Idiosyncratic volatility and expected returns under the Fama French five-factor model

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Preface

As part of the Master Finance curriculum of Tilburg University, we are required to write a master thesis. It is possible to write your thesis about suggested topics, but since no topic of this list triggered my attention and because my bachelor thesis topic did trigger my attention I chose this topic as my master thesis topic. The reason that it triggered my attention is partly due to the fact that I was not entirely satisfied with my Bachelor thesis. Although it was graded successfully with a 8. I had the feeling that I did not gain the knowledge about the subject as I wanted to. Therefore, I saw my master thesis as an opportunity to gain this missing knowledge.

The research was difficult, but conducting extensive investigation has allowed me to answer the question that was identified. The research on this topic is denoted in the literature as a puzzle. The puzzle still remains puzzling for me and still left me with a lot of questions. It indeed raised my knowledge of the subject but it also gave me the insight that I still do not have knowledge I want to have, particular in the field of mathematics and quantitative finance. Although I finished my Master Finance curriculum sufficiently I do not have the feeling that I could gain this knowledge in this curriculum or on an auto didactive way. Therefore, I recently started to follow some econometric courses to gain this knowledge. Maybe in the future this will help me to conduct an even more solid research relating to these topics.

Related to this shortcoming of my own knowledge I want to specially thank my supervisor prof. dr. F.C.J.M. de Jong for his excellence guidance in this thesis, helping me with my questions and identifying some mistakes.

Maarten Nies

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Abstract

This paper finds with the Trading Strategy methodology that lagged idiosyncratic risk positively is related with raw returns when idiosyncratic risk is measured with the Fama French 3 factor model. This relation is also revealed when idiosyncratic risk is measured with the Fama French 5 factor model. The trading strategy also shows that one could gain highly significant positive alphas for both models. Both findings, the findings of the raw returns and the alphas, are contrary to the findings of Ang et al. (2006), who find a negative relation, and Switzer and Picard (2015), who find no relation. While there is no difference in raw returns between the models, the most remarkable finding is the finding that there is a difference in alpha performances measurement when idiosyncratic risk is measured with the Fama French 5 factor model compared to when idiosyncratic risk is measured with the Fama French 3 factor model. Furthermore, this studies shows that this positive relationship of raw returns can be found with the Fama-Macbeth Approach for both Fama French factor models. This second approach also shows that it is possible that the sample period influences the relationship.

Table of content

Preface 2
Abstract 3
Introduction 6
Literature Review 7
1. Studies that find a positive relationship between idiosyncratic volatility and stock returns 7
2. Studies that find a negative relationship between idiosyncratic volatility and stock returns 8
Problem Analysis 9
Formulation of research question 10
Methodology 12
Ang et al. Trading Strategy 12
Fama-Macbeth Approach 13
Theoretical Framework 15
Returns 15
Measuring idiosyncratic volatility 15
Fama-French 3 Factor model 16
Fama-French 5 Factor model 17
Firm Characteristics 18
Size 18
Book to Market 18
Leverage 18
Liquidity 19
Trading Volume 19
Turnover 19
Research Design 20
Data Collection 20
Data description 21
Research results 25
Results Ang et al. Trading Strategy 25

Results Fama-Macbeth Approach 30
Conclusion 35
References 37
Appendix 41

Introduction

Risk of an investment in an asset can be divided into two components: systematic risk and unsystematic. Systematic risk is the risk intrinsic to the whole market or segment of the market. This risk affects the whole market and not just a particular asset. Unsystematic risk is the opposite of systematic risk and is the risk that is accounted to a particular assets. This risk can mitigated by diversification, systematic risk cannot. Unsystematic risk is also referred as idiosyncratic risk.

One of the key principles of modern portfolio theory (MPT) (Markowitz (1952); Sharpe (1964); Litner (1965)) is that investors hold either a well-diversified portfolio or the market portfolio in order to diversify idiosyncratic risk. As a result, within the framework of the Captial Asset Pricing Model (CAPM), idiosyncratic risk is not priced.

Campbell, Lettau, Malkiel, and Xu (2001) propose that a well-diversified portfolio contains about 50 different stocks. However, various research has shown that investors do not always maintain well-diversified portfolios. For example, Goetzmann and Kumar (2004) show that less than 10% of investor portfolios hold more than 10 stocks, that more than 50% contain no more than three stocks and that over 25% of portfolios contain only one stock. This implies that a significant amount of investors' portfolios are under-diversified.

Since the contributions of Merton (1987) and Levy (1978), idiosyncratic risk has attracted a lot of interest in the financial literature. Merton (1987) argues that an under-diversified investor demands a return premium for bearing idiosyncratic risk. He states that:

"The less diversified the portfolios, the higher the proportion of idiosyncratic risk impounded into expected returns making high idiosyncratic stocks earn more than low idiosyncratics stocks." (Merton, 1987)

Merton's (1987) theory therefore suggest that there is a positive relationship between idiosyncratic volatility and stock returns. Although this theory seems plausible, empirical evidence did not bring one to a consensus about the relationship between idiosyncratic volatility and stock returns.

The remainder of this paper is structured as follows. The introduction will further cope with an overview of the current state of literature about the relationship between idiosyncratic volatility and stock returns. Consecutive to this review the paper will provide an problem analysis, with this analysis a research question will be formulated. Afterwards, the paper discuss the methodology and the theoretical framework used within this methodology. Then the research design and the results will be exposed and finally this paper will end with a conclusion.

Literature Review

Some studies indeed find evidence consistent with Merton's (1987) theory discussed in the previous section. Finding a positive relationship between idiosyncratic volatility and stock returns. Other studies find a negative relationship. Some studies even contradicts both findings and suggest that the results found, are not significant given other implications. These stands of literature will be discussed briefly below.

1. *Studies that find a positive relationship between idiosyncratic volatility and stock returns*

One of the first studies examining the relationship between idiosyncratic volatility by Malkiel and Xu (1997) is based on portfolios of US stocks on 1963 through 1990 show a positive relationship between idiosyncratic volatility and the cross-section of monthly future stock returns.

Similarly, Goyal and Santa-Clara (2003) find a significant positive relation between average stock variance (largely idiosyncratic) and the return on the market for the sample period of July of 1962 to December of 1999. This under the condition that returns are a value-weighted. The findings of Goyal and Santa-Clara (2003) are harmonious with the findings of Wei and Zhang (2005) and Pukthuanthong-Le and Visaltanachoti (2009), who apply a similar value-weighted strategy. Although, in the US stock market from 1962-2000, Wei and Zhang (2005) did not yield significant economic gains using a trading strategy based on idiosyncratic volatility. Another criticism of Goyal and Santa-Clara's findings was put forward by Bali et al (2005), who argue that their results are not robust through time, and therefore do not provide convincing evidence of a significant positive relationship between idiosyncratic volatility and expected returns.

Bainbridge and Galagedera (2009) show evidence of a positive relationship between idiosyncratic volatility and expected stock returns for the Australian stock market. Nartea, Ward, and Yao (2011) found that this is also valid in four Southeast Asian stock markets (i.e. Singapore, Malaysia, Indonesia, and Thailand). Brooks, Li, and Miffre (2013) find that idiosyncratic risk is priced, which also implies a positive relationship. On the whole, these papers are consistent with Merton's theory that investors who have an under-diversified portfolio demand higher average returns to compensate them for bearing higher levels of idiosyncratic risk.

