TWO ESSAYS ON HOW DO INVESTORS PERCEIVE THE OPTIMAL CAPITAL STRUCTURE AND AN ESSAY ON MUTUAL FUND VOLATILITY DECOMPOSITION AND MANAGER SKILL

by

NIMA VAFAI

DISSERTATION

Submitted in partial fulfillment of the requirements for the
degree of Doctor of Philosophy at
The University of Texas at Arlington
August 2021

Arlington, Texas

Supervising Committee:

David Rakowski, Supervising Professor
John Adams
Larry Lockwood
Sanjiv Sabherwal
Ramgopal Venkataraman
Mahmut Yasar

ABSTRACT

Two Essays on How do Investors Perceive the Optimal Capital Structure and an essay on Mutual Fund Volatility Decomposition and Manager Skill

Nima Vafai, Ph.D.

The University of Texas at Arlington, 2021

Supervising Professor: David Rakowski

This dissertation explores the rational investment hypothesis proposed by classical theories at the stock and portfolio (mutual fund) level. My first two essays focus on the risk associated with the composition of debt and equity at the firm level. The third essay studies the total risk at the portfolio level in the mutual fund setting.

In the first essay, we examine the association between deviations from the optimal capital structure and firm-level stock returns by comparing different proxies for optimal capital structure from the literature and constructing improved industry-specific optimal capital structure measures. After comparing the performance of each measure, we use a partial adjustment model to study how firms reduce their gap from optimal leverage.

In the second essay, we model firms' deviations from the optimal capital structure as a new risk factor in the cross-section of stock returns. Using Monte-Carlo simulations to conduct bootstrapped mean-variance spanning tests, we examine whether the existing Fama and French

factors can explain this potential new risk factor. We also use Text Network Industry Classification (TNIC) to show whether the new risk factor is robust to alternative industry classification.

In the third essay, we use a volatility decomposition to identify the underlying sources of differences in the performance of low and high-volatility mutual funds. We then examine whether the difference in performance is fund-specific and due to the manager's skill, or it is a broad characteristic of market volatility. Last, we show how the difference in the performance of low and high volatility mutual funds is related to the existence of a beta anomaly in the mutual fund industry. Furthermore, we examine the idiosyncratic volatility relation with beta and risk-adjusted return (alpha) at the fund level.

ACKNOWLEDGEMENTS

It would not be possible to write this doctoral dissertation without the help and support of many kind people. I would like to thank my supportive and encouraging advisor, Dr. David Rakowski, for mentoring me through my Ph.D. journey. His patience with me and his insightful feedback pushed me to sharpen my thinking and brought my work to a higher level.

I also thank Dr. Sanjiv Sabherwal for his kind support. He is not only a wonderful mentor but also a great friend. Although he is swamped with many responsibilities as a department chair, he has always been there to help me unconditionally. I want to express my deep gratitude to Dr. Mahmut Yasar for his guidance and support in this journey. He is not only a great professor and mentor but also a very reliable friend. His advice and support have been invaluable, for which I am incredibly grateful.

I thank Dr. Ramgopal Venkataraman, who has always encouraged me throughout the last four years. His encouragement and guidance helped me steer through the difficult times. I want to express my gratitude to Dr. John Adams for everything, from answering all my basic questions to amazing conversations about asset pricing models.

Finally, I would like to thank Dr. Larry Lockwood for all of his help, encouragement, support, and friendship. His asset pricing class was the reason that I am encouraged to pursue this route in my research. His kind and friendly personality made every complicated equation easy to understand.

DEDICATION

To my father (baba), the hero of my life: Mohammad Hossein, without whom I would never have the motivation to make it this far. Although he passed away in December 2020, his passion for life, sense of humor, great personality, kindness, generosity, and advice will stay with me as long as I live the life. He has been the role model of my life, and as I promised him, I will succeed and do my best until I meet him again down the road.

To my mom, Zahra, who was my support from the very first day I came into existence.

To the love of my life, my wife Zahra, without her supports, it would be impossible to complete this dissertation.

To my sisters, Parvin and Nasrin, thank you for loving me, putting up with me, and being my support any time I needed it.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

TABLES

FIGURES

CHAPTER 1

How do investors perceive optimal capital structure? Evidence from industry-specific risk factors

Abstract

Here, in essay I, we examine the association between deviations from optimal capital structure and firm-level stock returns, as well as construct improved measures of industry-specific optimal capital structure. We compare the performance of multiple measures of optimal capital structure in revealing investors' expectations and find that a positive (negative) deviation from the optimal capital structure is significantly and positively (negatively) associated with a stock's excess return. Using the Fama and French (1993) three-factor model, we attribute this association between deviation from optimal capital structure and excess return to the risk loading on the stock. Moreover, using a partial adjustment model, we find that our improved measure of optimal capital structure performs better than alternative measures in capturing the movement of firms toward a target amount of leverage.

Keywords: capital structure; stock returns; risk factors; factor models; leverage.

JEL codes: G12, G14, G32.

I. Introduction

When it comes to capital structure or leverage, the finance literature has a couple of well-known competing theories about what is optimal for a firm. The trade-off theory (Modigliani and Miller, 1963; Kraus and Litzenberger, 1973; Myers, 1984) suggests that there is an optimal capital structure or leverage for each firm (optimal leverage is hereafter referred to as OL), which is the outcome of a trade-off between costs of debt and costs of equity. The pecking order theory (Myers, 1984) suggests that corporations choose the source of financing for projects in the order of financial cost. In other words, any corporation at any level of leverage, first, chooses retained earnings as long as possible, second, goes to debt until debt becomes too expensive, and, third, issues new equity. In this process, a corporation goes from one resource to the other resource of financing when the prior resource is depleted, and the company still has access to desirable projects.

Regardless of what theory best explains cross-sectional variation in leverage, in reality, firms attempt to maximize their overall value by choosing the best possible capital structure. However, firms might not accomplish this mission because of many external and internal reasons, including credit ratings, debt capacity, and poor negotiation skills of the managers. Hence, the cross-sectional variation in capital structure partly comes from natural differences in the OL that corporations aim for and partly comes from their inability (or intention) to deviate from the OL.

A deviation from the OL might result in a higher or lower risk loading on the firm's stock. If investors are risk averse, a higher (lower) level of risk should be compensated with a higher (lower) expected return. If this expected return represents compensation for a distinct source of risk that investors are averse to, then the excess return that investors demand from this perceived risk should not be explained by other sources of risks that have been established in the literature [i.e., the Fama and French (1993) factors]. We, therefore, proxy for expected returns with the realized excess returns relative to factors that are known from the existing literature.

We explore how a directional deviation from OL (either positive or negative) increases or decreases the risk of a firm and hence impacts the excess return on a firm's stock. We have two challenges to overcome. First, there is no consensus in the literature on what theory is the best to estimate OL. Second, views differ on what the best proxy is for this optimal point. To overcome these challenges, we use existing proxies for OL in the literature and compare how well they explain security prices. Also, we contribute to the literature by introducing two other proxies for OL.

If investors treat the directional deviations from OL as a priced risk factor, then deviations should be associated with positive or negative excess returns, after controlling for any additional risk factors. In other words, if the directional deviation from OL is perceived as a higher or lower risk, the investors should be compensated with a higher or lower excess return. For example, let us assume that we have two firms, firm A and firm B, that have identical fundamentals, and they both are in the same industry. The only difference between these two firms is their OL at time t. Firm A is at its assumed OL at time t, but firm B is significantly above its OL. If investors display lower demand for firm B, then its stock would sell at a price discount or, equivalently, a higher expected return relative to firm A. This difference in returns is the result of the compensation for the risk perceived by investors. Equation (1) is a simple valuation model, which is another way to show the current market price as a function of expected future cash flows (or dividends) and the market expected return (discount factor). Because a higher (lower) level of risk leads to a higher (lower) expected return (r), although the expected cash flow (or dividend) is the same for both firms, the higher (lower) risk leads to a lower (higher) current price for firm B. As Equation (1) shows, everything is fixed except the level of risk, and the lower expected rate of return (r) implies a lower current price:

$$M_t = \sum_{\tau=1}^{\infty} \frac{E(d_{t+\tau})}{(1+r)^{\tau}} = \sum_{\tau=1}^{\infty} \frac{E(y_{t+\tau} - dB_{t+\tau})}{(1+r)^{\tau}}, \tag{1}$$

where M_t is the market price at time t, $E(d_{t+\tau})$ is the expected dividend per share at the end of period $t + \tau$, and r is the expected rate of return or the internal rate of return on expected dividends. $y_{t+\tau}$, is total equity earnings for period $t + \tau$, and $dB_{t+\tau} = B_{t+\tau} - B_{t+\tau-1}$ is the change in total book equity (Fama and French, 2015).

Evaluating deviations from OL as a priced risk factor conveniently allows for an alternative perspective to be tested. Instead of representing a risk factor that decreases (increases) investors' demand and increases (decreases) expected returns, deviations from the OL might represent a predictive measure of future firm-level operating performance that is negatively (positively) associated with expected excess returns. We evaluate which of these explanations the data better support.

Prior studies commonly use a simple measure of debt-to-equity or debt-to-assets in the estimation of models to examine the impact of the cross-sectional variation of capital structure on a firm's excess return or use a theoretically estimated variable to proxy for OL (i.e., Fama and French, 1992, 2002). However, there is no consensus on the results of these studies. There has always existed a gap in the literature between the insignificance of the expected outcome of theories and empirical work's actual outcome. With this study, we are trying to fill this gap.

We introduce improved proxies, as well as use the existing proxies in the literature, to measure how much a specific firm departs from its OL compared with its benchmark, which we view as an industry-specific capital structure equilibrium. We construct ten portfolios of stocks each December based on those stocks' directional deviations from their respective optimal leverage using multiple proxies for the OL. Among the proxies we use, the industry median leverage performed better in revealing both the investors' expectations about the return and firms' intention in lowering their distance from the optimal leverage. We find that portfolios of stocks with lower leverage than their industry median have a significantly lower excess return than the portfolios of stocks with higher leverage than their industry in the prior year. Because portfolios are made based only on the prior-year deviation from the OL, all the other firm characteristics are assumed to be randomly assigned. We investigate this further by controlling for risk and other factors.

Motivated by prior studies (Bradley, Jarrell, and Kim, 1984; Titman and Wessels, 1988), we suggest that the capital structure of firms should be partially determined by industry. Some industries are highly capital intensive, and it might be acceptable in that industry to have high leverage. Moreover, Frank and Goyal (2009) show that the most reliable factor in explaining a firm's leverage is the median industry leverage. For these reasons, we suggest our first proxy, the industry median, as a potential candidate for OL. Also, the Fama and French (2002) point estimate of the target leverage is clustered by industry. Thus, to improve the reliability of the estimated OL, we suggest estimating the Fama and French (2002) equation in each industry separately.

