THE CROSS-SECTION OF EXPECTED STOCK RETURNS AND COMPONENTS OF IDIOSYNCRATIC VOLATILITY

by

Seyed Reza Tabatabaei Poudeh

MSc., Allameh Tabataba'i University, 2013
BSc., University of Isfahan, 2010

THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF SCIENCE
IN
BUSINESS ADMINISTRATION

UNIVERSITY OF NORTHERN BRITISH COLUMBIA

APRIL 2021

Abstract

We examine the relationship between stock returns and components of idiosyncratic volatility—two volatility and two covariance terms— derived from the decomposition of stock returns variance. The portfolio analysis result shows that volatility terms are negatively related to expected stock returns. On the contrary, covariance terms have positive relationships with expected stock returns at the portfolio level. These relationships are robust to controlling for risk factors such as size, book-to-market ratio, momentum, volume, and turnover. Furthermore, the results of Fama-MacBeth cross-sectional regression show that only alpha risk can explain variations in stock returns at the firm level. Another finding is that when volatility and covariance terms are excluded from idiosyncratic volatility, the relation between idiosyncratic volatility and stock returns becomes weak at the portfolio level and disappears at the firm level.

Keywords: idiosyncratic volatility, stock returns, time-varying alpha and betas, conditional model, stock returns volatility

Table of Contents

List of Tables

Glossary

Term	Definition
Additional components of idiosyncratic risk	Four additional terms included in idiosyncratic risk and resulted from the decomposition of total risk.
Alpha	The intercept in regression based on CAPM and FF-3 models.
Alpha Risk	The standard deviation of the time-varying alpha in one month, which is estimated from a regression of daily stock returns on the three Fama–French factors.
Beta Risk	The standard deviation of interaction between the time-varying component of beta and the respective FF-3 factors
Beta	The regression coefficient on risk factors (i.e., MKT, SMB, and HML.)
CAPM	The capital asset pricing model
Conditional FF-3	The conditional version of Fama-French three-factor model that incorporates instruments to account for time-varying property of alpha and betas.
Conditional_IVOL	Conditional idiosyncratic volatility is measured as the standard deviation of the regression residuals of daily stock returns in month t-1 based on the conditional FF-3 model.
FF-3	Fama-French three-factor model.

HML	High minus low" is the average return on the two value portfolios minus the average return on the two growth portfolios.
Instruments	Macroeconomic variables that affect the stock market (i.e., default spread, term spread, three-month t-bill rate, and dividend yield.)
MKT	The excess return on the market portfolio.
MPT	Modern portfolio theory.
SMB	"Small minus big" is the difference between the average returns on three small portfolios and the average returns of three big portfolios.
Time-varying beta	The beta consisted of constant and time-varying components conditional on macro-economic instruments.
Time-varying alpha	The alpha consisted of constant and time-varying components conditional on macro-economic instruments.
Unconditional FF-3	The conventional Fama-French three-factor model.
Unconditional_IVOL	Unconditional idiosyncratic volatility is measured as the standard deviation of the regression residuals of daily stock returns in month t-1 based on the unconditional FF-3 model.

Acknowledgment

I would like to express my deep and sincere gratitude to my co-supervisors, Dr. Chengbo Fu, and Dr. Jing Chen, for giving me the opportunity to research under their supervision. I would like to thank Dr. Chengbo Fu for giving me great support and valuable guidance all along the way of writing the thesis and also for providing me with RA opportunities. I want to thank Dr. Jing Chen for teaching me critical thinking and giving me profound insights about Finance. I want to thank my committee member Dr. Andy Wan for his constructive comments on this study, and external examiner, Dr. Waqar Haque, for his assessment of the thesis.

I want to thank Dr. Xin Ge, the chair of the MSc in Business Administration program, for her generous support and effective administration. I want to thank Dr. Reza Chowdhury for providing me with his invaluable advice and support during the time that he was my supervisor. I also thank all the faculty members of UNBC School of Business.

I want to thank Dr. Ali Saeedi, one of the best professors during my bachelor's studies at the University of Isfahan, for teaching me discipline and giving me the inspiration to continue my education.

I want to thank my mother, Zahra Tabatabaei, for all of her continuous support throughout my studies. She has always been the inspiration for believing in myself during hard times. I will never forget the sacrifices she made to raise me.

Dedication

I want to dedicate this thesis to my mother, who was there for me throughout all stages of my life. I would have never been able to achieve my educational goals without her unconditional love and support. I deeply love you, and I am always grateful for everything you have done for me.

This thesis is also dedicated to my amazing brothers, Ali Tabatabaei and Hossein Tabatabaei. I am enormously proud of you.

Chapter One:

Introduction

1.1 Background

The Modern Portfolio Theory (MPT) suggests that idiosyncratic risk is not priced in the equilibrium relationship between risk and expected returns (Markowitz, 1952). Although a long literature on asset pricing has studied the trade-off between risk and return based on MPT, it does not incorporate idiosyncratic risk into the models (e.g., Fama & French, 1993; Lintner, 1965; Sharpe, 1964). Several studies (e.g., Ang, Hodrick, Xing, & Zhang, 2006, 2009; Berrada & Hugonnier, 2013; Fu, 2009; Hai, Park, Tsai, & Eom, 2020; Nartea, Ward, & Yao, 2011; Spiegel & Wang, 2005; Xu & Malkiel, 2004) examined the relation between idiosyncratic risk and expected stock returns. However, these studies have not reached a consensus on this relationship. Sometimes, the relation between idiosyncratic risk and expected stock returns has been found to be positive (e.g., Fu, 2009; Nartea et al., 2011; Spiegel & Wang, 2005; Xu & Malkiel, 2004) and sometimes negative (e.g., Ang et al., 2006, 2009; Berrada & Hugonnier, 2013; Hai et al., 2020). Therefore, the inconclusive findings remain a puzzle called “Idiosyncratic Risk Puzzle.”

Two types of risk are associated with an asset investment: systematic and idiosyncratic risk. Idiosyncratic risk, also known as unsystematic risk, is a specific risk related to a particular asset such as a company’s stock. Systematic risk, by contrast, is inherent in the whole market and affects all the assets. Idiosyncratic risk can be mitigated through diversification. In contrast, systematic risk cannot be reduced by diversifying the investments.

Traditional asset pricing theories argue that idiosyncratic risk does not command a risk premium, so it is not priced. Modern portfolio theory suggests that investors should only be compensated for systematic risk in the equilibrium. Capital Asset Pricing Model (CAPM) (Lintner, 1965; Sharpe, 1964) suggest that only market risk as a systematic risk should be priced in the market, and investors do not receive a premium for bearing idiosyncratic risk. These explanations are based on the assumption that markets are complete and frictionless, and that investors can mitigate the idiosyncratic risk by having a well-diversified portfolio or the market portfolio. However, this assumption does not hold if some investors face constraints (e.g., liquidity needs, taxes) to hold the market portfolio. In this case, the remaining investors, i.e., the unconstrained investors, will also be incapable of holding the market portfolio because the total investment of both groups of investors makes up the whole market. Therefore, the inability to hold the market portfolio encourages investors to care about the total risk, including idiosyncratic risk, instead of only the market risk (Xu & Malkiel, 2004).

Xu and Malkiel (2004) argued that since investors cannot fully diversify their portfolio holdings, they expect to receive a premium for bearing idiosyncratic risk. Similarly, Merton (1987) argued that in an information-segmented market, under-diversified investors demand return compensation for holding stocks with higher idiosyncratic volatility as they assume a higher risk. Merton (1987) stated 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 idiosyncratic stocks.”

Therefore, Merton (1987) and Xu and Malkiel (2004) suggested that idiosyncratic volatility has a positive relationship with expected returns. This finding is contrary to the Modern Portfolio Theory, which does not predict a relation between idiosyncratic risks and expected stock returns. These findings are not the only surprising results from the existing literature. In a highly influential research, Ang et al. (2006) found a negative relation between idiosyncratic risk, as the standard deviation of the residuals from Fama and French (1993) model, and subsequent stock returns. This finding is puzzling and against the theories and studies that predicted no relation or positive relation between idiosyncratic volatility and expected returns. Ang et al. (2009) and Hou and Loh (2016) also confirmed this negative relationship.

Why do researchers not reach a consensus on the relationship between idiosyncratic risk and stock returns? Is it because of the deficiencies available in the asset pricing models? Merton (1987) stated that financial models (e.g., capital asset pricing models), which were developed based on the assumption that markets are frictionless and complete, are often inadequate to capture the complexity of rationality in action.

Empirical asset pricing still lacks a perfect model that captures all the dynamic patterns in stock returns. The Capital Asset Pricing Model (CAPM) (Black, 1972; Sharpe, 1964) is known as the backbone of the Modern Portfolio Theory. However, its pre-eminence has been challenged by studies that identified deficiencies in CAPM. A major deficiency in CAPM is that it does not include two important stock return predictors, i.e., market capitalization and book-to-market ratio (see, for example, Banz (1981), Chan, Hamao, and Lakonishok (1991), and Fama and French (1992), among others). In an effort to correct this deficiency, Fama and French (1993, 1995) recommended a three-factor model (hereafter FF-3) that includes a market factor and two risk factors related to size and book-to-market ratio.

While many studies have adopted the unconditional form of CAPM and FF-3 model, some researches (e.g., Ferson & Harvey, 1999; Jagannathan & Wang, 1998; Lettau & Ludvigson, 2001) used conditional models to predict future stock returns. These studies incorporated economy-wide instruments to develop conditional asset pricing models and showed that a conditional model performs better compared to an unconditional model. Ferson and Harvey (1999) found that the lagged instrumental variables capture variation in expected stock returns that is not explained by the FF-3 model. Ferson and Harvey (1999) modeled alpha and beta as linear functions of the lagged instrumental variables and showed that based on the lagged instruments, alpha and betas on the FF-3 factors are time-varying. Furthermore, Ferson and Harvey (1999) found that when a conditional FF-3 model controls for the time-varying property of alpha and betas, it is more efficient as compared to the unconditional FF-3 model in capturing dynamic patterns of the expected returns. Similarly, Avramov and Chordia (2006) adopted an optimal portfolio strategy and showed that the time-varying property of alpha provides improvements in the predictive power of the conditional models.

There is a vast amount of literature that finds positive or negative relationships between idiosyncratic volatility and expected stock returns. For example, Xu and Malkiel (2004) demonstrated a positive relation, and Ang et al. (2006) and Hou and Loh (2016) showed a negative relation between idiosyncratic risk and expected stock returns. These studies adopt an unconditional FF-3 model to estimate the idiosyncratic volatility. Ferson and

Harvey (1999) argued that the unconditional FF-3 model fails to account for the time-varying property of alpha and betas. When the time-varying property of these parameters is not incorporated into the model, some systematic patterns of expected stock returns will be included in the regression residuals. Since idiosyncratic volatility is estimated as the standard deviation of the residuals from the FF-3 model, it contains some components that exhibit dynamic patterns in predicting stock returns. Therefore, the estimated idiosyncratic risk is not completely idiosyncratic, and the negative relation between idiosyncratic volatility and expected stock returns might be misleading (Fu, 2018). Thus, using a conditional model can assist in estimating a more accurate idiosyncratic risk with fewer systematic patterns.

While a large number of studies have examined the relationship between variance and return (e.g., Bollerslev, Tauchen, & Zhou, 2009; Braun, Nelson, & Sunier, 1995; Campbell & Hentschel, 1992; Carr & Wu, 2009; Dennis, Mayhew, & Stivers, 2009; Duffee, 1995; French, Schwert, & Stambaugh, 1987; Glosten, Jagannathan, & Runkle, 1993), few studies have investigated this relation through idiosyncratic risk components (e.g., Fu, 2018).

Using the conditional FF-3 model developed by Ferson and Harvey (1999), Fu (2018) decomposed total risk based on a conditional FF-3 model, in which constant alpha and beta are replaced with time-varying alpha and betas, and found that four additional terms are embedded in the idiosyncratic risk estimated using an unconditional FF-3 model. These components are categorized into two volatility terms, the variance of alpha (alpha risk) and the variance of the interaction between the time-varying component of beta and its respective factors (beta risk), and two covariance terms. Fu (2018) examined the relationship between alpha-beta risk and future stock returns at both the portfolio and firm levels. He found that alpha risk can predict average stock returns at both the portfolio and individual firm levels.

Besides, using the cross-sectional model of Fama and MacBeth (1973), Fu (2018) found that the return predictability power of alpha risk is not influenced by idiosyncratic risk, instrumental variables, or the time-varying alpha. However, beta risk (volatility of betas) fails to predict returns in general. These findings suggest that alpha risk may lead to the negative impact of idiosyncratic volatility on average stock returns. However, Fu (2018) did not examine whether the alpha risk can explain the negative relationship between idiosyncratic risk and future stock returns.

While Fu (2018) examined the relationship between volatility terms (alpha risk and beta risk) and subsequent stock returns for equal-weighted portfolios, we investigate the relationship between all additional components of idiosyncratic risk and subsequent stock returns. This thesis aims to answer the following questions research questions:

1) Is there any relationship between additional components of idiosyncratic risk and expected stock returns for equal-weighted and value-weighted portfolios?
2) Is there any relationship between additional components of idiosyncratic risk and expected stock returns at the firm level?
3) Do all the four additional components explain all the systematic patterns included in the unconditional idiosyncratic risk?

1.2 Motivation for the Thesis

Contrary to the Modern Portfolio Theory and the CAPM model (Lintner, 1965; Markowitz, 1952; Sharpe, 1964) that argue idiosyncratic risk is not priced, some influential studies (Goyal & Santa-Clara, 2003; Xu & Malkiel, 2004) argue that investors should be compensated for holding imperfect diversified portfolios because they are bearing idiosyncratic risk due to the inability to hold the market portfolio. Motivated by the fact that there is a lack of diversification and that undiversified investors impact the market, Goyal and Santa-Clara (2003) measured average stock variance as a total risk, including idiosyncratic risk, rather than only systematic risk. They found a significant positive relation between average stock variance and the return on the market. They also found that it is the idiosyncratic component that causes the most variations in the average stock variance (approximately 80% of the total risk variance) in the explanation of market returns. Therefore, idiosyncratic matters to investors and should be priced in the market. However, studies that examine the relationship between idiosyncratic risk and expected stock returns yield inconclusive results; some of them suggest a positive relationship and another group of studies find a negative relationship between idiosyncratic risk and stock returns. These findings remain a puzzle in the literature. Moreover, studies have been conducted to explain the puzzle by searching for economic mechanisms that explain the relationship between idiosyncratic risks and expected stock returns. In a comprehensive study, Hou and Loh (2016) evaluated many explanations for the negative relationship between idiosyncratic risk and subsequent stock returns; however, they found that all the available explanations in the literature explained 29-54% of the puzzle in individual stock and 78-84% of the puzzle in the portfolio level. This shows that there is still a gap in the literature for finding new mechanisms that can explain the linkage between idiosyncratic risk and subsequent stock returns. To bridge this gap, this research will examine whether additional components of idiosyncratic risk decomposed by Fu (2018) can explain the negative relationship between idiosyncratic risk and subsequent stock returns.

1.3 Significant of this Thesis

Several studies examined the relationship between idiosyncratic risk and subsequent stock returns using the unconditional FF-3 and CAPM models. These studies measure idiosyncratic risk as the standard deviation of residuals from FF-3 and the CAPM model. Since these models do not include time-varying alpha and betas, which are components that can predict stock returns, they may fail to account for some systematic patterns in predicting stock returns. As a result, these systematic patterns can be incorporated into idiosyncratic risk. Therefore, idiosyncratic volatility relative to the FF-3 model might be misleading because the idiosyncratic risk is not purely idiosyncratic. Based on the study of Fu (2018), this research applies a conditional approach for decomposing risk and deriving four additional terms from unconditional idiosyncratic risk.

This research provides important contributions to the idiosyncratic risk and stock predictability literature by employing the conditional approach. The significant contributions of this research are as follows:

1. Following Fu's (2018) approach for decomposition of risk based on the conditional FF-3 model, we examine the relationship between all the additional components included in idiosyncratic risk, which is estimated using the residuals from the FF-3 model, and subsequent stock returns for both equal-weighted and value-weighted portfolio. We will also examine the same relationships at the firm level. Fu (2018) investigated the relation between the two volatility components (alpha and beta risk)

and stock returns for equal-weighted portfolios. However, no study has examined the predictive power of the two covariance terms for stock return prediction. In this way, the thesis contributes to the stock return predictability literature and idiosyncratic risk literature by providing evidence about what additional terms can predict stock returns.

2. Another contribution of this thesis is that it examines whether additional terms can explain the negative relationship between idiosyncratic risk and subsequent stock returns. In order to solve the idiosyncratic puzzle, numerous studies have suggested different economic mechanisms to relate idiosyncratic risk to subsequent stock returns; however, many mechanisms explain less than 10% of this relationship. All existing mechanisms explain only 29-54% of the idiosyncratic puzzle in individual stocks and 78-84% of the puzzle in the portfolio level in the literature (Hou & Loh, 2016). Therefore, this thesis adds to the literature by examining whether the additional terms can explain the relationship between idiosyncratic risk and subsequent stock returns.
3. Fu (2018) suggested that there are systematic patterns in idiosyncratic risk that negatively affect expected stock returns. In this study, we examined whether there is a relationship between idiosyncratic risk, which is estimated using an unconditional model, and expected stock returns. If this relation is derived by the additional idiosyncratic components representing systematic patterns in predicting stock returns, then excluding these components from idiosyncratic volatility should break or at least lessen the link between idiosyncratic risk and expected stock return. The result contributes to asset pricing literature by suggesting which model, whether conditional or unconditional models, is more efficient in explaining systematic patterns for predicting stock returns and estimating the pure idiosyncratic risk.

Chapter Two:

Literature Review

This chapter reviews relevant literature on the relationship between idiosyncratic volatility and expected stock returns at both the market and firm levels. This chapter is organized as follows: Section 2.1 describes earlier research on the relationship between idiosyncratic volatility and expected market returns; it summarizes the key findings on the direction and magnitude of this relationship. Section 2.2 focuses on the relationship between idiosyncratic volatility and expected stock returns.

2.1 Idiosyncratic Volatility and Expected Market Returns

Although several studies have examined the relationship between idiosyncratic volatility and expected market returns, they have not reached a consensus on the sign and significance of this relationship. Goyal and Santa-Clara (2003) and Jiang and Lee (2006) found a positive relationship, while Guo and Savickas (2006) found a negative relationship between idiosyncratic volatility and expected market returns.

Goyal and Santa-Clara (2003) argued that since investors are not usually well-diversified and have to bear the idiosyncratic risk to some extent, the relevant measure of risk should be the total risk instead of only systematic risk. They measured average stock risk on a monthly basis by calculating the average variance of individual stocks that are traded within a month. This measure of risk includes both idiosyncratic risk and systematic risk. Goyal and Santa-Clara (2003) used daily data from the Center for Research in Security Prices (CRSP) database for the sample period of 1963 to 1999 and found a positive relationship between equal-weighted average stock variance and the value-weighted market returns.

Goyal and Santa-Clara (2003) showed that 84% of the variation of the average stock variance is associated with the variation of the idiosyncratic component. Thus, they concluded that idiosyncratic risk is the dominant factor that determines the positive relationship between average stock variance and market returns.

While Goyal and Santa-Clara (2003) discovered a positive relationship between idiosyncratic volatility and market returns, Bali, Cakici, Yan, and Zhang (2005), Wei and Zhang (2005), Guo and Savickas (2006), and Brockman and Yan (2008) found that the positive relationship documented by Goyal and Santa-Clara (2003) disappears when an extended sample is used. Brockman and Yan (2008) used a 37-year sample from 1926 to 1962 and found that the relationship between idiosyncratic volatility and the future market return is insignificant.

Guo and Savickas (2006) found that the relationship between idiosyncratic volatility and the conditional excess market return is significantly negative. They estimate idiosyncratic volatility at a quarterly basis and argued that idiosyncratic volatility is more precisely measured at this frequency than on a monthly basis as used by Goyal and Santa-Clara (2003).

2.2 Idiosyncratic Volatility and Expected Stock Returns

Many studies have examined the relationship between idiosyncratic volatility and expected stock returns at the firm level. However, the results of these studies are mixed. A group of studies found a negative relationship between idiosyncratic volatility and expected stock returns (e.g., Ang et al., 2006, 2009; Berrada & Hugonnier, 2013; Brockman & Yan, 2008; Cao & Han, 2013; Duan, Hu, & McLean, 2010; Guo & Savickas, 2006, 2010; Hai et al., 2020). Another group of studies found a positive relationship (e.g., Fu, 2009; Nartea et al., 2011; Spiegel & Wang, 2005; Xu & Malkiel, 2004), and some other studies found no significant relationship between idiosyncratic risk and expected stock returns (e.g., Bali & Cakici, 2009; Berggrun, Lizarzaburu, & Cardona, 2016; Black, 1972; Fama & MacBeth, 1973; Jiang, Xu, & Yao, 2009; Lintner, 1965; Sharpe, 1964). Finally, some studies (e.g., Cao & Han, 2016; Khovansky & Zhylyevskyy, 2013) found both positive and negative relationships between idiosyncratic volatility and expected stock returns under certain circumstances.

2.2.1 Negative Relationship between Idiosyncratic Volatility and Expected Stock Returns

In a highly influential study, Ang et al. (2006) found a negative relationship between subsequent average stock returns and idiosyncratic volatility relative to the Fama and French (1993) model. In this research, they mostly used 1/0/1 portfolio formation strategy. They formed value-weighted quintile portfolios by sorting stocks on idiosyncratic volatility, which is defined as the standard deviation of residuals calculated using daily returns in the previous month. They hold these portfolios for one month and then rebalanced them on a monthly basis. Using a sample that includes all stocks on AMEX, NASDAQ and NYSE from July 1963 to December 2000, Ang et al. (2006) found that the difference in raw average returns between the quintiles with the highest and the lowest idiosyncratic volatility is about -1.06% per month. They also found that the difference in the FF-3 alphas between the highest and the lowest idiosyncratic volatility is -1.19% per month. This result shows that the FF-3 model cannot price the portfolios formed on idiosyncratic volatility. They performed series of robustness tests to examine whether these results hold after controlling for important cross-sectional effects such as size, book-to-market, leverage, liquidity, volume, turnover, bid-ask spreads, co-skewness, or dispersion in analysts' forecasts characteristics. They found that those attributes cannot explain the low average returns of stocks with high idiosyncratic volatility. They also found that the negative relationship between average stock returns and idiosyncratic volatility is still robust to different sub-periods (NBER recessions and expansions, volatile and stable period), different portfolio formation strategies, and various holding periods up to one year.

These results are against some economic theories that suggest a positive relationship between idiosyncratic volatility and expected returns (e.g., Merton, 1987; Xu & Malkiel, 2004). These theories state that when investors cannot diversify risk, they demand compensation for holding stocks with high idiosyncratic volatility. Some other earlier studies either found no relationship or positive relationship between idiosyncratic volatility and average returns (Lehmann, 1990; Lintner, 1965). Tinic and West (1986) and Xu and Malkiel (2004) argued that portfolios with higher idiosyncratic risk have higher average returns but did not present any significance level for their findings.

Ang et al. (2006) argued that the difference between their results and the results of earlier research is that those earlier studies did not examine idiosyncratic risk at the firm level or did not directly form portfolios by sorting stocks based on idiosyncratic volatility. As a result, earlier studies failed to find the negative relationship between average returns and idiosyncratic volatility. For example, Tinic and West (1986) and Xu and Malkiel (2004) formed a limited number of portfolios by sorting stocks on market beta and size. Moreover, Xu and Malkiel (2004) assigned idiosyncratic volatility of each of the 100 beta and size portfolios to all the stocks included in that particular portfolio, instead of using the idiosyncratic volatility of each stock.