Another leading study that finds a positive relation on this topic is a reply to Ang, Hodrick, Xing, and Zhang (2006, Ang et al. hereafter), who find a negative relation between idiosyncratic risk and expected return. Fu (2009) first identifies that idiosyncratic volatility is very volatile over time. Since idiosyncratic volatility is time-varying, he suggest that the one-month lagged idiosyncratic volatility may not be an appropriate proxy for the expected idiosyncratic volatility of this month. This implies that the lagged idiosyncratic volatility might not be a good estimation of expected idiosyncratic volatility. Hence, the results of Ang et al., that there is a negative relationship between the lagged idiosyncratic volatility and average returns, does not necessarily imply that the relation between idiosyncratic risk and the expected return is negative. To solve this problem, of time-varying idiosyncratic volatility, Fu (2009) uses an exponential generalized autoregressive conditional heteroskedastic (EGARCH) model to estimate the idiosyncratic volatilities. With these estimates Fu (2009) ran Fama-Macbeth (1973) regressions of monthly stock returns on the EGARCH estimates and found both statistically and economically significant positive relationship. Brockman and Schutte (2007) used this method in international and their results were consistent with Fu's (2009) results.

2. *Studies that find a negative relationship between idiosyncratic volatility and stock returns*

Ang et al. Zhang (2006) find that US stocks with higher lagged idiosyncratic volatility have abnormally lower equally-weighted returns, which they call "a substantive puzzle". Ang et al. found empirical evidence that the average return differential between the lowest and highest quintile portfolios formed on one-month lagged idiosyncratic volatilities is about –1.06% per month for the period 1963-2000. In their study, idiosyncratic volatility is calculated by taking the standard deviation of the residuals of the daily three-factor Fama and French (1993, hereafter FF3) model over the prior month. In more recent work Ang, Hodrick, Xing, and Zhang (2008) provide further evidence for their findings that higher lagged idiosyncratic volatility result in abnormally lower equally-weighted returns by extending their research to other G7 countries. Similar research is done by Guo and Savickas (2006) who shows that in the G7 countries over the period 1963 to 2002 period, the value-weighted idiosyncratic volatility is negatively and significantly related to subsequent quarterly excess stock market returns.

While a positive relation was found between idiosyncratic volatility and expected stock returns in Australian (Bainbridge and Galagedera, 2009) and Southeast Asian stock markets (Nartea, Ward, and Yao, 2011), Chang and Dong (2006) reveal a negative relationship between idiosyncratic volatility and expected stock returns in Japanese stock markets for the period 1975-2002. Koch (2010) also document this finding for the German stock market from 1974 to 2006.

Problem Analysis

All studies considered, the relationship between idiosyncratic volatility and stock returns still remains puzzling. Switzer and Picard (2015) states that most of the existing empirical research is based on the simple applications of basic factor models (e.g. CAPM or the FF3 model), or time series approaches (such as EGARCH) that are not directly linked to asset pricing models. These simple applications are usually applied on the US stock market.

One of the leading studies concerning this topic is the study of Ang et al. (2006), who finds that US stocks with higher lagged idiosyncratic volatility have abnormally lower equally-weighted returns. This study is based on the FF3 model and the US stock market. In later research Ang, Hodrick, Xing, and Zhang (2009) provide further evidence by expanding their study to other G7 countries. Ang et al. findings have attracted much attention. For example, Bali and Cakici (2008) proposed that Ang et al.'s findings largely depends on the data frequency used to estimate idiosyncratic volatility. Huang, Liu, Rhee and Zang (2007) conclude that the findings of Ang et al. are not robust due to the fact that the results are driven by short term monthly return reversals. Boyer, Mitton and Vorkink (2007) argue that idiosyncratic volatility is a good predictor of expected skewness and after controlling for expected skewness, the negative relationship found by Ang et al. greatly reduces.

Furthermore, Switzer and Picard (2015) re-analyse the relationship Ang et al. using a five-factor asset pricing model instead of the FF3. They extend the FF3 used by Ang et al. model by adding a momentum factor and an illiquidity factor to estimate the idiosyncratic volatility. The extension of FF3 model by the momentum factor is also known as the Carthart (1997) model and the illiquidity factor is proposed by Amihud (2002). They want to investigate whether extensions to the FF3-model may improve the measurement of idiosyncratic risk. They suggest that:

"A positive relationship between idiosyncratic volatility and expected returns could imply that some potential risk factors that are not incorporated in the factor models employed in this study are not or may not be completely diversifiable and may hence generate the pricing of idiosyncratic volatility." (Switzer & Picard, 2015)

So they suggest that trough their extension of the FF3 model and/or different sample space they (may) obtain different results compared to Ang et al. (2006). At the end, they find no evidence that idiosyncratic risk does not play a role on stock returns for the 16 developed markets analysed, including the United States with their sample period and estimation model. This is contrary to the negative relation found by Ang et al. (2006). But they lack of giving an insight on the difference in results between their FF5 model and the FF3 model. Therefore, the question arises whether one obtain different results if one uses a FF5 model instead of a FF3 model with the same methodology?

Formulation of research question

In contrast to Switzar and Picard (2015), this study contributes to the literature about idiosyncratic risk by expanding the Ang et al. (2006) framework not with the Carthart four-factor model or the five-factor model (four-factor model plus Amihud liquidity factor) but with the Fama French Five-factor (2015, hereafter FF5) in an United States sample. Put into different words, this study investigates whether stocks with past high idiosyncratic risk have low average returns when the idiosyncratic volatility is estimated by the FF5 model in an US sample with respect to the methodology of Ang et al. The specific methodology will be covered next section.

The suggestion of Switzer and Picard (2015) is that extending the FF3 model used in the work of Ang et al. (2006) with a/their FF5 model may improve the measurement of idiosyncratic volatility and consequently may affect the relationship between idiosyncratic risk and expected volatility. Therefore, the expectation is that the average idiosyncratic risk measured under the FF5 model is closer to 0 than the average idiosyncratic risk measured under the FF3, since idiosyncratic is the mean square of residuals of the regression model.

This FF5 extension is chosen for several reasons. First of all, the liquidity factor is left out since Switzer and Picard (2015) find that liquidity risk per se does not seem to add value in explaining divergent results. Secondly, because research of Novy-Marx (2013), Titman, Wei, and Xie (2004), and others says that the FF3 model is an incomplete model because its three factors miss much of the variation in average returns related to profitability and investment. The FF5 adds a profitability and an investment factor to the FF3 model. With these factors included the FF5 model directed at capturing the size, value, profitability, and investment patterns in average stock returns performs better than the FF3 model (Fama & French, A five-factor asset pricing model, 2015). In their work, Fama and French make clear that adding the momentum factor leads to poor results in combination with the profitability and investment factor, therefore the momentum factor is left.

In order to compare the findings of Ang et al. (2006) with the papers findings, the paper also exposes the findings in line with the Ang et al. (2006) framework. Contrary to the papers' own framework, this framework estimates idiosyncratic volatility with the Fama French three-factor (1993, hereafter FF3).

Additionally, to give some power to the prior findings and to look at the sample period effect. This paper examines the relation between idiosyncratic risk and expected under the FF5 model and FF3 model with the Fama-Macbeth method for the full sample space and several sample periods.

Methodology

As stated in the section above this paper uses two different methods. The first method is the same method used by Ang et al. (2006) and is referred in this paper as the Ang et al. Trading Strategy. This method is also used by Switzer and Picard (2015). The second method used is the Fama Macbeth approach. This twostep approach is also used in the second research of Ang et al. (2009) and in the research of Fu (2008. The two different methods are briefly explained below. The variables used in the two methods like idiosyncratic risk and the firm characteristics are covert in the next section "theoretical framework".

