LAGGED IDIOSYNCRATIC RISK AND ABNORMAL RETURN

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PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE IN FINANCE

In the Master of Science in Finance Program
of the
Faculty
of
Business Administration

SIMON FRASER UNIVERSITY

Fall, 2017

Approval

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Degree: **Master of Science in Finance**

Title of Project: **IDIOSYNCRATIC RISK AND ABNORMAL RETURN**

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Abstract

According to financial theory, idiosyncratic risk is eliminated within a diversified portfolio and therefore should not be related to expected return. However, in the last decade financial economists have started to debate and provide evidence that showed that either idiosyncratic risk is positively or negatively related to future abnormal return.

Our paper follows these recent studies and examines the relationship between idiosyncratic volatility and abnormal return in the following year. Hence, our measure of idiosyncratic volatility is an annual measure, and we use it to predict the abnormal return in the following year. We divide companies into five tranches of idiosyncratic volatility level each year, and then analyse and compare their abnormal return in the following year.

Our result suggests that stock returns are negatively related to the one-year lagged idiosyncratic volatilities. Most important, it seems that most of the explanatory power is derived from the highest idiosyncratic volatility level stocks as they yield the most negative abnormal returns in the following year.

Keywords: Idiosyncratic risk; Abnormal Return, Cross section, Different tranches

Acknowledgements

We give our most appreciation to Dr Amir Rubin for his dedication to help us finish this project. His bolster and efforts support us and lead us the direction for our research paper.

Moreover, we would like to thank to Alexander Vedrashko, the second reader, to spend decent amount of time and effort on our paper to help us prefect our work.

We also show our most sincere gratitude to everyone helping us through the whole course of this program, including SFU faculties, instructors, and staff at MSc. in Finance Program at Beedie School of Business, Simon Fraser University.

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1. Introduction

1.1 Overview:

By definition, idiosyncratic risk is not correlated with systematic market risk and since it can be eliminated in a diversified portfolio, and should not be related to expected return. Therefore, whether a firm has high or low idiosyncratic risk is not expected to be related to its performance. A lot of investors use diversification of the portfolio to avoid the unexpected slump in performance. This is mainly because when investors diversify the portfolio, the odds that any individual stock will adversely affect the portfolio's performance is minimized. Despite of the correlation between stocks, a diversified portfolio could temper the loss of adverse events from happening.

Systematic risk is related to major changes in the market that affect all stocks: those include changes in politics, war, human intervention, demographics, insider trading, natural hazard, and technology in the visible information market. These risks are easily captured with asset pricing models such as the CAPM, or Fama and French (1990). In this paper, we want to know whether indeed idiosyncratic risk is not related to abnormal return. A decent number of investors in the market don't hold a well-diversified portfolio, so their portfolios are exposed to idiosyncratic risk. Thus, the study can help investors understand whether there exists idiosyncratic risk – return trade-off, or whether idiosyncratic risk does not correlate with future return. The study of idiosyncratic risk could also help investors adjust their risk management strategy. The volatilities of stock returns consist of market volatility, industry volatility, and idiosyncratic volatility, where in recent years, idiosyncratic risk has been a larger fraction of total volatility (Rubin & Smith, 2010).

From the empirical analysis (Peterson & Smedema, 2011), the idiosyncratic risk is very volatile, making it is hard to predict. On the other hand, if funds managers could understand the idiosyncratic risk – return trade-off, managers would know whether it is important to hedge against this type of risk by diversifying it away, or whether one can use to make profit by employing some sort of trading strategy.

Since our main purpose is to conduct analysis for the relationship between idiosyncratic risk and lagged abnormal return, we draw data from Center for Research in Security Price, and using cross-section method to divide stocks into 5 tranches each year, from low volatility to high volatility. Then we use Fama-French four-factor model (Fama & French, 1992) to calculate the intercept, the difference between expected return and the actual (raw) return, as our abnormal return. In the last step, we apply the regression between the lagged idiosyncratic volatility and abnormal returns, and analyse the relationships.

Our result suggests that annual stock abnormal returns are significantly negatively related to the one-year lagged idiosyncratic volatilities. Mostly this result comes from the fact that the higher volatility tranche tends to have the relatively lower negative abnormal returns in the following year compared to the other volatility tranches.