Ang et al. (2006) examined whether aggregate volatility can explain the negative relationship between expected stock returns and idiosyncratic volatility. They found that stocks with higher sensitivity to aggregate volatility have low average returns. Therefore, the reason behind the negative average returns of stocks with high idiosyncratic risk might be that these stocks have higher exposure to aggregate volatility (Ang et al., 2006). After controlling for exposure to aggregate volatility, Ang et al. (2006) found that aggregate volatility partially explains the low returns of stocks with high idiosyncratic risk. Therefore, the negative relationship between lagged idiosyncratic risk and average returns of stocks remains a puzzle.

Since the findings of Ang et al. (2006) might be related to the specific small sample (U.S. stocks), Ang et al. (2009) examined the cross-sectional relationship between lagged idiosyncratic volatility and subsequent stock returns in a large sample of 27 developed markets, including seven (G7) markets (Canada, France, Germany, Italy, Japan, the United States, and the United Kingdom). They found that the negative relationship between idiosyncratic volatility and average returns is strongly significant in each of the (G7) markets and also in the broad sample of 27 developed markets; the difference in average return between portfolio and highest and lowest idiosyncratic risk is -1.31% per month. Thus, Ang et al. (2009) provided evidence that the small sample used by Ang et al. (2006) cannot explain the negative relationship between idiosyncratic volatility and average return.

Several studies find a similar negative relationship between idiosyncratic volatility and stock returns. Guo and Savickas (2006) used quarterly data over the sample period 1963:Q4-2002:Q4 to measure weighted-value idiosyncratic volatility. They found that idiosyncratic volatility is negatively related to future stock returns in the in-sample and out-of-sample tests. Guo and Savickas (2006) argued that idiosyncratic volatility is a macro variable that can capture systematic patterns of stock returns.

Using the CRSP database for the period of January 1926 to June 1962, Brockman and Yan (2008) found a negative and significant relationship between idiosyncratic volatility and subsequent stock returns by adopting a portfolio strategy and cross-sectional regression framework. While Ang et al. (2006) found this negative relation using the sample from July 1963 to December 2000, Brockman and Yan (2008) found the same relationship in the period prior to 1962. Therefore, the negative relationship documented by Ang et al. (2006) is not as a result of data snooping. Moreover, Brockman and Yan (2008) showed that their results are robust for different control variables, including size, turnover, share price, percent of zero returns, liquidity measure, and returns in the previous month.

In another study, Guo and Savickas (2010) replicated Ang et al.'s (2006) method of forming quintile portfolios sorted by CAPM-based idiosyncratic volatility and tested the relationship between idiosyncratic volatility and expected returns by using both a pre-1962 dataset from CRSP and modern G7 data. They found that the relationship between idiosyncratic volatility and expected returns are negative in different sample periods— that is, the extended sample period of period 1926-2005, modern sample over the period 1964-2005, and pre-1962 sample over period 1925-1963 for the U.S. and the period between January 1973 and December 2003 for G7 countries. Guo and Savickas (2010) found that the negative relationship between idiosyncratic volatility and expected stock returns holds for different periods and different countries. This finding shows that the negative effect of idiosyncratic volatility on expected returns, which is first documented by Ang et al. (2006), cannot be attributed to data snooping. Besides, similar to Ang et al. (2009), they showed that the negative idiosyncratic volatility effect is a universal phenomenon.

2.2.1.1 Different Explanations Suggested by the Literature

Many studies suggest different explanations for the relationship between idiosyncratic volatility and expected stock returns. Examples of the explanations are microstructure effect, private information, transaction cost, information dissemination (incomplete information, delay, and institutional ownership), lottery preferences of investors (skewness), leverage, higher moments, short interest, and arbitrage cost.

2.2.1.1.1 Market Microstructure Effect

Chen, Jiang, Xu, and Yao (2012) examined the robustness of the negative relationship between lagged idiosyncratic risk and future stock returns, which is documented by Ang et al. (2006), with different subsamples. They used the CRSP database for the sample period of 1963-2010 and created different subsamples based on the following criteria: 1) common stocks vs. non-common stocks, 2) firm size, and 3) stock price. Chen et al. (2012) found that the negative relationship between idiosyncratic volatility and expected stock returns still holds after controlling for all three criteria.

Chen et al. (2012) examined whether the idiosyncratic puzzle is robust to common stock and non-common stocks. They found that for the whole stock sample and the common stock sample, the difference in stock returns between the deciles with the highest and lowest idiosyncratic volatility is significantly negative for value-weighted (VW) portfolios and insignificant for equal-weighted (EW) portfolios. However, they found that for non-common stock samples, this relation is neither significant for VW nor EW portfolios. Next, they divided the stocks into two sub-samples of microcaps: small and big stocks to control for the firm size attribute. They also created sub-samples based on stock price: stocks higher than $10, stocks with price between $5 and $10, and stocks less than $5 (namely penny stocks). Chen et al. (2012) showed that for small and big stock sub-samples and the sub-sample of stocks less than $5, differences in returns between the deciles with the highest and lowest idiosyncratic volatility is significantly negative for both VW and EW portfolios. However, in microcaps and penny stocks sub-samples, those differentials are significant only for VW portfolios. Furthermore, Chen et al. (2012) estimated alpha by adopting Carhart's (1997) four-factor model and found that alpha confirms the above-mentioned negative relationship. These findings show that the idiosyncratic puzzle is not related to the market microstructure effect.

2.2.1.1.2 Control for Private Information

Easley and O'Hara (2004) argued that stocks with more private information have higher expected returns. Thus, stocks with a low (high) level of idiosyncratic volatility might have high (low) amounts of private information in their trades, and consequently, higher (lower) returns. Ang et al. (2009) controlled for a private information measure and found that this variable is not significant and the negative relationship between idiosyncratic volatility and stock returns still holds.

2.2.1.1.3 Control for Transaction Cost

Ang et al. (2009) also controlled for the effect of transaction cost using a measure suggested by Lesmond, Ogden, and Trzcinka (1999) and calculated it using the proportion of daily returns equal to zero. Ang et al. (2009) found that transaction cost is not significant, and it does not influence the relationship between idiosyncratic risk and return.

2.2.1.1.4 Control for Information Dissemination

Ang et al. (2009) examined whether information dissemination is an explanation for the negative relationship between idiosyncratic volatility and expected stock returns. Hou and Moskowitz (2005) argued that investors prefer stocks with fast information dissemination. They demand a higher return as a compensation for holding stocks with slow dissemination of information, as these stocks slowly reflect new information in their prices. Ang et al. (2009) hypothesized that stocks with low idiosyncratic risk are characterized by fast information dissemination; therefore, these stocks tend to have high average returns. However, they found that there is still a negative relationship between lagged idiosyncratic risk and expected stock, even after controlling for information dissemination. Therefore, information dissemination cannot explain the negative relation.

2.2.1.1.5 Lottery Preferences of Investors (Skewness)

Ang et al. (2009) also examined skewness as an explanation to the relationship between idiosyncratic volatility and stock returns. Barberis and Huang (2008) argued that under the cumulative prospect theory preference of Tversky and Kahneman (1992), skewness of stock returns might be priced. The reason is that when investors tend to buy positively skewed stocks, these stocks become overpriced and earn low future returns. If stocks with high idiosyncratic volatility are positively skewed, then the negative relationship between skewness and stock returns can explain the negative relationship between idiosyncratic volatility and stock return (Ang et al., 2009). However, Ang et al. (2009) found that the coefficient of skewness is not significant; therefore, it cannot explain the relationship between idiosyncratic volatility and stock returns.

2.2.1.1.6 High Short Interest Stocks and Arbitrage Cost

Duan et al. (2010) studied the relationship between idiosyncratic volatility and subsequent returns among high short interest stocks. They argued that stocks with high idiosyncratic risk have higher arbitrage costs, which prevents short sellers from easily arbitraging. They found that the relationship between lagged idiosyncratic risk and subsequent stock return is negative among high short interest stocks; when idiosyncratic volatility increases by one standard deviation, returns of subsequent months decrease by more than 1%. However, high short interest stocks with low idiosyncratic volatility cannot predict stock returns.

2.2.1.2 Idiosyncratic volatility and delta-hedged option returns

Cao and Han (2013) examined the effect of idiosyncratic volatility on subsequent returns of delta-hedged options. Using a sample of equity options from January 1996 to October 2009, Cao and Han (2013) found that the relationship between delta-hedged equity option return and idiosyncratic volatility of the underlying stocks are significant and negative. Options on stocks with high idiosyncratic volatility are more attractive, but harder to hedge; therefore, financial intermediaries demand higher compensation for selling such options. Consequently, the price of options on high idiosyncratic volatility stocks is higher, but the return of such options are lower (Cao & Han, 2013).

Majority of studies that find a negative relationship between lagged idiosyncratic and future stock returns employ the unconditional Fama-French three-factor model to estimate idiosyncratic volatility. Fu (2018) argued that the negative effect of idiosyncratic volatility on expected stock returns might be misleading because unconditional models do not incorporate the time-varying property of alpha and beta parameters into the model. Therefore, estimates of idiosyncratic volatility might include factors that can be proxies of systematic risk in predicting stock returns (Fu, 2018). Using a conditional FF-3 model, (Fu, 2018) decomposed total risk and found four additional components embedded in idiosyncratic risk. These additional terms are: the variance of alpha (alpha risk), the variance of the interaction between the time-varying component of beta and its respective factors (beta risk), and two covariance terms. Using a portfolio analysis and Fama-MacBeth's (1973) approach, Fu (2018) examined the relationship between lagged alpha and beta risk and future stock returns. He found that there is a significant and negative relationship between alpha risk and average stock returns. The return differential between portfolio with highest alpha risk and those with lowest alpha risk is -0.32% based on a long-short trading strategy. This negative relationship exists between beta risk and average stock returns, but it is less significant. Fu (2018) also examined the cross-sectional relationship between alpha risk and expected stock returns and found that this relationship is negative, even after controlling for idiosyncratic volatility, macroeconomic variables, and time-varying alpha itself. These findings imply that alpha and beta risks may drive the negative impact of idiosyncratic volatility on average stock returns. However, Fu (2018) did not examine the relation between covariance terms and subsequent stock returns.

2.2.2 No Significant Relationship between Idiosyncratic Volatility and Expected Stock Returns

Some studies find no significant relationship between idiosyncratic volatility and expected stock returns. For example, some studies have examined the relationship by controlling future earning shocks, the MAX effect, and using different schemes and samples

2.2.2.1 Future Earning Shocks and Information Disclosure

Jiang et al. (2009) found that the negative relationship between idiosyncratic volatility and expected stock returns is associated with the negative effect of future earning shocks on idiosyncratic volatility. They estimated idiosyncratic volatility for individual stocks quarterly from a sample of January 1974 to December 2002 by adopting the FF-3 model and using daily returns from the CRSP database. They found that the negative relationship between idiosyncratic volatility and subsequent stock returns becomes insignificant after controlling for future earning shocks.

2.2.2.2 Max Effect

Bali, Cakici, and Whitelaw (2011) examined whether the MAX effect, which is the extreme positive returns in the previous month, can explain the idiosyncratic puzzle. They found that the negative relationship between idiosyncratic volatility and subsequent stock returns disappeared after controlling for MAX in the U.S. market.

2.2.2.3 Different Schemes and Samples

Bali and Cakici (2009) examined the relationship between idiosyncratic volatility and expected stock returns in different settings. They created portfolios based on three weighting schemes (value-weighted, equal-weighted, and inverse volatility-weighted), two samples (CRSP and NYSE), and three different breakpoints (CRSP, NYSE, equal market share). They first replicated Ang et al. (2006) portfolio analysis by using the value-weighted scheme, CRSP breakpoint, and CRSP database for the sample period of July 1963 to December 2004. Bali and Cakici (2009) found a negative relationship between idiosyncratic volatility and expected stock; this study was consistent with the findings of Ang et al. (2006). However, when Bali and Cakici (2009) repeated the same analysis based on other combinations of different weighting schemes, samples, and breakpoints, they did not find a significant relationship between idiosyncratic volatility and future stock returns.

Berggrun et al. (2016) examined the relationship between idiosyncratic volatility and subsequent stock returns in the Mercado Integrado Latinoamericano[1] (MILA) over the period from 2001 to 2014 and did not find a significant relationship. Moreover, after controlling for size, book-to-market, past return, and liquidity effects, they did not find a statistically significant relationship between realized idiosyncratic volatility and expected stock returns.

2.2.3 Positive Relation between Idiosyncratic Volatility and Expected Stock Returns

Some studies found a positive relationship between idiosyncratic volatility and expected stock returns (e.g., Fu, 2009; Huang, Liu, Rhee, & Zhang, 2009; Nartea et al., 2011; Spiegel & Wang, 2005; Xu & Malkiel, 2004). These findings are consistent with Merton (1987) who explained that investors are compensated for bearing an additional risk such as idiosyncratic risk.

Using the CRSP database, Xu and Malkiel (2004) found a positive relationship between idiosyncratic volatility and expected stock returns under both the Fama and MacBeth (1973) and Fama and French (1993) testing frameworks. They also examined this relationship in the Japanese stock market and found that idiosyncratic volatility can explain cross-sectional stock returns. Therefore, data snooping is not the reason behind their findings. Furthermore, Xu and Malkiel (2004) controlled for size, book-to-market, and liquidity and found that the coefficient of idiosyncratic volatility is still positive and significant.

[1] Latin American Integrated Market

This finding is contrary to the CAPM approach, which argues that only systematic risk can explain the variations in stock returns, and investors should only be compensated for systematic risk. This approach is correct when investors can eliminate idiosyncratic risk by diversification in a frictionless market. However, investors cannot hold the market portfolio due to transaction costs, incomplete information, and institutional constraints such as taxes and liquidity need (Xu & Malkiel, 2004). When investors are unable to maintain a well-diversified portfolio, they cannot eliminate the idiosyncratic risk; so, they have to consider total risk rather than only systematic risk. Hence, idiosyncratic risk is incorporated into the stock price and commands a risk premium in the market (Xu & Malkiel, 2004).

Spiegel and Wang (2005) examined the effects of idiosyncratic volatility and liquidity on stock returns. Using CRSP monthly stock returns over the period from January 1962 to December 2003, they measured conditional idiosyncratic volatility based on FF-3 and EGARCH model. They argued that when expected idiosyncratic volatility is estimated based on EGARCH model, it can capture time variation in stock variance better than the static OLS model. Spiegel and Wang (2005) found that stock returns have a positive relationship with idiosyncratic volatility but are negatively related to the level of stock liquidity. They also examined whether liquidity explains the positive relationship between idiosyncratic volatility and stock returns. Spiegel and Wang (2005) demonstrated that the predictive power of idiosyncratic volatility remains after controlling for liquidity.

Fu (2009) examined the relationship between idiosyncratic volatility and expected stock returns. Fu (2009) showed that the autocorrelation of idiosyncratic risk in his sample is 0.33. Thus, idiosyncratic volatilities vary over time and the one-month lagged idiosyncratic volatility which is used by Ang et al. (2006) cannot be an appropriate proxy for the idiosyncratic volatility of the month. Furthermore, the relationship between idiosyncratic risk and stock returns should be examined by contemporaneous idiosyncratic volatility and stock returns (Fu, 2009). Using monthly stock returns data from the CRSP database, Fu (2009) estimated expected idiosyncratic volatility by employing exponential generalized autoregressive conditional heteroscedasticity (EGARCH) models.

First, Fu (2009) performed a Fama-MacBeth regression analysis of monthly stock returns on the idiosyncratic volatility, which is estimated by the EGARCH model, and found a significant positive relationship between idiosyncratic volatility and expected stock returns. He demonstrated that stocks with higher idiosyncratic volatility have higher stock returns on average of about 1% in a month. Besides, he tested the relationship using a zero-investment portfolio and found that the average return differential between stocks with high and low idiosyncratic volatility is positive (about 1.75% in a month). Furthermore, Fu (2009) argued that the negative relationship between idiosyncratic volatility and expected returns documented by Ang et al. (2006) is mostly explained by return reversal of stocks with a high level of idiosyncratic volatility. Fu (2009) found that stocks with high idiosyncratic risk have high contemporaneous returns. This positive return tends to become negative in the next month due to the return reversal effect. Fu (2009) found that after controlling for the return reversal effect, the negative relationship between lagged idiosyncratic risk and average stock returns disappeared.

Huang et al. (2009) used daily and monthly data from the CRSP database between July 1963 to December 2004 to estimate the conditional idiosyncratic volatility. This estimation was based on an exponential GARCH (EGARCH) model using monthly returns. Using this idiosyncratic volatility measure, they found that the relationship between idiosyncratic volatility and expected returns is positive and significant. Furthermore, they showed that these findings are repeated when different asset pricing models, sub-samples, and firm characteristics are adopted (e.g., momentum, liquidity, and leverage).

Nartea et al. (2011) examined the effect of idiosyncratic risk in ASEAN markets of Malaysia, Singapore, Thailand, Indonesia, and the Philippines. They followed Ang et al.'s (2006) method to form portfolios and calculate realized idiosyncratic volatility for the past month. Using data from pooled samples of those five Asian countries, Nartea et al. (2011) found a positive and significant relationship between lagged idiosyncratic volatility and expected stock returns. They also performed an in-country analysis and found a positive relationship in the stock markets of all of those Asian countries except the Philippines.

Although Nartea et al. (2011) replicated the analysis of Ang et al. (2006; 2009) analysis, they found contrary results to the negative relation documented by Ang et al.'s (2006; 2009). They argued that the reason for this inconsistency is that Ang et al. (2009) did not perform analysis specifically for emerging Asian markets when they tested the idiosyncratic volatility effect in developed markets.

2.2.4 Dual Relations between Idiosyncratic Volatility and Expected Stock Returns

Cao and Han (2016) examined the relationship between idiosyncratic risk and expected stock returns under the theory of costly arbitrage. Using U.S. stock market data (available in CRSP) between July 1963 and December 2006, they forecasted an idiosyncratic volatility by employing the EGARCH model. They found that the cross-sectional relationship between idiosyncratic risk and expected returns is determined by the direction of mispricing; among overvalued (undervalued) stocks, average stock returns decrease (increase) with idiosyncratic risk. They found no relationship when stocks are fairly priced.

According to the theory of costly arbitrage, mispricing is not completely eliminated when arbitration is costly, and a greater amount of mispricing exists in stocks with higher arbitration costs (transaction costs and holding costs). In some studies, idiosyncratic risk is known as a holding cost (see Pontiff, 2006). Idiosyncratic risk as an arbitrage cost restricts the ability of investors to short sell overvalued stocks and buy undervalued stocks. When stocks with a higher level of idiosyncratic risk are undervalued, arbitragers require higher returns to buy these stocks to compensate them for the higher arbitrage cost than stocks with low idiosyncratic risk (Cao & Han, 2016). Therefore, when stocks are undervalued, expected returns increase monotonically with the level of idiosyncratic risk. However, when stocks with high idiosyncratic risk are overvalued, expected returns decrease with the level of idiosyncratic risk (Cao & Han, 2016).

Khovansky and Zhylyevskyy (2013) examined the relationship between idiosyncratic volatility and expected stock returns using the Generalized Method of Moments (GMM) method. Using a sample of U.S. stock return data over the period of 2000 to 2011, they measured idiosyncratic volatility and estimated the idiosyncratic risk premium using stock returns from different holding periods (daily, weekly, monthly, quarterly, and annually). Khovansky and Zhylyevskyy (2013) found a positive and significant relationship between idiosyncratic volatility and expected stock returns by using daily return data. However, they found a negative and significant premium when using monthly, quarterly, and annual data. In addition, using weekly return data, they found a negative but insignificant idiosyncratic volatility premium. These different results show that different estimates of idiosyncratic volatility premium lead to different results for the relationship between idiosyncratic volatility and expected stock returns.

Chapter Three:

Data and Methodology

This chapter discusses the data, methodology, measurement of key variables, portfolio analysis, and the Fama-MacBeth cross-sectional analysis. Section 3.1 covers the data source used in the thesis, and section 3.2 explains the methodology for calculating variables and analysis.

3.1 Sample Data

In this research, different data sources are used. The main data source is the Center for Research in Security Prices (CRSP) that includes stocks traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotations (NASDAQ) from July 1963 to December 2018. Daily and monthly stock returns from the CRSP database were collected and stocks less than $5 were eliminated. Compustat database was used for collecting accounting data. All stocks available in the sample should have monthly accounting information for computing size and book-to-market ratio, based on Fama and French (1993). Based on the studies by French et al. (1987), Schwert (1989), and Fu (2018), we converted daily volatilities into monthly volatilities by multiplying them by the square root of the number of days a stock is traded in that month. For conversion, a stock should have at least 15 daily returns in a month.

Following Fu (2018) and Ferson and Harvey (1999), we used four economy-wide instruments to account for time-varying properties of alpha and betas in the conditional form of the FF-3 model. The four instruments include (1) *TERM:* the lagged spread between the 10-year and three-month Treasury yields (Adrian & Franzoni, 2009; Fama & French, 1989),

(2) *Default*: the spread between Moody's Baa and Aaa corporate bond yields (Avramov & Chordia, 2006; Fama, 1990), (3) *DIV*: the dividend yield on a value-weighted CRSP market portfolio, and (4) *T-bill*: the short-term risk-free rate, as measured by the secondary market rate of 3-month Treasury bills.

Data on Moody's Baa corporate bond yields, Moody's Aaa corporate bond yields, and Treasury yields were obtained from the Federal Reserve Bank of St. Louis website. Dividend yield on the value-weighted CRSP market portfolio were collected from the CRSP. We also obtained the data on three Fama-French factors[2]—market excess return (MKT), small minus big (SMB), and high minus low (HML)—from Kenneth R. French's website.

3.2 Methodology

3.2.1 Unconditional Idiosyncratic Components

Fu (2018) argued that the reason for the lack of consensus in terms of the relationship between idiosyncratic risk and stock returns might be that unconditional asset pricing models do not account for the time-varying property of alpha and beta. Hence, some systematic patterns may exist in idiosyncratic risk. As a result, the idiosyncratic risk might not exactly be idiosyncratic.

In this subsection, we demonstrate that the reason why idiosyncratic risk includes components associated with stock returns, while the FF-3 factor model does not account for the time-varying property of alpha and beta. We decompose the total stock variance based on a similar method to Campbell, Lettau, Malkiel, and Xu (2001) and Fu (2018). In the first

[2] MKT is the excess return on the market portfolio, which is measured as market return minus the one-month Treasury bill rate. SMB (Small Minus Big) is the difference between the average returns on three small portfolios and average returns of three big portfolios. HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios.

step, we decompose the total risk into systematic risk and idiosyncratic risk as shown in the following equation:

$$Var\left(R_{i,t}\right) = Var\left(R_{m,t}\right) + Var\left(r_{i,t}\right) + 2Cov\left(R_{m,t}, r_{i,t}\right) \tag{1}$$

where $R_{i,t}$ is the return of every stock or portfolio i at the time t. $Var\left(R_{i,t}\right)$ is the variance of returns of asset i, which is a proxy for total risk. $R_{m,t}$ is the systematic portion of the return of the asset at the time t, and $Var\left(R_{m,t}\right)$ is the systematic risk. $r_{i,t}$ is the idiosyncratic component of return, which is the unexplained portion of the stock return, and $Var\left(r_{i,t}\right)$ is the idiosyncratic risk. Since $Cov\left(R_{m,t}, r_{i,t}\right) = 0$ by definition, the idiosyncratic risk can be defined as $Var\left(r_{i,t}\right) = Var\left(R_{i,t}\right) - Var\left(R_{m,t}\right)$.