Ang et al. Trading Strategy

The method of Ang et al. starts with dividing the whole set of assets in five portfolios based on idiosyncratic volatility. This formation on basis of idiosyncratic volatility is done with a L/M/N trading strategy. The L stands for the estimations period of L months, the M for the waiting periods in months and the N is the holding periods in months. This means that the idiosyncratic risk for asset i is estimated on daily data over an L-month period from month t − L −M to month t −M. Based on the level of the lagged one month idiosyncratic volatility the set is divided into five portfolio's (quintiles). The first portfolio (quintile) has the lowest level of the lagged one month idiosyncratic volatility and the last quintile the highest level. This portfolio is held for one month, completing the 1/0/1 strategy Ang et al. uses. Every month the portfolios are rebalanced. After one month the equally weighted averages and the value weighted averages are taken for excess return, b/m and market cap per portfolio. In addition, the Jensen's alpha's and their t-statistics are calculated with respect to the FF5 and the FF3 model for every portfolio. The t-statistics are calculated with respect to Newey-West standard errors. The weights used for the weighted averages and weighted standard deviations are determined by the market capitalization of the stocks within the portfolio.

For example if we want to calculate the equally weighted average for excess return of portfolio one. There are N assets and T months. For every asset i at time t the idiosyncratic risk is estimated by the daily data of t-1 of asset i. Then at t, all i are divided in five portfolios based on their level of estimated idiosyncratic risk. This estimation and dividing is done at every t for every i. So at every t there are five portfolios. In case of equally weighted excess return, every excess return of asset i at time t is categorized in to a quintile. Then the equally weighted average of excess returns of all i in a portfolio one is taken to determine the portfolios excess return at time t. Finally, the time-series mean is taken of excess return of portfolio 1 for every t.

The final step of the Ang et al. trading strategy is to go long in the portfolio with the highest idiosyncratic volatility and going short in the portfolio with the lowest idiosyncratic volatility. This is step is why this paper refers to it as a trading strategy. The main purpose of this step is to find the results of this step with respect to the raw mean excess return and the alphas.

Fama-Macbeth Approach

Normally, the Fama-Macbeth approach is a method used to estimate parameters asset pricing models and consist of two steps to estimate the parameters. In the first step, the portfolios or assets returns are regressed against one or more factor time series. This gives the factor exposures. In the second step, the cross-section of portfolio or assets returns are regressed against these factor exposures. Every time this gives a time series of the risk premia coefficient for each factor. The average is taken of these coefficient for every factor, which gives the premium expected for a unit exposure to each risk factor over time.

In the first step consider we have n returns and m factors. Then ξ denotes the factor exposure and is calculated by n regressions, every regression on m factors:

$$Re_{it} = \alpha_i + \xi_i X_t + \varepsilon_{it} \; \forall i$$

Equation 1

$Re_{i,t}$ states for excess return of asset/portfolio i at time t. With i going from 1 through n and t going form 1 trough T. $X_{j,t}$ is the factor j at time time and the ξ_i's are the factor exposures. The second step computes T cross-sectional regressions of the returns on the m estimates of the ξs.

In this paper the first step of the regression is to regress, for every month, the cross-sectional firm excess returns onto lagged idiosyncratic volatility together with various firm characteristics. The specific firm characteristics will be covered in the next section. Then, for step two, the times series of the regression coefficients are used and test whether the average coefficient on the lagged idiosyncratic volatility measure is significantly different from zero (Ang et al., 2009). Hence, the equation of the second step becomes:

$$Re_{i,t} = \lambda_{t,0} + \lambda_t' \mathrm{z}_i + \gamma_t \sigma_i + \Omega_{it}$$

Equation 2

The z_i denotes the firm characteristics and the σ_i denotes the lagged idiosyncratic volatility, computed by daily data over the previous month with respect to the FF5 model or the FF3 mode. The main interest is the significance and sign of the γ_t coefficient.

Theoretical Framework

This section covers the variables used in the Ang et Al. Trading strategy and the Fama-Macbetch approach. The two main variables in these methods are excess returns and idiosyncratic risk. Additionally, some firm characterises are used in both methods. The contribution of this study to the existing literature is that this studies uses another method to estimate idiosyncratic volatility. Hence, in this study there are two different kind of idiosyncratic risk estimations. The first one is estimated with the common FF3 model and the second one is estimated with the FF5 model. Since the FF5 model is not well known, there is a theoretical background of asset pricing models and a closer look at the two asset pricing models used in this paper under the section "Measuring Idiosyncratic Risk".

Returns

R_{it} is the return of company i during period t. In this research the excess return is used. The normal return is calculated by taking the difference of the company's stock price of this period with the previous period plus paid dividend divided by the price of the company's stock of this previous period.

$$Normal\ return = \frac{P_t - P_{t-1} + Div}{P_{t-1}}$$

The excess return is the normal return minus the risk free rate. Where the risk free rate is based on the 3-month Treasury Bill.

$$Excess\ return = normal\ return - Risk\ free\ rate$$

Measuring idiosyncratic volatility

Idiosyncratic volatility is the standard deviation of the unexplained portion of an asset pricing model. Over several years different asset pricing models were developed and improved to determine the expected return on capital investments. It started with a single factor model, better known as the Capital Asset Pricing Model. Which was introduced by William F. Sharpe (1964), Jack Treynor (1961), Jan Mossin (1966) and John Litner (1965) separately. The beta was the single factor used in this CAPM and it explained how much an individual stock moved compared to the market. When a stock has a high beta it moves more than a stock with a lower beta compared to the market and thus has higher risk and return. It explains on average about 70% of the diversified portfolios returns.

In 1993, Kenneth French and Eugene Fama added two more factors to the single factor model. The three-factor model was a significant improvement over the single factor model. The three-factor model explains about 90% of the diversified portfolios return. This is due to the fact that this model adjust for the outperformance tendency. The outperformance tendency address that value and small-cap stocks outperform the market on a regular basis.

Although, the three factor model was a significant improvement of the single factor model, it did not explain some anomalies nor the cross-sectional variation in expected returns particularly related to profitability and investment (ValueWalk, 2015). In order to deal with this insight, French and Fama extended the three-factor model with two factors the three-factor model overlooked: Profitability and investment.

Beside the FF5 model, there are several other extension of the three factor model for example the Carthart four-factor model, which adds a momentum factor, or it is extended with the illiquidity factor is proposed by Amihud (2002). This paper will focus on the FF3 model and the FF5 model.

Fama-French 3 Factor model

Ang et al. (2006) concentrate on FF3 model to measure idiosyncratic volatility.

$$R_{it} = \alpha_i + \beta_t MKT_t + \beta_{ISMB} SMB_t + \beta_{IHML} HML_t + \varepsilon_{it}$$

Equation 3

Every month, the daily excess return is regressed on the daily FF3 factors. The first factor is the excess return on the market portfolio. The second factor is the return of the portfolio of large stocks minus the return on a portfolio of small stocks (SMB). The third factor is the return on a portfolio of high book to market minus a portfolio with low book to market (HML). The idiosyncratic volatility is defined as the standard deviation of the error term.

