level.

** Denotes a 0.05 significance level.

*** Denotes a 0.01 significance level.

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 11 demonstrate the estimated coefficients on explanatory variables in equation 38 for stock sectors by using random effect panel data regressions. All the findings are similar to the estimated coefficients from pooled and fixed 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 $EVOL$ 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 and fixed 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 $EMVOL$ 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 1 Random Effect Panel Data Regressions of Fama and MacBeth Model for Stock Sectors.

<table>
<thead>
<tr>
<th>MODEL</th>
<th>EVOL</th>
<th>EMVOL</th>
<th>VALUE</th>
<th>ILR</th>
<th>TURN</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.4314***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.066</td>
</tr>
<tr>
<td>2</td>
<td>0.3920***</td>
<td>1.2841***</td>
<td></td>
<td></td>
<td></td>
<td>0.070</td>
</tr>
<tr>
<td>3</td>
<td>0.3960***</td>
<td>1.4160***</td>
<td>(1.16×10^{-9})***</td>
<td>-1.8689</td>
<td></td>
<td>0.091</td>
</tr>
<tr>
<td>4</td>
<td>0.3960***</td>
<td>1.4163***</td>
<td>(1.16×10^{-9})***</td>
<td>-1.8689</td>
<td></td>
<td>0.091</td>
</tr>
<tr>
<td>5</td>
<td>0.3803***</td>
<td>1.3234***</td>
<td>(9.77×10^{-10})***</td>
<td>-1.3026</td>
<td>0.9553***</td>
<td>0.102</td>
</tr>
</tbody>
</table>

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.

* Denotes a 0.10 significance level.
** Denotes a 0.05 significance level.
*** Denotes a 0.01 significance level.

In addition, models 3-5 in Table 11 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, $cov(u_i, X_i) = 0$, where $X_i$ is the control variable. 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. It is similar to Redundant fixed effects test which demonstrates that fixed panel data regression is the true model.

5.6 Discussion

This study tries to explore whether idiosyncratic risk affect on expected stock returns as well as market risk. Our research show that the appropriate model to measure idiosyncratic risk and market risk are EGARCH (1,1) and GARCH(2,2),
respectively. This is because such volatility which captures both types of risk does not follow random walk. Thus, the standard deviations of regression residual are not suitable for represent idiosyncratic and market risk. Even though idiosyncratic volatility comes from CAPM, there is another model to estimate conditional expected idiosyncratic volatility such as the three-factor model.

The findings document that the appropriate model is fixed effect panel data regression model. More importantly, conditional expected idiosyncratic volatility has a positive effect on expected stock returns. Consistent with previous papers, conditional expected market volatility is positively related to expected stock returns. Although all the models control for liquidity variables, the significant effect still remains. It implies that investors obtain compensation for bearing idiosyncratic and market risk.
CHAPTER 6
Conclusion and Recommendation

Chapter Summary

The asset pricing model derived from the dynamic stochastic general equilibrium model states that idiosyncratic risk has a positive effect on expected stock returns. This result is contrary to previous papers that does not consider idiosyncratic as a determinant factor. Since such risk can be eliminate through diversification, only systematic risk affects expected returns.

More importantly, we show that empirical results are consistent with theoretical one. In the case of Thai stock market, conditional expected idiosyncratic volatility is positive and significantly correlated with expected stock returns. Additionally, conditional expected market volatility also has a positive effect on expected stock returns consistent with CAPM. In the case of SET and stock sector, such risk plays a more important role in determining expected stock returns for individual stocks and stock sectors.

Although, this study derives asset pricing model to show the effect of idiosyncratic risk, such model does not test for whether it capture the data yet. In addition, an aggregate productivity shock disappears in our model. It is because we assume that it is identical to one. Moreover, SET50 index returns are used for representing market return. It might cause different results for individual stocks between SET50 and SET.

6.1 Conclusion

So far, the asset pricing models do not consider idiosyncratic as an important factor in determining stock returns. It is because all of them assume that investors can construct efficient portfolio. This leads to elimination of diversified risk. Although there is a few studies try to examine the role of idiosyncratic risk, it does not develop model from the dynamic stochastic general equilibrium model.

Chapter 3 provides a new asset pricing models which derive from the dynamic stochastic general equilibrium model with idiosyncratic productivity shock. This theoretical section demonstrates that, in equilibrium, idiosyncratic risk is an important
determinant of expected stock returns.

More importantly, idiosyncratic productivity level which stands for idiosyncratic risk has a positive effect on expected returns on stock. Such findings change the key determinants of asset pricing model from consumption to production factor and idiosyncratic productivity shock. That is, capital and labor affect on expected stock returns in different direction. The labor has a positive effect, but capital has a negative one. Still, this conclusion is contrary to Lucas (1978), Beeden (1979), Mehra and Prescott (1985), Storesletten et al. (2001, 2007), Lettua (2003), Balvers and Huang (2007), Jerman (1988, 2010), Cochrane (1991, 1993, 1996), Alvarez and Jermann (2000), Gala (2005), Liu et al. (2009), and Belo (2010). It might be because almost all studies believe that idiosyncratic component of expected returns is uncorrelated with the stochastic discount factor. In particular, such result is consistent with empirical evidence for Thai stock market.