Existing studies use two main proxies to measure OL. The first is a cross-sectional comparison, which uses different firms' characteristics to find the point estimate for OL (Fama and French, 2002). The second suggested proxy for the optimal leverage is the time series average of the firm's leverage ratio. Kraus and Litzenberger (1973) use this average as a proxy for the optimal leverage that firms are seeking to reach. The idea behind this is that firms use the same combination of debt and equity to finance any new project, and each firm attempts to finance its projects with the most optimal debt-to-equity ratio. Hence, over time, the long-run average can proxy for the OL that a firm seeks.

We use both of the aforementioned proxies in this study and compare them with our suggested measures. We calculate deviations of each firm from each proxy for OL to see if the portfolios formed based on these deviations have differences in excess return. Sorting portfolios based on the deviations from these two proxies displays no observable pattern in the returns of these portfolios. However, our results show that, when compared with an industry benchmark, a positive deviation from OL is associated with a positive excess return and a negative deviation from the OL is associated with a negative excess return.

We attribute this difference in return to the difference in risk arising from the directional deviation from leverage. Firms with a positive deviation from OL hold a higher level of debt than their industry benchmark. Because debt increases the risk to shareholders, their excess return is compensation for the higher risk. If within-industry effects prevent this risk from being diversified away, or if investors otherwise treat this as a nondiversifiable risk, then the demand for high (low) risk securities would be lower (higher), resulting in lower (higher) equilibrium prices and hence higher (lower) expected returns. Using the other proxies for OL does not result in the same conclusion about the investors' expectations.

We use the Fama and French three-factor model to test our conjecture that the difference in the excess return of portfolios formed based on deviations from OL using different proxies is attributable to risk loading. Using the Fama and MacBeth (1973) regression procedure, we calculate the risk-adjusted excess return in each decile-sorted portfolio. We find that the Fama-French alpha is significantly higher (lower) for high (low) deviation portfolios using three out of four of our proxies for OL. This result is consistent with the explanation that excess return is the result of different risk loading in portfolios (Fama and French, 1993). We find no evidence that portfolios made by deviation from OL using the ten-year time series average as a proxy for OL captures the leverage risk loading, as reflected by the returns across portfolios. In contrast, we find the opposite result that a positive deviation from the OL leads to a negative expected return and vice versa. Nevertheless, the difference is not economically significant.

To measure the movement of leverage toward a firm's target, following Fama and French (2002), we use the partial adjustment model (PAM). We intend to test whether firms leverage returns to their target. In other words, we test managers' perception of the OL to explore whether firms intend to lower their distance from the OL using the PAM. In the framework for this test, the change in book leverage partially absorbs the difference between target leverage and lagged leverage (Fama and French, 2002). We find that our proxies for OL perform better than other proxies used in the literature in terms of explaining the movement of leverage and the speed and significance of adjustment. The R^2 of the PAM regression using the industry-clustered Fama and

French factors is 5% more than that of the comparable regression in Fama and French (2002). The R^2 of the PAM regression using the industry median as a proxy for OL is 17% more than the R^2 of the regression using the Fama and French industry-clustered factors as a proxy for OL. Also, the speed of the adjustment is higher and more significant when using our proxies for OL, implying that our proxies offer a better estimation of OL using empirical market data, compared with the measure used by Fama and French (2002) and Kraus and Litzenberger (1973).

Our primary motivation for this study is the lack of comprehensive evidence on the relation between the capital structure of public firms and their stock return. We contribute to the literature, first, by introducing the industry median as a proxy for OL and showing that this measure performs better in terms of economic and statistical significance compared with existing proxies and, second, by showing that a positive (negative) deviation from the OL is associated with higher (lower) risk loadings for the stock firm's stock return. We show that the difference in the ex ante risk leads to differences in the ex post monthly stock returns.

The rest of the paper is organized as follows. Section II is a brief literature review. Section III provides an explanation of the methodology, measurements, and econometrical tests employed to test our hypotheses. Section IV describes the primary sources of data and provides an overview of the sample's construction. Section V presents our findings. Section VI reports the results of the robustness check. Section VII concludes the paper.

II. Literature Review

There are different strands of literature that study capital structure from different perspectives. Two main factors in the studies are the tax shield benefit of debt and the agency costs of equity and debt.

Jensen and Meckling (1976) discuss that even before the existence of a tax shield advantage in the US, there was debt in the capital structure of firms. Hence, they introduce agency theory to explain the existence of OL. In their theory, equilibrium is reached by the interaction between the agency cost of equity and the agency cost of debt that minimizes the overall cost.

The theory of OL based on the tax shield benefits of debt capital was first developed by Modigliani and Miller (1963). The theoretical framework they built is handy and has some implications about the OL. Their interpretation of ${}^{\Delta B}/_{\Delta I}$, the change in debt over the change in the investment, is that if ${}^{B^*}/_{I^*}$ denotes the firm's long-run target debt ratio, then, for any particular investment, the assumption is that ${}^{dB}/_{dI} = {}^{B^*}/_{V^*}$, where V^* is the optimal firm's size. This statement implies that there should be an OL for each firm and that firms move toward the optimal ratio in the long run. Modigliani and Miller examine if the OL is best proxied by the book value of leverage, the replacement value of leverage, or the reproduction value of leverage. Modigliani and Miller conclude that the best proxy for the target OL is the average, in the long run, of the debt-to-market-value ratio.

The academic consensus by the mid-1970s was that the OL involves balancing the tax advantage of debt against the present value of bankruptcy costs. There have been several empirical works testing Modigliani and Miller's theory of capital structure, such as DeAngelo and Masulis (1980), Kim (1982), and Modigliani (1982). Also, Fama and French (2002) use a unique regression estimation model to estimate the optimal spot target leverage. Despite these attempts to theoretically and empirically identify the OL, a consensus is yet to exist on the most reliable way to measure the OL.

Kraus and Litzenberger (1973) develop a capital structure model that introduces the tax advantage of debt and bankruptcy penalties into a state preference framework. The market value of a levered firm is shown to equal the unlevered market value, plus the corporate tax rate times the market value of the firm's debt, less the complement of the corporate tax rate times the present value of bankruptcy costs. In contrast to prior studies of firms' valuation (traditional net income approach to valuation), if the firm's debt obligation exceeds its earnings, then the firm's market value is not necessarily a concave function of its debt obligations.

Kraus and Litzenberger (1973) introduced the trade-off theory, which was followed by Myers (1977) with in his research on the determinants of corporate finance. The trade-off theory is based on the idea that firms choose debt and equity (leverage ratio) by the trade-off between costs and benefits of debt and equity. The idea is based on the considered balance between the explicit and implicit costs of bankruptcy and agency cost on the one hand and the tax shield benefits of debt on the other hand. The most crucial aim of this theory is to explain the composition of companies' capital structure.

The market timing hypothesis is a nonexclusive alternative theory to Modigliani and Miller's framework on capital structure. The theory is based on the idea that firms pay attention to market conditions in an attempt to time the market. Based on the market timing theory, firms tend to issue equity when their market values are high relative to past market values and market-to-book value and to repurchase equity when the opposite is correct. Baker and Wurgler (2002), in their study of market timing and capital structure, find that the current capital structure is highly correlated to historical market values. Their results confirm the theory that the capital structure is the cumulative outcome of past attempts to time the equity market.

Myers (1984) mentions in his dynamic version of the pecking order theory that an increase in leverage lowers a firm's safe debt capacity and may lead to future underinvestment and a decrease in stock returns. However, the pecking order theory suggests that the stock return decreases with either positive or negative deviations from the OL (Kraus and Litzenberger, 1973a).

Bradley, Jarrell, and Kim (1984) use cross-sectional data to test for the optimal level of capital structure. They developed a theoretical model that captures the essence of the tax advantage and bankruptcy cost models of Kraus and Litzenberger (1973). Following the theory, they highlight three firm-specific factors that influence the firm's OL: (1) the variability of firm value, (2) the level of non-debt tax shields, and (3) the magnitude of the costs of financial distress.

Kraus and Litzenberger (1973) first reexamine the cross-sectional relation between 20-year average firm leverage ratios and industrial classification. Then, they regress the firm's leverage ratios on empirical proxy variables for the variability of firm value, the level of non-debt tax shields, and the magnitude of the costs of financial distress to test the more direct implications of the OL theory. They find that optimal firm leverage (taken as the 20-year average) is inversely related to the costs of financial distress and the benefits of non-debt tax shields.

De Jong, Verbeek, and Verwijmeren (2011b) study the static trade-off theory versus the pecking order theory. They find that, for their sample of US firms, the pecking order theory is a better descriptor of firms' issue decisions than the static trade-off theory. However, when they focus on repurchase decisions, they find that the trade-off theory has a better explanation of firms' capital structure decisions. Cai and Zhang (2006), as part of their empirical work, study the trade-off theory and its impact on the firm's value. They find nothing significant, which is consistent with the trade-off theory, but they find some pieces of evidence that support the pecking order theory.

In more recent work, DeAngelo and Roll (2015) study the stability of the capital structure, which is the result of the trade-off theory of capital structure. They find that capital structure stability is exceptional and not a rule for firms. They show that leverage stability happens mostly among low-leverage companies, and mostly it is temporal. They conclude that the target leverage models that place little or no weight on maintaining a particular leverage ratio are better in explaining the actual capital structures. Bhandari (1988) studies the debt (equity) ratio and finds no significant results. He shows no evidence to support the trade-off theory.

Opler and Titman (1994) find that firms that produce durable goods will have a lower demand for their products if they increase their probability of bankruptcy. Opler and Titman find that highly leveraged firms lose substantial market share to their more conservatively financed competitors in industry downturns. For only this reason, we should compare firms with their proper benchmarks when it comes to studying the capital structure.

Frank and Goyal (2009) examine the importance of different factors in explaining the capital structure decision of US public firms from 1950 to 2003. They find that industry median leverage, market-to-book ratio, tangibility, profits, size, and expected inflation are the most decisive factors in explaining the firms' market leverage. They find evidence that is weakly consistent with the trade-off theory. Our main takeaway from this paper is that, based on their findings, industry median leverage is the most reliable variable explaining firms' capital structure.

Flannery and Rangan (2006) use the partial adjustment model to test the existence of the optimal leverage and the speed of adjustment toward that optimal. They discuss that, in a frictionless world, firms are always at their optimal leverage. However, in the real world, with frictions, the immediate adjustment is costly and almost impossible. Hence, firms partially adjust their leverage. Flannery and Rangan find that a typical firm partially corrects its actual leverage and closes one-third of its gap with the target once every year.

In short, there are three main leading theories in the literature: trade-off, dynamic pecking order, and market timing theories. Although one of these theories might look theoretically superior to the other based on the reader's taste, none of them is empirically proven by a study that has not been rejected in favor of another theory. Also, there exist two main proxies for OL in the literature. First is the point estimate regression, which uses different firms' characteristics to find the point estimate for the optimal leverage (Fama and French, 2002). The second proxy for optimal leverage is the long-run average of the firm's leverage ratio. Kraus and Litzenberger (1973) use this average as a proxy for the OL that firms are seeking to reach. Moreover, in the literature, the PAM is used to test the existence of OL and the speed of adjustment of leverage toward its target.