Fama-French 5 Factor model

This research will focus on the FF5 model to measure idiosyncratic volatility, where the idiosyncratic volatility is still defined as the standard deviation of the error term.

$$R_{it} = \alpha_i + \beta_t MKT_t + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \beta_{iRMW} RMW_t + \beta_{iCMA} CMA_t + \varepsilon_{it}$$

Equation 4

The FF5 model is an extension of the FF3 model by adding two more factors: RMW, which is the difference between the return on two robust operating profitability portfolios and two weak operating profitability portfolios, and CMA, which is the difference between the return on two conservative investment portfolios and two aggressive investment portfolios. Additionally, the FF5 model is different from the FF3 model in that it takes the difference between the average return on nine small stock portfolios and on nine big portfolios for the SMB factor and the difference between the average return on the two value portfolios and two growth portfolios for the HML factor.

One interesting point Fama and French shows in their paper "A five asset-pricing model" is that the HML factor (also used in the 3 factor model) never improves the description from the four-factor model that drops HML. The HML is redundant when the investment and probability factors are taking into the equation at least for data they use. The HML factor is important when portfolio tilts are also of interest. The five factor model outperforms the four factor model when there are tilts toward size, value, profitability, and investment premiums.

Fama-French estimated that five factor model explains between 71% and 94% of the cross-section variance of expected returns for the Size, B/M, OP, and Inv portfolios they examined .They have proven that a five-factor model directed at capturing the size, value, profitability, and investment patterns in average stock returns performs better than the three-factor model because it lessens the anomaly average returns left unexplained (Fama and French, 2015).

According to the five factor model, high expected returns are achieved by small stocks that are profitable and value companies with low growth prospects (Fama and French, 2015).

Firm Characteristics

Since the purpose of this paper is to examine whether the idiosyncratic volatility puzzle found by Ang et al. (2006) can be found under the FF5 model and the difference with Ang et al. (2006). This paper uses firm characteristics proposed by Ang et al. (2006).

Size

The size effect is controlled by forming quintile portfolios based on log of market capitalization. Where market capitalization is:

$$Market\ Capitalization = Shares\ outstanding\ \times share\ price$$

Equation 5

This is done on a monthly bases. So each month the ending shares outstanding is multiplied by the ending share price. Based on the log of this market capitalization the companies are divided into quintiles. So each month a company can change between quintile. Fama and French (1992) research shows that stocks of firms with smaller market capitalization outperform stocks with larger market capitalization.

Book to Market

Book to market is the book-to-market ratio found by comparing the book value of a firm with the market value.

$$Book\ to\ market\ Ratio = \frac{Book\ value\ of\ firm}{Market\ value\ of\ \ firm}$$

Equation 6

While the book value of the firm is calculated by the firm's accounting value, the market value is the market capitalization captured above. It is generally thought that high book-to-market firms have high average returns, which is supported by Fama and French (1992).

Leverage

Leverage is the ratio of the total book value of assets to book value of equity.

$$Leverage\ ratio = \frac{Book\ value\ of\ assets}{Book\ value\ of\ equity}$$

Equation 7

Holding everything else equal, leverage increases expected equity returns. Asset volatility also prevents firms from increasing leverage.

Liquidity

One proxy to measure liquidity is set as the current ratio. Which measures the firm's capability to fulfill their short-term obligations and it is measured by dividing the current assets by the current liabilities.

$$Current\ ratio = \frac{Current\ Assets}{Current\ Liabilities}$$

Equation 8

Trading Volume

Trading Volume is the sum of the trading volumes during that month. It is expressed in units on hundred shares for this monthly data and rounded to the nearest of hundred trading volume. Gervais et al. (2001) found that stocks with higher volume have higher returns.

Turnover

The last control variable, turnover, is a proxy of market liquidity. This is measured by taking the trading volume divided by the total number of shares outstanding.

Amihud (2002) show that over time, expected market illiquidity positively affects ex ante stock excess return, suggesting that expected stock excess return partly represents an illiquidity premium. It also shows that stock returns are negatively related over time to contemporaneous unexpected illiquidity.

$$Turnover = \frac{Volume}{Shares\ outstanding}$$

Equation 2

Research Design

Ang et al. (2006) focus on the US stock market, this research will also focus on the US stock market. In particular, the focus will lie on stocks of the S&P 500. The time span of this research is from January 1970 to December 2015, and hence 45 years. This period is specifically chosen because the firm characteristics are published since June 1970 and ends in December 2015. All data will be obtained in STATA format, which is also the statistical software used in this research.

Data Collection

The variables covered in the theoretical framework will be based on the components of the S&P 500 between the time periods January 1970 to December 2015. For the first variable, idiosyncratic risk, 3 steps have to be taken to collect the necessary data. First, the Fama French daily factors over this period have to be gathered. Then all components of the S&P500 in this period have to be determined. At last the daily returns of all these historical components of the S&P500 have to be found. For the second variable, monthly returns, one step have to be taken. The monthly returns of the historical components of the S&P500 have to be downloaded.

The Fama French factors on a daily bases can be retrieved from Kenneth R. French his website. In the data library on this site, Kenneth R. French put all his data in a TXT format or CSV format. Under the header U.S. Research Returns Data one can found the Fama/French 3/5 Factors (2x3) [Daily] txt file. Which is converted into an excel format and imported into Stata File. Additionally, for measures in the trading strategy the monthly factors are retrieved in the same way.

Since the composition of the S&P500 changes over time, the current components couldn't be used and hence all historical components had to be found over the period 1 January 1970- 1 January 2016. For this, Compustat – North America on WRDS is used. Under the header Index Constituents, a list of CUSIP codes of the S&P500 components between 1 January 1970 to 1 January 2016 can be downloaded in EXCEL format using ticker code I0003 for the index. In the list were some errors and some CUSIP codes other than CUSIP9. The errors were deleted and the CUSIP codes other than CUSIP9 were translated into CUSIP9 using the CUSIP converter of WRDS. The CUSIP9 codes are converted into a TXT document.

The daily returns of all historical components of the S&P500 are retrieved form the CRPS daily stock database. The CUSIP9 codes are put into this data base to retrieve the variables: CUSIP, Company Name and Holding Period Returns. These variables for all historical components of the S&P500 can directly be downloaded as Stata format with a data range between 1 January 1970 and 1 January 2016.

The monthly returns are retrieved from the CRPS monthly stock database. Again the same CUSIP9 codes are put into this data base to retrieve the variables: CUSIP, Company Name and Holding Period Returns. The variables for all historical components of the S&P500 can directly be downloaded as Stata format with a data range between 1 January 1970 and 1 January 2016.The firm characteristics of the components of the S&P500 are extracted from the same database as the monthly returns.

Data description

The complete dataset consists of 143,426 finding and has the form of a panel data with an individual dimension (i) and a time dimension (t). Where the individual dimension is the variable permno, which is a specific code for each company, and the time dimension is the variable month, which is the specific month between 1 January 1970 and 1 January 2016. The dataset contains of 395 different companies. The time span is 552 periods with a periodicity of 1 month

Table 1 contains the descriptive statistics of main variables of the complete dataset. The variables that are shown, except the lagged variants, are used to test the relation between idiosyncratic risk and excepted returns. The variables ret and exret are respectively the monthly returns and the monthly excess return including dividend pay-out. FF5IVOL is the idiosyncratic volatility measured with the FF5 factor model and FF3IVOL is the idiosyncratic volatility measured with the FF3 factor model. The remaining variables are the firm characteristics that were covered in the theoretical framework.