2. Literature Review:

As our paper is testing the correlation between idiosyncratic volatility and abnormal return, there is no identical paper concentrating on exactly the same topic. Most scholars are interested in expected return and overall return, since they are more influential to market. Idiosyncratic risk has been capitalized as an important proxy for stock market for portfolio management and economic effects (Rubin & Smith, 2010). In order to capture idiosyncratic risk, some precedential studies implemented the Capital Assets Pricing Model to measure the unsystematic risk (Malkiel & Xu, 2006). However, since conventional CAPM only considers market risk, it is now considered inadequate for capturing all systematic risk. Fama & MacBeth (1973) suggests that Fama-French Model would be a better model than CAPM to get a better estimation for abnormal return by consideration of multiple factors. Fama-French has appeared to be the most popular approach to decide abnormal returns in the recent 25 years research.

Because of idiosyncratic risk existing in portfolio management, holding a single or few stocks could be lethal for investors with undiversified portfolios. The least diversified group with high idiosyncratic risk has 2.4% lower returns than highest diversified group (Goetzman & Kumar, 2004). Levy (1978) and Merton (1987) have exhibited their establishment of theory that there is a positive relationship between idiosyncratic risk and expected return. In spite of different methodology and database, completion of many studies before the millennium proves that the higher idiosyncratic risk, the lower the returns. Moreover, the same conclusion is drawn by Ang, Hodrick, Xing, and Zhang in 2006 that monthly stock returns over one month-lag volatilities are negatively correlated (Ang, Hodrick, Xing, & Zhang, 2006). Other research papers also reach the identical outcome.

Ang, Hodrick, Xing, Zhang (2006) specifically demonstrate the results that lowest idiosyncratic risk quintile portfolio outperforms the highest risk portfolio. Ang's paper focuses on the analysis between future returns and the past idiosyncratic risk, since the past idiosyncratic risk could be easily obtained, and idiosyncratic risk is also persistent. Ang's group employed data from 23 developed countries and applied a modified Fama-French Three-factor Model for each specific country. For instance, Ang's paper applies a local Fama-French Model for U.S. and Canada, regional Fama-French Model for Europe, and a global Fama-French Model for Asia Pacific in cross-section manner. Ang's investigation covers globally for both developed countries including G7, and developing countries. The paper presents that there is a strong negative relationship between lagged idiosyncratic volatility and future return, and more developed countries have a stronger negative effect, where U.S. has the strongest negative correlation with a Beta of -1.952, approximately triple times as the rest of the world, with a Beta of -0.67 (Ang, Hodrick, Xing, & Zhang, The Cross-Section of Volatility and Expected Returns, 2006)

Another study on idiosyncratic risk has been conducted two years later in 2008 by the same group (Ang, Hodrick, Xing, & Zhang, High idiosyncratic volatility and low returns: International and further U.S. evidence, 2008). In this paper, Ang's group pointed out in fact the Fama-French model might lead to a mispricing of idiosyncratic volatility. Therefore, Ang and his colleagues enhance the Fama-French model by adding extra momentum factor, using Carhart Four-Factor Model (Carhart, 1997). The main reason using the new model is to take consideration of the persistent effect for volatility in portfolio performance.

$$\mathrm{R} = \mathrm{R_f} + \beta_{mkt}(R_{mkt} - Rf) + \beta_{smb}SMB + \beta_{hml}HML + \beta_{umd}\mathrm{UMD} + \alpha + \varepsilon$$

Where R_f is the risk-free interest rate for each region, or the Treasury Bill Rate. β_{mkt} is the coefficient for the excess return between the benchmark return and the risk-free interest rate; β_{smb} is the coefficient for small capitalization minus big capitalization; SMB stands for Small minus big for market capitalization; β_{hml} is the coefficient for high book-to-market ratio minus low book-to-market ratio. HML is the coefficient for high minus low in book-to-market ratio. β_{umd} is the coefficient for momentum in persistence; and UMD stands for momentum; α *is* the intercept of the regression, and also the abnormal return "alpha"; ε is the error term.

