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Stock Return and Expected Idiosyncratic Risk

Evidence From Indonesian Stock Market

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Preface and Acknowledgement

I would like to express my gratefulness to God Almighty for making all of this possible. I would also like to express my gratitude for people and the universities for their countless supports for completing this thesis. These parties are:

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I understand that this thesis is not perfect, and have of some flaws. Thus, I aspire for readers to provide feedbacks and opinions for further improvements.

Abstract

Under the premise that stock return is not only explained by systematic risk, idiosyncratic risk can be priced as well. Previous research has shown that idiosyncratic risk is positively related with stock return. This study investigates whether idiosyncratic risk can explain stock return in Indonesian Stock Market from period of 2009 to 2019. It employed EGARCH models with Fama French Three Factors as the mean process to estimate expected idiosyncratic volatility. The findings showed a positive and significant relation between stock return and expected idiosyncratic volatility. However, the effect is not as profound after adjusting for time effect. In addition, the study also showed the relation between stock return and expected idiosyncratic volatility with different mean processes. Interestingly, significance level is increasing under all other mean processes while maintaining its positive sign. ANOVA test was conducted as well and showed that expected idiosyncratic volatility with different mean processes are statistically different from each other.

Keywords: Idiosyncratic risk, Stock returns, EGARCH, Fama French Three Factors, Indonesian Stock Market

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Introduction

Research Background

Modern Portfolio Theory (MPT) by Markowitz (1952) suggest that holding portfolio and including more assets to that portfolio could eliminates idiosyncratic risk. This theory is the theoretical foundation of Capital Asset Pricing Model (CAPM) which assume all investors holds diversified portfolio and only the systematic risk were priced. However, it is quite extreme to assume that all investors are holding diversified portfolio. Goetzmann et al (2004) shows that more than 25 % investors only hold one stock and more than a half of all investors holds equal or less than three stocks for their observation from 1991 to 1996. Since MPT suggest adding more assets can diversified the portfolio, it seems that holding a little amount of stocks cannot be consider as diversified. Moreover, Campbell et al (2002) suggest that randomly selected stocks need about 50 assets to achieve complete portfolio diversification.

Under the premise of investors still holds idiosyncratic risk on their portfolio, many hypotheses have been develop to proof whether idiosyncratic risk can be priced into stock returns, meaning that differences in stock returns cross-sectionally can be justified from bearing more idiosyncratic risk. Merton (1987) found that idiosyncratic risk is positively related to expected return in the cross-section. He infer that investors are expecting more returns by holding more expected idiosyncratic risk. However, Merton observed idiosyncratic risk subsequent to the current stock return, i.e. ex-post. Thus, the findings does not quite justified the expectation term and an estimation of expected idiosyncratic risk is required to test the hypothesis.

Ang et al (2006) suggest that monthly stock returns are negatively related to the one-month lagged idiosyncratic volatility that serve as a proxy of expected idiosyncratic risk. However, Fu (2009) find a significant positive relation between the estimated conditional idiosyncratic volatilities and expected return.

Diverse conclusions motivates this thesis to observe the empirical relationship of stock return with both actual and expected idiosyncratic risk, with more comprehensive discussion on expected idiosyncratic risk. Furthermore, investigate on how to estimate appropriate expected idiosyncratic risk is also this thesis main interests. Methodology subsection will discuss that idiosyncratic risk is highly time-varying, thus conditional volatility (EGARCH) is preferable than the lagged model.

Additionally, this thesis will use Indonesian Equity Market as the sample, specifically on stocks that are listed on KOMPAS 100 index, given that it constitutes a large share of Indonesian Equity Market.

Research Question

Inferring from the research background, it raises four questions :

1. What are the empirical relationship between expected stock return and idiosyncratic risk in Indonesian Stock Market?
2. What are the appropriate method to estimate expected idiosyncratic risk?
3. What are the empirical relationship between expected stock return and expected idiosyncratic risk in Indonesian Stock Market?
4. Does a zero-investment portfolio of shorting low expected idiosyncratic risk portfolio and long high expected idiosyncratic risk portfolio yield a positive or negative return?

The last research question is dependent to the former question, thus it may be redundant to included it. However, findings on question four has more pragmatic justification, which may yield significant information regarding expected idiosyncratic risk in practice, such as investment strategy.

Relevance of Study

Observing whether investors will be compensated by bearing idiosyncratic risk is the main purpose of this thesis. The revealing evidences are important for three reasons:

1. It justify the previous study regarding idiosyncratic risk with different geographic location samples.

2. The findings yield information regarding the degree of diversification by investors in Indonesian Stock Market.

3. The revealed evidences can be derive and then developed into investment strategy.

Scope and Limitations

This thesis is primarily focus on observing Indonesian Stock Market with period from 2009 to 2019. The main purpose of choosing this sample is the reason to believe that the majority investors in Indonesian Stock Market does not hold diversified portfolio (further discussion in the hypotheses development section). While the period was chose based on two reasons; (1) reason to believe that the structural breaks of the 2008 financial crisis might affect the empirical evidence [1]. (2) limited availability of financial data that goes back to 2009.

There are also several limitations of this thesis. First, this thesis only use companies listed on KOMPAS 100 as the sample. Although it represent large share of the Indonesian Stock Market, it mainly comprises of large and mid-cap companies. The availability of small-cap companies is limited, given that Indonesian Stock Market can be categorize as developing financial market. Second, given that there are various ways and combinations to estimate expected idiosyncratic risk, this thesis will only observed five methods. More comprehensive combinations will be ideal but requires more computational power due to its complexity. This topic will be explained more on the Conclusion section.

Theoretical Framework

Idiosyncratic Risk and Expected Return

The famous Capital Asset Pricing Model (CAPM) by Sharpe (1964) and Lintner (1965) holds two very restrictive properties. These are; all risky securities are available on the market and all investors hold portfolio of assets in the same proportions. The absence of transaction costs for CAPM assumptions are justifying even more that this theory

[1] Kinnunen et al (2007) observed idiosyncratic risk with two period samples of before and after financial crisis and found a reversal of the coefficient sign.

contradicts or not conforming the reality of financial market. For this reason, Levy (1978), investigate the equilibrium in an imperfect market and addresses on the constraint number of securities in the portfolio. He relaxed the assumption of a perfect market by allowing investors to hold stocks of a companies with small n as close to 1. From his research Levy (1978) found that the systematic risk, β, of traditional CAPM has little contribution with the equilibrium price determination. Another important finding by Levy was the positive correlation between market-adjusted return and residual variance which is the natural proxy for idiosyncratic risk. Another famous findings such as Merton (1987) and Malkiel et al (2002) also suggest that idiosyncratic risk is positively related to the expected return in the cross-section which mainly causes by under-diversification by investors. Under-diversified investors demand to be compensated by bearing extra idiosyncratic risk. As to this point, previous studies suggest the positive correlation between idiosyncratic risk and stock's expected return cross-sectionally.