The average monthly return is 1.52% over the whole period for the 395 companies. When the risk free is included, the excess return remains 1.17%. For both methods measuring idiosyncratic risk the average on a monthly bases takes a value around 1,80%. The average of log of market capitalizations is 14,95. The mean 0,61 of the book to market ratio implies that on average the book value is 0,61 times the market value and the other way around the book value of assets is 2,2 as high as the book value of equity. On average the companies are quite leverage. The current ratio, the proxy for liquidity, is 1.9. Furthermore, the companies have on average 440735.3 shares outstanding and a turnover ratio of 1.3.

Table 1 Descriptive statistics

variable	mean	sd	p25	p50	p75	N
ret	1.53	1.05	-3.92	1.19	6.47	143770
Exret	1.17	1.06	-4.29	0.85	6.13	143770
FF5IVOL	1.79	1.75	0.98	1.39	2.04	143110
FF3IVOL	1.82	1.76	1.00	1.41	2.07	143110
marktcap	14.96	1.93	13.80	15.19	16.24	143100
bm	.61	.65	.27	0.46	0.81	143426
leverage	2.24	1.21	.77	1.29	2.03	143426
liquidity	1.93	2.55	1.13	1.58	2.27	143426
t.volume	440735	119260	15755	101544	387382	143426
turnover	1.34	1.69	.38	0.84	1.68	143426

The figures 1 to 4 provide the time variation of some summary statics of the idiosyncratic volatility measured with FF5 and FF3 factor model over the full sample period on monthly bases. The positive trend of idiosyncratic volatility found by Campbell et al. (2001) between 1962 and 1997 is hard to notice for both the FF3IVOL and FF5IVOL. There seems to be a negative trend after 2001. The thing one can definitely notices are the 4 major peaks, these peaks occur during the 1973-75 recession, October 1987 (better known as black Monday), the burst of the Dot-com bubble between 1997-2001 and the 2008 fall Financial crisis. Of these peaks the Dot-com bubble has the widest peak and the financial crisis the highest in terms of median. The plots of the FF5IVOL and FF3IVOL are almost identical and follow the same pattern. For both the maxima of FF5IVOL and FF3IVOL are extremely higher than the averages.

Figure 1

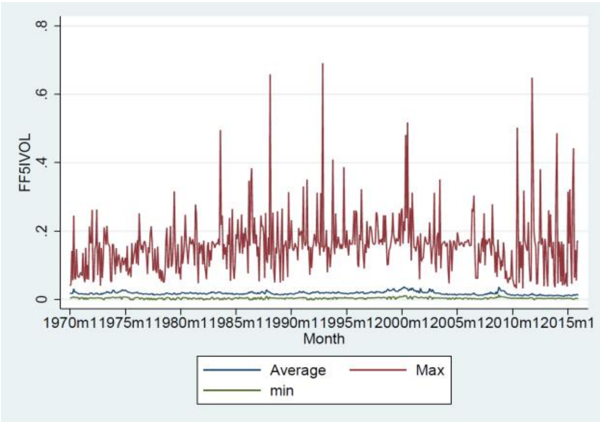


Figure 2

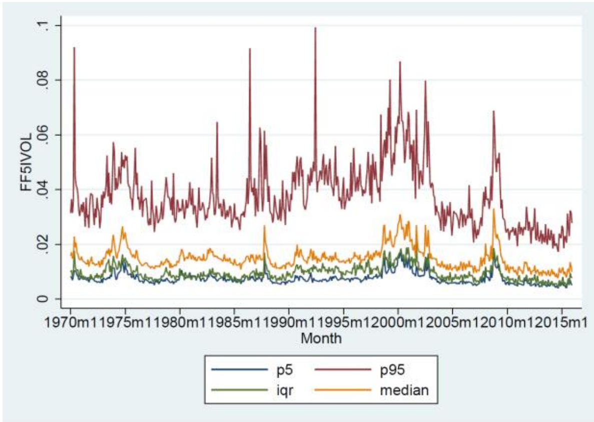


Figure 3

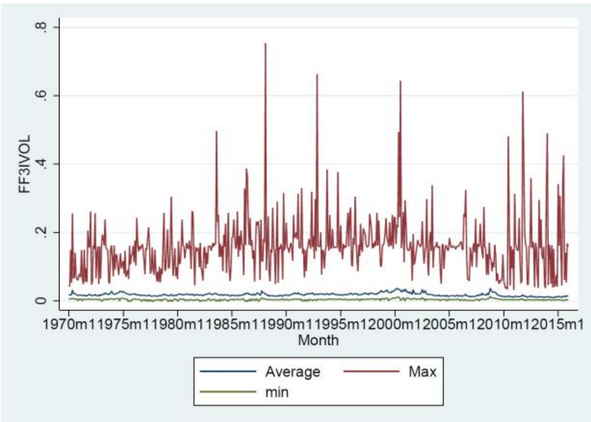
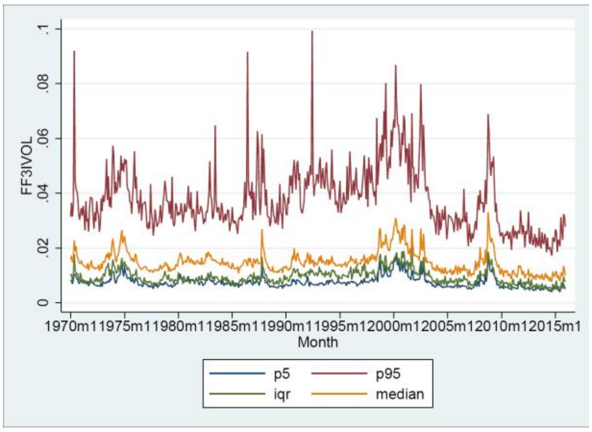


Figure 4



Although, it is hard to see in the figures, there is a minimal difference in statistics between FF5IVOL and FF3IVOL. As stated in the section "Formulation of Research Question" it would be interesting to test whether the minimal difference exposed by the figures 1 to 4 are statistical differences. Table 2 preforms a paired sample t test to test the difference between the two methods. As expected, the mean difference between the FF5IVOL and FF3IVOL is -.0002614 with a t statistic of -49.4571, where $t = \frac{d^{Mean}}{SE(d)}$, and hence there is a strong statistical difference between FF5IVOL and FF3IVOL. But note that for this t statistic there is not dealt with the autocorrelation and cross sectional correlation between FF5IVOL and FF3IVOL. So the t statistic is probably exaggerate.

Table 2 Paired Sample T-test

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
FF5IVOL	143,110	.0179525	.0000464	.017553	.0178615	.0180434
FF3IVOL	143,110	.0182139	.0000466	.017637	.0181225	.0183052
Diff	143,110	-.0002614	.000529	.0019995	-.0002718	-.000251

Table A1 in the appendix presents the time series mean correlation coefficients. This is estimated by taking the time series mean of the monthly correlations. The correlation between the idiosyncratic and their lagged variant is for both estimation methods about 0,22. The correlation between the FF5IVOL and FF3IVOL is more then 0,99 which could imply they may obtain almost identical results in the remaining of this research. This results also shows up in the lagged variant. The correlation between the contemporaneous idiosyncratic volatility and monthly return is very small for both the FF5 method as well as the FF3 method. When looking at the one-month lagged idiosyncratic volatility the correlation increases for both methods. This could indicate a positive relation between idiosyncratic volatility and expected returns. Both observation applies to the return and excess return, where the return has a correlation of almost 1 with the excess return.

Research results

This sections exposes the results for both the Ang et al. Tranding Strategy Method (2006) as well as the Fama-Macbeth approach.