Next, the following generalized factor model with N risk factors is considered:

$$R_{i,t} = \alpha_i + \beta'_i F_t + \varepsilon_{i,t} \tag{2}$$

Where F_t is an $N \times 1$ vector that includes N risk factor at the time t. β'_i is a $1 \times N$ vector containing the loadings on N factors for every stock i. In this research, since we adopt the FF-3 factor model, N is equal to three risk factors—MKT, SMB, and HML. Taking the equations 1 and 2 into the account, we decompose the stock returns variance based on an unconditional model (i.e., FF-3 factor model) as follows:

$$Var(R_{i,t}) = Var(\alpha_i + \beta'_i F_t) + Idio = Var(\beta'_i F_t) + Idio \tag{3}$$

where $Idio$ is identical to $\varepsilon_{i,t}$.

Ferson and Harvey (1999), Fu (2018) considered that the alpha and betas are time-varying and conditional on macro-economic instruments, and both are divided into two components: a constant and a time-varying component as follows:

$$\alpha_{i,t} = \alpha_{0,i} + \alpha_{1,i} \times Z_{t-1} \tag{4}$$

$$\beta_{i,t} = \beta_{0,i} + \beta_{1,i} \times Z_{t-1} \tag{5}$$

Where Z_{t-1} is an $L \times 1$ vector of the macro-economic instruments (i.e., TERM, Default, DIV, and T-bill in this research) at the time $t-1$. These instruments cause alpha and beta to change over time. L is the number of instruments, which are four in this study. $\alpha_{0,i}$ and $\beta_{0,i}$ are constant parameters, and $\alpha_{1,i}$ and $\beta_{1,i}$ are time-varying parameters for every stock or portfolio i at the time t in equations 4 and 5. In these two equations, $\alpha_{i,t}$and $\beta_{i,t}$ are conditional alpha and beta, respectively. These equations also fit into the unconditional version of alpha and beta if we assume that time-varying components of alpha and beta, $\alpha_{1,i}$ and $\beta_{1,i}$, are equal to zero. Considering the equation (4) and (5), we replace the unconditional version of alpha and beta with conditional alpha and betas in the equation (3). The resulting equation is as follows:

$$\begin{aligned} Var(R_{i,t}) = {} & Var(\alpha_{i,t}) + Var({\beta'}_i F_t) + 2Cov\left(\alpha_{i,t}, {\beta'}_i F_t\right) + Idio_c \\ = {} & Var(\alpha_{i,t}) + Var\left(\left({\beta'}_{0,i} + {\beta'}_{1,i} \times Z_{t-1}\right) F_t\right) + 2Cov\left(\alpha_{i,t}, {\beta'}_i F_t\right) \\ & + Idio_c \\ = {} & Var(\alpha_{i,t}) + Var\left({\beta'}_{0,i} F_t\right) + Var\left({\beta'}_{1,i} \times Z_{t-1} F_t\right) \\ & + 2Cov\left({\beta'}_{0,i} F_t, {\beta'}_{1,i} \times Z_{t-1} F_t\right) + 2Cov\left(\alpha_{i,t}, {\beta'}_i F_t\right) + Idio_c \end{aligned} \tag{6}$$

Where $Idio_c$is the conditional version of idiosyncratic volatility from a conditional asset pricing model. In the next step, we compare equation (6) with equation (3) and find that four additional terms are included in the variance of stock returns when conditional alpha and beta are entered into the model. In an unconditional model, when $\beta_{1,i}$ is assumed to be zero, then $\beta'_i = \beta'_{0,i}$ in the equation (3). The result of comparing equation (6) with equation (3) is the following equation:

$$Idio = Var(\alpha_{i,t}) + Var\left(\beta'_{1,i} \times Z_{t-1}F_t\right) + 2Cov\left(\beta'_{0,i}F_t, \beta'_{1,i} \times Z_{t-1}F_t\right) + 2Cov\left(\alpha_{i,t}, \beta'_i F_t\right) + Idio_c \tag{7}$$

Equation (7) shows that idiosyncratic risk, which is estimated from unconditional asset pricing models, consists of four additional terms plus conditional idiosyncratic risk. Four additional components are: the variance of alpha, the variance of interaction between the time-varying component of beta and respective factors (i.e., FF three factors: MKT, SMB, and HML), and two covariance terms. These four components are included in the idiosyncratic volatility when asset pricing models fail to account for the time-varying property of alpha and betas. Fu (2018) argued that if a time-varying conditional asset pricing model is a true model, the unconditional idiosyncratic risk is not purely idiosyncratic because these four components included in the idiosyncratic risk have the nature of the systematic risk. Thus, these four components are mistakenly included in the idiosyncratic risk. Additional components are defined as follows:

1. *Alpha Risk* (Vol_Alpha) is the standard deviation of the time-varying alpha in one month, which is estimated from a regression of daily stock returns on the three Fama–French factors
2. *Beta Risk* is the standard deviation of interaction between the time-varying component of beta and the respective FF-3 factors:
    a. Beta MKT Risk (Vol_Bmkt): the standard deviation of interaction between the time-varying component of MKT beta and MKT factor.

b. Beta SMB Risk (Vol_Bsmb): the standard deviation of interaction between the time-varying component of SMB beta and SMB factor.

c. Beta HML Risk (Vol_Bhml): the standard deviation of interaction between the time-varying component of HML beta and HML factor.

3. *Covariance Term 1* is the covariance between "the interaction of the constant component of beta and respective FF-3 factors" and "the interaction of the time-varying component of beta and the respective FF-3 factors":

   a. *Cov_Bmkt1*: the covariance of "the interaction between the constant component of MKT beta and MKT factor" and "the interaction between the time-varying component of MKT beta and MKT factor."

   b. *Cov_Bsmb1*: the covariance of "the interaction between the constant component of SMB beta and SMB factor" and "the interaction between the time-varying component of SMB beta and SMB factor."

   c. *Cov_Bhml1*: covariance of "the interaction between the constant component of HML beta and HML factor" and "the interaction between the time-varying component of HML beta and HML factor."

4. *Covariance Term 2* is the covariance of time-varying alpha and "interaction of the time-varying beta and the respective FF-3 factors":

   a. *Cov_Bmkt2*: covariance of time-varying alpha and "interaction between the time-varying MKT beta and MKT factor."

   b. *Cov_Bsmb2*: covariance of time-varying alpha and "interaction between the time-varying SMB beta and SMB factor."

   c. *Cov_Bhml2*: covariance of time-varying alpha and "interaction between the time-varying HML beta and HML factor."

In this study, time-varying alpha and time-varying beta are estimated based on a conditional FF-3 factor model (Eq. 8) developed by Ferson and Harvey (1999):

$$r_{i,t} = \left(\alpha_{0,i} + \alpha'_{1,i} Z_{t-1}\right) + \left(b_{0,i} + b'_{1,i} Z_{t-1}\right) F_t + \varepsilon_{i,t} \tag{8}$$

Where $r_{i,t}$ is the return of every stock or portfolio i at the time of t, Z_{t-1} is an $L \times 1$ vector of instruments known at the time $t - 1$, and the parameters of the model are $b_{0,i}$, $b_{1,i}$, $\alpha_{0,i}$, and $\alpha_{1,i}$. In the FF-3 factor model, $b_{0,i}$ is 3×1, $b_{1,i}$ is $3 \times L$, $\alpha_{1,i}$ is $1 \times L$, and $\alpha_{0,i}$ is a scalar. Similar to equations 1 and 2, L is the number of macro-economic instruments entered in the model.

3.2.2 Idiosyncratic Volatility Measurement

Unconditional idiosyncratic volatility (Unconditional_IVOL) is measured as the standard deviation of the regression residuals of daily stock returns in month $t - 1$ based on the FF-3 model. The *Conditional idiosyncratic volatility* (Conditional_IVOL) is measured as the standard deviation of the regression residuals of the daily stock returns of the month $t - 1$ based on the conditional FF-3 model (equation 8).

3.2.3 A Trading Strategy

In this research, we apply a trading strategy to perform portfolio analysis and examine the relationship between the additional components included in Unconditional_IVOL and portfolio returns. Similar to Ang et al. (2006), an *L/M/N* portfolio formation strategy was adopted to divide stocks into five portfolios according to their idiosyncratic volatility level. First, idiosyncratic volatility for the stock i is computed based on daily data over the L-month estimation period from month t – L – M to month t – M. Second, stocks are sorted into quintile portfolios based on the magnitude of lagged idiosyncratic volatility. Third, portfolios are held for N months and rebalanced each month. For example, in the 1/0/1 strategy, the idiosyncratic volatility of each stock is estimated based on daily data of one month (month t-1). Then, at month t, stocks are divided into five quintiles based on their level of lagged idiosyncratic volatility. Finally, the simple value-weighted average of returns is calculated for each portfolio at time t.

This process is repeated monthly, and a time-series of simple average returns is created for each quintile. Finally, the time-series mean is computed as the monthly return of each quintile. Besides, Fama and French (1993) alphas are calculated, and robust Newey and West (1987) t-statistics are reported for each quintile.

The same approach is employed in this research. In addition to sorting stocks based on their level of idiosyncratic volatility, we apply the trading strategy for all components of unconditional idiosyncratic volatility (volatility and covariance terms). While Ang et al. (2006) formed value-weighted portfolios, we form both value-weighted and equal-weighted portfolios by performing single, double, and triple sorts based on size, book-to-market ratio and all the components of unconditional idiosyncratic volatility. In the last step, the trading strategy goes long the quintile with the highest level of a specific attribution and shortens the quintile to the lowest level of the same attribution. This step is performed to find the difference in simple returns (and alphas) between stocks with the highest and lowest level of each additional component embedded in the unconditional idiosyncratic risk.

3.2.4 Fama-MacBeth Model

Fama-MacBeth cross-sectional approach is employed in this research to examine the relationship between additional components included in Unconditional_IVOL and expected stock returns at the firm level. Asset pricing models use risk factors to explain the variations in asset returns. Risk factors are related to macroeconomic or financial attributes. Fama and MacBeth (1973) model is a two-step regression that estimates parameters of asset pricing models and tests how risk factors explain portfolio or asset returns. The ultimate goal of the Fama-MacBeth model is to estimate risk premia for risk factors.

In the first step, each portfolio or asset return is regressed against risk factors to determine the asset's beta or factor exposure related to each risk factor. Assuming that there are n portfolio returns or asset returns and m risk factors, time-series regression is run for each asset to obtain m factor exposure (Betas):

$$R_{i,t} = \alpha_i + \beta_{i,F_1} F_{1,t} + \beta_{i,F_2} F_{2,t} + \cdots + \beta_{i,F_m} F_{m,t} + \epsilon_{i,t} \tag{9}$$

$R_{i,t}$ denotes the return of portfolio or asset i at the time t. i goes from 1 to n, and t goes from 1 to T for each portfolio or asset. It means that the following regression is run for each of n assets over a period from t=1 to t=T. $F_{j,t}$ is the risk factor j (from 1 to m), and β_{i,F_m} are factor exposures or loadings on risk factors, which explain the extent to which asset returns are exposed to risk factors.

In the second step, T cross-sectional regressions are performed to regress asset returns on the m estimated factor exposures from the first step. This step aims to estimate the exposure of the n asset returns to the m factor loadings over time.

$$R_{i,t} = \gamma_0 + \gamma_t \hat{\beta}_i + \acute{\gamma}_t \sigma_i + \epsilon_{i,t} \tag{10}$$

$R_{i,t}$ denotes the return of the portfolio or asset i at the time t, and t goes from 1 to T. $\hat{\beta}_i$ are m factor exposure estimated in the first step. This step creates a time-series of the coefficient $\gamma_t$which is the exposure to m factor loadings over time from t=1 to t=T. Some studies add various firm characteristics to the second stage of the Fama-MacBeth approach.

σ_i denotes the firm characteristics and other variables and the $\acute{\gamma}_t$ denotes the exposure to those firm characteristics and other variables.

The final step is to calculate risk premiums by taking the average of each γ time-series over the period from t=1 to t=T. For example, in order to compute risk premium γ_m for the factor F_m, we take the time-series average of γ_m. The same method applies for computing the t-statistic for the mth risk premium, which is calculated by $\frac{\gamma_m}{\sigma_m/\sqrt{T}}$. In addition, the Newey–West t-statistic is used to correct for heteroscedasticity and autocorrelation in residuals.

Chapter Four:

Results and Analysis

This chapter presents the results of the portfolio analysis and Fama-MacBeth cross-sectional regression. The first section of this chapter presents the results of one-way portfolio analysis. Section 4.2 shows the relationship between additional components included in the idiosyncratic volatility and expected stock returns through analyzing the two-way sorted portfolios. In this section, several variables are controlled for robustness tests. Section 4.3 gives a more in-depth analysis of the relationship between additional components and expected stock returns by analyzing the triple sorted portfolios. Section 4.4 presents the results of comparison of the relationship between unconditional idiosyncratic volatility and expected stock returns and the relationship between conditional idiosyncratic volatility and expected stock returns at the portfolio level. Section 4.5 reports the Fama-MacBeth regression outputs with different model specifications.

4.1 One-way Portfolio Analysis

In this section, we sort stocks into quintile portfolios based on the level of all the additional components included in unconditional idiosyncratic volatility one at a time, and then we hold equal-weighted portfolios for one month. We use 1/0/1 portfolio formation strategy to create portfolios based on one month of estimation and one month of holding period; then, we rebalance the portfolios monthly. Next, we calculate the yield by buying the portfolio with the highest level of a specific idiosyncratic volatility component and short selling the one with the lowest level of the same component. We also report the Jensen's alpha from CAPM and FF-3 model.

4.1.1 One-way Portfolios Sorted on Volatility Terms

Table 1 reports the average returns of equal-weighted portfolios sorted on volatility terms through panel A to panel D. First, the relationship between alpha volatility and subsequent stock returns is examined. Panel A shows that average returns decrease from 1.08% per month to 0.61% per month when we go from quintile 1 to quintile 5 (stocks with high alpha volatility). The difference in average returns between portfolios 5 and portfolio 1 is -0.51% per month, which is statistically significant with a robust *t*-statistic of -4.81. The difference in the FF-3 alphas between portfolio 5 and portfolio 1 is -0.54% per month, which is statistically significant at the significance level of 1%. Hence, the result from CAPM and FF-3 alphas is consistent with the negative yield of 0.51% per month. These results confirm that the relationship between alpha volatility and subsequent stock returns is significantly negative at the portfolio level.

In Panels B to D, we sort stocks based on their level of beta volatility terms—Beta MKT Volatility, Beta SMB Volatility, and Beta HML Volatility—and we find similar patterns to panel A. Panels B to D report the portfolio returns and yields from the long-short trading strategy. Panel B shows that the difference in average returns between portfolios 5 (stocks with highest Beta MKT Volatility) and portfolio 1 is -0.40% per month, which is statistically significant at the significance level of 1%. Panels C and D also show that the one-way sorting by Beta SMB Volatility and Beta HML Volatility yields negative spreads of -0.41% and -0.39% per month, respectively. The 5-1 differences in the FF-3 alphas are also significantly negative in all three panels, which is consistent with the negative yields. Furthermore, the negative differences in alphas show that the FF-3 model cannot price these portfolios.

Table 1

Portfolios Sorted by Volatility Terms

We create equal-weighted quintile portfolios every month by sorting stocks based on volatility terms relative to the conditional FF-3 model (equation (8)). Alpha Volatility is computed as the standard deviation of time-varying alpha, and Beta Volatilities (Beta Market, Beta SMB, and Beta HML) are defined as the standard deviations of time-varying betas using daily stock returns over the previous month. Then, quintile portfolios are formed every month based on alpha and beta volatilities. Portfolio 1 (5) is the portfolio of stocks with the lowest (highest) volatility terms. Mean and Std. Dev. are measured monthly and reported based on percentage, and then applied to total simple returns. Column "Size" is the log of average market capitalization for firms within the portfolio, and column "B/M" reports the average book-to-market ratio, which is calculated based on Fama and French (1993). The row "5-1" refers to the difference in monthly average returns between quintile 5 and quintile 1. The last two right columns report the Jensen's alpha estimated from CAPM or FF-3 model. The Newey–West adjusted t-statistics are reported in square brackets. The sample period is July 1963 to December 2018.

Rank	Mean	Std. Dev.	% Mkt Share	Size	B/M	CAPM Alpha	FF-3 Alpha
Panel A: Portfolios Sorted by Alpha Volatility							
1	1.08	4.15	34.4	5.78	0.73	0.62	0.6
						[3.76]	[3.67]
2	1.13	4.64	26.0	5.61	0.71	0.67	0.66
						[3.67]	[3.59]
3	1.05	4.98	19.4	5.39	0.70	0.58	0.57
						[2.94]	[2.91]
4	1.02	5.37	13.4	5.11	0.70	0.54	0.54
						[2.58]	[2.58]
5	0.61	5.80	6.9	4.62	0.69	0.11	0.12
						[0.51]	[0.53]
5 -1	-0.51***					-0.54***	-0.51***
	[-4.81]					[-5.37]	[-5.26]
Panel B: Portfolios Sorted by Beta Market Volatility							
1	1.06	4.46	27.6	5.57	0.72	0.59	0.58
						[3.36]	[3.29]
2	1.07	4.64	26.7	5.56	0.71	0.6	0.59
						[3.31]	[3.22]
3	1.07	4.86	21.9	5.45	0.71	0.61	0.6
						[3.18]	[3.16]
4	1.00	5.20	16.0	5.22	0.70	0.52	0.52
						[2.55]	[2.52]
5	0.67	5.74	7.7	4.70	0.70	0.17	0.19
						[0.78]	[0.84]
5 -1	-0.40***					-0.43***	-0.40***
	[-5.13]					[-5.68]	[-5.50]

(continued)

Table 1 – Continued

Rank	Mean	Std. Dev.	% Mkt Share	Size	B/M	CAPM Alpha	FF-3 Alpha
Panel C: Portfolios Sorted by Beta SMB Volatility							
1	1.08	4.44	27.8	5.56	0.72	0.61	0.61
						[3.50]	[3.44]
2	1.04	4.62	26.2	5.56	0.71	0.57	0.56
						[3.14]	[3.07]
3	1.06	4.85	22.0	5.46	0.70	0.59	0.58
						[3.12]	[3.07]
4	1.01	5.20	16.1	5.22	0.70	0.53	0.53
						[2.61]	[2.61]
5	0.69	5.76	7.8	4.71	0.70	0.2	0.21
						[0.91]	[0.95]
5 -1	-0.41***					-0.44***	-0.42***
	[-5.20]					[-5.82]	[-5.78]
Panel D: Portfolios Sorted by Beta HML Volatility							
1	1.05	4.48	27.0	5.50	0.72	0.58	0.57
						[3.31]	[3.23]
2	1.05	4.64	26.4	5.57	0.71	0.58	0.58
						[3.22]	[3.17]
3	1.06	4.83	22.0	5.46	0.71	0.59	0.58
						[3.09]	[3.05]
4	1.03	5.20	16.4	5.24	0.70	0.56	0.55
						[2.74]	[2.71]
5	0.66	5.76	8.2	4.74	0.69	0.17	0.18
						[0.78]	[0.82]
5 -1	-0.39***					-0.41***	-0.39***
	[-5.13]					[-5.62]	[-5.46]

*, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.

The evidence from panels B to D shows that all three beta volatility terms have a significantly negative relationship with subsequent stock returns. In summary, table 1 shows that all volatility terms have significant negative relationships with future stock returns; however, the long-short trading strategy yields the largest spread (-0.51%) when stocks are sorted by the alpha risk. In all the panels, the size and book-to-market ratios decrease monotonically from quintile 1 to quintile 5. Portfolio 1 (portfolio with the lowest volatilities) includes stock with a large size and high book-to-market ratios. On the contrary, quintile 5 (portfolio with the highest volatilities) includes stocks with small size and low book-to-market ratios. The low returns of quintile 5 raise a concern about the findings in table 1.

4.1.2 One-way Portfolios Sorted on Covariance Terms 1

Panels A to C of table 2 shows the average returns of equal-weighted portfolios sorted on covariance terms 1. In all panels, quintile 1 (stocks with the lowest level of covariance terms 1) has the lowest returns among the other portfolios. The long-short trading strategy yields a significant positive return in all panels.

Table 2
Portfolios Sorted by Covariance Terms 1

We create equal-weighted quintile portfolios every month by sorting stocks based on covariance term 1. This component is the covariance between "the interaction of the constant component of beta and respective FF-3 factors" and "interaction of the time-varying component of beta and the respective FF-3 factors". Therefore, we calculate three covariance terms— Cov_Bmkt1, Cov_Bsmb1, and Cov_Bhml1—associated with FF-3 factors. Next, quintile portfolios are formed every month based on covariance terms 1. Portfolio 1 (5) is the portfolio of stocks with the lowest (highest) covariance terms 1. Mean and Std. Dev. are measured monthly and reported based on percentage, and then applied to total simple returns. Column "Size" is the log of average market capitalization for firms within the portfolio, and column "B/M" reports the average book-to-market ratio, which is calculated based on Fama and French (1993). The row "5-1" refers to the difference in monthly average returns between quintile 5 and quintile 1. The last two right columns report the Jensen's alpha estimated from CAPM or FF-3 model. The Newey–West adjusted t-statistics are reported in square brackets. The sample period is July 1963 to December 2018.

Rank	Mean	Std. Dev.	% Mkt Share	Size	B/M	CAPM Alpha	FF-3 Alpha
			Panel A: Portfolios Sorted by Cov_Bmkt1				
1	0.66	5.74	7.7	4.70	0.70	0.17	0.18
						[0.77]	[0.83]
2	1	5.20	16.1	5.22	0.70	0.53	0.52
						[2.57]	[2.55]
3	1.07	4.86	22.0	5.45	0.71	0.6	0.6
						[3.17]	[3.13]
4	1.07	4.64	26.7	5.56	0.71	0.6	0.59
						[3.30]	[3.22]
5	1.06	4.46	27.5	5.56	0.72	0.59	0.58
						[3.36]	[3.28]
5 -1	0.40***					0.43***	0.40***
	[5.17]					[5.74]	[5.56]

(continued)

Table 2 – Continued

Rank	Mean	Std. Dev.	% Mkt Share	Size	B/M	CAPM Alpha	FF-3 Alpha
Panel B: Portfolios Sorted by Cov_Bsmb1							
1	0.69	5.76	7.8	4.71	0.70	0.2	0.21
						[0.91]	[0.95]
2	1.01	5.21	16.1	5.22	0.70	0.53	0.53
						[2.59]	[2.59]
3	1.07	4.85	22.1	5.46	0.71	0.59	0.59
						[3.14]	[3.09]
4	1.04	4.61	26.3	5.56	0.71	0.57	0.56
						[3.14]	[3.07]
5	1.08	4.45	27.7	5.55	0.72	0.61	0.61
						[3.5]	[3.44]
5 -1	0.41***					0.44***	0.42***
	[5.18]					[5.81]	[5.79]
Panel C: Portfolios Sorted by Cov_Bhml1							
1	0.67	5.76	8.2	4.74	0.69	0.18	0.18
						[0.79]	[0.83]
2	1.04	5.19	16.5	5.24	0.70	0.56	0.56
						[2.75]	[2.73]
3	1.07	4.82	22.2	5.47	0.70	0.6	0.59
						[3.14]	[3.1]
4	1.06	4.63	26.5	5.58	0.71	0.59	0.59
						[3.25]	[3.2]
5	1.04	4.51	26.6	5.48	0.72	0.57	0.57
						[3.24]	[3.19]
5 -1	0.37***					0.39***	0.37***
	[5.02]					[5.5]	[5.35]

*, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.