III. Measurements, Models, Methods, and Hypotheses Development

We use the industry median leverage as a benchmark for the OL. We suggest that the difference between firms' leverage and that of the industry average (median) is sufficient to proxy for the distance and direction that a firm is deviating from its OL. Our ground for choosing the industry median as a proxy for the OL is that the industry median contains much of the information about the relevant characteristics of firms in that industry. Frank and Goyal (2009) already show that the industry median leverage is the most important factor in explaining firms' market leverage.

We use two other proxies from the literature for the OL, along with our industry median proxy, to compare their performances with each other in showing the differences in returns of portfolios sorted based on the deviation from OL. Following Fama and French (2002), we define the book leverage as the book value of liabilities divided by the book value of total assets. In terms of Compustat variables, we use AT-SEQ as the total book debt and AT as the total assets. Equation (2) shows the corresponding calculations for the leverage, LV:

$$LV_{i,t} = \frac{AT_{i,t} - SEQ_{i,t}}{AT_{i,t}} \,. \tag{2}$$

Following Fama and French (1993), we want to test whether the factor based on deviations from OL can explain variations in the cross section of excess returns over time (panel data). To do so, we take the following steps to measure the impact of deviation from optimal capital on the average excess return. We begin by calculating the deviation of firms' leverage from the OL using the industry median as a proxy for OL each year. Then, we sort stocks based on their deviation from OL in ten portfolios to test whether there is a significant difference or pattern in the portfolio of returns. The deviation from OL is calculated based on Equation (3):

$$\Delta LV_{i,t} = LV_{i,t} - \widehat{LV_{i,t}}, \tag{3}$$

where $\Delta LV_{i,t}$ proxies for the deviation from optimal capital leverage, $\widehat{LV_{i,t}}$ is the assumed optimal book leverage of firm i at time *t*, and $LV_{t,i}$ is the actual leverage of firm i at time t calculated from Equation (2). We use three proxies for OL: two are from the literature and one is our proxy, industry median.

Portfolio Sorting

We sort stocks into ten portfolios for each year in each industry based on their ranking of deviation from OL. Then, we calculate the value-weighted excess return in each portfolio and report the average of each portfolio over the years. We repeat this procedure for each of the proxies and compare their performance in showing differences or patterns in the portfolio returns.

Model A (Characteristics)

We use a characteristics model to test our hypothesis of whether the deviation from OL can explain any part of the variation in the cross-sectional excess return controlling for other well-established factors in the literature. Equation (4) expresses returns as a function of firm characteristics, including the deviation from OL:

$$r_{i,t} = \alpha_t + \beta_1 \Delta LV_{i,t-1} + \beta_{2j} CLT_{i,t-1} + \varepsilon_{i,t}, \tag{4}$$

where $r_{i,t}$ is the monthly excess return of firm i at month t. $\Delta LV_{i,t-1}$ is the book leverage deviation from the estimated optimal ratio at time $t-1$. $CTL_{i,t-1}$ represents a matrix of j control variables that has time and cross-sectional variation. This vector of controls contains size, book-to-market equity, and market excess return.

We use the Fama and Macbeth (1973) method in estimating Equation (4). The Fama-MacBeth method by construction controls for time fixed effects. Thus, we run the cross-sectional regression in Equation (4) every year and take the average over the sample period. Then, we use the time series standard error of average slopes to calculate *t*-statistics using the Newey and West (1987) adjustment for standard errors and draw inferences. The Newey-West method (HAC) corrects heteroskedasticity and autocorrelation in the error term.

Model B (Risk Model)

After making the sorted portfolios based on the deviation from the OL, we run the Fama and French (1983) three-factor model on the value-weighted return of each portfolio. The alpha (intercept) in each portfolio is interpreted as the risk-adjusted excess return in that portfolio. However, the risk is adjusted only for the known factors, i.e., the Fama and French three factors in each portfolio. Thus, an undocumented risk factor might be the source of potential differences in alpha that has not been captured by other risk factors.

If we find no noticeable difference in the alphas of sorted portfolios, but we find differences in the portfolios' excess return. We thus can conclude that known risk factors explain the source of excess return. If the alphas follow the same pattern as the excess returns, then we can attribute return differences to the factor that portfolios are sorted by, which in this case is the deviation from OL.

Fama and French (2002) Target Leverage Estimation

The third proxy that we use for the OL is that of Fama and French (2002). We need to estimate two equations simultaneously to find the target leverage, OL, at each time t. In the Fama and French (2002) view of the pecking order and trade-off model, two endogenous variables are target leverage and target dividend ratio. Thus, we split the sample data set into two subsamples: first is non-dividend-paying firms and the second is dividend-paying firms. Following Fama and French, the dividend-paying subsample requires the dividend-paying firm to pay a dividend at time $t-1$.

For non-dividend-paying firms, target leverage is estimated by the regression model of Equation (5):

$$LV_{i,t+1} = b_0 + b_1 V_{i,t}/A_{i,t} + b_2 ET_{i,t}/A_{i,t} + b_3 DP_{i,t}/A_{i,t} + b_4 RDD_{i,t} + b_5 RD_{i,t}/A_{i,t} + b_6\, ln\left(A_{i,t}\right) + b_7 TP_{i,t+1} + e_{i,t+1}, \tag{5}$$

where $V_{i,t}$ is the market value, $A_{i,t}$ is the total assets, $ET_{i,t}$ is earnings before interest + tax expenses, $DP_{i,t}$ is the depreciation, $RD_{i,t}$ is the research and development (R&D) expenses, $RDD_{i,t}$ is a dummy that is one for firms with zero or no reported R&D, and $TP_{i,t+1}$, target leverage, is the fitted value from the first-stage reduced-form estimate of Equation (5) for dividend-paying firms for firm *i* at time *t*. Using the Fama and French (2002) setting, which is based on the trade-off and pecking order theories, exogenous driving variables for the target leverage are the profitability of assets in place, investment opportunities, non-debt tax shields, and volatility. In Equation (5), the proxies for profitability are $ET_t \, / \, A_t$ (ET_t is earnings before interest and taxes) and $V_t \, / \, A_t$. $V_t \, / \, A_t$ is a proxy for investment opportunities, along with $RD_t \, / \, At$. $RD_t \, / \, At$ is a proxy for non-debt tax shields, along with depreciation, $DP_t \, / \, At$. Finally, the log of assets, $ln(A_t)$, proxies for the volatility of earnings and net cash flows, as well as other factors related to the firm size. Also, because the firms in this group are not paying a dividend, we drop the dividend payout ratio variable, TP_{t+1}, from Equation (5); that is, its value is zero.

For dividend-paying firms in the Fama and French (2002) setting, target leverage is endogenous. Its value is determined by estimating Equations (5) and (6) jointly. For dividend-paying firms, we use the fitted value for $LV_{i,t+1}$, target leverage, estimated from the reduced form estimate of Equation (5).

$$D_{t+1}/A_{t+1} = a_0 + (a_1 + a_{1V}V_t/A_t + a_{1E}E_t/A_t + a_{lA}\,dA_t/A_t + a_{1D}RDD_t + a_{lR}RD_t/A_t + a_{1S}\ln(A_t) + a_{lL}LV_{t+1})Y_{t+1} \, / \, A_{t+1} + e_{t+1} \tag{6}$$

and

$$D_{t+1} = TP^{*}_{t+1}Y_{t+1}, \tag{7}$$

where E_t is the earnings before extraordinary items + interest, dA_t is $A_t - A_{t-1}$, and Y_t is the common stock earning at time *t*. We simplify the notation in Equations (6) and (7) and omit the firm subscript that should appear with the variables and residuals and the year subscripts of the coefficients. The simultaneous Equations (5) and (6) are also estimated using the Fama and MacBeth (1973) method. We use the time series standard error of average slopes to calculate *t*-statistics using the Newey and West (1987) adjustment for standard errors and draw inferences.

Fama and French (2002) Industry-Clustered Target Leverage Estimation

Fama and French (2002) estimate Equation (5) for non-dividend-paying firms and Equations (5) and (6) simultaneously for dividend-paying firms to find the target (optimal) leverage. Thus, they use estimated coefficients from Equations (5) and (6) to calculate the fitted values for each firm's OL. They use the market-wide data to estimate the cross-sectional coefficients and for the fitted values calculation.

We cluster the Fama and French (2002) equations by industry. Thus, at each time t, we estimate Equations (5) and (6) in each industry. Hence, the fitted values are calculated using the industry-specific estimated coefficients of Equations (5) and (6). We call the fitted values from this estimation the *FF-Ind target leverage* (i.e., OL) and use is it as our improved proxy for the OL.

Partial Adjustment Model

Our study includes a partial adjustment model to capture the movement of leverage toward its optimal target (Fama and French, 2002). Based on Fama and French's PAM, the change in the book leverage partially absorbs the difference between the target leverage (optimal), TL_{t+1}, and the lagged leverage, $L_t \,/\, A_t$:

$$L_{t+1}/A_{t+1} - L_t/A_t = a_0 + a_1[TL_{t+1} - L_t/A_t] + a_2 Z + e_{t+1}, \tag{8}$$

where *Z* represents a vector of current and past investment and earnings. *Z* variables are included in the model to test whether these variables produce any temporary movement in leverage away from its target (Fama and French, 2002). For simplicity in the notation, we drop the i subscript for all the variables.

We use the PAM to compare and test the performance of the Fama and French (2002) point estimate of target (optimal) leverage, 20-year average of the Kraus and Litzenberger (1973) proxy, and our proxy of the industry average. a_1 in Equation (8) is the speed of adjustment per year and, theoretically, is constrained to be between zero and one. The statistical significance of a_1 indicates the significance of leverage adjustment toward its target (optimal), and its economic magnitude shows the speed of adjustment per year.

IV. Data and Sample Construction

We use the following sources of data to conduct the analysis. Our data include all nonfinancial and non-utility firms in NYSE, AMEX, and NASDAQ. The Center for Research in Security Prices (CRSP) provides monthly returns and market capitalizations. To calculate our measures of deviation from OL, we use the accounting data from Compustat.

Due to the availability of industry classifications (SICH), the analysis is conducted using the data from 1982 to 2019. We include stocks with a share price of $5 or more. As part of the data cleaning process, we exclude observations if the excess return, date, *gvkey*, or our calculated variables of interest are missing. We also exclude utilities [Standard Industrial Classification (SIC) codes 4900–4949], financials (SIC codes 6000–6999), firms with zero or missing total debt, and firms with zero or missing total assets. The exclusion of financial firms is critical here because these firms are known to be highly levered. Thus, the interpretation of the leverage ratio for a financial firm could be different from that of a nonfinancial firm.

We retrieve the Fama and French historical factors, as well as their industrial classifications, from Kenneth French's website[1]. We merge Compustat data for all fiscal year-ends in calendar year $t-1$ with CRSP data for January to December of year t. This conservative gap is to ensure the reflection of accounting variables information on the returns. In the final step, we merge the Fama and French data with the merged Compustat-CRSP data set.