Results Ang et al. Trading Strategy

Table 4 and 5 reports the results of the Ang et al. Trading Strategy Method. Both tables are divided in a panel A and a panel B. For Panel A the idiosyncratic risk is estimated relative to the FF5 method and for panel B the idiosyncratic risk is estimated relative to the FF3 method. The rank represent the quintiles sorted by idiosyncratic risk on basis of the method of the panel. Rank 1 is the quintile with the lowest idiosyncratic risk and rank 5 with the highest idiosyncratic risk. The statistics in the columns labelled Mean and Std. Dev. are measured in monthly percentage terms and apply to equally weighted portfolio excess returns for table 3 and value weighted portfolio excess returns for table 4. The marketcap and b/m are respectively the averages of the equally weighted portfolio end month logged market capitalisation and the book-to-market ratio for table 3 and averages of the value weighted portfolio end month logged market capitalisation and the book to market ratio for table 4. The alpha columns report Jensen's alpha with respect to FF5 model and the FF3 model. This implies that the portfolios excess returns equally weighted excess returns for table 3 and value weighted for table 4 are regressed against the five Fama French factors of the FF5 model to obtain the FF5 alpha and regressed against the three Fama French factors of the FF3 model to obtain the FF3 alpha. The row " Diff 5-1" under the column rank refers to the difference in monthly returns excess return, FF5 Alpha and FF3 alpha between portfolio 5 and portfolio 1 and hence represents the trading strategy of going long in portfolio with high idiosyncratic risk and short in portfolio with low idiosyncratic risk. The square brackets reports robust Newey–West (1987) t-statistics.

In case where the figures are equally weighted, table 3, the monthly excess return increases from 0.71% to 1.69% in panel A and in panel B. Resulting in a difference of 0.98% between the raw means of portfolio 5 and portfolio 1 in both panels. Although the magnitude of the difference in both panels is the same, the t statistics are not. The differences in raw means are significant with t statistics of 2.66 for panel A and 2. 57 for panel B. This evidence is in favor of a positive relation between idiosyncratic risk and expected returns, which is contrary to the findings of Ang et al. who found a significant negative difference between portfolio 5 an portfolio 1 for raw returns.

In panel A the row Diff 5-1 exposes a difference of 0.93% with t static 7.05 under column FF5alpha and exposes a difference of 0.66% with t static 5.02 under the column FF3alpha. In panel B the difference in the FF5 alphas between portfolio 5 and portfolio 1 is 1.00% per month, with a t statistic of 8.24 and for the FF3 alpha respectively 0.88% with a t-statistic of 7.58. Hence the differences between the alphas of the FF5 as well as the alphas of the FF3 method are significant in both panels. Again this is contrary to the finding of Ang et al. (2006). In their research they find a significant negative difference between portfolio 5 and portfolio 1 for the CAPM and FF3 alpha. This implies in the case of Ang et al. (2006) that the trading strategy of going long in the highest idiosyncratic risk portfolio and going short in the lowest idiosyncratic risk portfolio would produces a negative alpha. Indicating that there are potentially large trading returns possible in going long (short) stocks with low (high) idiosyncratic volatility. In this research, going long in the portfolio 5 and going short in portfolio 1 would result in both cases in a significant positive alpha. The pattern of the alphas is also different in this research compared to Ang et al. (2006). In the research of Ang et al. the alpha starts positive and end below zero in the fifth portfolio. In this research there is no flip of sign of the alpha. Furthermore, the increase in alpha's in in al cases monotonic, where the decrease in alpha's is not in the research of Ang et al. Probably the most remarkable fact of the tables, and an answer on one of the research questions of this study, are the differences in pattern between the FF5 alpha's and the FF3 alpha's. While the FF5 alpha in the first and second portfolio in both panels is relative small and in significant, the FF3 alpha is a lot larger and significant. But the FF5 alpha in portfolio 5 is larger and more significant than the FF3 alpha in the same portfolio. This results in that the trading strategy leads to a bigger and more significant result for the FF5 model compared to the FF3 alpha. Hence, this makes clear that for measuring abnormal performances it does matter whether one uses a FF5 model for estimating idiosyncratic risk of a FF3 model. It does not matter for measuring raw returns whether the FF5 model is used or the FF3 model.

The marketcap and the b/m shows distinct patterns in both panels. The log market capitalization decreases monotonically in both panels form around 15.3 in portfolio 1 to 13.5 in portfolio 5. This implies that the low idiosyncratic risk portfolio (portfolio 1) contains generally of larger stocks then the high idiosyncratic risk portfolio (portfolio 5). The book to market ration shows a curious pattern in both panels. It first decreases slightly form portfolio 1 to portfolio 3 and then precipitously it slightly starts to increase in portfolio 4 growing to even a higher average then portfolio 1 in portfolio 5. These patterns, even the curious patterns of the b/m, can be found in the research of Ang et al. The difference between the findings of Ang et al. (2006) and these findings is that the log market capitalization is much higher and the b/m is lower. The higher log market capitalization was expected due to the fact that this research only contains stocks of the S&P 500.

The value weighted table shows almost identical figures and patterns. The main differences between the value weighted table and the equally weighted table can be found in the value of the results of the trading strategy, which is the row Diff 5-1. The value of differences in raw means in the value weighted table differ between panel A and panel B. While the value of the difference of raw means is equal in panel A and panel B in the equally weighted table.

A question that arises is why there is a difference between the finding of Ang et al. and the findings of this research, so why this research finds an positive relation instead of a negative relation. One possible explanation could be the difference in sample period. To give some insight to this explanation the Fama-Macbeth approach will also split up the full sample period in several other periods.

Table 3 Equally Weighted Trading Strategy

Rank	Mean	Std. Dev.	Marketcap	B/m	FF5alpha	FF3alpha
Panel A: Portfolios sorted by Idiosyncratic Volatility Relative To FF5						
1	0.71%	3.87%	15.35	0.67	0.04%	0.22%
					[0.53]	[2.84]
2	0.86%	4.46%	15.12	0.65	0.10%	0.29%
					[1.57]	[3.92]
3	1.04%	5.02%	14.82	0.64	0.25%	0.39%
					[3.23]	[5.16]
4	1.24%	5.64%	14.41	0.65	0.44%	0.54%
					[5.53]	[6.72]
5	1.69%	7.45%	13.56	0.71	0.96%	0.88%
					[8.69]	[8.17]
Diff 5-1	0.98%*				0.92%*	0.66%*
	[2.66]				[7.05]	[5.02]
Panel B: Portfolios sorted by Idiosyncratic Volatility Relative To FF3						
1	0.71%	3.87%	15.32	0.67	0.03%	0.22%
					[0.51]	[2.92]
2	0.87%	4.50%	15.09	0.64	0.12%	0.29%
					[1.92]	[4.15]
3	1.03%	5.08%	14.81	0.64	0.24%	0.38%
					[3.08]	[4.81]
4	1.32%	5.64%	14.39	0.64	0.53%	0.62%
					[6.42]	[7.75]
5	1.69%	7.64%	13.49	0.72	1.00%	0.88%
					[8.24]	[7.58]
Diff 5-1	0.98%*				0.96%*	0.67%*
	[2.57]				[6.95]	[4.84]