Further forward in time, Ang et al (2006) indeed confirm that stock returns are significantly related with expected idiosyncratic volatility for US samples. But surprisingly, they found a negative relation. They found stocks with high one month lagged idiosyncratic risk predicts low average returns. Ang et al (2006) findings imply that under-diversified investors are not compensated by bearing idiosyncratic risk which contradicts many previous theories. They estimate idiosyncratic volatility with relative to Fama French model and claim that this phenomenon cannot be explained by exposure to aggregate volatility risk. They also empirically account for size, value, liquidity effect and momentum, which still can't explain the phenomenon. Not long after the controversial discovery, Fu (2009) proofed that their idiosyncratic volatility does not follow a random walk process. The finding suggest that one month lagged volatility might not be a good estimate of expected idiosyncratic volatility.

Fu (2009) suggest that idiosyncratic volatilities are time-varying and employed EGARCH model to estimate expected idiosyncratic volatility. Fu found significant positive relation between the estimated conditional idiosyncratic volatilities and stock returns. He used the sample of monthly US stocks from the period of 1963 to 2006. The process includes capturing the residual variance relative to Fama French three factors model, estimated expected idiosyncratic volatility based on previous actual idiosyncratic volatility, and using Fama-Macbeth method to regress stock return with expected idiosyncratic volatility along with control variables such as size and value.

International Evidence(Emerging Markets)

Most of the empirical evidence of idiosyncratic risk and expected returns are US-based. It was quite difficult to find evidence from countries outside US. However, Okpara et al (2009) observe idiosyncratic volatility from Nigerian Stock Market. They employed similar procedures from Fu (2009) but with a significant simplification. Instead of estimating residual variance relative to Fama French three factors as a proxy for idiosyncratic volatility, they use CAPM model which only account for market beta. Okpara et al (2009) also did not control for size, value, liquidity and momentum for the cross-section regression. As a result, they found significantly negative relation between stock returns and expected idiosyncratic volatility. Their findings are consistent with Ang et al (2006) and they concluded that investor(s) in Nigerian Stock Market are fully diversified their portfolio so only systematic risk were priced. However, their results need to be further investigated since there are a lot of debate regarding the reliability of CAPM in measuring expected stock returns. The negative result might be induced by other systematic risk that CAPM didn't account for.

Angelidis (2010) examine the properties and portfolio management implications of value-weighted idiosyncratic volatility in 24 emerging markets across continents, including Indonesia. Angelidis (2010) method of estimating idiosyncratic volatility is by taking the standard deviation of the residual relative to CAPM model. He found a significant negative coefficient of idiosyncratic volatility for pooled samples across 24 countries. The results in emerging markets are similar to Okpara et al (2009) findings with slightly different approach.

Another international evidence is from Russia by Kinnunen et al (2017). They observe expected returns on industry-level in Russia and estimate the idiosyncratic risk using MIDAS regressions and a cross section of Russian industry portfolios. Their results are in line with the previous study but only on their second sample which is after the

2008-2009 global financial crisis. The first sample (before 2008 financial crisis) shows negative relation and switch into positive sign on the second sample. Both results are statistically significant. They argued that the reason for negative results on the first sample is due to investor hedging demands for their high exposure to oil and gas sector performance. While the switching sign after the financial crisis can be explained by the developments in market infrastructure. Regardless the result of the first sample, Kinnunen et al (2017) still concludes that the pricing of idiosyncratic risk is mainly driven by incomplete portfolio diversification and the significant premium of the idiosyncratic risk suggest inefficient allocation of financial resources in Russian stock markets.

Indonesian Stock Market

Investigating idiosyncratic risk is an uncommon topic for Indonesian Stock Market. Studies such as Nartea et al (2011) and Anggiyanti (2018) found that realized or actual idiosyncratic risk has positive and significant relationship with stock returns. However, neither estimating expected idiosyncratic risk nor observing the relationship with stock returns have been studied in Indonesian Stock Market before. Thus, given that expected idiosyncratic risk is conditional to the actual idiosyncratic risk, the oversimplified conclusion would be a positive and significant relationship as well between expected idiosyncratic risk and stock returns.

Stock Return Mean Models

The main method of estimating expected idiosyncratic risk in this thesis is using ARCH non-linear regression specifically using EGARCH model (details of the method will be discussed on methodology subsection). One of the properties of all ARCH family regression is to estimate the mean and variance process jointly. Hence, investigating past empirical evidences of stock returns mean model are needed.

Capital Asset Pricing Model. The idea that stock return is positively related with market risk premium is the foundation of CAPM model. Sekarwati (2016) confirmed the hypothesis of CAPM with companies listed on KOMPAS 100 index from 2011 to 2015. Moreover, using the same index sample, Liani (2017) concluded that CAPM is better than

Fama-French Three Factor Model based on the average expected return and the coefficient of variation of stocks.

Fama French Three Factors Model. Fama et al (1992) first introduced Fama-French Three Factors model that explain stock return with firm size effect and book-to-market ratio in addition to market risk premium. Wijaya et al (2017) found that stock returns in KOMPAS 100 index has positive significant relation of market risk premium, negative significant relation of firm size, and insignificant relation for book-to-market ratio. Another study that construct multiple portfolios based on the size and book-to-market ratio found the following results (Dewi & Suartana, 2018):

1. Market risk premium is positively related for all portfolio.
2. Size premium is positively related for all small size portfolio firm with different book-to-market ratio (S/H, S/M, S/L) and negatively related for all large size portfolio firm with different book-to-market ratio (B/H, B/M, B/L).
3. Book-to-market or value premium is positively related for portfolio with large and small size firm portfolio with high book-to-market ratio (B/H, S/H), negatively related for large and small size firm portfolio with low book-to-market ratio (B/L, S/L).

Obviously there are more various models that try to estimate expected stock return and capture the systematic risk which assumed to be related. However, this thesis will only focus on two most common mean models, i.e. CAPM and Fama-French Three Factor. As for the default mean model, Fama-French Three Factor model will be employed following studies such as Ang et al (2006), Brockman et al (2007), and Fu (2009).

Hypotheses Development

The main objective of this study is to examine whether under-diversified investors are compensated for bearing idiosyncratic risk in Indonesian Stock Market. Thus, it raises three hypotheses that can be developed from the research questions:

Hypothesis 1: *Expected stock return is positively related to idiosyncratic risk.*

There are many various researches that suggest expected return are indeed positively related to expected idiosyncratic risk. Among them are Levy (1978), Merton (1987), Malkiel et al (2002), Nartea et al (2011), Anggiyanti (2018), and many others. Under-diversification by investors might be the main reason of the positive relation.