V. Results

Table 1 shows the summary statistics of the measures, factors, and returns that we use for this study. Under the deviation category, we report the summary statistics of deviation from three OL measures that we use in this study. Because the calculation of industry median (Ind-Median) and the moving average (MA) measures rely only on leverage variables and, for most public firms, total assets and book equity variables are available on Compustat, the number of observations for Ind-Median and MA is significantly higher than other measures. The Fama and French (2002) target leverage estimation relies on other variables that are missing for some firms in Compustat.

[1] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Thus, we have a much smaller number of observations for Fama and French (FF) and Fama and French industry-clustered (FF-Ind) variables in Table 1.

>>>Insert Table 1 near here<<

The standard deviation for Ind-Median optimal leverage and deviation measures are also smaller compared with other measures. We attribute this to the smaller differences between the leverages intra-industry. Also, looking at their distributions, we see that other measures are clearly skewed to the right. However, our suggested measure shows an asymmetric distribution both for the OL and deviation from the OL.

Table 2 presents the Pearson correlations between deviation measures, OL measures, and other factors used in this study. $dE_{t+1}\ /\ A_{t+1}$, $dA_{t+1}\ /\ A_{t+1}$, dE_t / A_{t+1}, and $dA\ /\ A_{t+1}$ proxy for short-term variations in earnings and investment (Fama and French, 2002). The last row of Table 2 shows the correlation of the deviation of leverage from our suggested OL with those variables as well as other explanatory variables. Most important, we can see, compared with other measures of deviation, that our suggested proxy for deviation from OL has the highest significant statistical and economic correlation with short-term changes in the earnings and investment compared with other proxies.

>>>Insert Table 2 near here<<<

Table 3 presents the result of the portfolio sorting. At the end of each year $t-1$, stocks are sorted into ten portfolios based on their deviation from the OL using MA, FF, Ind-FF, and Ind-Median as proxies for OL. The first portfolio contains stocks with the most negative deviation from OL, and the tenth portfolio has stocks with the most positive deviation from OL. Columns 1 and 2 use 20-year moving averages and Fama and French (2002) as the OL, respectively. Columns 3 and 4 use Fama and French industry-clustered and industry median as the OL, respectively. The reported numbers in the table are the average monthly excess return in year t. The winner in capturing a pattern in the difference in the excess returns in the following year is column 4, which uses our suggested proxy for OL.

>>>Insert Table 3 near here<<<

As the last column of Table 3 presents, the first portfolio has the lowest and the tenth portfolio has the highest excess return in the current year. The pattern almost holds for the rest of the portfolios. A possible explanation for the departure from the pattern is the effect of other factors on the excess return in the middle portfolios (i.e., the stocks are not randomly assigned to each portfolio based on their other characteristics). Finally, the last row of Table 3 shows the excess return on going long in the tenth portfolio and short in the first portfolio. Again, the last column has the highest economic and statistically significant excess return.

Table 4 presents the results of estimating Equation (4), which tests the impact of deviation from OL in the context of the characteristics model. Controlling for market excess return, BE/ME (book equity over market equity), and size [$\ln(\text{market value})$], we examine the impact of deviation from OL using different proxies for OL. As column (4) of Table 4 shows, the coefficient of ΔLV is economically and statistically more significant compared with that of other models. This implies that deviation from OL using our suggested proxy has higher explanatory power compared with its alternatives. The signs of estimated coefficients for size, BE/ME, and market excess return are essentially unchanged across different specification, and this result indicates that our alternative measures of OL are not simply changing the loading on existing factors.

>>>Insert Table 4 near here<<<

After sorting portfolios based on their deviation from OL, we find that sorted portfolios at $t-1$ show significant differences in excess return at the current year, t. We attribute this to the different risk loading on stocks based on their deviation from OL. To examine our conjecture, we use the risk model (Model B) and regress the portfolio returns summarized in Table 3 on the Fama-French risk factors. Table 5 presents the intercepts (i.e., alphas) of these regressions for each portfolio.

>>>Insert Table 5 near here<<<

As the last column of Table 5 shows, the risk-adjusted excess return of sorted portfolios, alpha, follows almost the same pattern as the excess returns have in the last column of Table 3. This means that common risk factors do not explain the excess return in portfolios, and the source of risk-adjusted excess return can be attributed to an otherwise undocumented risk factor, which in this model is the deviation from OL. Fama-French and Fama-French industry-clustered proxies capture the excess return in the tail portfolios (first and tenth). Moreover, the last row of Table 5 (long-short) presents the risk-adjusted excess return from going long on the tenth portfolio and short on the first portfolio. The FF, FF-Ind, and Ind-Median measures consistently show a positive and significant risk-adjusted excess return in the long-short portfolio.

In our final test, we examine whether firms lessen their gap with OL consistent with the trade-off theory and with what speed they lessen their gap with OL every year. We use the PAM that Fama and French (2002) develop for the adjustment of leverage to test our improved proxy for OL. Table 6 presents the results of the estimation of Equation (8). In this table, TL_{t+1} is the variable of interest. Theoretically, the estimated coefficient of TL_{t+1} implies the speed of adjustment and must be between zero and one. The sign of the estimated coefficient also must be positive to be consistent with the direction of the adjustment. Estimated coefficients for TL_{t+1} using the moving average, Fama and French, Fama and French industry-clustered, and industry median as proxies of OL are 0.92, 0.06, 0.37, and 0.35, respectively. The MA method yields the largest coefficient estimate, but it is statistically insignificant, and the MA model returns the lowest R^2 of any measure. The FF-Ind measure gives the highest coefficient estimate of 0.37. However, the Ind-Median measure appears superior by several criteria. First, the Ind-Median is the only measure that makes the model intercept insignificant. Second, the Ind-Median gives a substantially improved R^2 measure relative to the other three measures. Last, the Ind-Median coefficient estimate is close to that of the FF-Ind measure and suggests that every year firms close 35% of their gap with their target leverage (OL).

>>>Insert Table 6 near here<<<

Consistent with the pecking order theory, we find that, all else equal, an increase in earnings decreases debt and hence the leverage. dE_{t+1} / A_{t+1} in Table 6 proxies for the change in the current year's earnings. The estimated coefficient for this variable is consistently negative and significant over all models, which implies an increase in earnings decreases debt. Hence, regardless of the lower cost of debt, firms use excess earnings to lower their debt level and finance their investments.

VI. Conclusion

This research is at the intersection of capital structure and asset pricing. We contribute to the literature in three preliminary manners. First, motivated by prior studies, we introduce two improved measures for optimal leverage: clustered Fama and French (2002) estimation model by industries and the industry median. Second, we show that deviations from OL change the risk loading on returns in a directional manner. Third, we show that using our improved measures as proxies for the OL, firms tend to reduce their gap with their target leverage (optimal capital structure) with higher speed and more significance compared with that studied in prior research.

We argue that because the leverage is related to investment opportunity (Fama and French, 2002), the business environment (Frank and Goyal, 2009), and probably other unknown factors, it should be studied in the industry context. We suggest using the industry median as a proxy for the OL for several reasons. First, the average (median) itself as a statistical measure has much information about the population of firms. Second, extreme forces from each end cancel out each other in the average (median) point. Third, in terms of riskiness, firms around the average should have just the average risk loading. Last, Frank and Goyal (2009) find that the industry median is a reliable factor in explaining the leverage.

We study the relationship between the current deviation from the OL and future excess return. We sort stocks in year $t-1$ based on their difference with OL in decile portfolios. Then, we calculate the average value-weighted excess return in each portfolio in year t. We find that portfolios sorted based on their deviation of underlying firms from OL at year $t-1$ have significant differences in their realized excess return in year t. In particular, the portfolio of stocks in the extreme end of negative deviation from OL (first portfolio) has the lowest excess return and the portfolio on the extreme opposite side (tenth portfolio) has the highest excess return.

We conjecture that the differences between the excess return in sorted portfolios can be attributed to the differences between the risk loading on the stocks in each portfolio. In other words, forming portfolios based on the deviation from OL sorts stocks based on their risk loading as well. We estimate the Fama-French risk factor model and document the risk-adjusted excess return, alpha, in each portfolio. We find the same pattern in the portfolio's alphas as we find in the excess return. Hence, we conclude that the differences in portfolio returns are attributed to another source of risk, which we identify as the deviation from the OL.

Finally, we use the general partial adjustment model to test the two theories. First, consistent with the trade-off theory, we examine whether firms seek a target leverage ratio and each year lessen their gap with that target. Second, consistent with the pecking order theory, we test if changes in earnings affect the debt holdings of firms. We find that, consistent with the trade-off theory, firms lessen 35% of their leverage gap with the OL every year using the industry median as a proxy for the optimal leverage. We estimate Fama and French (2002) model for OL clustered by industry and use it as an improved measure that proxies for OL and find that firms lessen 37% of their gap with OL every year. Also, we find that the current year's increase in earnings significantly decreases firms' debt holding.

References

Baker, M., & Wurgler, J. (2002). Market timing and capital structure. The Journal of Finance, 57(1), 1-32.

Bhandari, L. C. (1988). Debt/equity ratio and expected common stock returns: Empirical evidence. The Journal of Finance, 43(2), 507-528.

Bradley, M., Jarrell, G. A., & Kim, E. (1984). On the existence of an optimal capital structure: Theory and evidence. The Journal of Finance, 39(3), 857-878.

Cai, J., & Zhang, Z. (2006). Capital structure dynamics and stock returns.

Daniel, K., & Titman, S. (1997). Evidence on the characteristics of cross-sectional variation in stock returns. The Journal of Finance, 52(1), 1-33.

Daniel, K., Grinblatt, M., Titman, S., & Wermers, R. (1997). Measuring mutual fund performance with characteristic-based benchmarks. The Journal of Finance, 52(3), 1035-1058.

De Jong, A., Verbeek, M., & Verwijmeren, P. (2011). Firms' debt–equity decisions when the static trade-off theory and the pecking order theory disagree. Journal of Banking & Finance, 35(5), 1303-1314.

DeAngelo, H., & Roll, R. (2015). How stable are corporate capital structures? The Journal of Finance, 70(1), 373-418.

DeAngelo, H., & Masulis, R. W. (1980). Optimal capital structure under corporate and personal taxation. Journal of Financial Economics, 8(1), 3-29.

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.

Fama, E. F., & French, K. R. (2002). Testing trade-off and pecking order predictions about dividends and debt. The Review of Financial Studies, 15(1), 1-33.

Flannery, M. J., & Rangan, K. P. (2006). Partial adjustment toward target capital structures. Journal of financial economics, 79(3), 469-506.

Frank, M. Z., & Goyal, V. K. (2009). Capital structure decisions: which factors are reliably important?. *Financial management*, *38*(1), 1-37.

Hoberg, G., & Phillips, G. (2010). Product market synergies and competition in mergers and acquisitions: A text-based analysis. The Review of Financial Studies, 23(10), 3773-3811.

Hoberg, G., & Phillips, G. (2016). Text-based network industries and endogenous product differentiation. Journal of Political Economy, 124(5), 1423-1465.

Kraus, A., & Litzenberger, R. H. (1973). A state-preference model of optimal financial leverage. The Journal of Finance, 28(4), 911-922.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. The Journal of Finance, 49(5), 1541-1578.