In more detail, expected stock returns depends on the rate of time preference, depreciation rate, capital share, expected idiosyncratic productivity shock at time $t+1$, the percentage deviation of capital from steady state at time $t+1$, and the percentage deviation of labor from steady state at time $t+1$. In fact, expected idiosyncratic productivity shock, expected capital, and expected labor affect on expected returns on stock since all the parameters are very small value. The aggregate productivity level, however, does not show an effect on expected stock returns in our model.

Such relation will be tested with empirical evidence in Chapter 4 and 5. 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 and stock sectors 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 both individual stocks and stock sectors. The daily data for testing come from SET50 index, SET index 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 from SET50 index and
SET index is lower 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 consistent with Amihud and Mendelson (1989), Malkeil and Xu (2002), 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).

Another contribution is that expected conditional 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 substantially change its significant effect on expected stock returns for individual stocks and stock sector. In the case of SET and stock sector, the coefficients of market volatility, however, are larger than the ones of idiosyncratic volatility. This means that systematic risk is more important than idiosyncratic risk in the stock sectors and individual stocks in SET. That is, investors can reduce the effect of idiosyncratic risk through portfolio diversification like stock sector. In contrast, idiosyncratic risk plays a more important role in individual stocks in SET50 index. More typically, 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 stocks. In contrast, relative bid-ask spread is negatively related to expected stock returns for individual stocks in SET50 and SET. Indeed, the higher the relative bid-ask spread is, the lower the expected stock return to investors. Illiquidity ratio has a positive effect for individual stocks in SET index, and a negative effect for individual stocks in SET50 index. Yet, such variable has no
significant effect in case of stock sectors. Similarly, value of stock sector and turnover ratio of stock sector have significantly positive effects on expected stock returns. It implies that investors are able to earn the liquidity premium by investing in a frictionless stock market.

6.2 Limitations of the Dissertation

Even though this study derives asset pricing model to show the effect of idiosyncratic risk on expected stock returns, such model does not test for whether it capture the data yet. It is because the limitation of data for testing such as labor used, capital used for each firm.

In addition, the empirical evidence provides that idiosyncratic and market risks are positive and significantly related to expected stock returns. However, idiosyncratic risk plays a more important role only in individual stocks in SET50 index. This means that the movement of price and expected returns on stock in SET50 follows idiosyncratic risk more than systematic risk. It is partly because we use SET50 index returns as a proxy of market return, not SET index returns. Therefore, such returns are not identical to returns on market.

6.3 Recommendation

In the Stock Exchange of Thailand (SET), the time-varying idiosyncratic volatility plays a less important role than the time-varying market volatility in case of stock sectors and individual stocks in SET, 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 especially individual stocks in SET50. 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
(SET) and Securities Exchange and Commission (SEC) in selecting companies to list on the stock market. That is, the first priority of stock selection is idiosyncratic volatility similar to stocks in SET50. 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.
BIBLIOGRAPHY


APPENDICES
A. Solving household’s maximization problem

Household’s problem:

$$\max_{\{c_t, h_t, b_{t+1}, w_t\}} E_t \left\{ \sum_{t=0}^{\infty} \beta^t U(c_t, 1-h_t) \right\} ; 0 < \beta < 1$$

subject to

$$w_t h_t + \sum_i b_{it} + \sum_i s_{it} (d_{it} + q_{it}) = \sum_i \frac{b_{it+1}}{1+r_t} + \sum_i s_{it+1} q_{it} + c_t + T_t$$

Writing the problem in form of Lagrange function:

$$L = E_t \left\{ \sum_{t=0}^{\infty} \beta^t U(c_t, 1-h_t) \right\}$$

$$+ \eta_t \left\{ w_t h_t + \sum_i b_{it} + \sum_i s_{it} (d_{it} + q_{it}) - \sum_i \frac{b_{it+1}}{1+r_t} - \sum_i s_{it+1} q_{it} - c_t - T_t \right\}$$

To compute the first-order condition:

$$FOC_c : \quad \beta^t U_c (c_t, 1-h_t) = \eta_t$$

$$FOC_h : \quad \beta^t U_h (c_t, 1-h_t) = \eta_t w_t$$
\[ \text{FOC}_{t_{i+1}} : \quad \eta_{i+1} = \frac{\eta_i}{1 + r_i} \quad (5) \]

\[ \text{FOC}_{s_{i+1}} : \quad \eta_{i+1}(d_{s_{i+1}} + q_{s_{i+1}}) = \eta_i q_{s_i} \quad (6) \]

To compute Euler equations, combining equation (3) with (4), we obtains

\[ \begin{bmatrix} U_h(c_{s,1-h}) \\ U_c(c_{s,1-h}) \end{bmatrix} = w_i \quad (7) \]

Combining equation (3) with (5), yields

\[ \beta E_t \{ U_h(c_{s,1-h}) (1 + r_i) \} = U_c(c_{s,1-h}) \quad (8) \]