Panel A shows that the difference in average returns between quintile 5 (stocks with the highest level of Cov_Bmkt1) and quintile 1 is 0.40% per month, with a robust Newey and West (1987) *t*-statistics of 5.17. The 5-1 difference in average returns is also significant and positive when stocks are sorted by Cov_Bsmb1 or Cov_Bhml1 (see panels B and C). Panels A to C show that all three covariance ‘terms 1’ have a significant positive relationship with subsequent stock returns. The Jensen’s alphas from the CAPM and FF-3 model present consistent evidence for this positive relationship. In all panels, the difference in the FF-3 alphas between portfolio 5 and portfolio 1 is positive at the significance level of 1%. This result is consistent with the positive yield.

4.1.3 One-way Portfolios Sorted on Covariance Terms 2

Table 3 shows the equal-weighted portfolio returns and the trading strategy yields from stocks sorted on covariance terms 2. In Panels A to C, portfolio 1, which include stocks with the lowest level of covariance terms 2, has the lowest average returns among the other portfolios.

Table 3
Portfolios Sorted by Covariance Terms 2

We create equal-weighted quintile portfolios every month by sorting stocks based on covariance term 2. This component is the covariance between time-varying alpha and "interaction of the time-varying beta and the respective FF-3 factors". Thus, we calculate three covariance terms— Cov_Bmkt2, Cov_Bsmb2, and Cov_Bhml2—associated with FF-3 factors. Next, quintile portfolios are formed every month based on covariance terms 1. Portfolio 1 (5) is the portfolio of stocks with the lowest (highest) covariance terms 1. Mean and Std. Dev. are measured monthly and reported based on percentage, and then applied to total simple returns. Column "Size" is the log of average market capitalization for firms within the portfolio, and column "B/M" reports the average book-to-market ratio, which is calculated based on Fama and French (1993). The row "5-1" refers to the difference in monthly average returns between quintile 5 and quintile 1. The last two right columns report the Jensen's alpha estimated from CAPM or FF-3 model. The Newey–West adjusted t-statistics are reported in square brackets. The sample period is July 1963 to December 2018.

Rank	**Mean**	**Std. Dev.**	**% Mkt Share**	**Size**	**B/M**	**CAPM Alpha**	**FF-3 Alpha**
			Panel A: Portfolios Sorted by Cov_Bmkt2				
1	0.75	5.61	9.2	4.78	0.70	0.26	0.26
						[1.2]	[1.22]
2	1.03	5.04	17.8	5.30	0.70	0.56	0.56
						[2.81]	[2.81]
3	1.09	4.68	24.1	5.53	0.71	0.62	0.62
						[3.37]	[3.34]
4	1.08	4.60	27.4	5.61	0.71	0.61	0.59
						[3.35]	[3.27]
5	0.91	5.03	21.5	5.29	0.71	0.44	0.43
						[2.25]	[2.18]
5 -1	0.19***					0.20***	0.18***
	[3.04]					[3.35]	[3.00]

(continued)

Table 3 – Continued

Rank	Mean	Std. Dev.	% Mkt Share	Size	B/M	CAPM Alpha	FF-3 Alpha
Panel B: Portfolios Sorted by Covariance Cov_Bsmb2							
1	0.71	5.69	8.9	4.75	0.70	0.21	0.22
						[0.96]	[0.99]
2	1.05	5.13	18.2	5.30	0.70	0.57	0.56
						[2.87]	[2.8]
3	1.08	4.76	24.3	5.54	0.71	0.6	0.59
						[3.23]	[3.12]
4	1.09	4.54	27.7	5.61	0.71	0.62	0.62
						[3.46]	[3.43]
5	0.97	4.82	21.0	5.31	0.71	0.5	0.51
						[2.67]	[2.66]
5 -1	0.24***					0.28***	0.28***
	[3.68]					[4.32]	[4.45]
Panel C: Portfolios Sorted by Cov_Bhml2							
1	0.75	5.61	9.7	4.79	0.70	0.26	0.27
						[1.24]	[1.25]
2	1.04	5.03	18.4	5.32	0.71	0.57	0.56
						[2.87]	[2.84]
3	1.1	4.68	24.6	5.55	0.71	0.63	0.62
						[3.48]	[3.37]
4	1.1	4.59	27.2	5.60	0.71	0.64	0.63
						[3.50]	[3.44]
5	0.94	4.96	20.1	5.25	0.70	0.46	0.45
						[2.37]	[2.35]
5 -1	0.21***					0.22***	0.20***
	[3.40]					[3.48]	[3.28]

*, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.

The long-short trading strategy yields are significant and positive in all the panels. Furthermore, the 5-1 difference in FF-3 alphas between portfolio 5 and portfolio 1 is positive in panels A to C, with the significance level of 1%. The results from Jensen's alpha are consistent with the trading strategy yields. These findings provide evidence that covariance terms 2 (Cov_Bmkt2, Cov_Bsmb2, and Cov_Bhml2) are positively related to subsequent stock returns. However, Cov_Bsmb2 has the largest relationship with future stock returns, which is 0.24% per month with *t*-statistics of 3.68.

A comparison between positive the relationships in table 2 and table 3 shows that covariance terms 1 (_Cov_Bmkt1, Cov_Bsmb1, and Cov_Bhml1) has a larger relationship with average stock returns compared to covariance terms 2. (Cov_Bsmb1) has the largest relationship magnitude of 0.41% per month among all covariance terms.

All the panels in tables 2 and 3 shows an increasing trend for the size and book-to-market ratios from portfolio 1 to portfolio 5. In all panels, portfolio 1 (portfolio with the lowest covariance terms) includes stock with the smallest size and smallest book-to-market ratios.

In summary, tables 1 to 3 report the results on the relationship between additional terms, which are included in the lagged unconditional idiosyncratic risk, and stock returns. Four volatility terms (Vol_Alpha, Vol_Bmkt, Vol_Bsmb, and Vol_Bhml) have a negative relationship with subsequent stock returns. On the other hand, the relationship between additional covariance terms and subsequent stock returns is positive.

The negative relationship between volatility terms and subsequent stock returns is due to anomalously low returns of quintile 5. Similarly, the positive relationship between covariance terms and subsequent stock returns is due to anomalously low returns of quintile 1. The anomalously low returns raise some concerns about the robustness of results. For example, although portfolio 5 which is sorted by volatility terms contains 20% of all the stocks, the size of quintile 5 is less than 8.3% of the total market share (see table 1). While portfolio 1 includes 20% of the stocks sorted by different covariance terms, the size of portfolio 1 is less than 10% of total market capitalization (see tables 2 and 3). This raises the question of whether the negative effect of volatility components and positive effect of covariance terms on future stock returns are associated to only small-size stocks. To answer this question, we control size by forming two-way sorted portfolios in the following section. We also examine whether the relationships between individual additional terms and subsequent stock returns are repeated after controlling for some cross-sectional effects (size, book-to-market, turnover, and volume) which have been identified in the literature as anomalies.

4.2 Two-way Portfolio Analysis and Robustness Tests

This section presents the average stock returns of equal-weighted (EW) portfolios and value-weighted (VW) portfolios double sorted based on size and additional components of unconditional idiosyncratic volatility. First, stocks are sorted into five quintiles, and then each size quintile is divided into five quintiles by volatility and covariance terms, one at a time. In this way, 5 X 5 EW portfolios and 5 X 5 VW portfolios are formed. Next, we apply the 1/0/1 trading strategy for each size quintile by buying the portfolio with the highest level of additional components (volatility or covariance terms) and short selling the quintile with the lowest level of that particular additional component. Next, the long-short trading strategy yields or the difference in average returns between quintile 5 and quintile 1 is calculated. In controlling for size, we also estimate the alpha from CAPM and FF-3 models. The Newey-West *t*-statistics are reported in the square brackets.

We control for size, book-to-market ratios, volume, and turnover to check for the robustness of the relationship between additional components and subsequent stock returns. We also form quintile portfolios by using only NYSE stocks to examine the effect of size on the average returns of portfolios.

Although we perform the robustness checks for the relationship between all individual additional components and subsequent stock returns, we concentrate on alpha volatility and Cov_Bsmb1 that have the most significant relationships with future stock returns, among the other components in their volatility or covariance groups. We also perform two-way sort analyses for other individual additional components and present the results in tables A1 to A8 of Appendix.

4.2.1 Two-Way Portfolio Analysis and Controlling for Size

4.2.1.1 Two-way Portfolios Sorted on Alpha Volatility

Table 4 examines whether the negative relationship between alpha volatility and subsequent stock returns remains when different cross-sectional factors, such as size, book-to-market ratios, volume, and turnover are controlled.

In order to test the robustness of the results on the size, we conduct three tests. First, we sort NYSE stocks by alpha risk to examine the effect of size on the relationship between alpha risk and average returns of EW and VW portfolios. Applying a long-short trading strategy on EW portfolios yields negative returns of -0.20% per month, which is significant with a robust t-statistic of -2.85. This finding provides evidence that when the stock universe is limited to NYSE stocks, the negative relationship between alpha volatility and subsequent stock returns remains significant for EW portfolios, and this relationship is not associated with small stocks. However, this relationship does not exist for VW portfolios. Since NYSE sample has some small stocks, we conduct two additional examinations to assure that small stocks do not derive the negative relationship.

In the second examination, we sort CRSP stocks into double sorted EW and VW portfolios based on size and alpha volatility to control the size and examine the interaction of alpha risk and size. First, we sort stocks into quintile portfolios based on size. Then, stocks of each size quintile are sorted into five portfolios based on their level of alpha risk. As a result, in all size quintile, stocks with the highest level of alpha risks and lowest average returns are available in quintile 5. The long-short trading strategy yields are significantly negative for size quintiles 1 to 4. However, the negative yield is not significantly different from zero for size quintile 5. Size quintile 1 has the largest negative yield of -0.84% per month, with a robust t-statistics of -9.87. From size quintile 1 to size quintile 5, the magnitude of the negative yield decreases as the size increases. For the size quintiles 2 to 4, the 5-1 differences in average returns between EW portfolio 5 and EW portfolio 1 sorted on alpha risk are: 0.73%, -0.53%, and -0.33% per month, respectively. All of those 5-1 differences are significant at the significance level of 1%, with *t*-statistics all above 2.43 in absolute magnitude.

These findings are similar to Fu's (2018) results on the relationship between alpha risk and expected stock returns. Finally, the same pattern is repeated for VW portfolios. The result shows a negative and significant relationship between alpha risk and subsequent stock returns, which is robust to weighting schemes of equal-weighted and value-weighted.

For the third examination, we use the average returns across the five size quintiles to create quintile portfolios with dispersion in alpha volatility, but which include the sizes of all the firms. The row "Controlling for Size" shows the average returns of portfolios sorted on alpha risk after controlling for size. The 5-1 difference in average returns between EW portfolio 5 and EW portfolio 1 is -0.50% per month, with the robust t-statistics -5.41. However, the negative yield is not significant for VW portfolios.

All the three tests show that when we control for size, the negative relationship between alpha risk and future stock returns holds in EW portfolios analysis. However, in VW portfolio analysis, the negative relationship remains significant only when we control for size by forming two-way sorted portfolios. Furthermore, we estimate the Jensen's alpha based on CAPM and FF-3 model. The results from alphas confirm the negative relationship between alpha volatility and stock returns when size is controlled

We repeat the above analysis for the beta volatility terms— Beta MKT Risk (Vol_Bmkt), Beta SMB Risk (Vol_Bsmb), and Beta HML Risk (Vol_Bhml)— to check the robustness of their negative relationship with subsequent stock returns after controlling for size through three different settings—"NYSE Stocks Only", "Two-way sorted portfolios", and "Controlling for size". Table A1 to A3 of the Appendix show that the long-short trading strategy yields significant negative returns in all the three tests. Therefore, the negative relationship between beta volatility terms and subsequent stock returns still exist when we control for size.

Table 4

Average Returns and Alphas of Portfolios Double Sorted on Size and Alpha Risk

The table reports monthly average returns and Jensen's alphas from the CAPM and FF-3 model, with robust Newey–West (1987) t-statistics in square brackets. After controlling for various effects, the 1/0/1 strategy described in section 3.2.3 is applied for alpha volatility computed relative to conditional FF-3 model (equation (8)). Two sets of portfolios are formed based on equal-weighted and value-weighted weighting schemes. The column "Return 5-1" refers to the difference in average returns between portfolio 5 and portfolio 1. The columns "CAPM Alpha 5-1" and "FF-3 Alpha 5-1" refer to the difference in CAPM and FF-3 alphas between portfolio 5 and portfolio 1 for EW and VW portfolios. In the panel labeled "NYSE Stocks Only", we sort stocks into quintile portfolios based on the level of alpha volatility, using only NYSE stocks. We use daily data over the previous month to calculate alpha volatility and then rebalance the data monthly. In the panel labeled "Size Quintiles", each month stocks are sorted into quintiles, and then within each size quintile, stocks are sorted by alpha volatility. In the panels controlling for size, book-to-market, volume, and turnover, we perform a two-way sort. Each month, we first sort stocks based on the first characteristics (size, book-to-market, volume, or turnover), and then, within each quintile, we sort stocks based on alpha volatility computed by conditional FF-3 model. The five quintiles formed based on alpha volatility are then averaged over each of the five characteristic portfolios. Therefore, they represent alpha volatility quintiles controlling for the characteristics. The book-to-market ratio is defined as the total book value of equity divided by market value of equity based on Fama and French (1993), the volume is average dollar volume over the previous month, and turnover represents volume divided by the total number of shares outstanding over the past month. The sample period is July 1963 to December 2018.

Table 4 - Average Returns and Alphas of Portfolios Double Sorted on Size and Alpha Risk

		Ranking on Alpha Volatility					EW			VW		
		1 Low	2	3	4	5 High	Return 5-1	CAPM Alpha 5-1	FF-3 Alpha 5-1	Return 5-1	CAPM Alpha 5-1	FF-3 Alpha 5-1
NYSE Stocks Only		1.05	1.1	1.11	1.04	0.85	-0.20***	-0.22***	-0.21***	-0.06	-0.07	-0.08
		[6.17]	[5.92]	[5.81]	[5.15]	[4.01]	[-2.85]	[-3.17]	[-3.07]	[-0.66]	[-0.84]	[-0.85]
Size Quintiles	**Small 1**	1.21	1.13	1.11	0.91	0.37	-0.84***	-0.84***	-0.80***	-0.88***	-0.89***	-0.85***
		[6.29]	[5.10]	[5.08]	[3.68]	[1.59]	[-9.87]	[-9.39]	[-8.07]	[-9.05]	[-8.77]	[-7.75]
	2	1.18	1.14	1.08	0.95	0.45	-0.73***	-0.73***	-0.68***	-0.73***	-0.72***	-0.66***
		[6.44]	[5.64]	[5.13]	[4.18]	[2.03]	[-5.71]	[-5.49]	[-5.33]	[-5.79]	[-5.51]	[-5.28]
	3	1.14	1.09	1.06	0.99	0.61	-0.53***	-0.56***	-0.52***	-0.54***	-0.58***	-0.53***
		[6.94]	[6.13]	[5.66]	[4.79]	[3.13]	[-4.35]	[-4.75]	[-4.69]	[-4.35]	[-4.74]	[-4.69]
	4	1.07	1.12	1.12	1.09	0.74	-0.33**	-0.33**	-0.30**	-0.31**	-0.32**	-0.29**
		[6.38]	[6.88]	[6.68]	[6.11]	[3.85]	[-2.43]	[-2.49]	[-2.44]	[-2.30]	[-2.32]	[-2.29]
	Large 5	0.93	0.98	1.07	0.94	0.87	-0.07	-0.09	-0.07	-0.08	-0.09	-0.09
		[6.72]	[7.13]	[7.84]	[6.43]	[5.16]	[-0.66]	[-0.90]	[-0.77]	[-0.81]	[-1.01]	[-0.92]
Controlling for Size		1.11	1.09	1.09	0.97	0.61	-0.50***	-0.51***	-0.47***	-0.13	-0.15	-0.14
		[6.09]	[5.49]	[5.21]	[4.37]	[2.56]	[-5.41]	[-5.65]	[-5.36]	[-1.24]	[-1.47]	[-1.37]
Controlling for Book-to-Market		1.08	1.14	1.03	1.04	0.66	-0.42***	-0.45***	-0.44***	-0.09	-0.13	-0.14
		[6.03]	[5.83]	[4.96]	[4.67]	[2.74]	[-4.64]	[-5.26]	[-5.11]	[-0.76]	[-1.08]	[-1.14]
Controlling for Volume		1.06	1.14	1.06	1.01	0.6	-0.46***	-0.51***	-0.49***	-0.16	-0.2	-0.18
		[5.98]	[5.82]	[5.08]	[4.49]	[2.47]	[-4.56]	[-5.26]	[-5.24]	[-1.29]	[-1.57]	[-1.43]
Controlling for Turnover		1.09	1.11	1.07	0.98	0.62	-0.47***	-0.51***	-0.50***	-0.20**	-0.23**	-0.22**
		[5.86]	[5.53]	[5.15]	[4.44]	[2.69]	[-6.16]	[-7.28]	[-7.50]	[-2.00]	[-2.34]	[-2.22]

*, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.

4.2.1.2 Two-way Portfolios Sorted on Cov_Bsmb1

In a similar analysis to table 4, we check whether the positive relationship between covariance term "Cov_Bsmb1" and subsequent stock returns is robust to different risk factors.

We control for the size through three different settings. In the first test, NYSE stocks are sorted into quintile portfolios based on Cov_Bsmb1. The first row of table 5 shows that the difference in average returns between EW portfolio 5 and EW portfolio 1 is 0.18% per month, with the *t*-statistic of -3.20. This finding shows that when NYSE sample is used, the relationship between Cov_Bsmb1 and subsequent stock returns remains significantly positive for EW portfolios, which implies that the positive effect of Cov_Bsmb1 is not concentrated among small stocks.

Table 5

Average Returns and Alphas of Portfolios Double Sorted on Size and Cov_Bsmb1

The table reports monthly average returns and Jensen's alphas from the CAPM and FF-3 model, with robust Newey–West (1987) t-statistics in square brackets. After controlling for various effects, the 1/0/1 strategy described in section 3.2.3 is applied for Cov_Bsmb1 computed relative to conditional FF-3 model (equation (3)). Two sets of portfolios are formed based on equal-weighted and value-weighted weighting schemes. The column "Return 5-1" refers to the difference in average returns between portfolio 5 and portfolio 1. The columns "CAPM Alpha 5-1" and "FF-3 Alpha 5-1" refer to the difference in CAPM and FF-3 alphas between portfolio 5 and portfolio 1 for EW and VW portfolios. In the panel labeled "NYSE Stocks Only", we sort stocks into quintile portfolios based on the level of Cov_Bsmb1, using only NYSE stocks. We use daily data over the previous month to calculate Cov_Bsmb1 and then rebalance the data monthly. In the panel labeled "Size Quintiles", each month stocks are sorted into quintiles, and then within each size quintile, stocks are sorted by Cov_Bsmb1. In the panels controlling for size, book-to-market, volume, and turnover, we perform a two-way sort. Each month, we first sort stocks based on the first characteristics (size, book-to-market, volume, or turnover), and then, within each quintile, we sort stocks based on Cov_Bsmb1 computed by conditional FF-3 model. The five quintiles formed based on Cov_Bsmb1 are then averaged over each of the five characteristic portfolios. Therefore, they represent Cov_Bsmb1 quintiles controlling for the characteristics. The book-to-market ratio is defined as the total book value of equity divided by market value of equity based on Fama and French (1993), volume is average dollar volume over the previous month, turnover represents volume divided by the total number of shares outstanding over the past month. The sample period is July 1963 to December 2018.

Table 5 - Average Returns and Alphas of Portfolios Double Sorted on Size and Cov_Bsmb1

		Ranking on Covariance between SMB and Instruments					EW			VW		
		1 Low	2	3	4	5 High	Return 5-1	CAPM Alpha 5-1	FF-3 Alpha 5-1	Return 5-1	CAPM Alpha 5-1	FF-3 Alpha 5-1
NYSE Stocks Only		0.87	1.06	1.08	1.07	1.06	0.18***	0.19***	0.18***	0.1	0.11	0.11
		[4.09]	[5.39]	[5.73]	[5.86]	[5.93]	[3.20]	[3.42]	[3.24]	[1.29]	[1.37]	[1.42]
Size Quintiles	**Small 1**	0.52	0.96	1.05	1.08	1.14	0.65***	0.65***	0.62***	0.70***	0.70***	0.66***
		[2.15]	[4.28]	[4.69]	[4.71]	[5.73]	[7.15]	[6.86]	[6.10]	[7.09]	[6.86]	[6.10]
	2	0.56	0.99	1.1	1.06	1.12	0.60***	0.60***	0.57***	0.60***	0.60***	0.57***
		[2.39]	[4.60]	[5.60]	[5.69]	[5.54]	[4.81]	[4.88]	[4.77]	[4.78]	[4.83]	[4.73]
	3	0.69	0.97	1.1	1.04	1.08	0.41***	0.42***	0.42***	0.41***	0.43***	0.42***
		[3.51]	[4.68]	[6.01]	[6.30]	[6.10]	[3.90]	[4.11]	[4.31]	[3.84]	[4.00]	[4.18]
	4	0.82	1.09	1.05	1.06	1.13	0.33***	0.34***	0.31***	0.32***	0.32***	0.29***
		[4.40]	[6.00]	[6.60]	[6.27]	[6.93]	[3.27]	[3.36]	[3.31]	[2.95]	[2.98]	[2.94]
	Large 5	0.84	1.01	0.97	0.95	1	0.15	0.16*	0.13	0.16	0.17*	0.16*
		[4.92]	[6.75]	[6.92]	[7.16]	[7.28]	[1.63]	[1.77]	[1.63]	[1.61]	[1.73]	[1.69]
Controlling for Size		0.67	1	1.06	1.04	1.09	0.42***	0.43***	0.40***	0.19**	0.20**	0.19**
		[2.85]	[4.62]	[5.20]	[5.24]	[5.69]	[6.06]	[6.26]	[6.01]	[2.01]	[2.18]	[2.09]
Controlling for Book-to-Market		0.74	1.02	1.06	1.04	1.07	0.34***	0.36***	0.35***	0.12	0.15	0.15
		[3.17]	[4.74]	[5.21]	[5.30]	[5.67]	[4.77]	[5.37]	[5.30]	[1.10]	[1.36]	[1.43]
Controlling for Volume		0.68	1.01	1.07	1.04	1.07	0.40***	0.43***	0.42***	0.22*	0.25**	0.24**
		[2.82]	[4.66]	[5.28]	[5.33]	[5.64]	[5.23]	[6.00]	[5.97]	[1.90]	[2.22]	[2.14]
Controlling for Turnover		0.71	0.98	1.07	1.06	1.06	0.36***	0.40***	0.39***	0.18*	0.20**	0.18**
		[3.09]	[4.59]	[5.19]	[5.30]	[5.48]	[6.16]	[7.21]	[7.41]	[1.89]	[2.19]	[2.03]

*, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.

In the second test, we examine the interaction of Cov_Bsmb1 and size and control for size by creating double-sorted EW and VW portfolios based on size and Cov_Bsmb1. In all the size quintiles, portfolio 1 contains stocks with the lowest returns and the lowest level of Cov_Bsmb1. The long-short trading strategy yields a significantly positive spread in all size quintiles except for quintile 5. In the first size quintile, the difference in average returns between EW portfolio 5 and EW portfolio 1 is 0.65% per month, which is the largest significant positive yield. The magnitude of the positive yield decreases when moving from size quintile 1 to size quintile 5. Furthermore, we repeat the same analysis for VW portfolios and find a similar pattern to EW portfolios. These findings show that the relationship between Cov_Bsmb1 and subsequent stock returns remains positive even when size is controlled by creating double-sorted portfolios.