According to Campbell et al (2002), a minimum of 50 randomly selected stocks must be in a portfolio to achieve complete portfolio diversification. Since finding by Frensidy (2016) suggest that the average individual domestic investors in Indonesian Stock Market is 4.3 (with median of 2), it can be hypothesized that idiosyncratic risk can be priced in Indonesian Stock Market.

Hypothesis 2: *Expected Stock Return is positively related to expected idiosyncratic risk.*

To improve the justification of the thesis main objective, the expectation term of idiosyncratic risk must be take into account. Studies such as Brockman et al (2007) and Fu (2009) suggest that expected stock return is positively related with expected idiosyncratic risk.

Hypothesis 3: *Positive return of shorting low idiosyncratic risk portfolio and long high idiosyncratic risk portfolio.*

Fu (2009) conducted a return analysis of forming portfolio based on expected idiosyncratic volatility. Fu formed 10 portfolios ranked by low to high expected idiosyncratic volatility with monthly rebalancing. A zero-investment strategy of shorting the first portfolio and long the last portfolio yields 1.75% a month on average. The positive return implied that bearing more idiosyncratic risk does compensate investors with positive return. On this thesis, hypothesis 3 are dependent on hypothesis 2. If hypothesis 2 is true, the conclusion will be the same for hypothesis 3.

Data and Methodology

Data

All the data used in this thesis were acquired from Datastream with accessed from Erasmus University of Rotterdam. The data included are the adjusted close stock price, market capitalization, and price to book ratio of all companies listed on KOMPAS 100 index from 2009 to 2019. Various MSCI total return index such as; MSCI Indonesia, MSCI Indonesia Investable Growth, MSCI Indonesia Investable Value, MSCI Indonesia Large Capitalization, and MSCI Small Capitalization were acquired as well. In addition, the daily one-month Indonesia Interbank rate was taken and use as a proxy for risk-free rate. The details of each data will be explained in the following section.

Financial Data of Companies Listed on KOMPAS 100. This thesis acquired historical financial data of companies listed on KOMPAS 100 for two main reasons. First, the index comprises of 100 companies with large market capitalization and high liquidity, thus ensure the representative of Indonesia equity market according to its market share and higher frequency of daily transactions. Second, the limited availability of historical data for other index that may consists of recently issued and lower frequency stocks. Therefore, adjusted close stock price, market capitalization, and price to book ratio of companies listed on KOMPAS 100 were acquired.

This thesis use purposive sampling which only used list of companies that never been delisted from the period of 2009 to 2019. Out of 157 companies that has been listed in KOMPAS 100 for 10 years period, 58 companies were chosen. Furthermore, additional requirement of minimum 15 trading days of volume for each month were imposed. As a result, 45 companies were chosen as the samples of this thesis.

MSCI Indices. Morgan Stanley Capital International (MSCI) is an American investment firms that provides stock indexes based on certain characteristics. MSCI indexes are widely use among financial literature, thus this thesis uses various of MSCI indices to serve as proxies for certain dependent variables. All of the indices are the total return index, which account for the reinvestment of dividends before taxes. The descriptive explanation of each index is as following:

1. MSCI Indonesia is an index that represent Indonesian equity market. The index covers 85% of Indonesian equity universe. Thus, the daily log return of MSCI Indonesia, can be used as a proxy of market return.

2. MSCI Investable Growth is an index that represents growth stocks in Indonesia. It captures large and mid-cap equities exhibiting overall growth style characteristics

such as; long-term forward EPS growth rate, short-term forward EPS growth rate, current internal growth rate and long-term historical EPS growth trend and long-term historical sales per share growth trend.

3. MSCI Investable Value is an index that represents value stocks in Indonesia. It captures large and mid-cap equities with value style characteristics such as; book value to price, 12-month forward earnings to price and dividend yield.

4. MSCI Large Capitalization is an index that constitutes companies with large market capitalization in Indonesia. It covers approximately 70% of the free float-adjusted market capitalization.

5. MSCI Small Capitalization is an index that constitutes small market capitalization. It covers approximately 14% in Indonesian equity market.

Methodology

Intuitively, the relationship between return and risk should be symmetrical. Investors should be compensated by return for bearing extra risk. If idiosyncratic volatility is the natural proxy of idiosyncratic risk, we expect to observe positive empirical relationship between expected return and expected idiosyncratic volatility. However, both expected return and expected idiosyncratic volatility are unobservable. Following Fu (2009), the conventional practice is to set the realized return as the dependent variable where it is assumed to be the sum of expected returns and random error [2]. Thus, two equations can be formulate; (1) idiosyncratic volatility and the control variables such as BETA, *Ln*(MV), and *Ln*(B/M) are set as the independent variables, (2) expected idiosyncratic volatility and the control variables. Both equations are explicitly in this form:

$$R_{it} = \gamma_0 + \gamma_1 IVOL_{it} + \gamma_2 BETA_{it} + \gamma_3 Ln(MV)_{it} + \gamma_4 Ln(BM)_{it} + \epsilon_{it} \tag{1}$$

$$R_{it} = \lambda_0 + \lambda_1 E[IVOL]_{it} + \lambda_2 BETA_{it} + \lambda_3 Ln(MV)_{it} + \lambda_4 Ln(BM)_{it} + \upsilon_{it} \tag{2}$$

[2] (Fama & French, 1992), (Easley, Hvidkjaer, & O'Hara, 2002) and others employ the similar practice.

The dependent variable of this equation is the monthly stock returns which are calculated based on the log difference of each stock monthly adjusted close prices. Main differences of equation 1 and 2 lies on IVOL and E[IVOL]. E[..] stands for expectation with conditional information from previous periods. Thus, E[IVOL] is the expectation of idiosyncratic volatility conditional on information from previous t while IVOL is the actual or realized idiosyncratic volatility. BETA, *Ln*(MV) and *Ln*(B/M) serves as the control variables, since earlier studies documented market beta, firm size and book-to-market ratio have effects on stock returns [3]. BETA is the measured of stock return sensitivity relative to excess return of market. *Ln*(MV) measured the standardize market capitalization of a firm. *Ln*(B/M) measured the standardized book-to-market ratio of a firm[4].