Modigliani, F., & Miller, M. H. (1963). Corporate income taxes and the cost of capital: A correction. The American Economic Review, 53(3), 433-443.

Myers, S. C. (1984). The capital structure puzzle. The Journal of Finance, 39(3), 574-592.

Newey, W. K., & West, K. D. (1986). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix.

Titman, S., & Wessels, R. (1988). The determinants of capital structure choice. The Journal of Finance, 43(1), 1-19.

Table 1*:* Data Description for Publicly Traded, Nonfinancial US Companies, 1982-2019

This table shows the summary statistics for the sample used in this study. Deviation variables are calculated using $\Delta LV_{i,t} = LV_{i,t} - \widehat{LV_{i,t}}$, and different proxies for $\widehat{LV_{i,t}}$: moving average (MA), Fama and French (FF) point estimate, Fama-French clustered on industry (FF-Ind), and the industry median (Ind-Median). Factors are the Z vector of Equation (8), risk factors are the Fama and French three-factor model components, and $XRET$ is the monthly return in excess of the risk-free rate.

Variable	N	Mean	SD	Distribution		
				10th	50th	90th
Deviation						
MA	111,188	-0.026	0.602	-0.160	-0.010	0.136
FF	68,183	-0.005	2.445	-0.391	-0.017	0.434
FF-Ind	67,982	0.037	3.333	-2.175	-0.108	1.620
Ind-Median	112,544	0.001	0.196	-0.244	0.000	0.256
Proxies						
MA	74,873	0.504	0.627	0.207	0.457	0.785
FF	74,869	0.848	7.857	-0.406	0.538	2.395
FF-Ind	111,188	0.237	0.608	0.023	0.189	0.461
Ind-Median	115,104	0.523	0.175	0.298	0.515	0.758
Factors						
BEME	116,904	0.661	5.934	0.148	0.525	1.241
Size	116,904	5.999	1.969	3.529	5.891	8.606
dE_{t+1} / A_{t+1}	82,659	0.005	0.276	-0.109	0.009	0.101
dA_{t+1} / A_{t+1}	82,707	0.053	0.973	-0.137	0.067	0.343
dE_t / A_{t+1}	73,513	0.001	0.336	-0.096	0.009	0.085
dA / A_{t+1}	73,561	0.054	0.604	-0.121	0.061	0.281
Risk Factors						
RF	508	0.003	0.002	0.000	0.003	0.006
MKTRF	508	0.007	0.043	-0.047	0.012	0.060
SMB	508	0.000	0.031	-0.034	0.000	0.034
HML	508	0.003	0.029	-0.029	0.000	0.038
Monthly excess Return						
XRET	1,200,898	0.017	0.156	-0.127	0.007	0.162

Table 2*:* Pearson Correlation Coefficients Matrix

This table shows the significance and magnitude of the correlation between deviation from optimal capital structure using moving average (MA), Fama and French (FF) point estimate, Fama-French clustered on industry (FF-Ind), and the industry median (Ind-Median). The numbers in the table are the Pearson correlation coefficients, and the asterisks show the significance of the correlation.

	BEME	Size	dE_{t+1} / A_{t+1}	dA_{t+1} / A_{t+1}	dE_t / A_{t+1}	dA / A_{t+1}	FF	FF-Ind	MA	Ind-Median
ΔLV (MA)	-0.004***	0.011***	0.022***	0.031***	-0.009**	-0.075***	0.020***	0.002***	0.017***	0.014***
ΔLV (FF)	0.000	0.009**	0.003	0.002	0.001	0.002	0.004	0.018***	0.000	0.012***
ΔLV (FF-Ind)	0.002	0.036***	0.034***	0.005	0.010***	-0.006*	0.024***	-0.005	-0.936***	0.045***
ΔLV (Ind-Median)	0.008***	0.128***	0.055***	-0.017***	0.000	-0.023***	0.083***	0.011***	0.103***	-0.125***

* significance level of 10%
** significance level of 10%
*** significance level of 1%

Table 3: Sorted portfolios of mean return on $\Delta LV_{i,t}$

This table shows the value-weighted average excess monthly return in the portfolios sorted ascending on the deviation from optimal leverage ($\Delta LV_{i,t} = LV_{i,t} - \widehat{LV_{i,t}}$). Optimal leverage is measured by: moving average (MA), Fama and French (FF) point estimate, Fama-French clustered on industry (FF-Ind), and the industry median (Ind-Median). The numbers between parentheses are the *t*-statistics of the hypothesis that its above number is equal to zero.

Ranking on $\Delta LV_{i,t}$	MA	FF	FF-Ind	Ind-Median
1	0.0209	0.0165	0.0183	0.0156
	(35.73)	(27.97)	(29.62)	(31.87)
2	0.0181	0.0150	0.0153	0.0168
	(35.09)	(27.00)	(26.71)	(34.25)
3	0.0175	0.0153	0.0148	0.0173
	(34.80)	(26.74)	(27.4)	(35.22)
4	0.0175	0.0155	0.0162	0.0186
	(34.34)	(28.8)	(29.59)	(34.1)
5	0.0180	0.0174	0.0170	0.0203
	(34.90)	(31.30)	(30.61)	(35.58)
6	0.0190	0.0185	0.0189	0.0167
	(34.35)	(34.24)	(34.07)	(34.37)
7	0.0173	0.0170	0.0173	0.0168
	(33.97)	(31.85)	(32.82)	(34.54)
8	0.0166	0.0174	0.0163	0.0162
	(35.39)	(34.98)	(33.28)	(34.29)
9	0.0170	0.0173	0.0167	0.0194
	(33.09)	(34.9)	(33.47)	(36.1)
10	0.0186	0.0212	0.0202	0.0225
	(34.42)	(36.48)	(36.73)	(39.95)
High-Low	-0.0022*	0.0047**	0.0019***	0.0069***
	(-1.74)	(2.18)	(3.05)	(3.40)

*significance level of 10%
** significance level of 10%
*** significance level of 1%

Table 4: Characteristics models

This table presents estimated results of the characteristics model (Model A) of Equation (4), where monthly excess returns are the dependent variable. ΔLV variables are the deviation from optimal capital structure using moving average (MA), Fama and French (FF) point estimate, Fama-French clustered on industry (FF-Ind), and the industry median (Ind-Median) as proxies for the optimal capital structure, $\widehat{LV_{\iota,t}}$. Numbers in the table are reported as basis points and numbers between parentheses are *t*-statistics.

Variables	1	2	3	4
Intercept	0.035^{***}	0.035^{***}	0.035^{***}	0.037^{***}
	(51.800)	(52.250)	(52.190)	(54.510)
MKTRF	1.122^{***}	1.122^{***}	1.122^{***}	1.122^{***}
	(282.930)	(282.930)	(282.930)	(282.920)
BEME	0.005^{***}	0.005^{***}	0.005^{***}	0.004^{***}
	(13.200)	(13.080)	(13.130)	(12.750)
SIZE	-0.005^{***}	-0.005^{***}	-0.005^{***}	-0.005^{***}
	(-50.520)	(-50.820)	(-50.780)	(-53.340)
ΔLV (MA)	-0.001^{**}			
	(-1.940)			
ΔLV (FF)		0.0002^{***}		
		(2.920)		
ΔLV (FF-Ind)			0.000	
			(0.100)	
ΔLV (Ind-Median)				0.017^{***}
				(19.450)
Observations	725,099	725,099	725,099	725,099
Adj R^2	0.104	0.104	0.104	0.104

* significance level of 10%
** significance level of 10%
*** significance level of 1%

Table 5: Sorted portfolios of risk-adjusted excess return on $\Delta LV_{i,t}$

This table shows the alpha of Fama and French three-factor model in each portfolio. Portfolios are sorted ascending on deviation from optimal leverage based on ($\Delta LV_{i,t} = LV_{i,t} - \widehat{LV_{i,t}}$). variables are the deviation from optimal capital structure using moving average (MA), Fama and French (FF) point estimate, Fama-French clustered on industry (FF-Ind), and the industry median (Ind-Median) as proxies for the optimal capital structure. Numbers in the table are reported as annualized percentage and numbers between parentheses are *t*-statistics.

Ranking on $\Delta LV_{i,t}$	MA	FF	FF-Ind	Ind-Median
1.000	0.025	-0.245	-0.203	-0.713
	(30.5)	(-8.5)	(-3.3)	(-16.4)
2.000	-0.015	-0.198	-0.147	-0.591
	(-20.8)	(-18.8)	(-16.0)	(-14.2)
3.000	0.028	0.242	-0.004	-0.687
	(40.4)	(25.0)	(-20.4)	(-16.3)
4.000	-0.031	-0.213	-0.297	-0.764
	(-36.4)	(-19.5)	(-31.6)	(-14.0)
5.000	0.038	-0.082	0.184	0.792
	(33.8)	(-29.1)	(25.7)	(13.4)
6.000	0.033	0.287	0.186	-0.087
	(27.0)	(33.7)	(22.5)	(-3.3)
7.000	-0.024	0.251	-0.158	0.689
	(-25.2)	(31.6)	(-24.9)	(18.5)
8.000	0.009	0.210	0.177	0.790
	(10.2)	(26.8)	(24.8)	(20.2)
9.000	-0.017	0.145	0.169	0.825
	(-25.4)	(20.0)	(27.6)	(21.3)
10.000	0.023	0.452	0.254	0.932
	(23.6)	(57.3)	(33.0)	(17.8)
Long-short	-0.002***	0.697***	0.457***	1.645***
	(-3.2)	(5.2)	(4.1)	(4.6)

* significance level of 10%
** significance level of 10%
*** significance level of 1%

Table 6: Partial Adjustment Model

This table shows the results of Partial Adjustment Model by estimating Equation (8),
$L_{t+1}/A_{t+1} - L_t/A_t = a_0 + a_1[TL_{t+1} - L_t/A_t] + a_2 Z + e_{t+1}$.
First column use 20-years moving average (MA), second column use Fama and French (2002) point estimate (FF), third column use Fama and French (2002) point estimate clustered on industry and forth column use the improved measure (industry median) as a proxy for optimal leverage, $\widehat{LV_{\iota,t}}$.
Numbers between parentheses are the t-statistics.