In the third test, we control for size by sorting stocks based on Cov_Bsmb1 into quintile portfolios so that each quintile contains all size of firms. The row "Controlling for Size" shows that the 5-1 difference in average returns between portfolio 5 and portfolio 1 is 0.42% per month, which is significant at the 1% significance level.

The results from the three tests show that market capitalization does not explain the positive relationship between Cov_Bsmb1 and future stock returns in EW portfolios. This positive relationship remains for VW portfolios except when examining the relationship between Cov_Bsmb1 and subsequent stock returns by using the NYSE sample. Furthermore, the results from Jensen's alpha confirm the positive relationship between Cov_Bsmb1 and stock returns at the portfolio level when size is controlled.

We also perform the above-mentioned tests on EW portfolios and VW portfolios to examine whether size can explain the positive relationship between other covariance terms

(Cov_Bmkt1, Cov_Bhml1, Cov_Bmkt2, Cov_Bsmb2, and Cov_Bhml2) and subsequent stock returns. After controlling for size, we find that the Cov_Bmkt1, Cov_Bhml1, and Cov_Bhml2 maintain their positive relationships with future stock returns in EW portfolios. Tables A4 to A6 of the Appendix show that trading strategy yields are significantly positive throughout the three tests. With regard to Cov_Bmkt2 and Cov_Bsmb2, the trading strategy provides significant positive yields in all settings except when we test for "NYSE Stocks Only". We also repeat the tests by forming VW portfolios and find that positive trading strategy yields are observed when stocks are double sorted on size and covariance terms.

4.2.2 Controlling for Book-to-Market Ratios

Existing literature generally concludes that average returns are positively related to a firm's book-to-market ratio (e.g., Rosenberg, Reid, & Lanstein, 1985). If the book-to-market effect is expected to explain the negative effects of volatility terms, portfolios with the highest level of volatility terms must be mainly composed of growth stocks with lower average returns than value stocks. The results from tables 4, A1, A2, and A3 show that when we control for book-to-market ratios, negative effects of volatility terms on average returns do not disappear for EW portfolios. The 5-1 difference in average returns of the portfolios sorted according to volatility terms are all significantly negative. However, for VW portfolios, the negative volatility effects disappear.

Similarly, if the positive effect of covariance terms is explained by the book-to-market effect, portfolios with the highest level of covariance terms must be mainly composed of value stocks with higher average returns than growth stocks. The results of tables 5 and A4 to A8 show that when we control for book-to-market ratios, the positive effects of covariance terms on average returns do not disappear for EW portfolios. However, for VW portfolios, the positive relationships disappear. Overall, book-to-market ratios cannot explain the relationship between additional components and average returns in EW portfolios.

4.2.3 Controlling for Volume

Some studies find that stocks with higher volumes have higher returns (e.g., Gervais, Kaniel, & Mingelgrin, 2001). Accordingly, if the trading volume effect explains the negative effects of volatility terms, then stocks with high volatility terms must have low trading volume. The results of tables 4 and A1 to A3 show that when we control for volume, the negative effects of volatility terms on average returns do not disappear for EW portfolios. The 5-1 difference in average returns of portfolios sorted on volatility terms is significantly negative at the 1% significance level. Besides, the negative relationships are marginally significant at the 10% significance level for VW portfolios.

With regards to covariance terms, if the volume effect is expected to explain their positive effects on subsequent stock returns, then portfolios with the highest covariance terms must be mainly composed of stocks with higher volume. The results of tables 5 and A4 to A8 show that when we control for volume, the positive effects of covariance terms on average returns do not disappear for EW portfolios. However, when we form VW portfolios, the positive effect of Cov_Bmkt1, Cov_Bhml1, and Cov_Bsmb1 becomes marginally significant, and it disappears for other covariance terms. Overall, the volume cannot explain the relationship between additional components and average returns in EW portfolios.

4.2.4 Controlling for Turnover

Empirical findings indicate that portfolios with higher average returns mainly consist of stocks with higher turnover (Grinblatt & Titman, 1994). If turnover is expected to explain the negative relationships between volatility terms and stock returns, then portfolios with the highest level of volatility terms must be mainly composed of stocks with lower turnover. The results of tables 4 and A1 to A3 show that when we control for turnover, the negative effects of volatility terms on average returns do not disappear for EW and VW portfolios. The 5-1 difference in average returns of portfolios sorted based on those terms is significantly negative.

With regards to covariance terms, if the turnover effect is expected to explain their positive effect on stock returns, then portfolios with the highest covariance terms must be mainly composed of stocks with higher turnover. The results of tables 5 and A4 to A8 show that when we control for turnover, the positive effects of covariance terms on average returns do not disappear for EW portfolios. However, the positive effects of covariance terms become weak or disappear for VW portfolios. Overall, turnover cannot explain the relationship between additional components and average returns in EW portfolios.

Overall, two-way sorted portfolio analysis shows that alpha risk and beta risk have negative relationships with average returns in both EW and VW portfolios. Alpha risk has a more significant negative relationship with average returns through size quintiles 1 to 4 compared to beta volatility (Vol_Bmkt, Vol_Bsmb, and Vol_Bhml). An analysis of the double-sorted portfolios shows that Cov_Bmkt1, Cov_Bsmb1, and Cov_Bhml1 have significant positive relationships with average returns in both EW and VW portfolios. Cov_Bmkt2, Cov_Bsmb2, and Cov_Bhml2 also have positive relationships with average returns; however, this relationship is small compared to the relationship between each covariance terms of Cov_Bmkt1, Cov_Bsmb1, and Cov_Bhml1 with average returns. Cov_Bsmb1 has the highest significant positive relationship with average returns compared to other covariance terms in EW and VW portfolios. The relationship between all the additional terms embedded in unconditional idiosyncratic risk and average returns are robust to size, book-to-market ratio, volume, and turnover in EW portfolios. However, in VW portfolios, the relationship between additional terms and average returns disappeared after controlling for "NYSE Stocks," size, book-to-market, and volume.

4.3 Triple Sort

In previous sections, we investigated the relationship between additional terms — embedded in unconditional idiosyncratic risk— and stock portfolio returns in single-sorted portfolios and double-sorted portfolios. To further investigate this relationship, we sort stocks into 3 X 3 X 3 portfolios by size, book-to-market ratio, and individual additional terms. In other words, we first sort stocks into three size portfolios, and then each size portfolio is divided into three portfolios by book-to-market ratio. In the third step, each double-sorted portfolio is sorted into three portfolios by each individual volatility or covariance terms. Then monthly average returns are computed for EW portfolios and VW portfolios.

Since alpha volatility and Cov_Bsmb1 have the most significant relationships with stock returns, we present and discuss their relationships with stock returns through triple sorting analysis in this section. We also repeat this analysis for other additional terms and present the results in tables A9 to A11 of the Appendix.

Table 6 reports the average returns of 3 X 3 X 3 portfolios sorted by size, book-to-market ratio, and alpha risk in three panels. Panel A reports the average returns of low book-to-market portfolios. The difference in average returns between EW portfolios 5 and EW portfolio 1 is negative and significant across all the three different sized portfolios with low book-to-market ratio. Panel B shows the average returns and trading strategy yields from medium book-to-market portfolios. The negative yield is highly significant only for small-cap stocks with a medium book-to-market ratio. Although the relationship between alpha risk and future stock returns is negative and significant for small-cap stocks, the magnitude of the relationship is small compared to the portfolios with the same size under low book-to-market stocks in panel A. The magnitude of the relationship becomes even smaller for high book-to-market stocks in panel C. The results in table 6 show that the negative alpha risk effect is not significant among large-cap stocks.

Table 6
Triple Sort by Size, Book-to-market, and Alpha Risk

The table reports monthly average returns of tripe sorted portfolios, with robust Newey–West (1987) t-statistics in square brackets. We first sort stocks into three size portfolios, and then stocks of each size portfolio are sorted into three portfolios by book-to-market ratio. In the third step, each double-sorted portfolio is sorted into three portfolios by alpha risk. Then monthly average returns are computed for EW portfolios. Panel A reports the monthly average returns for portfolios with low book-to-market stocks sorted on three different size groups and alpha volatility. Panel B and C present the monthly average returns for portfolios with medium and high book-to-market ratios, respectively. The row labeled "High-Low" presents the difference in average returns between the portfolio with the high level of alpha risk and the portfolio with the low level of alpha risk. The rows labeled "CAPM Alpha" and "FF-3 Alpha" report the difference in alphas between the portfolio with the high level of alpha risk and the portfolio with the low level of alpha risk. The last row labeled "VW Portfolios: High-Low" shows the difference in average returns for Value-weighted portfolios.

Alpha Risk	Panel A			Panel B			Panel C		
	Low Book-to-Market			Medium Book-to-Market			High Book-to-Market		
	Small Cap	Mid Cap	Large Cap	Small Cap	Mid Cap	Large Cap	Small Cap	Mid Cap	Large Cap
Low	0.99	1.15	0.98	1.22	1.06	0.93	1.38	1.33	1.16
Medium	0.94	0.91	1.02	1.1	1.05	0.89	1.34	1.34	1.18
High	0.23	0.43	0.75	0.7	0.9	0.91	0.99	1.16	1.17
High-Low	-0.76***	-0.71***	-0.24**	-0.52***	-0.17*	-0.02	-0.39***	-0.18*	0.01
	[-9.88]	[-8.46]	[-2.12]	[-5.34]	[-1.86]	[-0.31]	[-5.37]	[-1.67]	[0.16]
CAPM Alpha	-0.76***	-0.71***	-0.24**	-0.53***	-0.19**	-0.03	-0.39***	-0.20*	-0.01
	[-10.65]	[-8.37]	[-2.14]	[-5.36]	[-2.25]	[-0.45]	[-5.35]	[-1.93]	[-0.10]
FF-3 Alpha	-0.76***	-0.70***	-0.22*	-0.51***	-0.19**	-0.02	-0.37***	-0.19*	0
	[-11.56]	[-7.88]	[-1.94]	[-5.23]	[-2.32]	[-0.35]	[-4.61]	[-1.87]	[0.03]
VW Portfolios: High-Low	-0.72***	-0.71***	-0.16	-0.49***	-0.14	-0.12	-0.40***	-0.14	0.04
	[-6.63]	[-8.04]	[-1.59]	[-4.31]	[-1.54]	[-1.34]	[-5.25]	[-1.26]	[0.68]

*, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.

The CAPM alphas and FF-3 alphas show that the negative relationship between alpha risk and portfolio stock returns is more pronounced for all small-cap stocks, especially small-cap stocks with low book-to-market ratios in panel A. The row labeled "VW Portfolios: High-Low" shows the trading strategy yields relative to VW portfolios. Similar to the results from EW portfolios, the negative relationship between alpha risk and portfolio returns is negative and significant for small-cap size stocks, and the magnitude of the negative relationship becomes smaller for small-cap size with medium or high book-to-market ratio.

We repeat the triple sorting analysis for the beta volatility terms— Beta MKT Risk (Vol_Bmkt), Beta SMB Risk (Vol_Bsmb), and Beta HML Risk (Vol_Bhml). Table A9 of the Appendix reports similar results to that of table 6. Based on long-short trading strategy yields and Jensen's Alpha from the CAPM and FF-3 model, the negative relationships between beta volatilities and stock returns are significantly negative for small-cap stocks. This negative relationship is the strongest for small-cap stocks with low book-to-market ratios.

Table 7 reports the average returns of 3 X 3 X 3 EW and VW portfolios sorted by size, book-to-market ratio, and Cov_Bsmb1 in three panels. Panel A shows that the positive relationship between Cov_Bsmb1 and EW portfolio returns is significant for small-cap and medium-cap portfolios with low book-to-market ratios. However, when going from small-cap stocks to large-cap stocks, the magnitude of the positive relationship decreases. Panel B reports the average returns and trading strategy yields for stocks with medium book-to-market ratios. The results in Panel B are similar to those in panel A; it shows that the positive relationship is significant among small-cap and medium-cap stocks, with a 5% significance level. However, the magnitude of positive relationship is small compared to the same size portfolio with low book-to-market ratios. Panel C shows that the positive relationship is only significant for small-cap stocks with a high book-to-market ratio. CAPM alphas and FF-3 alpha confirm that the positive relationship is stronger among small stocks, especially stocks with low book-to-market ratios.

Table 7
Triple Sort by Size, Book-to-market, and Cov_Bsmb1

The table reports monthly average returns of tripe sorted portfolios, with robust Newey–West (1987) t-statistics in square brackets. We first sort stocks into three size portfolios, and then stocks of each size portfolio are sorted into three portfolios by book-to-market ratio. In the third step, each double-sorted portfolio is sorted into three portfolios by Cov_Bsmb1. Then monthly average returns are computed for EW portfolios. Panel A shows the monthly average returns for portfolios with low book-to-market stocks sorted on three different size groups and Cov_Bsmb1. Panel B and C present the monthly average returns for portfolios with medium and high book-to-market ratios, respectively. The row labeled "High-Low" presents the difference in average returns between the portfolio with the high level of Cov_Bsmb1 and the portfolio with the low level of Cov_Bsmb1. The rows labeled "CAPM Alpha" and "FF-3 Alpha" report the difference in alphas between the portfolio with the high level of Cov_Bsmb1 and the portfolio with the low level of Cov_Bsmb1. The last row labeled "VW Portfolios: High-Low" shows the difference in average returns for Value-weighted portfolios.

Cov_Bsmb1	Panel A			Panel B			Panel C		
	Low Book-to-Market			Medium Book-to-Market			High Book-to-Market		
	Small Cap	Mid Cap	Large Cap	Small Cap	Mid Cap	Large Cap	Small Cap	Mid Cap	Large Cap
Low	0.33	0.55	0.83	0.78	0.85	0.94	1.1	1.17	1.16
Medium	0.92	0.96	0.93	1.07	1.1	0.84	1.34	1.33	1.18
High	0.92	0.97	0.99	1.16	1.05	0.96	1.27	1.32	1.17
High-Low	0.60***	0.43***	0.16*	0.38***	0.19***	0.02	0.17**	0.14*	0.02
	[6.10]	[5.23]	[1.67]	[5.03]	[2.84]	[0.27]	[2.42]	[1.76]	[0.27]
CAPM Alpha	0.58***	0.44***	0.17*	0.39***	0.20***	0.03	0.17**	0.14*	0.03
	[6.23]	[5.23]	[1.76]	[4.94]	[2.88]	[0.41]	[2.40]	[1.79]	[0.47]
FF3 Alpha	0.55***	0.44***	0.14	0.38***	0.21***	0.03	0.15**	0.16*	0.01
	[6.55]	[5.24]	[1.58]	[4.58]	[3.02]	[0.41]	[2.08]	[1.93]	[0.20]
VW Portfolios: High-Low	0.60***	0.42***	0.17*	0.36***	0.16**	-0.01	0.17**	0.14*	0.02
	[5.55]	[5.27]	[1.70]	[4.91]	[2.26]	[-0.10]	[2.42]	[1.70]	[0.20]

*, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.

The triple sorting analysis is also repeated for other covariance terms. Tables A10 and A11 of the Appendix report similar results to that of table 7. Based on long-short trading strategy yields and Jensen's Alpha from the CAPM and FF-3 model, the positive relationship between covariance terms and stock returns are significantly positive for small-cap stocks. This negative relationship is the strongest for small-cap stocks with low book-to-market ratios.

Overall, the analysis of triple-sorted portfolios shows that alpha volatility has the most significant negative relationship with the average returns among volatility terms. The negative relationship is significant for stocks from all size groups (small-cap, mid-cap, and large-cap) with low book-to-market ratios. The negative relationship is not significant for large-cap stocks with a medium book-to-market ratio and a high book-to-market ratio. The same results are observable for Vol_Bsmb; however, the 5-1 difference in average returns is smaller than alpha risk. Among covariance terms, Cov_Bsmb1 has the most significant positive relationship with the average returns. The positive relationship is significant for stocks from all size groups (small-cap, mid-cap, and large-cap) within low book-to-market portfolios. However, this relationship is not significant for large-cap stocks with medium and high book-to-market ratios.

4.4 Unconditional and Conditional Idiosyncratic Risk

In this section, the effect of Unconditional_IVOL and Conditional_IVOL on average portfolio returns is examined separately. Panel A of table 8 shows the average returns of EW and VW portfolios sorted by Unconditional_IVOL. It shows that the average returns of EW portfolios increase from 1.1% per month to 1.25% per month going from quintile 1 to quintile 3. However, average returns decrease from quintile 3 to quintile 5. Quintile 5 includes stocks with the highest unconditional idiosyncratic volatility, and has the lowest average returns of 0.29% per month. The difference in average returns between portfolio 5 and portfolio 1 is -0.81% per month, with a robust Newey-West t-statistics of -5.40.

Table 8
Portfolios Sorted by Unconditional and Conditional Idiosyncratic Volatility

We create equal-weighted quintile portfolios every month by sorting stocks based on unconditional idiosyncratic volatility relative to the FF-3 model (Panel A) and also based on conditional idiosyncratic volatility from the conditional FF-3 model (equation (8)). Idiosyncratic volatility is defined as the standard deviations of regression residuals estimated using daily stock returns over the previous month. Quintile portfolios are formed every month based on idiosyncratic volatility. Portfolio 1 (5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatility. Mean and Std. Dev. are measured monthly and reported based on percentage, and then applied to total simple returns. Column "Size" is the log of average market capitalization for firms within the portfolio, and column "B/M" reports the average book-to-market ratio, which is calculated based on Fama and French (1993). The row "5-1" refers to the difference in monthly average returns between quintile 5 and quintile 1. The last two right columns report the Jensen's alpha estimated from CAPM or FF-3 model. The Newey–West adjusted t-statistics are reported in square brackets. The last row labeled "VW Portfolios: High-Low" shows the difference in average returns for Value-weighted portfolios. The sample period is July 1963 to December 2018.

Rank	**Mean**	**Std. Dev.**	**% Mkt Share**	**Size**	**B/M**	**CAPM Alpha**	**FF-3 Alpha**
			Panel A: Portfolios Sorted by Unconditional_IVOL				
1	1.1	3.66	46.28	6.11	0.74	0.64	0.62
2	1.2	4.52	25.98	5.80	0.71	0.74	0.73
3	1.25	5.10	14.63	5.32	0.70	0.78	0.77
4	1.03	5.76	8.49	4.88	0.69	0.54	0.55
5	0.29	6.21	4.62	4.38	0.68	-0.21	-0.2
5 -1	-0.81***					-0.86***	-0.82***
	[-5.40]					[-6.02]	[-5.96]
VW Portfolios: High-Low	-0.62***					-0.70***	-0.68***
	[-3.41]					[-4.05]	[-3.89]
			Panel B: Portfolios Sorted by Conditional_IVOL				
1	1.05	4.39	29.14	5.55	0.73	0.58	0.57
2	1.08	4.67	25.55	5.56	0.71	0.62	0.62
3	1.02	4.89	20.71	5.41	0.70	0.55	0.54
4	1	5.25	15.68	5.20	0.70	0.53	0.52
5	0.71	5.70	8.93	4.78	0.69	0.21	0.22
5 -1	-0.34***					-0.37***	-0.35***
	[-4.28]					[-4.76]	[-4.64]
VW Portfolios: High-Low	-0.1					-0.14	-0.13
	[-0.86]					[-1.31]	[-1.18]

The difference in FF-3 alphas between portfolio 5 and portfolio 1 is -0.82% per month, which is highly significant at the significance level of 1%. The trading strategy yields negative returns of -0.62% per month for VW portfolios, which is significant at the level of 1%. Overall, results show that the relationship between Unconditional_IVOL and subsequent average returns is significant and negative for EW and VW portfolios.

Panel B shows the average returns of EW and VW portfolios sorted by Conditional_IVOL. The results are similar to those of Panel A. The difference in average returns between portfolio 5 and portfolio 1 is -0.34% per month, with a robust Newey-West t-statistics of -4.28. Thus, similar to portfolios sorted on Unconditional_IVOL, there is a negative and significant relationship between Conditional_IVOL and future stock returns. However, the magnitude of the relationship is small for portfolios sorted on Conditional_IVOL. It implies that when we incorporate the time-varying alpha and betas into the FF-3 model, those additional terms are not included in the conditional idiosyncratic volatility. Thus, when we eliminate additional terms from idiosyncratic risk, the magnitude of the negative relationship between idiosyncratic risk and subsequent stock return decreases. We can conclude that additional components can explain the negative effect of idiosyncratic volatility to some extent. Furthermore, the row labeled "VW Portfolios: High-Low" shows that the negative relationship between Conditional_IVOL and average returns is not significant for VW portfolios.

Another implication of portfolio analysis is that the conditional FF-3 model is more efficient in explaining systematic patterns for predicting stock returns, as fewer systematic patterns are included in the regression residuals. Therefore, conditional idiosyncratic volatility can be a better estimation of idiosyncratic risk.

4.5 Fama-MacBeth regression

Table 9 reports the results of the firm-level Fama and MacBeth (1973) regressions of monthly stock returns on all the additional components included in unconditional idiosyncratic volatility for the period of July 1963 to December 2018.

Model 1 shows that unconditional idiosyncratic volatility, which is estimated based on the FF-3 model, negatively and significantly relates to monthly stock returns after controlling for potential risk factors such as size, book-to-market, momentum, and liquidity. Every one percent increase in the idiosyncratic risk leads to a 0.23% decrease in monthly stock returns. Model 1 shows that those risk factors cannot explain the negative relationship.

After accounting for time-varying properties of alpha and beta, model 2 shows that conditional idiosyncratic volatility does not have a significant relationship with stock returns. The reason is that when we account for time-varying properties of alpha and beta in the FF-3 model, the systematic patterns available in residuals decrease. Therefore, the idiosyncratic volatility estimated from the conditional FF-3 model does not explain the stock returns compared to the unconditional version of idiosyncratic volatility.

Model 3 shows that when Alpha and beta risks are added, alpha risk has a negative and significant relationship with stock returns. As the alpha risk increases by one percent, the expected stock return decreases by -0.031%. There is also a negative relationship between Vol_Bsmb and stock return; however, the magnitude of the relationship is much smaller (-0.005) compared to the relationship between alpha risk and expected stock returns. Furthermore, conditional idiosyncratic risk is still insignificant.

We incorporate all the additional components, which are embedded in idiosyncratic risk, into model 5. The results of regression 5 show that none of the covariance terms are significantly related to subsequent stock returns. Among all the additional terms, alpha risk has a negative and significant relationship with subsequent stock returns. The magnitude of the relationship is -0.04% with the robust Newey-West *t*-statistics of -2.15. The magnitude of the relationship between Vol_Bsmb and expected stock returns is very small (-0.0009). The conditional idiosyncratic volatility is also insignificant in model 4.