Idiosyncratic Volatility. In order to have a quality estimate of expected idiosyncratic volatility, we have to understand what is the observable idiosyncratic volatility of stock return. Idiosyncratic volatility can be defined as a firm-specific risk which unrelated to the systematic risk that can explain stock return. Model such as CAPM by Sharpe (1964) and Litner (1965) and Fama French Three Factors by Fama et al (1992) are famous model that try to capture the systematic risk. Thus, the standard deviation of the residuals from the model that captures systematic risk can be defined as the idiosyncratic volatility. Following the work of Ang et al (2006) and Fu (2009), Fama French Three Factors model will be employed to capture the idiosyncratic volatility as well as the factors coefficient as the control variables. Moreover, according to Fama et al (1992), Fama French Three Factor model explain approximately 90% of the variability in returns while CAPM only explains 75% of the returns. The estimation will follow equation below:

$$R_{it} - R_f = \alpha_0 + BETA_i(R_{m_{it}} - R_f) + HML_i(R_{h_{it}} - R_{l_{it}}) + SMB_i(R_{s_{it}} - R_{b_{it}}) + \varepsilon_{it} \quad (3)$$

The dependent variable is the daily log return of each stocks with period from January 2009 to December 2019. The dependent variable will be regress monthly on the Fama

[3] (Fama & French, 1992) explains the effect of size and book-to-market.

[4] Since the data acquired is price-to-book ratio, simply raise the p/b ratio to the power of negative one will convert it to book-to-market ratio.

French Three factors. The detail calculations of each three factors are as follow: (1) excess market return or the risk premium ($R_m - R_f$) is the difference of MSCI Indonesia return over one-month Indonesia Interbank rate, (2) excess return of value stocks ($R_h - R_l$) is the difference of MSCI Indonesia Value Index return over MSCI Indonesia Growth Index return, and (3) excess return of small cap stocks ($R_s - R_b$) is the difference of MSCI Indonesia Small Cap Index return over MSCI Large Cap Index return. The two latter calculations of the factors are a common practice to measure the factor with sample outside US[5].

Equation 3 will be regress as a time-series for every month. In each day of the monthly regression, the residuals, ε_{it} , were estimated and the daily standard deviation of residuals were calculated with the following formula:

$$S_e = \sqrt{\frac{\sum \varepsilon_{it}^2}{n-k}}$$

Residuals, numbers of trading days within every month, and parameters are denoted as ε , n , and k respectively. The daily standard deviation of residuals is then transformed to monthly standard deviation of residuals by multiplying the daily standard deviation by the square root of the number of trading days in that month. In the pooled sample of 6072 monthly idiosyncratic volatility (132 for each company), the mean is 2.44% with standard deviation of 2.57%.

From equation 3, BETA, will also be estimated for each company and each month in the same 10 years period.

Expected Idiosyncratic Volatility. There are several ways to estimate expected idiosyncratic volatility. The easiest way is to simply use the one-period lagged of idiosyncratic volatility which a model suggested by Ang et al (2006) to explain monthly stock returns. But to have a quality estimate of expected idiosyncratic volatility, the time series properties of it must be taken into account.

The model suggested by Ang et al (2006) assume that idiosyncratic volatility follows

[5] (Vidal-García, Vidal, Boubaker, Riadh, 2018) employ the same strategy of measuring HML and SMB returns using indices since there are no availability of the factors return on Kenneth French database.

a random walk process which is characterized by a strong first-order autocorrelation and immediately fall after the first lag. The last column of Table 1 shows the average autocorrelation of the actual or realized idiosyncratic volatility from the first lag to the fifth lag. It appears that the first-order autocorrelation is quite low with an average of 0.262 and decaying slowly. The results are similar to the findings of Fu (2009) with 0.33 first-order autocorrelation for US stock markets.

To prove furthermore that idiosyncratic doesn't follow a random walk process, Dickey-Fuller tests are performed on each stock idiosyncratic volatilities. Table 2 shows the average t-statistics, p-values, and the Dickey-Fuller 1%, 5%, and 10% critical values that follows Dickey-Fuller distribution. 41 out of 45 companies are rejected for the null hypothesis of following random walk process. 41 companies account for 91.11% of the sample, thus it is not appropriate to use one-month lagged idiosyncratic as expected idiosyncratic volatility.

Other method to estimate expected idiosyncratic volatility is to employ Autoregressive Conditional on Heteroskedasticity (ARCH) non-linear regression. Similar method was employed by Fu (2009) that resorted EGARCH to capture one-month ahead expected idiosyncratic volatility.

ARCH model was first introduced by Engle (1982) with the purpose of capturing the variance of the residuals or the error terms. It is widely use to for financial market data that exhibit time-varying behavior. One of the favorable character of ARCH model, is the ability of estimating the mean and variance process jointly.

As an improvement to ARCH model that only uses the squared residuals as a condition for the variance, General Autoregressive Conditional on Heteroskedasticity was proposed by Bollerslev (1986) by adding the lagged conditional variance term. A step further, EGARCH by Nelson (1991) and GJR-GARCH by Glosten et al (1993) were introduced. Both models are attractive to financial market data since it accounts for 'heavy tail'. A negative shock to financial time series is likely to cause volatility to rise by more than a positive shock of the same magnitude[6]. Such asymmetric phenomenon is

[6] (Nelson, 1991) and (Glosten, Jangannathan, Runkle, 1993) confirm the asymmetries between volatility follow by positive and negative shocks.

usually called the leverage effects.

Both EGARCH and GJR-GARCH has attractive properties that suits the characteristics of stock returns. However, most study conducted to estimate expected idiosyncratic volatility are in favor of EGARCH model. Studies by Spiegel et al (2005), Brockman et al (2007), and Fu (2009) are good examples that favor in the model. Furthermore, Engle et al (1993) test the specifications of various volatility models using Lagrange Multiplier tests and concluded EGARCH to be the best model. Thus, the EGARCH model will be employed to estimate expected idiosyncratic volatility.

The next step is to determine the order of the lagged term. To keep the model parsimonious, the test will include the permutation of EGARCH(p , q) where $1 \leq p \leq 3$ and $1 \leq q \leq 3$. The explicit form of the equation is as follow:

$$R_{it} - R_f = \alpha_0 + BETA_i(R_{m_{it}} - R_f) + HML_i(R_{h_{it}} - R_{l_{it}}) + SMB_i(R_{s_{it}} - R_{b_{it}}) + \varepsilon_{it}$$

$$\varepsilon_{it} \sim N(0, \sigma_{it}^2)$$

$$ln\sigma_{it}^2 = \omega_0 + \sum_{i=1}^{p} \theta_{1_i} ln\sigma_{i,t-1}^2 + \sum_{i=1}^{q} \theta_{2_i} \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{it}^2}} + \sum_{i=1}^{q} \theta_{3_i} \left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}} \right] \tag{4}$$

One of methods to evaluate the order of GARCH model is by measure the forecast performance of each model with different lag order (Brooks, 2014). Mean Squared Error (MSE) is a common practice to evaluate model performance by measuring the forecast error. MSE is defined as the following formula:

$$MSE = \frac{\sum_{i=1}^{t} (S_e - E(\sigma))^2}{t}$$

S_e and $E(\sigma)$ represents the actual or realized idiosyncratic volatility and conditional idiosyncratic volatility.