These authors also employ the Fama-French MacBeth cross-sectional regressions in order to cope the problem of computation with standard error (Fama & MacBeth, 1973)

$$R_i(t, t+1) = c + \gamma\sigma_i(t-1, t) + \lambda_\beta\beta_i(t, t+1) + \lambda_z z_i(t) + \varepsilon_i(t+1)$$

where $R_i(t, t+1)$ is the outperforming return from month t to month (t+1), $\sigma_i(t-1, t)$ is the idiosyncratic volatility form (t-1) to t. $\beta_i(t,\ t+1)$ is the risk factor spanning from month t to (t+1); and $z_i(t)$ is the attribution of character for individual company. The outcome from the results (Ang, Hodrick, Xing, & Zhang, High idiosyncratic volatility and low returns: International and further U.S. evidence, 2008) shows the consistency with the prior observation using sort on expected volatility. The fifth tranche with the highest volatility still has a negative correlation against abnormal returns. However, using the forward volatility after sorting, the first, forth, and fifth tranches all have negative correlation with the returns.

The most recent research by Fangjian Fu (2008) tests the relationship between idiosyncratic risk and the cross-section expected return, which is the expected return as predicted by the asset pricing model, rather than the actual return observed in the market. Though this approach is somewhat different than what investors may care about, the intuition and methodology allows us to discover whether idiosyncratic volatility is so persistent that it will have no relation with future expected return. Fu (2008) makes the point that idiosyncratic risk is hard to predict since different clusters (industries, years, geography) exist in the data, and because idiosyncratic volatility is heteroscedasticity, the assumption of constant variance is inappropriate. To solve heteroscedasticity, (Fu, 2008) deploys GARCH (Generalized Autoregressive Conditional Heteroscedasticity) to simulate the volatility. In the end, Fangjian Fu concludes that (Ang, Hodrick, Xing, & Zhang, High idiosyncratic volatility and low returns: International and further U.S. evidence, 2008) didn't consider of the noise that idiosyncratic risks are time-varying, therefore, Ang's result that high idiosyncratic risk will result low return is not reliable. In Fangjian Fu's observation (Fu, 2008), high idiosyncratic risk will lead to a high expected return. Essentially, Fangjian Fu (Fu, 2008) is focusing on idiosyncratic risk along with expected return, but Ang's group (Ang, Hodrick, Xing, & Zhang, The Cross-Section of Volatility and Expected Returns, 2006) concentrates on the relationship between idiosyncratic risk and average return.

3. Data and Summary Statistics

3.1 Data Source

The primary security data are drawn from Wharton Research Data Service's CRSP monthly stock file of CRSP SAS Database. Files in the section are updated once each year, in early February.

The CRSP monthly stock files provides several kinds of information on individual securities during certain periods, including identify information, price history, and distribution history.

To have analysis and run regression with a larger number of data, we search the entire database of records to download the data. In our case, the sample contains about 5000 stocks in CRSP Database and consists of 3,954,388 observations with all related security information, such as permno code, date, company name, cusip number, monthly security holding period return and monthly value weighted return (includes distributions) from January 1962 to December 2016.

Table 1: Statistics of Stocks Returns

Return and value-weighted return distributional properties.

Variable	Observations	Mean	Std. Dev.	Min	Max
Return	3,793,111	.010835	.1718447	-.9880952	24
Value-weighted return	3,954,388	.009024	.0447758	-.225363	.1655848

Fama-French model and Carhart Four-factor model data is also obtained from the Wharton Research Data Service' *Fama-French Portfolios and Factors* Database. The Four-factor model data covers a monthly frequency data during the period of 1962 to 2016. The data files have five variables: small Minus Big (SMB), High Minus Low(HML), Excess Return on the Market (MKTRF), Momentum (UMD), and One Month Treasury Bill Rate (RF).

Both CRSP monthly securities data and Four-factor model data downloaded from Wharton Research Data Service are saved in Stata file (*.dta). Thus, we can sort and process the data using Stata software in the next step.

Table 2: Fama-French Factors for Abnormal Returns

Where mkrtf stands for market excess return over risk-free interest rate, smb stands small capitalization minus big capitalization, hml stands for high book-to-market ratio minus low book-to-market ratio, rf stands for risk-free interest rate, and umd stands for the momentum factor.