Table 9
Firm-level Cross-sectional Regression

This table presents the results from firm-level Fama and MacBeth (1973) regressions of daily returns on all additional components—volatility and covariance terms. Alpha risk is the standard deviation of time-varying alpha from daily stock returns in the previous month (t-1). Beta risk is defined as the standard deviations of time-varying beta MKT, beta SMB, and beta HML. Alpha and beta risks are converted to monthly risks by multiplying the standard deviations by the square root of the number of trading days for a specific stock each month. A stock should have at least 15 daily returns in a month to be included in the risk estimation. Covariance terms — Cov_Bmkt1, Cov_Bsmb1, Cov_Bhml1, Cov_Bmkt2, Cov_Bsmb2, and Cov_Bhml2— are defined in section 3.2.1. All covariance terms are calculated using daily data for each month. Conditional_IVOL is the conditional idiosyncratic volatility calculated as the standard deviation of regression residuals of daily stock returns in the month t-1 based on the conditional FF-3 factor model (equation 3). Beta is the regression coefficient of the past 24 monthly excess returns on excess market returns. Me and B/M are the size and book-to-market ratio and calculated following Fama and French (1993). Ret $(-2, -7)$ is the momentum calculated as compound gross return from the month $(t-7)$ to $(t-2)$. TURN and CVTURN are proxies for liquidity. Turn is the average volume turnover calculated over the past three years, and CVTURN is the coefficient of variance of TURN calculated over the past three years following Chordia, Subrahmanyam, and Anshuman (2001). The Newey–West adjusted t-value is reported in brackets. To avoid the effect of possibly spurious outliers, all explanatory variables below the 0.5 (above 99.5) percentile are set equal to the 0.5 (99.5) percentile. *, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively

(Continued)

Table 9. Firm-level cross-sectional regression

	Model 1	Model 2	Model 3	Model 4
Intercept	0.03***	0.02***	0.03***	0.03***
	[5.29]	[3.21]	[3.89]	[4.03]
Beta	0.08	0.04	0.05	0.06
	[1.19]	[0.64]	[0.83]	[0.90]
Ln(ME)	-0.14***	-0.11***	-0.12***	-0.12***
	[-5.28]	[-3.74]	[-4.30]	[-4.42]
Ln(B/M)	0.14**	0.16***	0.15***	0.15***
	[2.54]	[2.90]	[2.75]	[2.79]
Ret(-2, -7)	0.91***	0.93***	0.92***	0.93***
	[5.59]	[5.56]	[5.56]	[5.62]
Ln(Turn)	-0.06	-0.09**	-0.08*	-0.08**
	[-1.43]	[-2.15]	[-1.95]	[-1.99]
Ln(CVTURN)	-0.26***	-0.3***	-0.3***	-0.29***
	[-4.91]	[-5.61]	[-5.43]	[-5.44]
Unconditional Idio	-0.23***			
	[-8.90]			
Conditional Idio		-4.05E+07	5.26E+07	1.65E+07
		[-1.20]	[1.07]	[0.30]
VOL_Alpha			-0.031**	-0.045**
			[-2.55]	[-2.15]
VOL_Bmkt			0.0001	-0.0001
			[0.41]	[-0.43]
VOL_Bhml			0.0008	0.0026
			[0.41]	[0.76]
VOL_Bsmb			-0.0005*	-0.0009*
			[-1.90]	[-1.74]
Cov_Bmkt1				0
				[-0.21]
Cov_Bsmb1				-0.002
				[-1.11]
Cov_Bhml1				0.83
				[0.95]
Cov_Bmkt2				-0.13
				[-0.10]
Cov_Bsmb2				-2.72
				[-1.55]
Cov_Bhml2				-1.1
				[-0.52]
Adj. R2	0.06***	0.058***	0.061***	0.066***
.	[23.79]	[23.62]	[24.61]	[25.82]

Overall, the results of Fama-Macbeth regression show that among all the additional terms, only alpha risk has a highly significant and negative relationship with expected stock returns. However, the other additional terms do not have significant relationships with expected stock returns at the firm level. In addition, the portfolio analysis shows that the negative effect of conditional idiosyncratic volatility is weak compared to unconditional idiosyncratic volatility. On the other hand, the result of Fama-Macbeth regression shows that there is no relationship between conditional idiosyncratic volatility and expected stock returns. We can conclude that no systematic patterns are included in the idiosyncratic volatility relative to the conditional FF-3 model. Thus, the conditional model can explain the stock returns better than its unconditional counterpart.

Chapter Five:

Conclusion

5.1 Findings

Numerous studies have examined the relationship between idiosyncratic risk and stock returns based on an unconditional version of conventional asset pricing models (e.g., CAPM and FF-3). They have found different directions for this relationship. However, conventional factor models do not account for the time-varying property of alpha and beta; therefore, they leave significant systematic patterns of stock returns in the residuals (Ferson & Harvey, 1999). As a result, the estimated idiosyncratic volatility is not completely unsystematic due to the presence of systematic patterns in the pricing errors. Therefore, the relationship between idiosyncratic risk and stock returns documented by previous studies (e.g., Xu and Malkiel, 2004; Ang et al. 2006, 2009; Berrada and Hugonnier, 2013; Hai et al. 2020) might be misleading because this relationship might be derived by systematic patterns that are mistakenly included in idiosyncratic volatility, not the idiosyncratic risk itself. This thesis examines the asset pricing role of volatility and covariance components of idiosyncratic risk by using a large sample of stocks listed on NYSE, AMEX, and NASDAQ from July 1963 to December 2018. First, following Fu's (2018) framework, the total risk is decomposed into its systematic and idiosyncratic components based on the conditional FF-3 model. Then, constant alpha and betas are replaced with time-varying alpha and betas. Alpha and betas are allowed to be changed as a linear function of lagged macro-economic instruments. After decomposition of the total risk, four additional components (two volatility and two covariance terms) are found in the idiosyncratic volatility estimated based on the unconditional FF-3 model.

First, this study aims to investigate the stock returns predictive power of idiosyncratic volatility components at the portfolio and firm level. The results show that volatility terms have negative relationships with stock returns at the portfolio level. The difference in average returns between portfolios with the highest and lowest level of volatility terms are negative and significant, and alpha risk has the strongest negative relationship with stock returns among the other volatility terms. In contrast, covariance terms are positively related to subsequent stock returns. The long-short trading strategy yields a positive spread between portfolios with the highest and lowest level of covariance terms, and Cov_Bsmb1 has a more significant positive relationship with stock returns among covariance terms at the portfolio level. The results of the robustness tests indicate that the relationship between idiosyncratic volatility components and subsequent stock returns is robust to controlling for size, book-to-market, volume, and turnover for equal-weighted portfolios at the portfolio level. However, the relationship disappears or becomes weak for value-weighted portfolios.

Another finding of this research is that the relationship between stock returns and components of idiosyncratic volatility is not exclusively associated with small stocks. The results of two-way and three-way portfolio analysis show that these relationships are available in different size portfolios, i.e., portfolios with small, medium, and large-cap stocks. Furthermore, the analysis of triple-sorted portfolios shows that the negative effect of volatility terms and positive impact of covariance component on stock returns are more significant among small-cap stocks, especially those with low book-to-market ratios.

To investigate the relationship between components of idiosyncratic volatility and stock returns at the firm level, this research adopts the Fama-Macbeth (1973) two-stage regression method. The cross-sectional regression results show that among all components of idiosyncratic volatility, only alpha volatility is significant and explains the variations in stock returns. This finding indicates that alpha volatility is negatively related to subsequent monthly stock returns at the firm level. This result is robust to controlling for size, book-to-market ratio, momentum, turnover, CAPM beta, turnover, and coefficient of variance of turnover. Another finding is that, while the relationship between covariance terms and stock returns is significant and positive at the portfolio level, it is statistically insignificant at the firm level. Therefore, covariance terms can predict stock returns only at the portfolio level.

Second, this study examines whether idiosyncratic volatility components can explain the negative relationship between idiosyncratic risk and subsequent stock returns. To solve the idiosyncratic volatility puzzle, several studies suggest different economic mechanisms to explain the negative relationship between idiosyncratic risk and expected stock returns; however, those mechanisms do not completely explain the relationship (Hou & Loh, 2016). This study finds that when the systematic patterns are excluded from the idiosyncratic volatility, the relationship between idiosyncratic risk and subsequent stock returns becomes weak for equal-weighted portfolios. However, it disappears for value-weighted portfolios at the portfolio level. This finding indicates that systematic patterns that are mistakenly considered as idiosyncratic risk do not completely explain the relationship between subsequent stock returns and idiosyncratic volatility at the portfolio level. Furthermore, empirical results of the Fama-MacBeth cross-sectional model show that unconditional idiosyncratic risk has a significant negative relationship with stock returns. On the other hand, the conditional idiosyncratic volatility is not significant in explaining the variations of monthly stock returns at the firm level. This is because when a conditional version of the FF-3 model is employed for estimation of idiosyncratic volatility, those systematic patterns that derive the negative relationship between idiosyncratic risk and stock returns are not included in the idiosyncratic volatility.

The contribution of this thesis is two-folded. First, it contributes to stock return predictability literature by introducing the covariance terms of idiosyncratic volatility as new predictors of stock returns at the portfolio level. Second, this study contributes to the idiosyncratic risk literature by suggesting the components of idiosyncratic volatility as mechanisms that partially explain the idiosyncratic volatility puzzle at the portfolio level. While previous studies are mostly focused on maximum daily return, one-month return reversal, the Amihud illiquidity measure, uncertainty, and earning surprises to explain the relationship between idiosyncratic risk and expected stock returns, this research focuses on idiosyncratic risk by comprehensively examining its components. In this way, this thesis sheds more light on the idiosyncratic volatility puzzle.

The results of this study give some indications that the time-varying property of alpha and beta omitted by unconditional factor models can play a role in asset pricing. In this regard, this thesis raises a caution flag for researchers and investors, especially those who would adopt the unconditional factor models such as FF-3 to estimate the idiosyncratic volatility. This idiosyncratic volatility is not a perfect proxy for idiosyncratic risk as it contains systematic patterns.

5.2 Limitation of this thesis

The limitation faced in this study is related to the data sample. The findings of this thesis are associated with U.S. stock market data from July 1963 to December 2018. There is lack of comprehensive data source including specific-country data such as Fama-French factors for different countries. These serve as limitations to this study in terms of the investigation of the relationship between subsequent stock returns and components of idiosyncratic volatility in an international sample, including developing and other developed markets. Although the findings of this study is related to the U.S. markets, they are very important because NYSE and NASDAQ are the two largest stock markets in the world. Another limitation is that the thesis uses a factor model limited to three Fama-French factors to estimate the components of idiosyncratic volatility.

5.3 Recommendations for future research

With regard to the limitations of this thesis, future research can be conducted to examine the relationship between subsequent stock returns and components of idiosyncratic risk in a broad international sample. This sample can include developed markets such as G7 markets (Canada, France, Germany, Italy, Japan, the United States, and the United Kingdom), and emerging markets such as BRICK (Brazil, Russia, India, and China). Besides, future research can use an international sample to address the question of whether the components of idiosyncratic volatility explain the idiosyncratic volatility puzzle in different markets. Future research could also be conducted to repeat this study by adopting the conditional version of different factor models, such as the Carhart four-factor model (Carhart, 1997) and Fama-French five-factor model (Fama & French, 2015) to test the robustness of the findings of this study to different asset pricing models. It would also be interesting to examine the behavior of idiosyncratic volatility components over different sample periods (e.g., volatile market periods, stable market periods, recessions, and expansion periods of the economy). It is also recommended that scholars investigate the reasons for the anomalously low returns of quintile 5, sorted on volatility components and low returns of quintile 1, sorted on covariance components of idiosyncratic volatility.

Bibliography

Adrian, T., & Franzoni, F. (2009). Learning about beta: Time-varying factor loadings, expected returns, and the conditional CAPM. *Journal of Empirical Finance, 16*(4), 537-556.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The Cross-Section of Volatility and Expected Returns. *The Journal of Finance, 61*(1), 259-299. doi:10.1111/j.1540-6261.2006.00836.x

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2009). High idiosyncratic volatility and low returns: International and further U.S. evidence. *Journal of Financial Economics, 91*(1), 1-23. doi:https://doi.org/10.1016/j.jfineco.2007.12.005

Avramov, D., & Chordia, T. (2006). Asset Pricing Models and Financial Market Anomalies. *The Review of Financial Studies, 19*(3), 1001-1040. doi:10.1093/rfs/hhj025

Bali, T. G., & Cakici, N. (2009). Idiosyncratic Volatility and the Cross Section of Expected Returns. *Journal of Financial and Quantitative Analysis, 43*(1), 29-58. doi:10.1017/S002210900000274X

Bali, T. G., Cakici, N., & Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics, 99*(2), 427-446. doi:https://doi.org/10.1016/j.jfineco.2010.08.014

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics, 9*(1), 3-18. doi:https://doi.org/10.1016/0304-405X(81)90018-0

Barberis, N., & Huang, M. (2008). Stocks as Lotteries: The Implications of Probability Weighting for Security Prices. *American Economic Review, 98*(5), 2066-2100. doi:10.1257/aer.98.5.2066

Berggrun, L., Lizarzaburu, E., & Cardona, E. (2016). Idiosyncratic volatility and stock returns: Evidence from the MILA. *Research in International Business and Finance, 37*, 422-434. doi:https://doi.org/10.1016/j.ribaf.2016.01.011

Berrada, T., & Hugonnier, J. (2013). Incomplete information, idiosyncratic volatility and stock returns. *Journal of Banking & Finance, 37*(2), 448-462. doi:https://doi.org/10.1016/j.jbankfin.2012.09.004

Black, F. (1972). Capital Market Equilibrium with Restricted Borrowing. *The Journal of Business, 45*(3), 444-455.

Bollerslev, T., Tauchen, G., & Zhou, H. (2009). Expected Stock Returns and Variance Risk Premia. *The Review of Financial Studies, 22*(11), 4463-4492. doi:10.1093/rfs/hhp008

Braun, P. A., Nelson, D. B., & Sunier, A. M. (1995). Good News, Bad News, Volatility, and Betas. *The Journal of Finance, 50*(5), 1575-1603. doi:10.1111/j.1540-6261.1995.tb05189.x

Brockman, P., & Yan, X. (2008). The Time-Series Behavior and Pricing of Idiosyncratic Volatility: Evidence from 1926 to 1962. *IO: Theory*.

Campbell, J. Y., & Hentschel, L. (1992). No news is good news: An asymmetric model of changing volatility in stock returns. *Journal of Financial Economics, 31*(3), 281-318. doi:https://doi.org/10.1016/0304-405X(92)90037-X

Campbell, J. Y., Lettau, M., Malkiel, B. G., & Xu, Y. (2001). Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk. *The Journal of Finance, 56*(1), 1-43. doi:https://doi.org/10.1111/0022-1082.00318

Cao, J., & Han, B. (2013). Cross section of option returns and idiosyncratic stock volatility. *Journal of Financial Economics, 108*(1), 231-249. doi:https://doi.org/10.1016/j.jfineco.2012.11.010

Cao, J., & Han, B. (2016). Idiosyncratic risk, costly arbitrage, and the cross-section of stock returns. *Journal of Banking & Finance, 73*, 1-15. doi:https://doi.org/10.1016/j.jbankfin.2016.08.004

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance, 52*(1), 57-82. doi:https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Carr, P., & Wu, L. (2009). Variance Risk Premiums. *The Review of Financial Studies, 22*(3), 1311-1341. doi:10.1093/rfs/hhn038

Chan, L. K. C., Hamao, Y., & Lakonishok, J. (1991). Fundamentals and Stock Returns in Japan. *The Journal of Finance, 46*(5), 1739-1764. doi:https://doi.org/10.1111/j.1540-6261.1991.tb04642.x

Chen, L., Jiang, G., Xu, D., & Yao, T. (2012). Dissecting the Idiosyncratic Volatility Anomaly. *SSRN Electronic Journal*. doi:10.2139/ssrn.2023883

Dennis, P., Mayhew, S., & Stivers, C. (2009). Stock Returns, Implied Volatility Innovations, and the Asymmetric Volatility Phenomenon. *Journal of Financial and Quantitative Analysis, 41*(2), 381-406. doi:10.1017/S0022109000002118

Duan, Y., Hu, G., & McLean, R. D. (2010). Costly arbitrage and idiosyncratic risk: Evidence from short sellers. *Journal of Financial Intermediation, 19*(4), 564-579. doi:https://doi.org/10.1016/j.jfi.2009.06.003

Duffee, G. R. (1995). Stock returns and volatility a firm-level analysis. *Journal of Financial Economics, 37*(3), 399-420. doi:https://doi.org/10.1016/0304-405X(94)00801-7

Easley, D., & O'Hara, M. (2004). Information and the Cost of Capital. *The Journal of Finance, 59*(4), 1553-1583. doi:10.1111/j.1540-6261.2004.00672.x

Fama, E. F. (1990). Stock Returns, Expected Returns, and Real Activity. *The Journal of Finance, 45*(4), 1089-1108. doi:https://doi.org/10.1111/j.1540-6261.1990.tb02428.x

Fama, E. F., & French, K. R. (1989). Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics, 25*(1), 23-49. doi:https://doi.org/10.1016/0304-405X(89)90095-0

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance, 47*(2), 427-465. doi:https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3-56. doi:https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F., & French, K. R. (1995). Size and Book-to-Market Factors in Earnings and Returns. *The Journal of Finance, 50*(1), 131-155. doi:10.1111/j.1540-6261.1995.tb05169.x

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics, 116*(1), 1-22. doi:https://doi.org/10.1016/j.jfineco.2014.10.010

Fama, E. F., & MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy, 81*(3), 607-636.

Ferson, W. E., & Harvey, C. R. (1999). Conditioning Variables and the Cross Section of Stock Returns. *The Journal of Finance, 54*(4), 1325-1360. doi:10.1111/0022-1082.00148

French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of Financial Economics, 19*(1), 3-29. doi:https://doi.org/10.1016/0304-405X(87)90026-2

Fu, C. (2018). Alpha Beta Risk and Stock Returns—A Decomposition Analysis of Idiosyncratic Volatility with Conditional Models. *Risks, 6*(4), 1-11.

Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics, 91*(1), 24-37. doi:https://doi.org/10.1016/j.jfineco.2008.02.003

Gervais, S., Kaniel, R., & Mingelgrin, D. H. (2001). The High-Volume Return Premium. *The Journal of Finance, 56*(3), 877-919. doi:https://doi.org/10.1111/0022-1082.00349

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *The Journal of Finance, 48*(5), 1779-1801. doi:10.1111/j.1540-6261.1993.tb05128.x

Goyal, A., & Santa-Clara, P. (2003). Idiosyncratic Risk Matters! *The Journal of Finance, 58*(3), 975-1007. doi:10.1111/1540-6261.00555

Grinblatt, M., & Titman, S. (1994). A Study of Monthly Mutual Fund Returns and Performance Evaluation Techniques. *Journal of Financial and Quantitative Analysis, 29*(3), 419-444.

Guo, H., & Savickas, R. (2006). Idiosyncratic Volatility, Stock Market Volatility, and Expected Stock Returns. *Journal of Business & Economic Statistics, 24*(1), 43-56. doi:10.1198/073500105000000180

Guo, H., & Savickas, R. (2010). Relation between time-series and cross-sectional effects of idiosyncratic variance on stock returns. *Journal of Banking & Finance, 34*(7), 1637-1649. doi:https://doi.org/10.1016/j.jbankfin.2010.03.010

Hai, H. V., Park, J. W., Tsai, P.-C., & Eom, C. (2020). Lottery mindset, mispricing and idiosyncratic volatility puzzle: Evidence from the Chinese stock market. *The North American Journal of Economics and Finance, 54*, 101266. doi:https://doi.org/10.1016/j.najef.2020.101266

Hou, K., & Loh, R. K. (2016). Have we solved the idiosyncratic volatility puzzle? *Journal of Financial Economics, 121*(1), 167-194. doi:https://doi.org/10.1016/j.jfineco.2016.02.013

Hou, K., & Moskowitz, T. J. (2005). Market Frictions, Price Delay, and the Cross-Section of Expected Returns. *Review of Financial Studies, 18*(3), 981-1020.

Huang, W., Liu, Q., Rhee, S. G., & Zhang, L. (2009). Return Reversals, Idiosyncratic Risk, and Expected Returns. *The Review of Financial Studies, 23*(1), 147-168. doi:10.1093/rfs/hhp015

Jagannathan, R., & Wang, Z. (1998). An Asymptotic Theory for Estimating Beta-Pricing Models Using Cross-Sectional Regression. *The Journal of Finance, 53*(4), 1285-1309. doi:10.1111/0022-1082.00053

Jiang, G. J., Xu, D., & Yao, T. (2009). The Information Content of Idiosyncratic Volatility. *The Journal of Financial and Quantitative Analysis, 44*(1), 1-28.

Jiang, X., & Lee, B.-S. (2006). The Dynamic Relation Between Returns and Idiosyncratic Volatility. *Financial Management, 35*(2), 43-65. doi:10.1111/j.1755-053X.2006.tb00141.x

Khovansky, S., & Zhylyevskyy, O. (2013). Impact of idiosyncratic volatility on stock returns: A cross-sectional study. *Journal of Banking & Finance, 37*(8), 3064-3075. doi:https://doi.org/10.1016/j.jbankfin.2013.02.034

Lehmann, B. N. (1990). Residual risk revisited. *Journal of Econometrics, 45*(1), 71-97. doi:https://doi.org/10.1016/0304-4076(90)90094-A

Lesmond, D. A., Ogden, J. P., & Trzcinka, C. (1999). A New Estimate of Transaction Costs. *Review of Financial Studies, 12*(5), 1113-1141.

Lettau, M., & Ludvigson, S. (2001). Resurrecting the (C)CAPM: A Cross-Sectional Test When Risk Premia Are Time-Varying. *Journal of Political Economy, 109*(6), 1238-1287.

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics, 47*(1), 13-37. doi:10.2307/1924119

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance, 7*(1), 77-91. doi:10.1111/j.1540-6261.1952.tb01525.x

Merton, R. C. (1987). A Simple Model of Capital Market Equilibrium with Incomplete Information. *The Journal of Finance, 42*(3), 483-510. doi:10.1111/j.1540-6261.1987.tb04565.x

Nartea, G. V., Ward, B. D., & Yao, L. J. (2011). Idiosyncratic volatility and cross-sectional stock returns in Southeast Asian stock markets. *Accounting & Finance, 51*(4), 1031-1054. doi:10.1111/j.1467-629X.2010.00384.x

Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica, 55*(3), 703-708. doi:10.2307/1913610

Pontiff, J. (2006). Costly arbitrage and the myth of idiosyncratic risk. *Journal of Accounting and Economics, 42*(1), 35-52. doi:https://doi.org/10.1016/j.jacceco.2006.04.002

Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive evidence of market inefficiency. *The Journal of Portfolio Management, 11*(3), 9. doi:10.3905/jpm.1985.409007

Schwert, G. W. (1989). Why Does Stock Market Volatility Change Over Time? *The Journal of Finance, 44*(5), 1115-1153. doi:https://doi.org/10.1111/j.1540-6261.1989.tb02647.x

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance, 19*(3), 425-442. doi:10.1111/j.1540-6261.1964.tb02865.x

Spiegel, M. I., & Wang, X. (2005). Cross-Sectional Variation in Stock Returns: Liquidity and Idiosyncratic Risk. *Yale ICF Working Paper, No. 05-13, EFA 2005 Moscow Meetings Paper, Available at SSRN: https://ssrn.com/abstract=709781*.

Tinic, S. M., & West, R. R. (1986). Risk, Return, and Equilibrium: A Revisit. *Journal of Political Economy, 94*(1), 126-147. doi:10.1086/261365

Tversky, A., & Kahneman, D. (1992). Advances in Prospect Theory: Cumulative Representation of Uncertainty. *Journal of Risk and Uncertainty, 5*(4), 297-323.

Xu, Y., & Malkiel, B. G. (2004). Idiosyncratic Risk and Security Returns. *Available at SSRN: https://ssrn.com/abstract=255303 or http://dx.doi.org/10.2139/ssrn.255303*.