Before evaluating the forecast error by MSE, it is not appropriate to estimate the conditional idiosyncratic volatility using the whole period[7]. Thus, the estimation will use 30 months prior data as training period for the first forecast, and keep adding the following

[7] It will cause look ahead bias that uses financial data that has not been occurred yet.

months after event has occurred (expanding window). As a result, 102 forecasted monthly conditional idiosyncratic volatility estimated for each company from July 2011 to December 2019.

The MSE are calculated for each model of; EGARCH (1, 1), EGARCH (1, 2), EGARCH (1, 3), EGARCH (2, 1), EGARCH (2, 2), EGARCH (2, 3), EGARCH (3, 1), EGARCH (3, 2), and EGARCH (3, 3) for each company. The lowest average of MSE is EGARCH (3, 3) with value of 0.0065. As a conclusion, EGARCH (3, 3) will be employed to estimate one-month ahead expected idiosyncratic volatility.

Results and Discussion

Descriptive Statistics

Before presenting the main results, this sub-section will briefly discuss some important characteristics of the variables. Table 3 shows the descriptive statistics of each variable used for the main regression. There are three important information that we can infer from the table: (1) Pooled average stock return (after adjusting for risk-free rate) is 0.4% with standard deviation of 11.5%. Large standard deviation of return is not surprising since it varies across time and company. The standard deviations of stock return across company and time are 0.8% and 5.37% respectively (not presented on the table). It is evident that there are both time and cross-section variation with larger variation across time, thus adjusting model for time effect is a non-trivial matter. (2) Average standardize market capitalization ratio is 17.046 with standard deviation of 1.296 which shows that there are not much of variation across samples. Using companies listed on KOMPAS 100 index which has similar characteristics in terms of market capitalization is the main reason for the small variation. (3) Average standardize book-to-market ratio shows a negative value. It means that the sample is mainly comprises of company that has low book-to-market ratio (below one). Low book-to-market ratio suggest an overvaluation of stocks or commonly refer as growth stocks.

Main Regressions

This sub-section will discuss the main results with different panel regression methods as mentioned before. Fama-Macbeth, Fixed Effect, and Random Effect has been employed to test the effect of idiosyncratic volatility and expected idiosyncratic volatility on stock return, individually.

Idiosyncratic Volatility Regression. As expected, actual idiosyncratic volatility has positive and significant effect on stock return under three different panel regression methods as shown in Table 4. It is consistent with previous study such as Levy (1978), Merton (1987), and many others. There is not much information to be extracted since the proxy was estimated ex-post. One conclusion might be the justification that market participants in Indonesian Stock Market are not fully-diversified their portfolio which is highly probable as mentioned in hypothesis 1. Other conclusion is the motivation to presume that expected idiosyncratic risk is positively related with stock return as well, given it is the appropriate estimation of one-period ahead idiosyncratic risk.

Expected Idiosyncratic Volatility. Expected idiosyncratic volatility revealed as positive and significant with different significant level for different methods (Table 5). The empirical relationship infer that bearing higher expected idiosyncratic risk stocks will be compensated by more return. This results confirmed hypothesis 2 and consistent with previous studies such as Brockman et al (2007), Fu (2009), and others. Different significance level might be explained by the different characteristics of employing different regression methods. As mentioned before, Fama-Macbeth is appealing in the presence of time effect, while Fixed and Random Effect are adjusting for company effect. Since time effect in stock return is much larger relative to company effect[8], adjusting Fixed and Random Effect for time effect is needed. More comprehensive discussion will be shown in Robustness Check section.

Control Variables. The coefficient results of control variables such as BETA, *Ln*(MV), and *Ln*(B/M) for both equation 1 and 2 were slightly different but has the same conclusion. It can be concluded into three points: (1) The relation of BETA and stock

[8] 0.4% and 5.37% standard deviation across company and period respectively

return is statistically indifferent than 0 or flat. (2) Ln(MV) appears to be positive and significant under Fixed Effect and Random Effect while insignificant under Fama-Macbeth. The result suggest that higher market capitalization will lead to higher stock return. (3) Ln(B/M) has negative and significant relation with stock return under all three methods. It suggest low stock return for stocks with high book-to-market ratio. Another way to infer it, low book-to-market or growth stocks is compensated for more return.

While the coefficient of BETA is consistent with the previous study, size effect and book-to-market are not (Fama and French, 1992). Dewi et al (2019) observed the same conclusion of positive size effect for small size firm portfolio and negative book-to-market effect for low book-to-market firm portfolio. While it is probable for the sample of this thesis was constructed by firms with low book-to-market ratio[9], it is unlikely to be constructed by firms with low market capitalization[10]. More probable explanation is that large-cap companies had higher level of trust from investors, thus causing increases in stock prices which argued by Meutia et al (2019) that also found positive relation between firm size and stock return for companies listed on LQ45 index[11]. Hence, the reversal of both size and book-to-market ratio coefficient might be driven by the sample variation that biases towards blue chip companies.

Zero-Investment Portfolio

Zero-investment portfolio is a portfolio constructed by long top 10% stocks with highest factor exposure and short bottom 10% with lowest factor exposure. On this thesis, the zero-investment portfolio will be rebalanced monthly. The purpose of this analysis is to show more pragmatic justification of the relationship for each independent variables. Table 6 shows the monthly average return for both equally weighted and value weighted portfolio relative to its factor exposure. The table confirm the relationship of each factor toward stock return based on the panel regression. Indeed, expected idiosyncratic volatility yield positive average monthly return of 0.33%. Therefore, hypothesis 3 is confirmed as well.

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[9] Ln(BM) average is -0.549, negative Ln(BM) indicates value below one for book-to-market.

[10] The characteristics of the index is large-cap and frequently traded.

[11] Both LQ45 and KOMPAS 100 index has similar characteristics and has a sets of same constituents.

Robustness Check

The purpose of this section is to explore further the sensitivity of employing different regression methods, estimation method and etc. The robustness check will only explore the sensitivity and validity of expected idiosyncratic volatility since it is the main variable interest of this thesis.

Fixed Effect and Random Effect

It may be trivial to test which model is favorable between Fixed Effect and Random Effect, since both models yield the same conclusion. Nevertheless, it is also appealing to be sure of choosing more robust model. Hausman-Wu test that follow chi-squared (χ^2) distribution was conducted to choose between both models.

Fixed Effect is consistent under the null and alternative hypothesis while Random Effect is more efficient under the null, and inconsistent on the alternative hypothesis. Following equation 2, it yields a very high χ^2 with p-value of close to zero. Consequently, it can be concluded that the time-invariant characteristics appears to be highly correlated with the independent variables which makes Fixed Effect is more robust.