Combining equation (3) with (6)

\[ \beta E_t \{ U_h(c_{s,1-h}) \frac{d_{s_{i+1}} + q_{s_{i+1}}}{q_{s_i}} \} = E U_c(c_{s,1-h}) \quad (9) \]

Let’s denote \( R'_{i+1} \) as returns on stock \( i \) at time \( t + 1 \)

Define:

\[ R'_{i+1} = \frac{q_{s_{i+1}} + d_{s_{i+1}}}{q_{s_i}} \]

Substituting it into equation 9, this equation then becomes
\[
\beta E_t \left\{ \frac{U_c(\xi_{t+1}, 1-h_{t+1})}{U_c(\xi_{t}, 1-h_{t})} R_{t+1}^c \right\} = 1
\]  

(10)

B. Solving firm’s maximization problem

Production function and constraints are as follows:

\[
F(z_t, \xi_{t}, k_{it}, h_{it}) = \left( e^{\varphi_1} \right) \kappa_{it} \theta h_{it}^{1-\theta}
\]  

(11)

\[
z_t = \bar{z} + \psi z_{t-1} + \nu_t \quad ; \quad \nu_t \sim N\left(0, \sigma^2_{\nu}\right) \]  

(12)

; \quad 0 < \psi < 1

\[
\xi_{it} = \bar{\xi} + \varepsilon_{it-1} + \mu_t \quad ; \quad \mu_t \sim N\left(0, \sigma^2_{\mu}\right) \]  

(13)

; \quad 0 < \tau < 1

\[
(1-\delta)k_{it} + F(z_t, \xi_{it}, k_{it}, h_{it}) + \frac{b_{it+1}}{1+r_{i}} = b_{it} + d_{it} + k_{it+1} + w_i h_{it}
\]  

(14)

The state variables are: \( X_i = (k_{it}, \xi_{it}, z_t, b_{it}, H_i) \)

The control variables are: \( h_{it}, k_{it+1}, b_{it+1}, d_{it} \)

Writing the Bellman equation, we get

\[
V(X_{it}) = \max_{\{b_{it}, k_{it+1}, d_{it+1}, d_{it}\}} \left\{ d_{it} + E_t \left( M_{it+1} V\left(X_{it+1}\right) \right) \right\}
\]  

(15)

subject to

\[
(1-\delta)k_{it} + \left( e^{\varphi_1} \right) \kappa_{it} \theta h_{it}^{1-\theta} + \frac{b_{it+1}}{1+r_{i}} = b_{it} + d_{it} + k_{it+1} + w_i h_{it}
\]
Solving Bellman equation, then the maximization problem for firm is:

\[
V(X_u) = \max_{\{b_{it}, k_{it}, d_{it}, v_{it}\}} \left\{ d_{it} + E_t \left( M_{r+1} V \left( X_{r+1} \right) \right) + \lambda_{it} \left\{ (1-\delta)k_{it} + \left( e^{\gamma}e_{it} \right) k_{it}^{\theta}h_{it}^{1-\theta} + \frac{b_{it+1} - b_{it} - d_{it} - \delta k_{it+1} - w_t h_{it}}{1 + r_t} \right\} \right\}
\]

The first-order conditions are:

\[
FOC_{b_{it}} : \quad (1-\theta) + (e^{\gamma}e_{it}) k_{it}^{\theta}h_{it}^{1-\theta} = w_t \tag{16}
\]

\[
FOC_{k_{it+1}} : \quad E_t \left[ M_{r+1} V \left( X_{r+1} \right) \right] = \lambda_{it} \tag{17}
\]

\[
FOC_{b_{it}} : \quad E_t \left[ M_{r+1} V \left( X_{r+1} \right) \right] + \frac{\lambda_{it}}{1 + r_t} = 0 \tag{18}
\]

\[
FOC_{d_{it}} : \quad 1 = \lambda_{it} \tag{19}
\]

The envelope conditions are:

\[
V_k (X_u) = \lambda_{it} \left[ (1-\delta) + \theta \left( e^{\gamma}e_{it} \right) k_{it}^{\theta}h_{it}^{1-\theta} \right] \tag{20}
\]

\[
V_b (X_u) = -\lambda_{it} \tag{21}
\]

The Euler equations are as follows:

Combining \( FOC_{d_{it}} \) with \( FOC_{b_{it}} \) and \( V_k (X_u) \), we get

\[
E_t \left[ M_{r+1} V \left( X_{r+1} \right) \right] = 1 \tag{22}
\]
Combining $FOC_{d_t}$ with $FOC_{b_t+1}$ and $V_b(X_{t+1})$, we get

From equation 19

$$1 = \hat{\lambda}_t$$

Substituting it into equation 18, we obtains

$$E_t \left[ M_{t+1} V_b(X_{t+1}) \right] + \frac{1}{1 + r_t} = 0$$

Therefore, equation 23 and 25 are the particular Euler equations for derive further the relationship between idiosyncratic risk and expected returns which show the optimal choices.