Appendix

A. Two-way portfolio analysis

Tables 4 and 5 of section 4.2.1 show that the negative relations of alpha volatility and subsequent stock returns and positive relation of Cov_Bsmb1 and future stock returns remain significant even after controlling for different cross-sectional factors—size, book-to-market ratios, volume, and turnover. In this section, we present the results portfolios double sorted on those factors and other volatility and covariance terms through tables A1 to A8.

Note for tables A1 to A8

Average Returns and Alphas of Portfolios Double Sorted on Size and Cov_Bsmb1

Tables A1 to A8 report monthly average returns and Jensen's alphas from the CAPM and FF-3 model, with robust Newey–West (1987) t-statistics in square brackets. After controlling for various effects, the 1/0/1 strategy described in section 3.2.3 is applied for alpha volatility computed relative to conditional FF-3 model (equation (8)). Two sets of portfolios are formed based on equal-weighted and value-weighted weighting schemes. The column "Return 5-1" refers to the difference in average returns between portfolio 5 and portfolio 1. The columns "CAPM Alpha 5-1" and "FF-3 Alpha 5-1" refer to the difference in CAPM and FF-3 alphas between portfolio 5 and portfolio 1 for EW and VW portfolios. In the panel labeled "NYSE Stocks Only", we sort stocks into quintile portfolios based on the level of alpha volatility, using only NYSE stocks. We use daily data over the previous month to calculate alpha volatility and then rebalance the data monthly. In the panel labeled "Size Quintiles", each month stocks are sorted into quintiles, and then within each size quintile, stocks are sorted by volatility and covariance terms. In the panels controlling for size, book-to-market, volume, and turnover, we perform a two-way sort. Each month, we first sort stocks based on the first characteristics (size, book-to-market, volume, or turnover), and then, within each quintile, we sort stocks based on volatility or covariance terms computed by the conditional FF-3 model. The five quintiles formed on those terms are then averaged over each of the five characteristic portfolios. Therefore, they represent alpha volatility quintiles controlling for the characteristics. The book-to-market ratio is defined as the total book value of equity divided by market value of equity based on Fama and French (1993), volume is average dollar volume over the previous month, turnover represents volume divided by the total number of shares outstanding over the past month. The sample period is July 1963 to December 2018.

Table A1

Average Returns and Alphas of Portfolios Double Sorted on Size and Beta Market Risk

		Ranking on Beta MKT Risk					EW			VW		
		1 Low	2	3	4	5 High	Return 5-1	CAPM Alpha 5-1	FF-3 Alpha 5-1	Return 5-1	CAPM Alpha 5-1	FF-3 Alpha 5-1
NYSE Stocks Only		1.08	1.08	1.04	1.08	0.88	-0.19***	-0.20***	-0.19***	-0.12	-0.12	-0.11
		[5.99]	[5.89]	[5.54]	[5.36]	[4.14]	[-3.46]	[-3.65]	[-3.52]	[-1.43]	[-1.50]	[-1.34]
Size Quintiles	**Small 1**	1.1	1.14	1.05	0.96	0.5	-0.62***	-0.63***	-0.58***	-0.65***	-0.65***	-0.61***
		[5.79]	[5.09]	[4.69]	[4.08]	[2.16]	[-6.12]	[-5.80]	[-5.05]	[-5.78]	[-5.52]	[-4.97]
	2	1.12	1.12	1.07	0.93	0.58	-0.55***	-0.54***	-0.51***	-0.54***	-0.53***	-0.51***
		[5.75]	[5.52]	[5.15]	[4.34]	[2.71]	[-4.85]	[-4.94]	[-4.68]	[-4.87]	[-4.97]	[-4.77]
	3	1.08	1.07	1.11	0.93	0.67	-0.40***	-0.41***	-0.40***	-0.39***	-0.42***	-0.40***
		[6.02]	[6.26]	[6.22]	[4.63]	[3.35]	[-3.79]	[-4.04]	[-4.15]	[-3.68]	[-3.96]	[-4.12]
	4	1.07	1.11	1.1	1.05	0.8	-0.27**	-0.28**	-0.24**	-0.26**	-0.27**	-0.22**
		[6.33]	[7.28]	[6.50]	[5.78]	[4.18]	[-2.44]	[-2.52]	[-2.38]	[-2.28]	[-2.29]	[-2.13]
	Large 5	0.99	0.94	1	0.96	0.88	-0.1	-0.1	-0.08	-0.1	-0.11	-0.09
		[7.35]	[6.62]	[7.45]	[6.25]	[5.61]	[-1.33]	[-1.32]	[-1.16]	[-1.07]	[-1.19]	[-1.01]
Controlling for Size		1.07	1.08	1.07	0.97	0.68	-0.38***	-0.39***	-0.36***	-0.13	-0.15	-0.13
		[5.57]	[5.42]	[5.22]	[4.46]	[2.89]	[-5.52]	[-5.64]	[-5.34]	[-1.45]	[-1.64]	[-1.42]
Controlling for Book-to-Market		1.05	1.07	1.08	1.01	0.73	-0.31***	-0.34***	-0.32***	-0.15	-0.19*	-0.19*
		[5.54]	[5.45]	[5.31]	[4.61]	[3.11]	[-4.62]	[-5.18]	[-4.94]	[-1.44]	[-1.85]	[-1.80]
Controlling for Volume		1.05	1.08	1.06	1	0.68	-0.37***	-0.40***	-0.38***	-0.20*	-0.23**	-0.22**
		[5.53]	[5.51]	[5.20]	[4.58]	[2.81]	[-4.84]	[-5.57]	[-5.47]	[-1.77]	[-2.12]	[-2.01]
Controlling for Turnover		0.58	0.62	0.59	0.48	0.22	-0.36***	-0.37***	-0.36***	-0.24**	-0.27***	-0.25***
		[3.16]	[3.30]	[3.03]	[2.38]	[1.05]	[-6.91]	[-6.90]	[-6.91]	[-2.58]	[-2.92]	[-2.75]

*, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.

Table A2

Average Returns and Alphas of Portfolios Double Sorted on Size and Beta SMB Risk

		Ranking on Beta SMB Risk					EW			VW		
		1 Low	2	3	4	5 High	Return 5-1	CAPM Alpha 5-1	FF-3 Alpha 5-1	Return 5-1	CAPM Alpha 5-1	FF-3 Alpha 5-1
NYSE Stocks Only		0.62	0.63	0.63	0.61	0.42	-0.19***	-0.19***	-0.18***	-0.09	-0.1	-0.1
		[3.62]	[3.55]	[3.47]	[3.22]	[2.05]	[-3.42]	[-3.42]	[-3.26]	[-1.12]	[-1.21]	[-1.25]
Size Quintiles	**Small 1**	1.13	1.08	1.03	0.96	0.53	-0.63***	-0.63***	-0.61***	-0.69***	-0.69***	-0.66***
		[5.79]	[4.67]	[4.61]	[4.24]	[2.20]	[-6.74]	[-6.52]	[-5.80]	[-6.82]	[-6.65]	[-5.90]
	2	1.11	1.07	1.1	1	0.56	-0.59***	-0.59***	-0.56***	-0.58***	-0.59***	-0.56***
		[5.50]	[5.71]	[5.56]	[4.65]	[2.40]	[-4.70]	[-4.78]	[-4.63]	[-4.70]	[-4.75]	[-4.62]
	3	1.08	1.05	1.1	0.96	0.69	-0.40***	-0.41***	-0.41***	-0.40***	-0.42***	-0.41***
		[6.08]	[6.30]	[5.94]	[4.67]	[3.53]	[-3.83]	[-4.03]	[-4.20]	[-3.77]	[-3.93]	[-4.07]
	4	1.14	1.05	1.04	1.1	0.82	-0.34***	-0.35***	-0.32***	-0.32***	-0.32***	-0.30***
		[7.03]	[6.15]	[6.55]	[6.07]	[4.39]	[-3.32]	[-3.42]	[-3.35]	[-2.97]	[-2.99]	[-2.95]
	Large 5	1	0.95	1	1.02	0.83	-0.15*	-0.16*	-0.14*	-0.17*	-0.18*	-0.17*
		[7.27]	[7.16]	[7.28]	[6.80]	[4.88]	[-1.69]	[-1.83]	[-1.69]	[-1.70]	[-1.81]	[-1.78]
Controlling for Size		1.09	1.04	1.09	1	0.66	-0.41***	-0.42***	-0.40***	-0.19**	-0.21**	-0.20**
		[5.68]	[5.24]	[5.22]	[4.63]	[2.84]	[-5.99]	[-6.20]	[-5.94]	[-2.08]	[-2.26]	[-2.17]
Controlling for Book-to-Market		1.08	1.04	1.06	1.02	0.74	-0.34***	-0.36***	-0.36***	-0.11	-0.14	-0.14
		[5.70]	[5.29]	[5.22]	[4.72]	[3.17]	[-4.84]	[-5.43]	[-5.34]	[-1.06]	[-1.29]	[-1.36]
Controlling for Volume		1.07	1.05	1.07	1.01	0.68	-0.40***	-0.43***	-0.41***	-0.21*	-0.23**	-0.23**
		[5.66]	[5.34]	[5.25]	[4.65]	[2.84]	[-5.17]	[-5.92]	[-5.90]	[-1.78]	[-2.08]	[-2.01]
Controlling for Turnover		1.07	1.05	1.06	0.99	0.71	-0.37***	-0.40***	-0.40***	-0.18*	-0.21**	-0.19**
		[5.52]	[5.27]	[5.18]	[4.59]	[3.09]	[-6.30]	[-7.38]	[-7.59]	[-1.95]	[-2.27]	[-2.12]

*, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.

Table A3

Average Returns and Alphas of Portfolios Double Sorted on Size and Beta HML Risk

		Ranking on Beta HML Risk					EW			VW		
		1 Low	2	3	4	5 High	Return 5-1	CAPM Alpha 5-1	FF-3 Alpha 5-1	Return 5-1	CAPM Alpha 5-1	FF-3 Alpha 5-1
NYSE Stocks Only		1.08	1.02	1.07	1.1	0.86	-0.22***	-0.22***	-0.23***	-0.17**	-0.18**	-0.20**
		[6.02]	[5.60]	[5.65]	[5.57]	[4.06]	[-3.91]	[-4.12]	[-4.11]	[-2.12]	[-2.17]	[-2.39]
Size Quintiles	**Small 1**	1.01	1.07	1.13	0.92	0.61	-0.41***	-0.42***	-0.39***	-0.46***	-0.47***	-0.44***
		[5.33]	[4.85]	[4.99]	[3.77]	[2.55]	[-4.09]	[-4.04]	[-3.54]	[-4.91]	[-4.85]	[-4.25]
	2	1.13	1.03	1.12	0.99	0.53	-0.60***	-0.59***	-0.55***	-0.61***	-0.60***	-0.56***
		[5.75]	[5.39]	[5.40]	[4.76]	[2.33]	[-5.62]	[-5.42]	[-5.26]	[-5.96]	[-5.70]	[-5.50]
	3	1.06	1.1	1.07	0.96	0.69	-0.37***	-0.38***	-0.37***	-0.38***	-0.39***	-0.38***
		[6.15]	[6.55]	[5.75]	[4.72]	[3.54]	[-3.93]	[-4.05]	[-4.15]	[-4.06]	[-4.20]	[-4.30]
	4	1.1	1.05	1.05	1.13	0.81	-0.29***	-0.30***	-0.28***	-0.26**	-0.26**	-0.24**
		[6.69]	[6.14]	[6.52]	[6.29]	[4.36]	[-2.82]	[-2.89]	[-2.85]	[-2.52]	[-2.53]	[-2.51]
	Large 5	0.98	0.96	0.99	1	0.83	-0.14*	-0.15*	-0.14*	-0.11	-0.12	-0.13
		[6.91]	[7.31]	[7.26]	[7.06]	[4.92]	[-1.76]	[-1.96]	[-1.84]	[-1.05]	[-1.24]	[-1.27]
Controlling for Size		1.05	1.04	1.08	1	0.69	-0.35***	-0.36***	-0.34***	-0.13	-0.15*	-0.16*
		[5.49]	[5.22]	[5.26]	[4.60]	[2.95]	[-5.27]	[-5.51]	[-5.21]	[-1.43]	[-1.65]	[-1.67]
Controlling for Book-to-Market		1.05	1.06	1.06	1.04	0.74	-0.30***	-0.32***	-0.31***	-0.15	-0.18*	-0.19*
		[5.47]	[5.41]	[5.24]	[4.79]	[3.12]	[-4.59]	[-5.11]	[-5.00]	[-1.35]	[-1.72]	[-1.81]
Controlling for Volume		1.05	1.05	1.07	1.03	0.68	-0.36***	-0.39***	-0.37***	-0.20*	-0.23**	-0.23**
		[5.45]	[5.36]	[5.27]	[4.72]	[2.82]	[-4.93]	[-5.57]	[-5.43]	[-1.82]	[-2.15]	[-2.10]
Controlling for Turnover		1.06	1.05	1.05	1.02	0.69	-0.36***	-0.39***	-0.38***	-0.23**	-0.25***	-0.25***
		[5.35]	[5.26]	[5.13]	[4.75]	[2.99]	[-6.72]	[-7.70]	[-7.77]	[-2.39]	[-2.73]	[-2.65]

*, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.

Table A4

Average Returns and Alphas of Portfolios Double Sorted on Size and Cov_Bmkt1

		Ranking on Cov_Bmkt1					EW			VW		
							Return	CAPM Alpha	FF-3 Alpha	Return	CAPM Alpha	FF-3 Alpha
		1 Low	2	3	4	5 High	5-1	5-1	5-1	5-1	5-1	5-1
NYSE Stocks Only		0.88	1.07	1.04	1.08	1.07	0.18***	0.19***	0.18***	0.13	0.13*	0.12
		[4.16]	[5.32]	[5.55]	[5.92]	[5.98]	[3.31]	[3.48]	[3.35]	[1.56]	[1.65]	[1.52]
Size Quintiles	**Small 1**	0.51	0.94	1.05	1.15	1.1	0.61***	0.62***	0.57***	0.64***	0.64***	0.61***
		[2.22]	[3.96]	[4.76]	[5.05]	[5.82]	[6.30]	[6.00]	[5.14]	[5.94]	[5.70]	[5.08]
	2	0.57	0.95	1.06	1.12	1.12	0.56***	0.56***	0.52***	0.55***	0.54***	0.52***
		[2.65]	[4.44]	[5.12]	[5.56]	[5.73]	[5.02]	[5.12]	[4.89]	[4.99]	[5.09]	[4.94]
	3	0.68	0.93	1.1	1.06	1.08	0.39***	0.41***	0.40***	0.39***	0.41***	0.40***
		[3.41]	[4.59]	[6.15]	[6.27]	[6.03]	[3.82]	[4.10]	[4.17]	[3.70]	[4.01]	[4.13]
	4	0.8	1.06	1.08	1.12	1.07	0.27**	0.29**	0.24**	0.26**	0.27**	0.23**
		[4.17]	[5.83]	[6.43]	[7.41]	[6.24]	[2.43]	[2.51]	[2.35]	[2.29]	[2.29]	[2.12]
	Large 5	0.88	0.95	1	0.94	1	0.11	0.11	0.1	0.12	0.13	0.11
		[5.56]	[6.23]	[7.48]	[6.60]	[7.40]	[1.49]	[1.50]	[1.37]	[1.26]	[1.39]	[1.25]
Controlling for Size		0.68	0.97	1.06	1.08	1.07	0.39***	0.39***	0.36***	0.15	0.17*	0.15
		[2.90]	[4.45]	[5.21]	[5.43]	[5.59]	[5.57]	[5.73]	[5.43]	[1.63]	[1.84]	[1.63]
Controlling for Book-to-Market		0.73	1.01	1.08	1.07	1.05	0.32***	0.34***	0.32***	0.14	0.17*	0.17
		[3.08]	[4.64]	[5.30]	[5.43]	[5.54]	[4.69]	[5.28]	[5.06]	[1.28]	[1.68]	[1.63]
Controlling for Volume		0.67	1	1.05	1.09	1.05	0.38***	0.41***	0.39***	0.21*	0.25**	0.23**
		[2.79]	[4.62]	[5.18]	[5.56]	[5.54]	[4.90]	[5.66]	[5.56]	[1.86]	[2.24]	[2.13]
Controlling for Turnover		0.7	0.96	1.06	1.08	1.06	0.35***	0.38***	0.37***	0.23**	0.25***	0.23***
		[3.07]	[4.48]	[5.14]	[5.44]	[5.41]	[6.15]	[7.08]	[7.09]	[2.42]	[2.78]	[2.58]

*, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.

Table A5

Average Returns and Alphas of Portfolios Double Sorted on Size and Cov_Bhml1

		Ranking on Cov_Bhml1					EW			VW		
		1 Low	2	3	4	5 High	Return 5-1	CAPM Alpha 5-1	FF-3 Alpha 5-1	Return 5-1	CAPM Alpha 5-1	FF-3 Alpha 5-1
NYSE Stocks Only		0.86	1.1	1.08	1.03	1.07	0.20***	0.21***	0.21***	0.16*	0.17**	0.19**
		[4.07]	[5.53]	[5.69]	[5.65]	[5.95]	[3.58]	[3.80]	[3.80]	[1.93]	[2.03]	[2.25]
Size Quintiles	**Small 1**	0.62	0.92	1.12	1.09	1.01	0.37***	0.39***	0.36***	0.43***	0.44***	0.41***
		[2.61]	[3.82]	[4.88]	[4.94]	[5.15]	[3.79]	[3.79]	[3.32]	[4.48]	[4.46]	[3.99]
	2	0.54	0.98	1.13	1.04	1.12	0.58***	0.57***	0.53***	0.59***	0.58***	0.54***
		[2.36]	[4.67]	[5.50]	[5.34]	[5.57]	[5.87]	[5.62]	[5.32]	[6.22]	[5.90]	[5.54]
	3	0.67	0.98	1.08	1.09	1.04	0.37***	0.38***	0.37***	0.38***	0.39***	0.37***
		[3.46]	[4.79]	[5.79]	[6.52]	[5.95]	[3.95]	[4.09]	[4.22]	[4.10]	[4.25]	[4.38]
	4	0.8	1.15	1.07	1.05	1.09	0.29***	0.30***	0.28***	0.26**	0.27**	0.25**
		[4.28]	[6.39]	[6.47]	[6.24]	[6.49]	[2.75]	[2.82]	[2.76]	[2.51]	[2.52]	[2.47]
	Large 5	0.84	1	0.98	0.95	0.99	0.14*	0.15**	0.14**	0.1	0.11	0.13
		[4.92]	[7.15]	[7.17]	[7.20]	[7.19]	[1.87]	[2.10]	[1.98]	[1.05]	[1.23]	[1.29]
Controlling for Size		0.69	1.01	1.07	1.05	1.05	0.35***	0.35***	0.33***	0.13	0.14	0.15*
		[2.95]	[4.64]	[5.27]	[5.24]	[5.41]	[5.25]	[5.49]	[5.21]	[1.40]	[1.60]	[1.65]
Controlling for Book-to-Market		0.74	1.04	1.08	1.06	1.04	0.30***	0.31***	0.30***	0.13	0.17	0.18*
		[3.12]	[4.81]	[5.32]	[5.39]	[5.39]	[4.50]	[5.00]	[4.91]	[1.23]	[1.59]	[1.70]
Controlling for Volume		0.67	1.03	1.07	1.05	1.04	0.36***	0.39***	0.37***	0.20*	0.23**	0.23**
		[2.81]	[4.77]	[5.28]	[5.37]	[5.40]	[5.03]	[5.68]	[5.56]	[1.78]	[2.09]	[2.09]
Controlling for Turnover		0.69	1.03	1.05	1.05	1.05	0.36***	0.38***	0.38***	0.23**	0.26***	0.26***
		[3.00]	[4.78]	[5.13]	[5.25]	[5.31]	[6.73]	[7.68]	[7.74]	[2.49]	[2.82]	[2.79]

*, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.

Table A6

Average Returns and Alphas of Portfolios Double Sorted on Size and Cov_Bhml2

		Ranking on Cov_Bhml2					EW			VW		
		1 Low	2	3	4	5 High	Return 5-1	CAPM Alpha 5-1	FF-3 Alpha 5-1	Return 5-1	CAPM Alpha 5-1	FF-3 Alpha 5-1
NYSE Stocks Only		0.91	1.09	1.07	1.06	1.06	0.18***	0.17***	0.18***	0.12*	0.13*	0.13*
		[4.49]	[5.68]	[5.76]	[5.81]	[5.52]	[3.51]	[3.42]	[3.49]	[1.69]	[1.77]	[1.75]
Size Quintiles	**Small 1**	0.67	0.95	1.17	1.17	0.93	0.31***	0.31***	0.30***	0.34***	0.34***	0.34***
		[3.01]	[4.09]	[5.65]	[5.38]	[4.40]	[3.70]	[3.59]	[3.26]	[3.62]	[3.61]	[3.35]
	2	0.66	1.01	1.16	1.17	0.94	0.30***	0.29***	0.26***	0.29***	0.28***	0.25***
		[3.06]	[4.41]	[6.29]	[5.82]	[4.87]	[3.35]	[3.22]	[2.78]	[3.27]	[3.14]	[2.69]
	3	0.76	1.07	1.08	1.09	0.97	0.23***	0.23***	0.23***	0.25***	0.26***	0.26***
		[4.28]	[6.10]	[6.01]	[5.99]	[4.94]	[3.29]	[3.18]	[3.18]	[3.57]	[3.49]	[3.42]
	4	0.85	1.13	1.12	1.09	1.01	0.17***	0.17***	0.15***	0.15***	0.15**	0.13**
		[4.98]	[6.59]	[7.18]	[6.43]	[5.60]	[3.12]	[2.98]	[3.03]	[2.67]	[2.48]	[2.49]
	Large 5	0.94	1.02	1	0.92	0.94	0	0	-0.01	0.1	0.09	0.09
		[6.57]	[7.34]	[7.23]	[6.23]	[6.14]	[0.04]	[0.00]	[-0.10]	[1.25]	[1.22]	[1.36]
Controlling for Size		0.77	1.04	1.08	1.08	0.96	0.20***	0.20***	0.19***	0.12	0.12	0.12
		[3.47]	[4.89]	[5.45]	[5.48]	[4.57]	[3.82]	[3.70]	[3.44]	[1.49]	[1.47]	[1.43]
Controlling for Book-to-Market		0.79	1.04	1.08	1.09	0.98	0.20***	0.21***	0.20***	0.14	0.14	0.13
		[3.51]	[4.93]	[5.49]	[5.59]	[4.73]	[3.56]	[3.69]	[3.51]	[1.34]	[1.34]	[1.26]
Controlling for Volume		0.74	1.07	1.08	1.09	0.95	0.23***	0.24***	0.23***	0.16	0.17*	0.17
		[3.22]	[5.05]	[5.57]	[5.56]	[4.54]	[3.80]	[4.01]	[3.87]	[1.57]	[1.66]	[1.64]
Controlling for Turnover		0.77	1.01	1.09	1.1	0.96	0.21***	0.22***	0.21***	0.12	0.13	0.14
		[3.50]	[4.80]	[5.48]	[5.53]	[4.57]	[4.57]	[4.80]	[4.88]	[1.49]	[1.60]	[1.62]

*, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.