Fama-Macbeth and Fixed Effect

As mentioned before, it is not very clear on how to compare models between Fama-Macbeth and Fixed Effect. There are no systematic test to compare both models. However, since time effect has larger variation, adjusting Fixed Effect for time-varying characteristics is necessary. Hence, to compare both models as close as possible, panel regression of Fixed Effect which takes account for time effect as well was conducted. It follows equation below:

$$R_{it} = \phi_0 + \phi_1 E[IVOL]_{it} + \phi_2 BETA_{it} + \phi_3 Ln(MV)_{it} + \phi_4 Ln(BM)_{it} + \sum_{i=2}^{102} PERIOD_i + \nu_{it} \quad (5)$$

The equation is similar to equation 2 with the addition of dummy variables of every period in the sample[12]. Table 7 shows Fixed Effect regression which account for time effect. Both

[12] Sample period is monthly sample from July 2011 to December 2019 (102).

coefficient and standard error of expected idiosyncratic volatility are lower relative to standard Fixed Effect with significance level drop to 5% level. The change of coefficient after adjusting for time effect show that expected idiosyncratic has time-varying characteristics.

Despite of lower significance, expected idiosyncratic volatility still holds on being positive and significant. Perhaps the relation between stock return and expected idiosyncratic risk is not profound as being expected or there are better way to estimate expected idiosyncratic risk given the characteristics of stock return in Indonesia.

Different Expected Idiosyncratic Volatility

Lagged Idiosyncratic Volatility. Having a quality estimate of expected idiosyncratic volatility is perhaps the most important process on this thesis. As discussed before, the absence of autocorrelation in idiosyncratic volatility restrict the usage of lagged model to estimate expected idiosyncratic volatility. Although it was explained and empirically tested with Dickey-Fuller test and autocorrelation table, running the regression on equation 2 but with one-lagged idiosyncratic volatility as expected idiosyncratic volatility will clearly show the limitation of lagged model[13]. As seen on Table 8, one-lagged idiosyncratic volatility coefficient is positive and significant with Fixed Effect method before controlling for time effect (Model 2). But after controlling for time effect on Model 3, the coefficient drastically dropped and statistically not different than zero. As for Fama-Macbeth method (Model 1), the same conclusion can be inferred, which is not surprising because the method was controlling for time effect by construction. Hence, the result confirmed Fu (2009) statement of idiosyncratic volatility being a time-varying variable, and the lagged terms is not a good proxy for expected idiosyncratic volatility.

Mean Processes of EGARCH. Using EGARCH model is much favorable than the lagged model. But its appealing feature of estimating the mean and variance process simultaneously increase the complexity of choosing the best model to estimate expected idiosyncratic volatility. The default mean process of this thesis is the Fama French Three factor model. But on this sub-section, different mean process such as CAPM, Constant

[13] Proposed model by Ang et al (2006)

Mean, Zero Mean, and Autoregressive (AR) (1) model will be compared. Equation below describe explicitly models mentioned on previous sentenced:

$$R_{it} - R_f = \alpha_0 + BETA_i(R_{m_{it}} - R_f) + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \sigma_{it}^2) \tag{6}$$

$$R_{it} - R_f = \mu_0 + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \sigma_{it}^2) \tag{7}$$

$$R_{it} - R_f = \alpha_0 + \phi_i R_{i_{t-1}} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \sigma_{it}^2) \tag{8}$$

$$ln\sigma_{it}^2 = \omega_0 + \sum_{i=1}^{p} \theta_{1_i} ln\sigma_{i,t-1}^2 + \sum_{i=1}^{q} \theta_{2_i} \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{it}^2}} + \sum_{i=1}^{q} \theta_{3_i} \left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}} \right]$$

Equation 6 describe EGARCH model with CAPM mean process. CAPM is one of famous model to capture systematic risk on stock return. Okpara et al (2009) employed the same mean process for Nigerian Stock Market.

Equation 7 is describing two model; (1) the constant mean model when μ_0 is non-zero. (2) the zero mean model when μ_0 has zero value. Both are the standard mean process for volatility modelling in ARCH, which assume the absence of autocorrelation of stock returns (Brooks, 2014).

Finally, Equation 8 describe the AR (1) mean model. The same method was used by Ferenstein et al (2004) that tried to model stock return with AR-GARCH processes.

All of the expected idiosyncratic volatility with different mean processes were estimated following the same method as mentioned on the Methodology section. Afterwards, all of them were regressed following equation 2 with Fama-Macbeth and Fixed Effect adjusted for time effect method, Table 9 and 10 shows the results respectively. The same conclusion could be inferred from both methods, expected idiosyncratic volatility with different mean processes only change the level of significance while maintaining the positive coefficient sign. Hence, variations of stock return mean processes does not alter the evidence that expected idiosyncratic volatility is positively related with stock returns.

While Constant Mean, Zero Mean, and AR(1) model does not causally explained systematic risk on stock return, CAPM does. Drastic increase in significance level of expected idiosyncratic volatility following CAPM mean model might indicate that stock return in Indonesian Stock Market follows CAPM model. As mentioned on theoretical framework, previous study also suggest the CAPM model is better than Fama French Three Factor Model (Liani, 2017).

Although causal relationship of expected idiosyncratic volatility with different mean process is evident, the differences of the significance level has not been explore yet. To test whether there is a statistical difference in variance, pooled ANOVA test was conducted. Table 11 shows the F-Stat of 190.78 with a p-value close to zero. However, pooled ANOVA test might lead to an oversimplification conclusion. Thus, ANOVA test of different expected idiosyncratic volatility was conducted for each company. 80% of companies rejected the null of equal variances. Therefore, it can be concluded that expected idiosyncratic volatility with different mean process is statistically different, and choosing the appropriate mean model is a non-trivial matter.

Zero-Investment portfolio were constructed as well to confirmed the regression results (Table 12). Positive return on portfolio constructed by expected idiosyncratic volatility is drastically larger on those four different mean processes. In practice, AR(1), Constant Mean, and Zero Mean model might be more favorable as investment strategy, but it does not provide any economic explanation for stock return.

For concluding remarks, this section shows evidence that: (1) expected idiosyncratic volatility is time-varying, thus linear regression method must adjusted for time effect as well. Both Fama-Macbeth and Fixed Effect adjusted for time effect are appropriate. (2) Lagged idiosyncratic volatility is not appropriate as a proxy for expected idiosyncratic volatility. (3) Different mean processes of conditional idiosyncratic volatility leads to the same positive relation, but with different magnitude. (4) Different mean processes of conditional idiosyncratic volatility is statistically different with each other.