Variable	Observations	Mean	Std. Dev.	Min	Max
mktrf	667	.0050457	.0442342	-.2324	.161
smb	667	.0019918	.0304792	-.1688	.2171
hml	667	.0036925	.0279352	-.111	.129
rf	667	.0038435	.0026279	0	.0135
umd	667	.006631	.0417622	-.3439	.1836

3.2 Data Processing

Step 1: Generate the variable year. We need to sort the data by year for further analysis and research because the downloaded monthly data is arranged by date.

Step 2: Calculate the active returns and corresponding standard deviation. We calculate the monthly active return by taking monthly security return subtract the relevant value-weighted market return, then define the standard deviation of active returns as our proxy for idiosyncratic volatility.

Step 3: Drop all the observations that have no 12-months-data. Since we are studying annual return and volatility, we only keep the observations relevant to our research. Only stocks with all 12-months-data in a fiscal year will be preserved at year t-1, but if a stock is delisted in the year of the abnormal return calculation, it is included (as otherwise, we would end up with a biased sample).

Step 4: Divide idiosyncratic volatilities into five groups. Rather than dividing all idiosyncratic volatility data into tranches, we use a loop and divide idiosyncratic volatility of each year into five different tranches from tranche#1 to tranche#5, where the first tranche has the lowest volatility, while the fifth tranche has the highest volatilities. Thus, the risk that all high idiosyncratic volatilities concentrate on few particular years can be avoided, and results could be more accurate.

Step 5: Move the idiosyncratic volatility 12 months earlier to create lagged volatility. The goal of the paper is to find out the relation between lagged idiosyncratic volatility and abnormal return. Thus, it is essential to keep abnormal return bound to lagged idiosyncratic volatility 12 months earlier. Also, lagged idiosyncratic volatility group can be sorted in this step.

Step 6: Merge with returns of Fama-French and Four-factors model. Import the small Minus Big (SMB), High Minus Low(HML), Excess Return on the Market (MKTRF), and Momentum (UMD), so that we put original security files and factors return together.

Step 7: Achieve alpha, abnormal return. Alpha can be achieved by running a regression of excess return of each firm per year on four factors (excess return is calculated by taking firms' monthly security return and subtract the one-month Treasury bill rate).

Step 8: Find out the relation between abnormal return and lagged idiosyncratic volatility. Since our file already includes abnormal return, lagged idiosyncratic volatility, lagged idiosyncratic volatility group and the year.

3.3 Statistics Summary

Table 3: Statistics for Regression between Idiosyncratic Risks and Abnormal Returns
"

Variable	Observations	Mean	Std. Dev	Min	Max
Lagged volatility	271,480	.121805	.1024206	.0003403	6.949343
Abnormal return	270,395	.0009398	.0760921	-5.643331	9.388128