	MA	FF	FF-Ind	Ind-Median
Intercept	0.86***	0.23***	0.76***	0.09
	(3.28)	(15.84)	(3.38)	(0.21)
TL_{t+1}	0.92	0.06**	0.37***	0.35***
	(1.38)	(3.94)	(13.32)	(17.42)
L_t	-1.00***	-0.45***	-1.00***	-0.47***
	(-18.81)	(-10.37)	(-9.10)	(-17.98)
dE_{t+1} / A_{t+1}	-2.61***	-0.11***	-2.77***	-0.14***
	(-3.06)	(-3.05)	(-3.09)	(-4.85)
dA_{t+1} / A_{t+1}	0.23	-0.26***	0.25	-0.26***
	(1.02)	(-3.89)	(1.08)	(-3.58)
dE_t / A_{t+1}	-0.99	-1.43	-0.96	0.02
	(-1.45)	(0.15)	(-1.37)	(1.47)
dA / A_{t+1}	-0.13	-0.42	-0.12	0.03
	(-0.33)	(0.67)	(-0.28)	(1.30)
Observations	73240	68188	68115	71746
Adj-R^2	0.21	0.52	0.55	0.72

* significance level of 10%
** significance level of 10%
*** significance level of 1%

CHAPTER 2

An Optimal Capital Structure Risk Factor
Evidence from industry-specific benchmarks

Abstract

This essay investigates the impact of deviation from the optimal capital structure on ex post excess stock returns. Using the Fama and French (1993–2015) methodology of mimicking portfolios, we model deviations from optimal capital structure as a new risk factor. We find that this factor is significantly associated with the cross section of stock returns and that a risk-mimicking portfolio can explain the risk loading on the cross-sectional excess return that is not explained by Fama and French risk factors. Using Monte Carlo simulations with bootstrapped mean variance–spanning tests, we show that existing Fama and French factors do not explain (i.e., span) the risk factor we introduce. Moreover, we use the Text-based Network Industry Classifications (TNIC) developed by Hoberg and Phillips (2010, 2016) that classifies firms into different industries based on the text analysis of firms' 10-K report to show that our results are robust to the method used for industry classification.

Keywords: capital structure; stock returns; risk factors; factor models; leverage.

JEL codes: G12, G14, G32.

I. Introduction

In essay I, we showed that industry median leverage provides a good estimate of a firm's optimal leverage (OL). Here, in essay II, we focus on the arbitrage portfolio created by the deviation from the OL. Following the methodology used by Fama and French (1993–2015) to mimic the size and book equity over market equity (BE/ME) risk premiums [i.e., SMB (small minus big), HML (high minus low)], we create an arbitrage portfolio where the short leg is the low debt-to-equity ratio and the long leg is the high debt-to-equity ratio. We call this new risk-mimicking portfolio HDL (high debt minus low debt). Because the industry classification determines the composition of firms' capital structure (Bradley et al., 1984; Titman and Wessels, 1988), for each firm, we need to build the mimicking portfolio based on its corresponding industry. Consistent with our findings in essay I, we expect to find a positive loading of the leverage risk factor on the return in this factor model setting.

The proxy we use for the OL is the industry median because, in essay I, we find that it performs well on several metrics compared with alternative measures of OL. To ensure robust industry classifications, we use both the Fama and French 48 (FF48) industry classification and the novel Text-based Network Industry Classifications (TNIC) method. TNICs are estimated using firm pairwise similarity scores from text analysis of firms' Form 10-K product descriptions. The TNIC is the product of Hoberg and Phillip (2010, 2016), and the TNIC data are retrieved from their website.[2]

[2] https://hobergphillips.tuck.dartmouth.edu/

The TNIC methodology is like Facebook network friends. Here, competitors of a particular firm are defined in a way that each firm has its own distinct set of competitors. TNICs are updated annually based on the 10-K report and are more informative than other conventional classifications such as Standard Industrial Classification (SIC), North American Industry Classification System (NAICS), and FF48. Hoberg and Phillips (2010, 2016) show that TNIC sharply improves upon SIC and NAICS codes in explaining many different firm-specific decisions, including firm profitability, Tobin's Q, and dividends. Hence, we favor TNIC over other classifications, use it as the primary source of industry classification, and use the Fama-French 48 industry classification for the robustness check.

The main concern in our study of risk loading is the possibility that the mimicking (arbitrage) portfolio that we introduce is explained (spanned) by the combination of other Fama and French risk portfolios. To test this, we use the Huberman and Kandel (1987) mean variance–spanning test. Huberman and Kandel (1987) test whether the frontier of portfolios made by particular sorts spanned another portfolio; that is, if the frontier made by the new factor that we produced is spanned by the other risk factors in the literature (i.e., the Fama-French factors) and the risk factor we introduce is nothing distinct but a combination of other risk factors from prior researches. The mean variance–spanning test is a stricter method of testing whether the known risk factors explain the new factor.

Because the distribution of the arbitrage return made by the new factor (or in general any other arbitrage portfolios) does not necessarily follow a χ^2 distribution, we use the Monte Carlo procedure to find bootstrapped critical values for testing the null hypothesis. The null hypothesis here is that other the HDL factor is spanned by existing Fama-French factors. Using conventional critical values can be misleading and are biased toward rejecting the null hypothesis. Using the Monte Carlo procedure, we generate bootstrapped critical values that make the rejection of the null hypothesis more difficult and decrease the probability of a type I error.

Following the Fama and French (1993–2015) methodology, we expect to see the sign of loading on the risk factors consistent with the direction of their loading. For example, we expect to see a positive estimated coefficient for SMB when we use market-wide data. Similarly, we expect to observe a positive coefficient estimate on the HDL risk factor. We find that, consistent with our initial expectations on the direction of risk loading, there is a positive loading on the HDL factor. For robustness, we split our sample data into two time periods: before the 2008 recession and after the 2008 recession. The positive loading that we estimate is statistically and economically significant loading over both periods.

II. Literature Review

The capital asset pricing model (CAPM) of Sharpe (1964), Mossin (1966), Black (1972), and Lintner (1975) identifies the market return or excess return as the first "factor" that is potentially important in explaining variation in the cross section of stock returns. Early tests of the single-factor model were inconclusive (Roll, 1969; Jacob, 1971; Fama and MacBeth, 1973; Lee and Jen, 1978). Researchers then began to expand the CAPM, motivated by Ross's arbitrage pricing theory (Ross, 1973, 1976) and the existence of anomalies in the cross section of stock returns (Basu, 1977, 1983; Banz, 1981; Keim, 1983; Schwert, 1983; Reinganum, 1981, 1983). The Fama and French (1993) three-factor model was introduced to incorporate the relationships between the stock excess returns and the strongest factor candidates at the time: market returns, firm size, and the value factor.

Following the Fama and French (1992, 1993) models, there was an explosion of factors that add marginal power to explain the cross section of stock returns. Major examples include momentum (Jegadeesh and Titman, 1993; Carhart, 1997), profitability (Fama and French, 2006), investment (Titman, Wei, and Xie, 2004), and dividends (Black and Scholes, 1974; Campbell and Shiller, 1988). Motivated by the later evidence of Novy-Marx (2013), Titman et al. (2004), and others about the explanatory power of profitability and investment in explaining the cross-sectional variations in return, Fama and French (2015) introduce their five-factor model. Fama and French (2015) adds profitability (RMW, robust minus weak) and investment (CMA, conservative minus aggressive) factors to their three-factor model.

In addition to the RMW and CMA factors, Fama and French (2015) introduce useful methods for evaluating the importance of new factors. In their models, RMW is the difference between the returns on diversified portfolios of stocks with robust and weak profitability (Fama and French, 2015). CMA is the difference between the returns on diversified portfolios of the stocks of low and high investment firms that they call conservative and aggressive, respectively. Fama and French suggest that if new factors, such as RMW and CMA, have explanatory power for variation in the cross section of returns, then the model intercept (alpha) should become smaller and less significant. They further suggest that, in the best scenario, if the estimated intercept is not significantly different from zero, then the mean variance–efficient tangency portfolio, which prices all assets, combines the risk-free asset, the market portfolio, SMB, HML, RMW, and CMA. We adopt this approach and evaluate the impact of an OL factor on our models' intercepts.

Along with Fama and French (2015), numerous additional papers provide alternative methods to evaluate potential new factors in the cross section of stock returns. Prominent examples include Ferson and Harvey (1999), Harvey, Liu, and Zhu (2016), Yan and Zheng (2017), Stambaugh and Yuan (2017), Barillas and Shanken (2018), Fama and French (2018), Feng, Giglio, and Xie (2020), Kozak, Nagel, and Santosh (2020), and Hou, Xue, and Zhang (2015, 2020).

Among the wide variety of potential tests for new factor models, our approach combines a focus on the magnitude of the model intercept and the extent to which a new factor is spanned by existing factors. The focus on alpha follows most closely from studies by Fama and French (2015, 2018), Barillas and Shanken (2017), and Barillas, Kan, Robotti, and Shanken (2020). Our incorporation of a mean variance–spanning approach derives from the work of Huberman and Kandel (1987), as modified by Jobson and Korkie (1989), Kandel and Stambaugh (1989), Lettau and Pelger (2020a, 2020b), Kozak, Nagel, and Santosh (2020), Kim, Korajczyk, and Neuhierl (2021), and Giglio and Xiu (2021). The mean variance–spanning approach is also used outside the context of factor pricing models to evaluate market integration (Bekaert and Urias, 1996; Chiang, Wisen, and Zhou, 2007), security design (Rakowski and Shirley, 2020), and fund management (Li and Qui, 2014). DeRoon and Nijman (2001) provide a useful comparison of the applications of mean variance–spanning tests.

III. Data and Sample

We use the following sources of data to conduct the analysis. Our data include all nonfinancial and non-utility firms in NYSE, AMEX, and NASDAQ. As in essay I, the Center for Research in Security Prices (CRSP) provides monthly returns and market capitalizations. To calculate our measures of deviation from OL, we use the accounting data from Compustat.

We include stocks with a share price of $5 or more. As part of the data cleaning process, we exclude observations if the excess return, date, gvkey, or our calculated variables of interest are missing. We also exclude utilities (SIC codes 4900–4949), financials (SIC codes 6000–6999), firms with zero or missing total debt, and firms with zero or missing total assets. The exclusion of financial firms is important because these firms are known to be highly levered. Thus, the interpretation of the leverage ratio for a financial firm could be different from that of a nonfinancial firm.

Due to the availability of industry classifications (SICH), the analysis is conducted using the data of from 1982 to 2019. We supplement SICH codes with TNIC data from Hoberg and Phillips (2010, 2016). TNIC data are retrieved from Hoberg and Phillips's website. Hoberg and Phillips's data are based on web crawling and text parsing algorithms that process the text in the business descriptions of 10-K annual filings on the Securities and Exchange Commission (SEC) Electronic Data Gathering, Analysis, and Retrieval (EDGAR) website from 1996 to the present. The TNIC classification is based on a clustering algorithm that groups firms together to maximize within-industry similarity while achieving a goal of *N* industries.

We retrieve the Fama and French historical factors, as well as their industrial classifications, from Kenneth French's website[3]. We merge Compustat data for all fiscal year-ends in calendar year $t - 1$ with CRSP data for January to December of year t. This conservative gap

[3] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

is to ensure the reflection of accounting variables information on the returns. In the final step, we merge the Fama and French data with the merged Compustat-CRSP data set.

We construct the new risk factor, HDL, following Fama and French (1993). The mimicking portfolio is made by subtracting the average return of the portfolio of the highest 30% leverage from the lowest 30% leverage in the associated industry. The industries are defined based on the Text-based Network Industry Classifications of Hoberg and Phillips (2010, 2016). According to this classification, a firm classification might change from year to year due to the fact that results of text analysis generate a different industry classification for a particular firm.