Conclusion

This thesis found empirical evidence that idiosyncratic volatility is positive and significantly related with stock returns for sample of companies listed on KOMPAS 100 from period of 2009 to 2019. The finding is consistent with previous studies. The evidence indicate that market participants in Indonesian Stock Market are not fully-diversified their portfolio as suggested by model that explain expected stock return.

As for the main variable of interest, expected idiosyncratic volatility has positive and significant relation with stock returns as well. Although, the significance level drop after adjusting the model for time effect. Zero-investment portfolio were also constructed to confirmed the positive relation. Indeed, positive return of 0.332% and 0.490% for equally-weighted and value-weighted portfolio constructed by expected idiosyncratic volatility shows the positive relations with relatively small magnitude. The evidence suggest that investors are expecting more return by bearing higher expected idiosyncratic risk stocks. Despite for being consistent with previous studies, the effect is not as profound.

Different mean processes were also tested on this thesis. Interestingly, the significance level or the magnitude of the effect increases significantly. The evidence show AR(1) mean process for conditional idiosyncratic volatility yield the best estimation. However, it does not have an economic explanation on describing stock returns. Thus, CAPM mean process is more favourable for academic purpose. And indeed, expected idiosyncratic volatility following CAPM mean model has larger significance level relative to Fama French Three Factor mean model. The evidence might indicate that CAPM model is better at capturing systematic risk that explain stock returns.

It was also tested that different conditional idiosyncratic volatility following different mean process is statistically different from each other. Thus, choosing and evaluating mean model to estimate expected idiosyncratic volatility is important and necessary.

Finally, the last conclusion suggest that zero-investment portfolio on expected idiosyncratic volatility with AR(1) mean process yield the highest return. Since the expected idiosyncratic volatility is measured for one-period ahead, the zero-investment portfolio is applicable for investment strategy. Following AR(1) mean process, the investment strategy would yield 1.879% and 2.168% monthly return before transaction cost for equally-weighted and value-weighted portfolio.

Further Research and Suggestions

As mentioned on Introduction section, there are several limitations for this thesis. Hence, there are two suggestions for further research to improve on this thesis findings:

1. **Wider samples**. The motivations of trying to capture a representative samples with limited availability of long past-horizon data leads to the decision of choosing companies listed on KOMPAS 100. Despite of the samples represent large share of Indonesian Equity Market, its biases toward certain characteristics. Consequently, it causes the reversal coefficients for the default mean model. Hence, wider samples that is more representative is encouraged for further research.

2. **Testing more combinations of ARCH non-linear model**. As discussed before, ARCH family regressions has a lot different models to offer. Testing different models with different lag orders is the ideal process to estimate expected idiosyncratic volatility. However, since idiosyncratic volatility is time-varying, testing and evaluating ARCH models for each period is needed. For a long sample period, this process need high computational power to test a lot of combinations but would lead to a better estimation of expected idiosyncratic volatility.

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Table 1

Average Mean, Standard Deviation, and Autocorrelation Table

Average of mean, standard deviation, and first to fifth lag autocorrelation of idiosyncratic volatility

	Mean	SD	Autocorrelation				
			1	2	3	4	5
IVOL	-6.044	0.002	0.262	0.171	0.138	0.111	0.097

Table 2

Augmented Dickey-Fuller Test

Average t-statistics, p-values, and critical values of ADF test. Last column is the amount of rejected null hypothesis (Random Walk) in percentage

	t-stat	p-value	Critical Value			Rejected
			1%	5%	10%	
IVOL	-6.044	0.002	-3.497	-2.89	-2.582	89.13%

Note. IVOL was tested individually for each company, 41 out of 45 were rejected

Table 3

Descriptive Statistics Table

Pooled Mean, Standard Deviation, Median, First Quartile, Third Quartile, and Total Observation for each variables

Variables	Mean	SD	Median	Q1	Q3	N
RET	0.004	0.115	0.002	-0.006	0.066	4590
IVOL	0.024	0.025	0.022	0.016	0.029	4590
E [IVOL]	0.089	0.047	0.083	0.058	0.105	4590
BETA	1.228	0.47	1.219	0.884	1.523	4590
Ln(MV)	17.046	1.296	16.979	16.153	17.852	4590
Ln(MV)	-0.549	0.757	-0.652	-1.105	-0.104	4590

Table 4

Actual Idiosyncratic Volatility Regressions Table

Linear regression results of stock returns on actual idiosyncratic volatility and control variables with Fama-Macbeth, Fixed Effect, and Random Effect panel method.

VARIABLES	(1) Fama-Macbeth	(2) Fixed Effect	(3) Random Effect
BETA	0.002	-0.011	-0.000
	(0.005)	(0.007)	(0.003)
Ln(MV)	0.002	0.019***	0.002**
	(0.002)	(0.006)	(0.001)
Ln(BM)	-0.013***	-0.024***	-0.015***
	(0.003)	(0.007)	(0.003)
IVOL	3.170***	0.538***	0.540***
	(0.282)	(0.066)	(0.066)
Constant	-0.284***	-0.339***	-0.050
	(0.035)	(0.096)	(0.042)
Observations	4,590	4,590	4,590
R-squared	0.273	0.038	0.029
Number of Periods	102		
Number of Company		45	45
Company Effect		Yes	Yes

Note. Standard Errors used are Newey-West lagged 1 for Fama-Macbeth and Company Clustered for Fixed Effect and Random Effect; *** $p<0.01$, ** $p<0.05$, ** $p<0.1$.

Table 5

Expected Idiosyncratic Volatility Regressions Table

Linear regression results following Equation 1 with Fama-Macbeth, Fixed Effect, and Random Effect panel method.

	(1)	(2)	(3)
VARIABLES	Fama-Macbeth	Fixed Effect	Random Effect
BETA	-0.001	-0.010	0.001
	(0.005)	(0.007)	(0.003)
Ln(MV)	0.001	0.018***	0.003**
	(0.002)	(0.006)	(0.001)
Ln(BM)	-0.013***	-0.024***	-0.015***
	(0.004)	(0.007)	(0.003)
E [IVOL]	0.131*	0.169***	0.192***
	(0.070)	(0.047)	(0.040)
Constant	-0.039	-0.322***	-0.071***
	(0.039)	(0.103)	(0.024)
Observations	4,590	4,590	4,590
R-squared	0.188	0.027	
Number of Periods	102		
Number of Company		45	45
Company Effect		Yes	Yes

Note. Standard Errors used are Newey-West lagged 1 for Fama-Macbeth and Company Clustered for Fixed Effect and Random Effect; *** $p<0.01$, ** $p<0.05$, ** $p<0.1$.