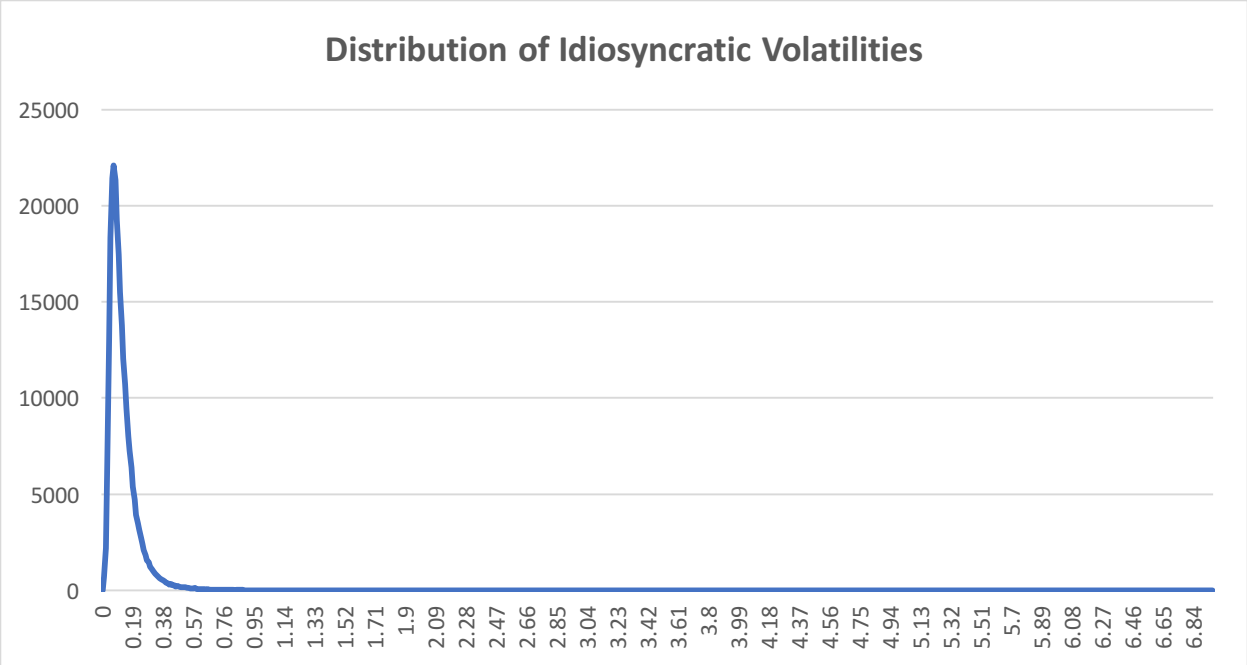

Figure 1 Distribution of Idiosyncratic Volatilities

The table shown above emphasize the existence of idiosyncratic volatility. Although CRSP database is large enough to diversify, the mean of about 12% does show the importance of non-systematic risk.

With Regards to abnormal return, the mean alpha is tiny, which makes economic sense. That is, a company is very difficult to create a unique competitive advantage and generate a significant abnormal return. The figures of min and max of alpha are also meaningful: a firm bear non-systematic risk does not guarantee a positive abnormal return. However, as we have both a positive mean alpha and mean lagged volatility in our data, it is interesting to find out if there is a consistent relationship between them and we might take advantage of that.

4. Methodology

We have used all the data in CRSP, and we use Fama-French and Carhart model (Carhart, 1997) being the best approach to determine the abnormal return regarding to different capitalizations, different book-to-market ratio, and momentum. Fama-French model is a characteristic-based approach that takes into account that value-stocks always outperform growth-stocks, small firms always outperform large firms, and the momentum stocks keep decreasing or increasing for a short period. We collect all the stocks' price in the duration from 1962 to 2016 from CRSP (Center for Research Stock Price), calculate the monthly return, and subtract value-weighted market return to get excess return. We then define the standard deviation of excess returns as our measure of idiosyncratic volatility. We divide stocks into five different tranches each year from tranche#1 to tranche#5, where the first tranche has the least volatility, while the last tranche has the highest volatilities.

4.1 Measuring Idiosyncratic Risk:

There are many ways to calculate the idiosyncratic risk. Cao, Han (2016) and Fu (2008) use exponential GARCH model to simulate idiosyncratic risk for time-varying variance volatility. Our proxy is based on previous year volatility and is rather simple.

$$Idiosyncrtic\ Risk = \sqrt{\frac{\sum_{i=1}^{12} |r_i - r_{mkt}|^2}{12}}$$

where r_i stands for the holding period return, and r_{mkt}stands for benchmark return.

As stated before, we calculate excess return using stock return over the market return. After that, we compute monthly standard deviation for the excess return for the whole year using monthly

data. Though the measure is simple, we note that it is based on one year of monthly data, so if it has predictability on next year's abnormal return, we can probably apply minor modifications of the measure to make results stronger.

We sort stock return into different tranches according to the scale of volatility for each year. The first tranche has the least volatility, while the last tranche has the highest volatilities.

4.2 Measuring Abnormal Return

For abnormal returns, we use Fama and French (1990) and Carhart (1997) Four-Factor Model to evaluate abnormal returns. On the right side of the formula, "$\beta_{mkt}(R_{mkt} - Rf) + \beta_{smb}SMB + \beta_{hml}HML + \beta_{umd}\mathrm{UMD}$" is the expected return α is the abnormal return.

$$\mathrm{R} - \mathrm{R_f} = \beta_{mkt}(R_{mkt} - Rf) + \beta_{smb}SMB + \beta_{hml}HML + \beta_{umd}\mathrm{UMD} + \alpha + \varepsilon$$

Where $\mathrm{R_f}$ is the risk-free interest rate, or the Treasury Bill Rate. β_{mkt} is the coefficient for the excess return between the benchmark return and the risk-free interest rate; β_{smb} is the coefficient for small capitalization minus big capitalization; SMB is Small minus big for market capitalization; β_{hml} is the coefficient for high book-to-market ratio minus low book-to-market ratio. HML is the coefficient for high minus low in book-to-market ratio. β_{umd} is the coefficient for momentum in persistence; and UMD stands for momentum; α is the intercept of the regression, and also the abnormal return "alpha"; ε is the error term. To get abnormal return we calculate the intercept of a regression that is applied for each company each year.