IV. Measurements, Models, Methods, and Hypotheses Development

Following Fama and French (1993), we test if the variation in the cross section of the average return over time (panel data) is explained by introducing our new factor. To do so, we calculate the arbitrage-mimicking portfolio using the deviation from OL. The deviation from the OL is calculated based on Equation (1):

$$\Delta LV_{i,t} = LV_{i,t} - \widehat{LV_{\iota,t}}, \tag{1}$$

where $\Delta LV_{i,t}$ proxies for the deviation from optimal capital leverage and $\widehat{LV_{\iota,t}}$ is the OL of firm i at time t. We use the industry leverage median as a proxy for $\widehat{LV_{\iota,t}}$. $LV_{t,i}$ is the actual leverage of firm i at time t.

Our factor model is expressed as

$$r_{i,t} = \alpha_t + \beta_1 HDL_{ind,t} + \beta_2 (mkt - rf)_t + \beta_3 (smb)_t + \beta_4 (hml)_t + \mathrm{A} + \varepsilon_{i,t}, \tag{2}$$

where $HDL_{ind,t}$ represents the high minus low debt at time t for industry ind, $(mkt - rf)_t$ is the market excess return, $(smb)_t$ is the size factor, $(hml)_t$ is the value factor, and A is a vector of firm and time fixed effects. The risk model is similar to the three-factor model of Fama and French (2015), except we add a new risk factor, HDL. This factor is short on the first three decile portfolios, which have the lowest (negative) deviation from OL, and long on the last three decile portfolios, which have the highest (positive) deviation from OL. However, instead of taking the high (low) $\Delta LV_{i,t}$ of the whole market for each long-short portfolio, we take that high (low) ratio from firm i's industry class.

Text-based Network Industry Classifications (TNIC)

Hoberg and Phillips (2010, 2016) show that TNIC sharply improves upon SIC and NAICS codes in explaining many firm-specific decisions, including firm profitability, Tobin's Q, and dividends. According to their explanation of the process, the TNIC is the product of web crawling and text parsing algorithms. Algorithms process the text in the business descriptions section of 10-K annual filings on the SEC EDGAR website from 1996 to the present. According to Item 101 of Regulation S-K, firms are legally required to describe the products they offer to the market and update the description based on the corresponding fiscal year. We retrieve the TNIC data from the Hoberg and Phillips website and merge the data with the Compustat and CRSP database[4]. We do not observe major differences in our results when using TNIC, SIC, or the Fama-French 48 industry classification. The significance and signs of estimated coefficients are similar, and the estimated parameters are not economically different using each classification.

[4] https://hobergphillips.tuck.dartmouth.edu/

Mean Variance–Spanning Tests, Monte Carlo Procedure, and Factors Correlation

We examine whether the HDL factor that we created is absorbing the loadings of other risk factors or is a distinct source of risk. To test this, we use two main methods. First, we check whether the HDL is a linear combination of Fama and French (FF) risk factors by regressing HDL on the FF factors. Second, we use the mean variance–spanning test of Huberman and Kandel (1987) to see whether the frontier of the mimicking portfolio of the HDL factor is spanned by the frontier of the traditional FF factors.

We regress HDL on the FF factors with the following model:

$$HDL_t = \alpha + \beta_1 \mathrm{Mktrf}_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 \mathrm{UMD}_t + \varepsilon_t. \tag{3}$$

Next, following Huberman and Kandel (1987), we test the joint hypotheses that $\alpha = 0$ and $\beta_2 + \beta_3 + \beta_4 = 1$ in Equation (3). Because the distribution of HDL is not necessarily χ^2, and using conventional critical values might be misleading, we use the Monte Carlo procedure to generate bootstrapped critical values. We estimate critical values by generating random coefficients in each Monte Carlo loop and calculate the randomly generated dependent variable of Equation (3). Then, after regressing randomly generated dependent variables on the factors, we store the χ^2 statistic. After doing this procedure for 1,000 rounds, we determine the 90th and 99th percentile ranking of the test statistics for to use them as critical values for testing the joint null hypotheses that $\alpha = 0$ and $\beta_2 + \beta_3 + \beta_4 = 1$ in Equation (3). The Monte Carlo bootstrapped critical values make the rejection of the joint null hypotheses of the mean variance–spanning test more difficult.

V. Results

As shown in Table 1, the correlation between the newly introduced risk factor using monthly return data, HDL, and the Fama and French monthly factors is statistically significant, but not economically meaningful. The highest correlation is with MKTRF, but the level is only 0.03778. The remaining correlations are all close to zero.

>>>Insert Table 1 near here<<<

To test if HDL is a combination of other factors, we test Equation (3) in two different manners. First, we regress Equation (3) to see the magnitude of R^2 as well as the economic and statistical significance of coefficients. All the observations we use in Equation (3) are built monthly using monthly return data. Table 2 shows the results of regressing HDL factors on other factors. To calculate the *t*-statistics reported in parentheses, we use the HCC option in the SAS procedure and estimate the heteroskedasticity-consistent standard errors. As we can see, other factors cannot explain the variation in the HDL risk factor, as the adjusted R^2 is close to zero.

>>>Insert Table 2 near here<<<

If the other risk factors, SMB, HML, and UMD, could explain the HDL factor, it means that HDL does not bring anything new to the table and, if included in the model, would absorb some of the effects of other risk factor variables. However, the estimation result reported in Table 2 confirms that the new factor that we introduce in this study is independent enough from FF factors to be included in an asset pricing model. The justification for this claim is that the adjusted R^2 is economically insignificant (0.3%) in Table 2.

Next, we test the joint hypotheses of $\alpha = 0$ and $\beta_2 + \beta_3 + \beta_4 = 1$ with estimated coefficients of Equation (3). In the first step, we estimate the critical values of the statistical test using the Monte Carlo bootstrapping procedure. The estimated critical values of χ^2 are reported in Panel A of Table 3, running the Monte Carlo procedure 1,000 times. The results of testing these joint hypotheses using the bootstrapped critical values are reported in Panel B of Table 3. From Panel B of Table 3, we reject the joint null hypotheses $\alpha = 0$ and $\beta_2 + \beta_3 + \beta_4 = 1$ jointly for 41 out of 46 industries with a 90% confidence level and 37 out of 46 industries with a 99% confidence level. The result of the mean variance–spanning test shows that the frontier made by the Fama-French factors does not span the HDL factor. Hence, HDL is not a combination of other factors, and it is introducing a distinct measure to the literature. All the risk factors used for the Monte Carlo procedure are monthly and are build using monthly returns.

>>>Insert Table 3 near here<<<

Table 4 shows the estimated results of adding the monthly HDL factor to Fama-French risk factor models by estimating Equation (2) monthly. To calculate the *t*-statistics reported in parentheses, we use the HCC option in the SAS procedure and estimate the heteroskedasticity-consistent standard errors. The first two columns of Table 4 show the results of using MRKT, SMB, and HML along with HDL factors in two different time periods (before and after the 2008 recession). Columns 3 and 4 show the same results by adding the UMD factor of the Carhart (1997) model to see whether the results are robust. We find that the HDL remains positively and significantly associated with stock returns in both periods. The estimated coefficients are not only consistently statistically significant, but also their economic magnitude is significant over different periods.

>>>Insert Table 4 near here<<<

In Table 5, we replicate Table 4 but change the industry classification from TNIC to Fama-French 48. Table 5 shows the estimation of Equation (2) using the Fama-French 48 industry classification to calculate the HDL factor. To calculate the *t*-statistics reported in parentheses, we use the HCC option in the SAS procedure and estimate the heteroskedasticity-consistent standard errors. As the HDL row of this table shows, there is a positive loading on HDL that is consistent over different time periods and the addition of UMD as a new factor using monthly return for building risk factors and as a dependent variable on the right-hand side of Equation (2). Thus, consistent with our expectations, HDL is not sensitive to the industry classification, and both classifications generate the same results.

>>>Insert Table 5 near here<<<

VI. Conclusion

In essay I, we study how investors perceive optimal capital structure and how they react to it. We argue that because OL is related to investment opportunity (Fama and French, 2002), the business environment (Frank and Goyal, 2009), and probably other unknown factors, it should be studied in the industry context. We find that among several proxies for OL, including our two proposed measures, the industry median has the best performance in explaining investors' and managers' reactions to the deviation from the OL, as realized by stock returns.

Building on our findings in essay I, we use the Fama and French (1993–2015) methods to build a factor that mimics the risk loaded due to the deviation of firms from their optimal capital leverage. We build HDL by shorting the first three decile portfolios, which have the lowest (negative) deviation from optimal capital structure, and going long on the last three decile portfolios, which have the highest (positive) deviation from OL. Unlike Fama and French, we construct these portfolios at the industry level. We use both the Fama-French 48 industry classification and the Text-based Network Industry Classifications and find that our results are robust regardless of the industry classification we use to build our HDL factor.

We test whether the HDL factor can be explained by other known risk factors. In particular, we test whether the HDL factor that we create is spanned by other traditional risk factors. We show that HDL has a low correlation with traditional factors. We show that HDL is not well explained by traditional factors based in a regression setting. We reject the null hypothesis that HDL is spanned by existing factors in the context of a mean variance–spanning test with both standard and bootstrapped critical values.

Overall, we find that HDL explains a distinct incremental portion of the cross-sectional variation in the stock returns that is not explained by the other risk factors. The loading on HDL is consistently positive over different time periods. Overall, the results here, of essay II, reinforce the findings from essay I that deviation from industry median leverage is a potentially distinct and useful (in explaining the cross section of stock returns) new measure of optimal leverage.

References

Banz, R. W. (1981). The relationship between return and market value of common stocks. Journal of financial economics, 9(1), 3-18.

Barillas, F., & Shanken, J. (2017). Which alpha?. The Review of Financial Studies, 30(4), 1316-1338.

Barillas, F., & Shanken, J. (2018). Comparing asset pricing models. The Journal of Finance, 73(2), 715-754.

Barillas, F., Kan, R., Robotti, C., & Shanken, J. (2020). Model comparison with sharpe ratios. Journal of Financial and Quantitative Analysis, 55(6), 1840-1874.

Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. The journal of Finance, 32(3), 663-682.

Basu, S. (1983). The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence. Journal of financial economics, 12(1), 129-156.

Bekaert, G., & Urias, M. S. (1996). Diversification, integration and emerging market closed-end funds. the Journal of Finance, 51(3), 835-869.

Black, F., & Scholes, M. (1974). The effects of dividend yield and dividend policy on common stock prices and returns. Journal of financial economics, 1(1), 1-22.

Black, F. (1972). Capital market equilibrium with restricted borrowing. The Journal of business, 45(3), 444-455.

Bradley, M., Jarrell, G. A., & Kim, E. (1984). On the existence of an optimal capital structure: Theory and evidence. The Journal of Finance, 39(3), 857-878.

Campbell, J. Y., & Shiller, R. J. (1988). The dividend-price ratio and expectations of future dividends and discount factors. The Review of Financial Studies, 1(3), 195-228.

Carhart, M. M. (1997). On persistence in mutual fund performance. The Journal of finance, 52(1), 57-82.

Chiang, K. C., Wisen, C. H., & Zhou, T. X. (2007). Emerging market bonds as an asset class: Mean-variance spanning. The Journal of Investing, 16(3), 104-110.