Table 4 Value Weighted Trading Strategy

Rank	Mean	Std. Dev.	Marketcap	B/m	FF5alpha	FF3alpha
Panel A: Portfolios sorted by Idiosyncratic Volatility Relative To FF5						
1	0.71%	3.92%	15.48	0.66	0.04%	0.22%
					[0.49]	[2.84]
2	0.86%	4.48%	15.23	0.64	0.11%	0.30%
					[1.73]	[4.10]
3	1.05%	5.03%	14.93	0.63	0.26%	0.40%
					[3.33]	[5.31]
4	1.25%	5.63%	14.53	0.65	0.47%	0.56%
					[5.98]	[7.14]
5	1.73%	7.37%	13.72	0.69	1.03%	0.94%
					[9.55]	[9.00]
Diff 5-1	1.02%*				0.99%*	0.73%*
	[2.79]				[7.69]	[5.57]
Panel B: Portfolios sorted by Idiosyncratic Volatility Relative To FF3						
1	0.76%	4.17%	16.77	.72	0.04%	0.24%
					[0.48]	[2.94]
2	0.90%	4.59%	15.53	.65	0.15%	0.33%
					[2.18]	[4.39]
3	1.03%	5.02%	14.90	.63	0.26%	0.40%
					[3.38]	[5.15]
4	1.29%	5.52%	14.08	.62	0.52%	0.61%
					[6.52]	[7.76]
5	1.62%	7.23%	12.80	.66	0.94%	0.83%
					[8.57]	[7.83]
Diff 5-1	0.86%*				0.90%*	0.59%*
	[2.34]				[6.76]	[4.34]

Results Fama-Macbeth Approach

In this section the monthly excess firm returns are regressed with the Fama-Macbeth approach on a constant; the firms idiosyncratic risk over the past month with respect to the FF5 model in table 5 and with respect to the FF3 model in table 6; size dummy variables of the firm and several other end month firm characteristics. These regressions are done for the full sample period as well as for several time periods (1970-1979, 1980-1989, 1990-1999, 2000-2009 and 2010-2015). The figures without parentheses in the tables 5 and 6 reports the coefficients of the Fama-Macbeth regressions. The figures in parentheses shows the corresponding robust t statistics. The asterisk next to the coefficients represents the p-value. When the p-value is less than 0.01 the coefficient has one asterisk, it has two asterisks if the p-value is less than 0.05 and three asterisks if the p-value is less than 0.1.

Every month the firm is sorted into a quintile based on their end month log market capitalization. This log market capitalization sorting is represented by the dummy variables "SIZEQ1" to "SIZEQ4". "bm" is the end month book-to-market ratio and all other control variables (leverage, liquidity, trading volume and turnover) are synonymous covert in the section "Firm Characteristics". Every observation has a unique combination of the indices i and t. The amount of observations can be found in the row "Observations". The number of group row represents the T, which is the total amount of months.

In both tables 5 and 6 the coefficients on the idiosyncratic risk are positive and statistically significant for the full sample set. The magnitude of the coefficients is slightly higher when idiosyncratic risk is measured with the FF5 model. Then the coefficients is 0.158, while it is 0.156 when idiosyncratic risk is measured with the FF3 model, but there is no difference in the t statistics. This evidence from the positive and statistically significant coefficients suggest a positive relation between the one month lagged idiosyncratic risk and expected returns. It again shows, just like the evidence exposed by the trading strategy, that there is little/no difference between measuring idiosyncratic risk with FF5 model or FF3 model for the raw excess returns. The positive relation is contrary to the findings of Ang et al. (2006) and even the findings of Ang et al. (2009). Ang et al. (2009) exposes a significant negative idiosyncratic risk coefficient with the Fama-Macbeth approach. Note that, due to the large dispersion of the firms sizes in their sample, Ang et al. (2009) uses value-weighted Fama-Macbeth regressions.

The dummy variables of size and b/m variable follow the findings of Fama and French (1992). The SIZEQ1 has the highest positive magnitude decreasing to SIZEQ4 and all size variables are significant. This implies that smaller firms on average have higher returns than larger firms. The b/m variable is also positive and statistically significant and so is providing evidence that b/m is positively related to average returns. These findings are in line with the results of Fama and French (1992) that growth firms tend to have lower returns than value firms, also known as the outperformance tendency. Leverage is the only insignificant variable in the full sample period. Trading value is significant and negative and hence contradicts the findings of Gervais (2001), who says that stocks with higher trading volume tend to have higher returns. The proxy for liquidity, turnover, has a positive and significant sign. This implies that more liquid stocks have a higher returns, which is definitely not an illiquid premium. When this was the case there had to be a negative sign for the turnover coefficient.

There is a serious difference between the time periods. Although every period has a positive sign for FF5IVOL and FF3IVOL, there is a noticeably difference in magnitude. The period 2000-2009 has a coefficient that is almost 3 times as high as the coefficient in the period 1980-1989. The period 2000-2009 has also a significant coefficients just while the period 1980-1989 has not. Note that the amount of observations of the insignificant coefficients in some cases is almost half the observations of the significant coefficients. This evidence does not out rule that the difference between the results of Ang et al. and that these results are influenced by the sample period.

Furthermore, the signs of the dummy variables in several different periods are consistent with the literature. The book to market value takes a positive sign in all most all cases in both except the last period but is only significant in the first period and the period with the most observations. Leverage is insignificant negative in the first periods and insignificant positive next two periods, then again it turns signs an becomes insignificant negative in the last two periods. Trading volume is in all periods highly significant negative and turnover is only in the first 3 periods significant positive.

Table 5 Fama-Macbeth Regressions with FF5L1IVOL

VARIABLES	(1) Full Sample	(2) 70-79	(3) 80-89	(4) 90-99	(5) 00-09	(6) 10-15
FF5L1IVOl	0.158***	0.108	0.0786	0.173***	0.298***	0.112
	(4.20)	(1.00)	(1.13)	(3.20)	(3.24)	(1.52)
SIZEQ1	-0.0116***	-0.0155***	-0.0122***	-0.0154***	-0.00700*	-0.00569**
	(-6.58)	(-3.17)	(-3.39)	(-4.14)	(-1.96)	(-2.40)
SIZEQ2	-0.00859***	-0.00754**	-0.0114***	-0.0157***	-0.00350	-0.00245
	(-6.78)	(-2.42)	(-4.23)	(-5.30)	(-1.35)	(-1.46)
SIZEQ3	-0.00731***	-0.00634**	-0.00960***	-0.0126***	-0.00359	-0.00238
	(-6.75)	(-2.55)	(-4.94)	(-5.03)	(-1.34)	(-1.49)
SIZEQ4	-0.00583***	-0.00356*	-0.00848***	-0.0112***	-0.00296	-0.00101
	(-6.75)	(-1.77)	(-5.07)	(-5.45)	(-1.55)	(-0.80)
bm	0.00276**	0.00537***	0.00182	0.000902	0.00690***	-0.00385
	(2.42)	(2.82)	(0.81)	(0.28)	(2.70)	(-1.61)
leverage	-2.18e-05	-0.00122	0.000956	0.000269	-9.37e-05	-1.34e-05
	(-0.09)	(-1.30)	(1.56)	(1.47)	(-1.00)	(-0.27)
liquidity	0.000755**	-4.50e-05	0.00140	0.000532	0.000958	0.00104*
	(1.97)	(-0.04)	(1.31)	(1.01)	(1.32)	(1.84)
Trading volume	-1.54e-07***	-5.51e-07***	-1.21e-07***	-3.35e-08***	-3.50e-09***	-1.27e-09**
	(-4.78)	(-3.90)	(-5.22)	(-5.03)	(-4.01)	(-2.58)
turnover	0.0105***	0.0226***	0.0138***	0.0103***	0.000787	0.00104
	(7.60)	(4.50)	(5.16)	(5.60)	(0.61)	(1.06)
Constant	0.00769***	0.00102	0.00940*	0.0133***	0.00270	0.0150***
	(3.95)	(0.22)	(1.895)	(3.63)	(0.69)	(4.27)
Observations	142,836	21,217	24,804	31,908	39,310	25,597
R-squared	0.138	0.173	0.138	0.140	0.128	0.091
Number of groups	552	120	120	120	120	72