4.3 Regression for Idiosyncratic Volatility and Abnormal Return

In the last step, all we need to do is to employ regressions between lagged idiosyncratic volatilities and abnormal returns. We are running different regressions for different tranches, eliminating clusters (year, permno). First regression explains the relationship between lagged idiosyncratic risk and abnormal return despite of tranches; Second regression is between idiosyncratic volatility group and abnormal return; and the third one is we run the regressions of abnormal return on each lagged idiosyncratic volatility group, where we get one regression for each tranche.

4.4 Confidence level

All the statistics are calculated at 95 percent confidence level. The t-test is an approach to determine the statistical significance of our data. That is, we have 95 percent of confidence that our sample will fall within the confidence interval in our sample. Once t statistic is larger than 1.96 or smaller than -1.96, it rejects the null hypothesis, which is considered statistically significant.

4.5 Controlled Variables

In our model, idiosyncratic volatility is the independent variable, and we implement controlled variables in several approaches. We controlled all lagged idiosyncratic volatilities, lagged idiosyncratic volatilities groups, and each lagged idiosyncratic volatility group, and consequently we get a result for each controlled variable. Also, years and permno has been used to divide volatilities into different group in order to eliminate clusters.

5. Empirical Result

In this section, we run regression analysis to assess the relationships between lagged idiosyncratic volatility and abnormal return in three different ways. The goal is to find the effect of idiosyncratic volatility on abnormal return in the following year. Each year, the idiosyncratic volatilities of all CRSP securities during 1962 to 2016 are broken down into five groups based on the size: group 1 stands for a group with lowest idiosyncratic volatility and group 5 contains largest idiosyncratic volatility within a year. Specifically, higher quintile goes to group 5 and lowest quintile goes to group 1. We sort all stocks to idiosyncratic volatility groups at the end of each calendar month and use it to predict next year's abnormal return. Abnormal return is the intercept from a regression where the dependent variable is excess return and the dependent variable is the Fama and French (1990) three factor model and the Carhart (1997) momentum factor.

Table 4: Abnormal return across idiosyncratic volatility groups

The table provides the mean next year's abnormal return (referred to as alpha) across the 5 different idiosyncratic volatility groups. Abnormal return is the intercept of a regression where the dependent variable is the excess return of the security and the independent variable are the four-factor (three factors of Fama and French (1990) and the Carhart (1997) momentum factor. Lagged idiosyncratic volatility group is an integer 1-5, where 1 is the lowest quintile lagged idiosyncratic volatility group and 5 is the highest quintile idiosyncratic volatility group, where lagged idiosyncratic volatility is the standard deviation of the previous year's monthly excess return defined as the security return minus the value-weighted return. *, **, *** represent significant at 10%, 5%, %, respectively. All measures are on monthly basis.

Vol Group #	Observations	Mean Alpha	Mean Diff from 1	t stats	Mean idiosyncratic volatility Vol
1 Low	55,170	0.0174108			0.0359312
2	55,724	0.0347052	0.0172944	-6.3462***	0.0395853
3	54,871	0.0411996	0.0237888	-6.6289***	0.0602997
4	53,222	0.0294144	0.0120036	-2.4689**	0.0878582
5 High	51,408	-0.0714144	-0.0888252	13.4047***	0.1242467

Tables 4 provides t test results on two sample t test with equal variance. Simply speaking, we run the t test on lagged abnormal returns between the idiosyncratic volatilities of group 1 and other groups, thus, some basic statistics, like observation numbers, mean alpha, alpha volatilities on each group are provided.

In addition to the mean alpha of each group, the table provides the difference between the mean alpha of the group and that of group 1, as well as t statistics. For example, mean alpha in group 5 is about 8.8% lower compared to that in group 1, and t statistic of 13.40 show its significance of mean difference between group 1 and group 5. Therefore, we might create a long-short strategy based on that finding; to long group 1 and short group 5, then hold for an entire year ought to bring an 8.8% abnormal return to portfolio. (Peterson & Smedema, 2011) implements the same long-short strategy by long low-volatility tranche and short high-volatility tranche as a hedge tool, and create an overall positive return.