Table 6

Zero-Investment Portfolio Table

Portfolio constructed by long top 10% and short bottom 10% with respect to the factors

Portfolio	BETA	Ln(MV)	Ln(BM)	E [IVOL]	IVOL
Equal-Weighted	-1.469%	1.833%	-2.783%	0.332%	7.520%
Value-Weighted	-1.937%	1.824%	-2.993%	0.490%	8.412%

Note. Portfolio was constructed with monthly rebalancing.

Table 7

Expected Idiosyncratic Volatility adjusted for Time Effect Table

Linear regression results following Equation 1 with Fama-Macbeth, Fixed Effect, and Fixed Effect adjusted for time effect.

VARIABLES	(1) Fama-Macbeth	(2) Fixed Effect	(3) Fixed Effect
BETA	-0.001	-0.010	-0.011
	(0.005)	(0.007)	(0.007)
Ln(MV)	0.001	0.018***	-0.009
	(0.002)	(0.006)	(0.010)
Ln(BM)	-0.013***	-0.024***	-0.049***
	(0.004)	(0.007)	(0.011)
E [IVOL]	0.131*	0.169***	0.087**
	(0.070)	(0.047)	(0.039)
Constant	-0.039	-0.322***	0.195
	(0.039)	(0.103)	(0.157)
Observations	4,590	4,590	4,590
R-squared	0.188	0.027	0.239
Number of Periods	102		
Number of Company		45	45
Company Effect		Yes	Yes
Time Effect		No	Yes

Note. Standard Errors used are Newey-West lagged 1 for Fama-Macbeth and Company Clustered for Fixed Effect and Random Effect; *** $p<0.01$, ** $p<0.05$, ** $p<0.1$.

Table 8

One-lagged Idiosyncratic Volatility Regressions Table

Linear regression results of stock returns on one-month lagged idiosyncratic volatility and control variables with Fama-Macbeth, Fixed Effect, and Fixed Effect adjusted for time effect.

VARIABLES	(1) Fama-Macbeth	(2) Fixed Effect	(3) Fixed Effect
BETA	-0.000	-0.010	-0.011
	(0.005)	(0.007)	(0.007)
Ln(MV)	0.001	0.018***	-0.010
	(0.002)	(0.006)	(0.010)
Ln(BM)	-0.015***	-0.024***	-0.050***
	(0.004)	(0.007)	(0.010)
E $[\text{IVOL}]_{t-1}$	0.088	0.156***	0.063
	(0.064)	(0.056)	(0.057)
Constant	-0.024	-0.321***	0.208
	(0.038)	(0.102)	(0.147)
Observations	4,589	4,589	4,589
R-squared	0.180	0.026	0.239
Number of Periods	102		
Number of Company		45	45
Company Effect		YES	YES
Time Effect		NO	YES

Note. Standard Errors used are Newey-West lagged 1 for Fama-Macbeth and Company Clustered for Fixed Effect and Random Effect; *** p<0.01, ** p<0.05, ** p<0.1.

Table 9

Different Idiosyncratic Volatility with Fama-Macbeth Regressions Table

Linear regression results following Equation 1 with different expected idiosyncratic volatility mean processes using Fama-Macbeth method.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	FF3 Model	CAPM Model	Constant Model	Zero Model	AR(1) Model
BETA	-0.001	-0.001	-0.002	-0.003	-0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Ln(MV)	0.001	0.003	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Ln(BM)	-0.013***	-0.014***	-0.014***	-0.014***	-0.014***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
E $[\text{IVOL}]_{FF3}$	0.131*				
	(0.070)				
E $[\text{IVOL}]_{CAPM}$		0.180***			
		(0.064)			
E $[\text{IVOL}]_{Constant}$			0.201***		
			(0.077)		
E $[\text{IVOL}]_{Zero}$				0.214***	
				(0.073)	
E $[\text{IVOL}]_{AR(1)}$					0.213***
					(0.069)
Constant	-0.039	-0.066*	-0.059*	-0.061*	-0.062*
	(0.039)	(0.037)	(0.034)	(0.033)	(0.034)
Observations	4,590	4,590	4,590	4,590	4,590
R-squared	0.188	0.186	0.199	0.199	0.192
Number of Periods	102	102	102	102	102

Note. Standard Errors used are Newey-West lagged 1; *** p<0.01, ** p<0.05, ** p<0.1.

Table 10

Different Idiosyncratic Volatility with Fixed-Effect adjusted for Time Effect Regressions Table.

Linear regression results following Equation 1 with different expected idiosyncratic volatility mean processes using Fixed Effect adjusted for time effect method.

VARIABLES	(1) FF3 Model	(2) CAPM Model	(3) Constant Model	(4) Zero Model	(5) AR(1) Model
BETA	-0.011	-0.010	-0.012*	-0.011*	-0.011*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Ln(MV)	-0.009	-0.006	-0.004	-0.003	-0.003
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
Ln(BM)	-0.049***	-0.045***	-0.043***	-0.042***	-0.043***
	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)
E $[\text{IVOL}]_{FF3}$	0.087**				
	(0.039)				
E $[\text{IVOL}]_{CAPM}$		0.182***			
		(0.063)			
E $[\text{IVOL}]_{Constant}$			0.250***		
			(0.048)		
E $[\text{IVOL}]_{Zero}$				0.239***	
				(0.045)	
E $[\text{IVOL}]_{AR(1)}$					0.256***
					(0.047)
Constant	0.195	0.141	0.092	0.077	0.086
	(0.157)	(0.151)	(0.163)	(0.166)	(0.168)
Observations	4,590	4,590	4,590	4,590	4,590
R-squared	0.239	0.241	0.243	0.243	0.244
Number of Company	45	45	45	45	45
Company Effect	Yes	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes	Yes

Note. Standard Errors used are Company Clustered; *** p<0.01, ** p<0.05, ** p<0.1.

Table 11
Pooled ANOVA Table

F-test and Barlett's equal variances test for different groups of expected idiosyncratic volatility

Portfolio	E [IVOL] FF3	E [IVOL] CAPM	E [IVOL] Constant	E [IVOL] Zero	E [IVOL] AR(1)
Mean	0.090	0.095	0.109	0.109	0.108
SD	0.047	0.046	0.043	0.044	0.044
$F(4,4585)$	190.78				
Barlett's $\chi^2(4)$	39.308				
p-value	0.000				

Note. p-values are close to zero for both F-test and Barlett's test

Table 12
Zero-Investment Portfolio with different Expected Idiosyncratic Volatility

Portfolio constructed by long top 10% and short bottom 10% with respect to the factors

Portfolio	E [IVOL] FF3	E [IVOL] CAPM	E [IVOL] Constant	E [IVOL] Zero	E [IVOL] AR(1)
Equal-Weighted	0.332%	1.073%	1.526%	1.467%	1.879%
Value-Weighted	0.490%	1.290%	1.801%	1.743%	2.168%

Note. Portfolio was constructed with monthly rebalancing.