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6 Fama-Macbeth Regressions with FF3L1IVOL

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Full Sample	70-79	80-89	90-99	00-09	10-15
FF3L1IVOL	0.156***	0.101	0.0767	0.173***	0.292***	0.121*
	(4.20)	(0.96)	(1.11)	(3.21)	(3.23)	(1.69)
SIZEQ1	-0.0117***	-0.0156***	-0.0123***	-0.0154***	-0.00691*	-0.00572**
	(-6.59)	(-3.19)	(-3.36)	(-4.15)	(-1.92)	(-2.42)
SIZEQ2	-0.00860***	-0.00755**	-0.0114***	-0.0157***	-0.00340	-0.00247
	(-6.78)	(-2.42)	(-4.27)	(-5.30)	(-1.32)	(-1.48)
SIZEQ3	-0.00735***	-0.00635**	-0.00965***	-0.0127***	-0.00367	-0.00240
	(-6.80)	(-2.54)	(-4.98)	(-5.05)	(-1.38)	(-1.51)
SIZEQ4	-0.00585***	-0.00360*	-0.00855***	-0.0112***	-0.00293	-0.00102
	(-6.79)	(-1.78)	(-5.11)	(-5.50)	(-1.53)	(-0.80)
bm	0.00276**	0.00538***	0.00186	0.000873	0.00689***	-0.00388
	(2.42)	(2.81)	(0.83)	(0.27)	(2.69)	(-1.62)
leverage	-9.85e-06	-0.00118	0.000957	0.000269	-8.79e-05	-1.31e-05
	(-0.04)	(-1.25)	(1.56)	(1.48)	(-0.94)	(-0.27)
liquidity	0.000752*	-4.24e-05	0.00141	0.000531	0.000943	0.00103*
	(1.96)	(-0.04)	(1.32)	(1.00)	(1.30)	(1.83)
Trading volume	-1.54e-07***	-5.48e-07***	-1.23e-07***	-3.38e-08***	-3.58e-09***	-1.29e-09**
	(-4.74)	(-3.85)	(-5.28)	(-5.03)	(-4.15)	(-2.60)
turnover	0.0105***	0.0226***	0.0139***	0.0103***	0.000741	0.00101
	(7.58)	(4.49)	(5.17)	(5.59)	(0.58)	(1.03)
Constant	0.00770***	0.00101	0.00944*	0.0133***	0.00268	0.0149***
	(3.95)	(0.22)	(1.90)	(3.64)	(0.69)	(4.24)
Observations	142,836	21,217	24,804	31,908	39,310	25,597
R-squared	0.138	0.173	0.138	0.140	0.128	0.091
Number of groups	552	120	120	120	120	72

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.01

Conclusion

In the sample period 1970-2015 this paper find contradicting evidence against the findings of Ang et al. (2006) for the S&P 500. It shows that stocks with past high idiosyncratic risk have high average returns over the full sample period when idiosyncratic risk is measured with the FF5 method and the FF3 method. Both methods applied in this study to test this relation reveals a positive significant relation.

The Ang et al. Trading Strategy, which sort the sample set in 5 portfolios based on idiosyncratic risk and goes long in the highest idiosyncratic risk portfolio and short in the lowest, exposes a positive significant difference in raw average returns between the portfolio 5 and portfolio 1 . This positive significant difference can be found in the value weighted and the equally weighted case when the portfolios are sorted based idiosyncratic risk measured with the FF5 method as well as the FF3 method. It seems that it does not matter whether an equally weighted method is used or a value weighted method is used. Although, there is a little difference, this difference does not seems to be large enough. For the raw returns it also does not matter whether the FF5 method is used to estimate idiosyncratic volatility or whether the FF3 model is used. Both methods give almost the same results with respect to the raw returns. But, and this is probably the most remarkable finding of the paper, it does matter which model is used for the alpha performances. Indeed, both methods find a highly significant positive alfa in the trading strategy, which is already contrary to the findings of Ang et al., who find a significant negative alpha, and which is contrary to the finding of Switser and Picard, who find an insignificant alpha different from zero. But both methods differ in the first two portfolios and in the magnitude of the difference and the according t statistic. For the FF5 model the first two portfolios are not significant different from zero while this is the case for the FF3 model and the alpha of the last portfolio is much higher for the FF5 model compared to the FF3 model. Resulting in a much more profitable and significant trading strategy for the FF5 model compared to the FF3 model.

The Fama-Macbeth approach results in strong significant positive coefficients for the one month lagged idiosyncratic risk FF5 case and the one month lagged idiosyncratic risk

FF3 case for the full sample period. Both methods reveals almost the same coefficient and confirms the findings of the trading strategy method that it does not matter whether FF5 model is used or the FF3 model is used for estimating idiosyncratic volatility. The positive coefficient is contrary to the findings of Ang et al. (2009) who find a negative coefficients with this approach for the US sample set. The size variable and the book to market variable are conforming to the work of Fama and French (1992) which means there is indeed an outperformance tendency. Although the coefficients are positive in every period, the studies shows that the magnitude of this sign of idiosyncratic risk coefficients is not the same in every period. Some periods have three times higher coefficient than other periods. Indicating that we cannot rule out that the differences between the findings of Ang et al. and this paper is influenced by the sample period.

Note that this research does not use the same sample set as Ang et al. (2006). Ang et al. uses all stocks on AMEX, NASDAQ, and the NYSE, while this research only uses various stocks on the S&P 500. This implies that this research only uses the 500 largest companies based on market capitalization from the NYSE or NASDAQ. Therefore, it would be interesting to extend the sample set to the sample set of Ang et al. and then conduct the same research. Maybe the difference in the findings can be explained by the difference in sample sets. A more rational explanation of these differences and findings is for further research.

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Appendix

Table 1 Panel Data Descriptive Statisctcs

Variables	Ret	exRet	FF5IVOL	FF5L1IVOl	FF3IVOL	FF3L1IVOL	Marktcap	BM	Leverage	Liquidity	Volume	Turnover
Ret	1	0,9997	0,0050	0,0124	0,0047	0,0128	0,0259	0,0661	0,0183	-0,0023	-0,0393	-0,0197
exRet		1	0,0019	0,0094	0,0016	0,0098	0,0395	0,0607	0,0234	-0,0056	-0,0263	-0,0099
FF5IVOL			1	0,2133	0,9922	0,2185	-0,2073	0,0166	0,0155	-0,0096	-0,0760	0,1888
FF5L1IVOL				1	0,2143	0,9900	-0,2113	0,0346	0,0205	-0,0078	0,0346	0,0383
FF3IVOL					1	0,2199	-0,2035	0,0148	0,0159	-0,0109	-0,0718	0,1938
FF5L1IVOL						1	-0,2099	0,0347	0,0194	-0,0117	0,0386	0,0437
Marktcap							1	-0,3797	0,1227	-0,1760	0,4974	0,3069
BM								1	-0,1171	0,0815	-0,0757	-0,0973
Leverage									1	-0,2928	0,1129	0,1257
Liquidity										1	-0,1239	-0,0860
Volume											1	0,5871
Turnover												1