Table 5: Regression of idiosyncratic volatility predictive of next year's abnormal return
The table provides regression results where the dependent variables is the abnormal return of a security. Abnormal return is the intercept of a regression where the dependent variable is the excess return of the security and the independent variable are the four factor (three factors of Fama and French (1990) and the Carhart (1997) momentum factor. Lagged idiosyncratic volatility is the standard deviation of the previous year's monthly excess return defined as the security return minus the value-weighted return. Lagged idiosyncratic volatility group is an integer 1-5, where 1 is the lowest quintile lagged idiosyncratic volatility group and 5 is the highest quintile idiosyncratic volatility group. Errors are clustered at the firm level, and *, **, *** represent significant at 10%, 5%, %, respectively.

Variables	(1) Abnormal Return	(2) Abnormal Return	(3) Abnormal Return	(4) Abnormal Return
Lagged idiosyncratic volatility	-0.0392***	-0.0797***		
	(-26.47)	(-40.88)		
Lagged idiosyncratic volatility group			-0.0015***	-0.0029***
			(-14.33)	(-18.17)
Constant	0.0025	0.0099***	0.0038*	0.0115***
	(1.10)	(4.21)	(1.68)	(4.74)
Observations	270,395	270,395	270,395	270,395
R-squared	0.007	0.174	0.005	0.169
r2_a	0.00702	0.0854	0.00520	0.0804
Firm Fixed Effect	NO	YES	NO	YES
Year Fixed Effect	YES	YES	YES	YES

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

In the table 5, the dependent variable is the abnormal return (the intercept of the Four-factor mode). In the first two regressions, the independent variable is the one year lagged volatility and in the last two regressions the independent variable is the lagged idiosyncratic volatility groups. All regressions yield similar results, where a higher level of idiosyncratic volatility leads to a negative abnormal return next year.

Based on the correlation found above, we may consider selling stocks with a high idiosyncratic volatility this year, or buy stocks with a low idiosyncratic volatility this year.

Other paper tries to find the correlation between expected return and idiosyncratic risk. This is different from what we are testing. However, the tuition is the same. (Merton, 1987) has declared from his paper that expected return is always positive.

Table 6: Cross section of lagged idiosyncratic volatility effect in abnormal return
The table provides regression results where the dependent variables is the abnormal return of a security. Abnormal return is the intercept of a regression where the dependent variable is the excess return of the security and the independent variable are the four factors (three factors of Fama and French (1990) and the Carhart (1997) momentum factor. The independent variable in the regression is integer number, from 1 to 5. Errors are clustered at the firm level, and *, **, *** represent significant at 10%, 5%, %, respectively.

Abnormal Returns	Low Group1	Group2	Group3	Group4	High Group5
Lagged Idiosyncratic Volatility	0.0872***	-0.0157	-0.0150	-0.0474**	-0.0458***
	(2.65)	(-0.67)	(-0.52)	(-1.99)	(-7.24)
Constant	-0.0001	-0.0025	0.0028	0.0051*	0.0023
	(-0.06)	(-1.63)	(1.19)	(1.89)	(0.65)
Observations	55,170	55,724	54,871	53,222	51,408
R-squared	0.010	0.008	0.005	0.008	0.017
Adjusted	0.00858	0.00698	0.00449	0.00685S	0.0158
Year Fixed Effect	YES	YES	YES	YES	YES

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

Table 6 provides the abnormal returns across 5 groups, where group1 has the lowest volatility and group 5 has the highest volatilities. We run regression of abnormal returns for each lagged idiosyncratic volatility group, finding how the volatilities in each group are related to corresponding abnormal returns.

By this way, it can be observed that group 5 has a very significant result and group 1&group 4 also have a somewhat meaningful result according to their t-statistic value. The findings are consistent with our prior results in table 5. A higher level of lagged idiosyncratic volatility leads to a negative abnormal return; companies with the lower lagged idiosyncratic bring a significantly higher abnormal return.