Table A7

Average Returns and Alphas of Portfolios Double Sorted on Size and Cov_Bmkt2

		Ranking on Cov_Bmkt2					EW			VW		
		1 Low	2	3	4	5 High	Return	CAPM Alpha	FF-3 Alpha	Return	CAPM Alpha	FF-3 Alpha
							5-1	5-1	5-1	5-1	5-1	5-1
NYSE Stocks Only		0.91	1.05	1.11	1.07	1	0.08	0.09*	0.07	0.06	0.07	0.05
		[4.39]	[5.41]	[5.99]	[5.84]	[5.21]	[1.56]	[1.82]	[1.44]	[0.84]	[0.99]	[0.69]
Size Quintiles	**Small 1**	0.56	1.04	1.07	1.14	0.95	0.41***	0.40***	0.38***	0.42***	0.40***	0.38***
		[2.43]	[4.42]	[5.20]	[5.39]	[4.35]	[5.01]	[4.78]	[4.19]	[4.60]	[4.49]	[3.89]
	2	0.68	0.99	1.12	1.12	0.9	0.24***	0.24***	0.21***	0.27***	0.27***	0.23***
		[3.39]	[5.01]	[5.48]	[5.39]	[4.11]	[3.05]	[3.01]	[2.72]	[3.24]	[3.16]	[2.87]
	3	0.75	1	1.14	1.1	0.9	0.18**	0.20***	0.18**	0.18**	0.20***	0.18**
		[4.10]	[5.35]	[6.35]	[6.30]	[4.59]	[2.39]	[2.67]	[2.44]	[2.41]	[2.75]	[2.53]
	4	0.89	1.05	1.1	1.1	0.98	0.09	0.09	0.06	0.1	0.1	0.07
		[4.95]	[6.06]	[6.93]	[6.77]	[5.49]	[1.22]	[1.26]	[0.78]	[1.39]	[1.36]	[0.96]
	Large 5	0.88	1	0.96	0.99	0.93	0.05	0.06	0.04	0.04	0.05	0.04
		[5.55]	[7.82]	[7.12]	[6.83]	[6.08]	[1.02]	[1.05]	[0.77]	[0.61]	[0.74]	[0.55]
Controlling for Size		0.74	1.01	1.09	1.09	0.93	0.19***	0.19***	0.17***	0.06	0.07	0.05
		[3.20]	[4.78]	[5.44]	[5.53]	[4.44]	[3.45]	[3.48]	[3.08]	[0.70]	[0.84]	[0.64]
Controlling for Book-to-Market		0.78	1.04	1.08	1.09	0.93	0.14***	0.16***	0.14***	0.04	0.06	0.05
		[3.33]	[4.92]	[5.52]	[5.58]	[4.49]	[2.61]	[2.95]	[2.63]	[0.39]	[0.59]	[0.57]
Controlling for Volume		0.74	1.04	1.09	1.08	0.9	0.16***	0.18***	0.16***	0.08	0.1	0.09
		[3.13]	[4.92]	[5.51]	[5.52]	[4.32]	[2.67]	[3.06]	[2.76]	[0.81]	[0.98]	[0.87]
Controlling for Turnover		0.77	1.03	1.08	1.08	0.9	0.13***	0.15***	0.14***	0.07	0.09	0.08
		[3.37]	[4.87]	[5.39]	[5.43]	[4.34]	[2.80]	[3.30]	[3.06]	[0.87]	[1.10]	[0.96]

*, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.

Table A8

Average Returns and Alphas of Portfolios Double Sorted on Size and Cov_Bsmb2

		Ranking on Cov_Bsmb2					EW			VW		
		1 Low	2	3	4	5 High	Return 5-1	CAPM Alpha 5-1	FF-3 Alpha 5-1	Return 5-1	CAPM Alpha 5-1	FF-3 Alpha 5-1
NYSE Stocks Only		0.91	1.08	1.1	1.07	0.99	0.08	0.09*	0.09*	-0.02	-0.02	-0.02
		[4.35]	[5.44]	[5.97]	[5.87]	[5.23]	[1.57]	[1.73]	[1.72]	[-0.22]	[-0.23]	[-0.25]
Size Quintiles	**Small 1**	0.54	1.07	1.06	1.16	0.92	0.37***	0.39***	0.39***	0.42***	0.44***	0.44***
		[2.36]	[4.85]	[4.85]	[5.03]	[4.51]	[5.41]	[5.41]	[5.41]	[5.06]	[5.08]	[5.21]
	2	0.64	1.04	1.07	1.11	0.97	0.32***	0.32***	0.32***	0.33***	0.33***	0.32***
		[2.88]	[4.84]	[5.63]	[5.40]	[4.97]	[3.77]	[3.75]	[3.48]	[3.67]	[3.57]	[3.35]
	3	0.67	1.1	1.09	1.06	0.97	0.26***	0.30***	0.28***	0.27***	0.30***	0.28***
		[3.38]	[5.61]	[6.29]	[6.00]	[5.61]	[3.34]	[3.77]	[3.75]	[3.20]	[3.60]	[3.62]
	4	0.85	1.11	1.11	1.07	1.02	0.15**	0.16**	0.15**	0.11	0.12*	0.11
		[4.49]	[6.60]	[6.58]	[6.93]	[5.93]	[2.12]	[2.20]	[2.06]	[1.63]	[1.75]	[1.64]
	Large 5	0.81	1	1.03	0.96	0.97	0.15*	0.17**	0.16**	0.1	0.11	0.1
		[4.76]	[6.73]	[7.37]	[7.64]	[6.82]	[1.86]	[2.05]	[2.04]	[1.19]	[1.31]	[1.22]
Controlling for Size		0.69	1.06	1.09	1.07	0.95	0.25***	0.27***	0.26***	0.11	0.12	0.12
		[2.97]	[4.98]	[5.36]	[5.45]	[4.65]	[4.30]	[4.70]	[4.61]	[1.38]	[1.58]	[1.51]
Controlling for Book-to-Market		0.77	1.05	1.05	1.08	0.99	0.19***	0.22***	0.22***	0.03	0.05	0.06
		[3.26]	[4.93]	[5.26]	[5.65]	[4.94]	[3.15]	[3.78]	[3.89]	[0.30]	[0.51]	[0.67]
Controlling for Volume		0.71	1.04	1.08	1.08	0.94	0.23***	0.26***	0.27***	0.08	0.1	0.1
		[2.96]	[4.84]	[5.34]	[5.65]	[4.62]	[3.55]	[4.17]	[4.35]	[0.86]	[0.98]	[0.98]
Controlling for Turnover		0.72	1.02	1.07	1.09	0.98	0.22***	0.25***	0.26***	0.04	0.06	0.06
		[3.17]	[4.81]	[5.26]	[5.51]	[4.84]	[4.53]	[5.34]	[5.56]	[0.54]	[0.68]	[0.67]

*, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.

B. Triple Sort

In section 4.3, we investigated the relationship between two additional terms — alpha volatility and Cov_Bsmb1— and unconditional idiosyncratic risk through forming 3 X 3 X 3 portfolios. In this section of the Appendix, we present the results of the investigation based on other additional terms.

Table A9
Triple sort by size, book-to-market, and Beta Volatilities

The table reports monthly average returns of tripe sorted portfolios, with robust Newey–West (1987) t-statistics in square brackets. We first sort stocks into three size portfolios, and then stocks of each size portfolio are sorted into three portfolios by book-to-market ratio. In the third step, each double-sorted portfolio is sorted into three portfolios separately by Vol_Bmkt, Vol_Bsmb, and Vol_Bhml. Then monthly average returns are computed for EW portfolios. In sections 1 to 3, panel A reports the monthly average returns for portfolios with low book-to-market stocks sorted on three different size and beta volatilities. Panel B and C present the monthly average returns for portfolios with medium and high book-to-market ratios, respectively. Row labeled "High-Low" presents the difference in average returns between the portfolio with the high level of alpha risk and the portfolio with the low level of beta volatilities. The rows labeled "CAPM Alpha" and "FF-3 Alpha" report the difference in alphas between the portfolio with the high level of beta volatilities and the portfolio with the low level of beta volatilities. The last row labeled "VW Portfolios: High-Low" shows the difference in average returns for Value-weighted portfolios.

Section 1: Triple sort by size, book-to-market, and Vol_Bmkt

Vol_Bmkt	Panel A			Panel B			Panel C		
	Low Book-to-Market			Medium Book-to-Market			High Book-to-Market		
	Small Cap	Mid Cap	Large Cap	Small Cap	Mid Cap	Large Cap	Small Cap	Mid Cap	Large Cap
Low	0.99	1.03	1	1.14	1.06	0.94	1.28	1.3	1.15
Medium	0.85	0.93	0.96	1.09	0.99	0.88	1.36	1.34	1.23
High	0.31	0.53	0.78	0.79	0.95	0.91	1.07	1.19	1.12
High-Low	-0.67***	-0.49***	-0.20**	-0.34***	-0.1	-0.02	-0.22***	-0.11	-0.01
	[-10.24]	[-5.04]	[-2.57]	[-4.24]	[-1.11]	[-0.32]	[-3.17]	[-1.27]	[-0.23]
CAPM Alpha	-0.66***	-0.50***	-0.20**	-0.33***	-0.11	-0.03	-0.23***	-0.12	-0.01
	[-10.54]	[-4.95]	[-2.55]	[-3.99]	[-1.23]	[-0.38]	[-3.24]	[-1.37]	[-0.17]
FF3 Alpha	-0.64***	-0.50***	-0.18**	-0.30***	-0.11	-0.03	-0.19**	-0.13	0.01
	[-9.77]	[-5.16]	[-2.24]	[-3.73]	[-1.21]	[-0.39]	[-2.47]	[-1.59]	[0.13]
VW Portfolios: High-Low	-0.62***	-0.45***	-0.17*	-0.31***	-0.12	-0.06	-0.23***	-0.09	0
	[-7.72]	[-4.28]	[-1.90]	[-3.74]	[-1.15]	[-0.67]	[-3.58]	[-1.07]	[-0.06]

(continued)

Table A9 – Continued

Section 2: Triple sort by size, book-to-market, and Vol_Bsmb									
	Panel A			**Panel B**			**Panel C**		
Vol_Bsmb	**Low Book-to-Market**			**Medium Book-to-Market**			**High Book-to-Market**		
	Small Cap	**Mid Cap**	**Large Cap**	**Small Cap**	**Mid Cap**	**Large Cap**	**Small Cap**	**Mid Cap**	**Large Cap**
Low	0.94	0.98	0.99	1.17	1.06	0.96	1.27	1.33	1.18
Medium	0.92	0.95	0.93	1.07	1.09	0.84	1.34	1.33	1.18
High	0.32	0.55	0.83	0.77	0.85	0.94	1.1	1.18	1.15
High-Low	-0.62***	-0.44***	-0.16*	-0.39***	-0.21***	-0.02	-0.16**	-0.14*	-0.03
	[-6.80]	[-5.42]	[-1.67]	[-5.16]	[-2.92]	[-0.35]	[-2.39]	[-1.77]	[-0.40]
CAPM Alpha	-0.60***	-0.45***	-0.17*	-0.40***	-0.22***	-0.03	-0.17**	-0.14*	-0.04
	[-6.91]	[-5.37]	[-1.77]	[-5.08]	[-2.97]	[-0.49]	[-2.39]	[-1.79]	[-0.60]
FF3 Alpha	-0.57***	-0.45***	-0.14	-0.39***	-0.23***	-0.03	-0.15**	-0.16*	-0.02
	[-7.31]	[-5.40]	[-1.59]	[-4.75]	[-3.10]	[-0.50]	[-2.07]	[-1.91]	[-0.34]
VW Portfolios: High-Low	-0.62***	-0.43***	-0.18*	-0.37***	-0.17**	0.01	-0.17**	-0.14*	-0.02
	[-6.08]	[-5.42]	[-1.82]	[-5.07]	[-2.42]	[0.07]	[-2.50]	[-1.71]	[-0.17]

Section 3: Triple sort by size, book-to-market, and Vol_Bhml									
	Panel A			**Panel B**			**Panel C**		
Vol_Bhml	**Low Book-to-Market**			**Medium Book-to-Market**			**High Book-to-Market**		
	Small Cap	**Mid Cap**	**Large Cap**	**Small Cap**	**Mid Cap**	**Large Cap**	**Small Cap**	**Mid Cap**	**Large Cap**
Low	0.83	1.02	0.93	1.16	1.01	0.93	1.27	1.31	1.2
Medium	0.85	0.98	1.01	1.12	1.02	0.9	1.4	1.33	1.15
High	0.48	0.48	0.81	0.74	0.97	0.89	1.04	1.2	1.17
High-Low	-0.35***	-0.53***	-0.11	-0.42***	-0.04	-0.03	-0.23***	-0.1	-0.02
	[-3.78]	[-7.03]	[-1.41]	[-5.05]	[-0.50]	[-0.50]	[-3.30]	[-1.17]	[-0.36]
CAPM Alpha	-0.34***	-0.53***	-0.13	-0.43***	-0.05	-0.04	-0.23***	-0.12	-0.03
	[-3.86]	[-6.91]	[-1.59]	[-4.88]	[-0.66]	[-0.55]	[-3.10]	[-1.31]	[-0.63]
FF3 Alpha	-0.31***	-0.53***	-0.11	-0.42***	-0.06	-0.04	-0.20**	-0.12	-0.04
	[-3.73]	[-6.83]	[-1.35]	[-4.59]	[-0.74]	[-0.56]	[-2.55]	[-1.35]	[-0.75]
VW Portfolios: High-Low	-0.36***	-0.51***	-0.03	-0.41***	-0.03	0	-0.30***	-0.1	0.06
	[-3.14]	[-6.75]	[-0.37]	[-5.09]	[-0.30]	[-0.06]	[-3.93]	[-1.11]	[0.83]

*, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.

Table A10
Triple sort by size, book-to-market, and covariance terms 1

The table reports monthly average returns of tripe sorted portfolios. We first sort stocks into three size portfolios, and then stocks of each size portfolio are sorted into three portfolios by book-to-market ratio. In the third step, each double-sorted portfolio is sorted into three portfolios separately by Cov_Bmkt1 and Cov_Bhml1. Then monthly average returns are computed for EW portfolios. In sections 1 and 2, panel A reports the monthly average returns for portfolios with low book-to-market stocks sorted on three different size and covariance terms 1. Panel B and C present the monthly average returns for portfolios with medium and high book-to-market ratio, respectively. The description on other rows is similar to that of table A9. *, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.

Section 1: Triple sort by size, book-to-market, and Cov_Bmkt1									
	Panel A			**Panel B**			**Panel C**		
Cov_Bmkt1	**Low Book-to-Market**			**Medium Book-to-Market**			**High Book-to-Market**		
	Small Cap	**Mid Cap**	**Large Cap**	**Small Cap**	**Mid Cap**	**Large Cap**	**Small Cap**	**Mid Cap**	**Large Cap**
Low	0.29	0.52	0.79	0.79	0.95	0.91	1.06	1.18	1.12
Medium	0.85	0.94	0.95	1.09	1	0.88	1.37	1.35	1.24
High	1.01	1.02	1	1.14	1.05	0.94	1.29	1.3	1.14
High-Low	0.71***	0.49***	0.21**	0.35***	0.09	0.01	0.23***	0.12	0.01
	[10.25]	[5.03]	[2.56]	[4.32]	[0.98]	[0.19]	[3.44]	[1.35]	[0.25]
CAPM Alpha	0.71***	0.50***	0.21**	0.34***	0.11	0.02	0.24***	0.12	0.01
	[10.54]	[4.95]	[2.51]	[4.08]	[1.10]	[0.26]	[3.43]	[1.46]	[0.18]
FF3 Alpha	0.68***	0.49***	0.19**	0.30***	0.1	0.01	0.20***	0.14*	-0.01
	[9.71]	[5.18]	[2.20]	[3.79]	[1.06]	[0.21]	[2.64]	[1.67]	[-0.11]
VW Portfolios: High-Low	0.67***	0.44***	0.16*	0.31***	0.11	0.06	0.25***	0.09	0.01
	[8.10]	[4.21]	[1.86]	[3.78]	[1.06]	[0.65]	[3.77]	[1.10]	[0.20]
Section 2: Triple sort by size, book-to-market, and Cov_Bhml1									
Low	0.48	0.49	0.8	0.75	0.98	0.89	1.05	1.21	1.18
Medium	0.88	0.97	1	1.12	1.02	0.89	1.43	1.32	1.14
High	0.81	1.02	0.93	1.15	1.02	0.94	1.26	1.3	1.19
High-Low	0.33***	0.52***	0.12	0.39***	0.02	0.03	0.21***	0.09	0
	[3.58]	[6.35]	[1.49]	[4.65]	[0.26]	[0.56]	[3.17]	[1.02]	[0.07]
CAPM Alpha	0.32***	0.53***	0.14*	0.40***	0.03	0.04	0.22***	0.1	0.02
	[3.66]	[6.28]	[1.72]	[4.56]	[0.40]	[0.63]	[3.02]	[1.17]	[0.33]
FF3 Alpha	0.30***	0.53***	0.12	0.39***	0.04	0.04	0.19**	0.11	0.02
	[3.66]	[6.16]	[1.49]	[4.19]	[0.46]	[0.58]	[2.44]	[1.20]	[0.43]
VW Portfolios: High-Low	0.34***	0.50***	0.03	0.39***	0.01	0.02	0.29***	0.08	-0.06
	[3.03]	[6.17]	[0.37]	[4.60]	[0.06]	[0.22]	[3.87]	[0.89]	[-0.82]

Table A11
Triple sort by size, book-to-market, and covariance terms 2

The table reports monthly average returns of tripe sorted portfolios, with robust Newey–West (1987) t-statistics in square brackets. We first sort stocks into three size portfolios, and then stocks of each size portfolio are sorted into three portfolios by book-to-market ratio. In the third step, each double-sorted portfolio is sorted into three portfolios separately by Cov_Bmkt2, Cov_Bsmb2, and Cov_Bhml2. Then monthly average returns are computed for EW portfolios. In sections 1 to 3, panel A reports the monthly average returns for portfolios with low book-to-market stocks sorted on three different size and covariance terms 2. Panel B and C present the monthly average returns for portfolios with medium and high book-to-market ratio, respectively. Row labeled "High-Low" presents the difference in average returns between the portfolio with the high level of covariance terms and the portfolio with the low level of covariance terms. The rows labeled "CAPM Alpha" and "FF-3 Alpha" report the difference in alphas between the portfolio with the high level of covariance terms and the portfolio with the low level of covariance terms. The last row labeled "VW Portfolios: High-Low" shows the difference in average returns for Value-weighted portfolios.

Section 1: Triple sort by size, book-to-market, and Cov_Bmkt2

	Panel A			**Panel B**			**Panel C**		
Cov_Bmkt2	**Low Book-to-Market**			**Medium Book-to-Market**			**High Book-to-Market**		
	Small Cap	**Mid Cap**	**Large Cap**	**Small Cap**	**Mid Cap**	**Large Cap**	**Small Cap**	**Mid Cap**	**Large Cap**
Low	0.29	0.52	0.79	0.79	0.95	0.91	1.06	1.18	1.12
Medium	0.85	0.94	0.95	1.09	1	0.88	1.37	1.35	1.24
High	1.01	1.02	1	1.14	1.05	0.94	1.29	1.3	1.14
High-Low	0.71***	0.49***	0.21**	0.35***	0.09	0.01	0.23***	0.12	0.01
	[10.25]	[5.03]	[2.56]	[4.32]	[0.98]	[0.19]	[3.44]	[1.35]	[0.25]
CAPM Alpha	0.71***	0.50***	0.21**	0.34***	0.11	0.02	0.24***	0.12	0.01
	[10.54]	[4.95]	[2.51]	[4.08]	[1.10]	[0.26]	[3.43]	[1.46]	[0.18]
FF3 Alpha	0.68***	0.49***	0.19**	0.30***	0.1	0.01	0.20***	0.14*	-0.01
	[9.71]	[5.18]	[2.20]	[3.79]	[1.06]	[0.21]	[2.64]	[1.67]	[-0.11]
VW Portfolios: High-Low	0.67***	0.44***	0.16*	0.31***	0.11	0.06	0.25***	0.09	0.01
	[8.10]	[4.21]	[1.86]	[3.78]	[1.06]	[0.65]	[3.77]	[1.10]	[0.20]

(continued)

Table A11 – Continued

Section 2: Triple sort by size, book-to-market, and Cov_Bsmb2

Cov_Bsmb2	**Panel A**			**Panel B**			**Panel C**		
	Low Book-to-Market			**Medium Book-to-Market**			**High Book-to-Market**		
	Small Cap	**Mid Cap**	**Large Cap**	**Small Cap**	**Mid Cap**	**Large Cap**	**Small Cap**	**Mid Cap**	**Large Cap**
Low	0.33	0.55	0.83	0.78	0.85	0.94	1.1	1.17	1.16
Medium	0.92	0.96	0.93	1.07	1.1	0.84	1.34	1.33	1.18
High	0.92	0.97	0.99	1.16	1.05	0.96	1.27	1.32	1.17
High-Low	0.60***	0.43***	0.16*	0.38***	0.19***	0.02	0.17**	0.14*	0.02
	[6.10]	[5.23]	[1.67]	[5.03]	[2.84]	[0.27]	[2.42]	[1.76]	[0.27]
CAPM Alpha	0.58***	0.44***	0.17*	0.39***	0.20***	0.03	0.17**	0.14*	0.03
	[6.23]	[5.23]	[1.76]	[4.94]	[2.88]	[0.41]	[2.40]	[1.79]	[0.47]
FF3 Alpha	0.55***	0.44***	0.14	0.38***	0.21***	0.03	0.15**	0.16*	0.01
	[6.55]	[5.24]	[1.58]	[4.58]	[3.02]	[0.41]	[2.08]	[1.93]	[0.20]
VW Portfolios: High-Low	0.60***	0.42***	0.17*	0.36***	0.16**	-0.01	0.17**	0.14*	0.02
	[5.55]	[5.27]	[1.70]	[4.91]	[2.26]	[-0.10]	[2.42]	[1.70]	[0.20]

Section 3: Triple sort by size, book-to-market, and Cov_Bhml2

Cov_Bhml2	**Panel A**			**Panel B**			**Panel C**		
	Low Book-to-Market			**Medium Book-to-Market**			**High Book-to-Market**		
	Small Cap	**Mid Cap**	**Large Cap**	**Small Cap**	**Mid Cap**	**Large Cap**	**Small Cap**	**Mid Cap**	**Large Cap**
Low	0.48	0.49	0.8	0.75	0.98	0.89	1.05	1.21	1.18
Medium	0.88	0.97	1	1.12	1.02	0.89	1.43	1.32	1.14
High	0.81	1.02	0.93	1.15	1.02	0.94	1.26	1.3	1.19
High-Low	0.33***	0.52***	0.12	0.39***	0.02	0.03	0.21***	0.09	0
	[3.58]	[6.35]	[1.49]	[4.65]	[0.26]	[0.56]	[3.17]	[1.02]	[0.07]
CAPM Alpha	0.32***	0.53***	0.14*	0.40***	0.03	0.04	0.22***	0.1	0.02
	[3.66]	[6.28]	[1.72]	[4.56]	[0.40]	[0.63]	[3.02]	[1.17]	[0.33]
FF3 Alpha	0.30***	0.53***	0.12	0.39***	0.04	0.04	0.19**	0.11	0.02
	[3.66]	[6.16]	[1.49]	[4.19]	[0.46]	[0.58]	[2.44]	[1.20]	[0.43]
VW Portfolios: High-Low	0.34***	0.50***	0.03	0.39***	0.01	0.02	0.29***	0.08	-0.06
	[3.03]	[6.17]	[0.37]	[4.60]	[0.06]	[0.22]	[3.87]	[0.89]	[-0.82]

*, **, *** represent the statistical significance level at 10%, 5%, and 1%, respectively.