To sum up, these results we discovers are somewhat reasonable. As many researches has concluded that in the same period that idiosyncratic volatility goes up, abnormal returns raise up as well. For instance, Peterson& Smedema (2011) shows us that expected returns have positive correlation with idiosyncratic risk. From the financial theory that phenomenon of return reverse, companies with large volatility are doing well in the current year has a likelihood that it will not be doing well in consecutive years, especially for small market capitalization and growth-sided company (Booth, Hng-Gay, & Leung, 2016). On the other hand, a stable and mature value-sided company might have a low volatility, these firms usually give a stable dividend pay-out while growing company's return is volatile and highly relied on price appreciation.

5.1 Results:

1. Only results of group 5 is strongly significant, and group 1& group 4 is somewhat significant.
2. Volatilities in group 1, 4 and 5 show a negative correlation with future abnormal return.
4. Group 1 has a positive largest coefficient while group 4&5 both has a negative largest coefficient.
5. Observations are large enough to determine.

Explanation:

1. High volatilities are deemed to have a higher abnormal return during same period.

2. High volatilities are usual in small and growth company. Low volatilities are usual in a mature and stable company: mature company gives a stable dividend pay-out while growing company's return is fluctuational and highly relied on price appreciation.

3. Many growth-side companies, such as biology and technology firms are founded on the list of group 5.

4. Fama French is not able to avoid the effect of size, leverage completely, since study using CAPM lead to an amplified result.

6. Conclusion

Our research is unprecedented, dedicating to demonstrate abnormal return with the respect to idiosyncratic volatility. We investigate the relationship between lagged idiosyncratic volatilities and abnormal returns. We demonstrate that lagged idiosyncratic volatilities are negatively correlated to the abnormal returns. In the separated tranches by the scale of volatilities, the high volatilities tranche reports low abnormal returns in the following year. We have used the lagged idiosyncratic risk method to measure monthly idiosyncratic volatility, and we also use Fama-French Four Factors Model to simulate abnormal return for accuracy. The tranches one, four, and five results are both economically and statistically significant, which supports our theory for under-diversification portfolios abnormal return.

7. Further Research

There are further researches and tests we can pursue to provide a more detailed and reliable theory for lagged idiosyncratic risk and abnormal returns.

Data Frequency: In (Aabo, Pantzalis, & Park, 2016), (Goyal & Pedro, 2003), (Khovansky & Zhylyevskyy, 2013), all studies employed data from daily abnormal returns to estimate idiosyncratic risk. Especially, (Goyal & Pedro, 2003) employed daily, weekly, and monthly data, and generated different results. When the data becomes more intensive, idiosyncratic risk also becomes more condense, since the daily data sample size becomes larger than monthly data size.

Divide more tranches: Another distinction we did in our research differs from others is the number of tranches. In (Boehme, Danielsen, & Sorescu, 2009), the idiosyncratic risk was divided into 10 equal number tranches, where every decile has a separate correlation between idiosyncratic risk and abnormal returns. Ten tranches present out a more clear and specific picture about the relationship between idiosyncratic risk and abnormal returns.

Selection for Benchmark: In our approach, we use the excess turn which is real return subtracts market return. We have been used the value-weighted market return. However, we could also use equally weighted market return to calculate idiosyncratic risk, in that way which we would have a smaller standard deviation, and we also would have a weaker correlation than the one we did.

Idiosyncratic risk estimation: Both for our simplicity and convenience, we use standard deviation of outperforming-market return as our idiosyncratic risk. That is not exactly the best measure for

idiosyncratic volatility, but it is good enough for our purpose. However, (Fu, 2008) Fu has implemented generalized autoregressive conditional heteroscedasticity to simulate volatility, which is a technique to solve time-varying volatility problems. GARCH is a great method for a long-time spanning, which we may use for comparison against other methods to measure idiosyncratic volatility. If we choose to use the daily data to generate monthly idiosyncratic volatilities, GARCH could be also a valuable method to simulate the volatilities.

Technology Companies in Tranche Five: As we have investigated, the tranche five, which has the highest volatility, has the lowest abnormal return in the following year. As we look at the group five specifically, we find that a lot of technology companies are located at tranche five, where the inherent risk is high. Investing in technology companies are high risk, high reward, and this is mainly because the inherent risk, and uncertainty of technology companies. Therefore, technology companies with high volatility are likely to do badly in the following year.

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