Daniel, K., & Titman, S. (1997). Evidence on the characteristics of cross-sectional variation in stock returns. The Journal of Finance, 52(1), 1-33.

DeRoon, F. A., & Nijman, T. E. (2001). Testing for mean-variance spanning: a survey. Journal of empirical finance, 8(2), 111-155.

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.

Fama, E. F., & French, K. R. (2002). Testing trade-off and pecking order predictions about dividends and debt. The Review of Financial Studies, 15(1), 1-33.

Fama, E. F., & French, K. R. (2015). Incremental variables and the investment opportunity set. Journal of Financial Economics, 117(3), 470-488.

Fama, E. F., & French, K. R. (2006). Profitability, investment and average returns. Journal of financial economics, 82(3), 491-518.

Fama, E. F., & French, K. R. (2015). Incremental variables and the investment opportunity set. Journal of Financial Economics, 117(3), 470-488.

Fama, E. F., & French, K. R. (2018). Choosing factors. Journal of financial economics, 128(2), 234-252.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. Journal of political economy, 81(3), 607-636.

Feng, G., Giglio, S., & Xiu, D. (2020). Taming the factor zoo: A test of new factors. The Journal of Finance, 75(3), 1327-1370.

Ferson, W. E., & Harvey, C. R. (1999). Conditioning variables and the cross section of stock returns. The Journal of Finance, 54(4), 1325-1360.

Giglio, S., & Xiu, D. (2021). Asset pricing with omitted factors. Journal of Political Economy, 129(7), 000-000.

Harvey, C. R., Liu, Y., & Zhu, H. (2016). … and the cross-section of expected returns. The Review of Financial Studies, 29(1), 5-68.

Hoberg, G., & Phillips, G. (2010). Product market synergies and competition in mergers and acquisitions: A text-based analysis. The Review of Financial Studies, 23(10), 3773-3811.

Hoberg, G., & Phillips, G. (2016). Text-based network industries and endogenous product differentiation. Journal of Political Economy, 124(5), 1423-1465.

Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. The Review of Financial Studies, 28(3), 650-705.

Hou, K., Xue, C., & Zhang, L. (2020). Replicating anomalies. The Review of Financial Studies, 33(5), 2019-2133.

Huberman, G., & Kandel, S. (1987). Mean-variance spanning. The Journal of Finance, 42(4), 873-888.

Jacob, N. L. (1971). The measurement of systematic risk for securities and portfolios: Some empirical results. Journal of Financial and Quantitative Analysis, 6(2), 815-833.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of finance, 48(1), 65-91.

Jobson, J. D., & Korkie, B. (1989). A performance interpretation of multivariate tests of asset set intersection, spanning, and mean-variance efficiency. Journal of financial and quantitative analysis, 24(2), 185-204.

Kandel, S., & Stambaugh, R. F. (1989). A mean-variance framework for tests of asset pricing models. The review of financial studies, 2(2), 125-156.

Keim, D. B. (1983). Size-related anomalies and stock return seasonality: Further empirical evidence. Journal of financial economics, 12(1), 13-32.

Kim, S., Korajczyk, R. A., & Neuhierl, A. (2021). Arbitrage portfolios. The Review of Financial Studies, 34(6), 2813-2856.

Kozak, S., Nagel, S., & Santosh, S. (2020). Shrinking the cross-section. Journal of Financial Economics, 135(2), 271-292.

Kraus, A., & Litzenberger, R. H. (1973). A state-preference model of optimal financial leverage. The journal of finance, 28(4), 911-922.

Lee, C. F., & Jen, F. C. (1978). Effects of measurement errors on systematic risk and performance measure of a portfolio. Journal of Financial and Quantitative Analysis, 13(2), 299-312.

Lettau, M., & Pelger, M. (2020). Estimating latent asset-pricing factors. Journal of Econometrics, 218(1), 1-31.

Lettau, M., & Pelger, M. (2020). Factors that fit the time series and cross-section of stock returns. The Review of Financial Studies, 33(5), 2274-2325.

Li, S., & Qiu, J. (2014). Financial product differentiation over the state space in the mutual fund industry. Management Science, 60(2), 508-520.

Lintner, J. (1975). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. In Stochastic optimization models in finance (pp. 131-155). Academic Press.

Mossin, J. (1966). Equilibrium in a capital asset market. Econometrica: Journal of the econometric society, 768-783.

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

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. Journal of financial economics, 108(1), 1-28.

Rakowski, D., & Shirley, S. (2020). What drives the market for exchange-traded notes?. Journal of Banking & Finance, 111, 105702.

Reinganum, M. R. (1981). Misspecification of capital asset pricing: Empirical anomalies based on earnings' yields and market values. Journal of financial Economics, 9(1), 19-46.

Reinganum, M. R. (1983). The anomalous stock market behavior of small firms in January: Empirical tests for tax-loss selling effects. Journal of financial economics, 12(1), 89-104.

Roll, R. (1969). Bias in fitting the Sharpe model to time series data. Journal of Financial and Quantitative Analysis, 4(3), 271-289.

Ross, S. A. (1973). Return, risk and arbitrage. Rodney L. White Center for Financial Research, The Wharton School, University of Pennsylvania.

Schwert, G. W. (1983). Size and stock returns, and other empirical regularities. Journal of financial Economics, 12(1), 3-12.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. The journal of finance, 19(3), 425-442.

Stambaugh, R. F., & Yuan, Y. (2017). Mispricing factors. The Review of Financial Studies, 30(4), 1270-1315.

Titman, S., & Wessels, R. (1988). The determinants of capital structure choice. The Journal of finance, 43(1), 1-19.

Titman, S., Wei, K. J., & Xie, F. (2004). Capital investments and stock returns. Journal of financial and Quantitative Analysis, 39(4), 677-700.

Yan, X. S., & Zheng, L. (2017). Fundamental analysis and the cross-section of stock returns: A data-mining approach. The Review of Financial Studies, 30(4), 1382-1423.

Table 1: Correlation Metrix
This table presents the Pearson correlations coefficient of risk factor portfolios using TNIC data. Three factors of Fama and French (1993), UMD of Carhart (1997), and HDL.

	HDL	MKTRF	SMB	HML	UMD
HDL	1				
MKTRF	0.03778	1			
	<.0001				
SMB	0.00077	0.2308	1		
	0.9328	<.0001			
HML	0.0242	-0.13883	-0.26201		
	0.0083	<.0001	<.0001	1	
UMD	-0.02121	-0.28929	0.08783	-0.20899	1
	0.0206	<.0001	<.0001	<.0001	

Table 2: Explanatory power of Fama-French factors in explaining the HDL factors

This table shows the estimated coefficients of Fama-French factors on HDL using Equation (3) controlling for time fixed effect. Here the dependent variable is HDL. HDL is made using TNIC and monthly returns. All other factors are formed based on monthly return data. The numbers inside parentheses are the t-statistics. t-statistics are calculated using heteroskedasticity-consistent standard errors.

$$HDL_t = \alpha + \beta_1 \mathrm{Mktrf}_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 \mathrm{UMD}_t + \varepsilon_t \quad (3)$$

	(HDL)
Intercept	0.00193
	(1.2)
MKTRF	0.18411***
	(3.97)
SMB	-0.01532
	(0.22)
HML	0.02003
	(0.28)
UMD	0.03856
	(0.73)
Observations	11660
Adj-R^2	0.30%

* Significance level of 10%
** significance level of 10%
*** significance level of 1%

Table 3: Mean-Variance-Spanning test; 1000 Monte-Carlo procedure and final test results

The critical values for 90% and 99% confidence level are reported in Panel A. Critical values are the results of 1000 Monte-Carlo procedure. Panel B shows the number of significant industry and their average test stat.

Panel A: 1000 Monte-Carlo Critical value results

χ^2 critical value	Mean
90%	4.65
99%	9.25

Panel B: Test statistics results

Test results	Number of significant Industries	Average of χ^2 statistics for significant industries
90%	41	51.29
99%	37	56.07

Table 4: Risk model estimation results: TNIC industry classifications.

This table shows the results of estimating Equation (2) using monthly return:

$$r_{i,t} = \alpha_t + \beta_1 HDL_{ind,t} + \beta_2 (mkt - rf)_t + \beta_3 (smb)_t + \beta_4 (hml)_t + \mathrm{A} + \varepsilon_{i,t} \quad (2)$$

The dependent variable here is the value-weighted stock return. The variable of interest is HDL. The numbers inside parentheses are the *t*-statistics, which are calculated using heteroskedasticity-consistent standard errors.

	(1) Before the Recession (t < December 2007)	(2) After the Recession (t > June 2009)	(3) Before the Recession (t < December 2007)	(4) After the Recession (t > June 2009)	(5) Full Sample
Alpha	0.00286***	0.00133**	0.00367***	0.00339***	0.00248***
	(5.57)	(2.29)	(7.12)	(4.27)	(3.27)
MKTRF	1.00429***	1.03469***	0.95615***	0.98334***	1.00376***
	(85.64)	(61.67)	(76.96)	(48.8)	(73.25)
SMB	0.15587***	0.20476***	0.17577***	0.21219***	0.20719***
	(9.99)	(8.05)	(11.23)	(10.24)	(9.53)
HML	0.28652***	-0.00208**	0.24148***	0.39387***	0.24015***
	(17.42)	(-2.39)	(14.33)	(14.38)	(13.97)
UMD			-0.11918***	-0.12809***	-0.124526***
			(-11.57)	(-8.81)	(-9.57)
HDL	0.15655***	0.14084***	0.14569***	0.13308***	0.14065
	(11.36)	(17.67)	(19.39)	(14.52)	(16.93)
Observations	11913	5714	11913	5714	17,627
Adj-R^2	41.13%	52.42%	41.58%	37.43%	39.92%

* significance level of 10%
** significance level of 10%
*** significance level of 1%

Table 5: Risk model estimation results: Fama and French 48-industry classifications.

This table shows the results of estimating Equation (2), introducing the HDL factor. The dependent variable here is the value-weighted return. HDL factor is calculated based on Fama and French 48 industry classification using monthly return data. The numbers inside parentheses are the *t*-statistics, which are calculated using heteroskedasticity-consistent standard errors.

$$r_{i,t} = \alpha_t + \beta_1 HDL_{ind,t} + \beta_2(mkt - rf)_t + \beta_3(smb)_t + \beta_4(hml)_t + \mathrm{A} + \varepsilon_{i,t} \tag{2}$$

	(1) Before the Recession (t < December 2007)	(2) After the Recession (t > June 2009)	(3) Before the Recession (t < December 2007)	(4) After the Recession (t > June 2009)	(5) Full Sample
Alpha	0.06589***	0.00018	0.02367***	0.00339***	0.0023283***
	(3.19)	(1.19)	(7.84)	(3.59)	(3.96)
MKTRF	1.09233***	1.01897***	0.83214***	0.67201***	0.903863***
	(63.64)	(59.67)	(43.19)	(50.29)	(54.20)
SMB	0.14863***	0.19028***	0.17577***	0.28204***	0.19918***
	(7.15)	(9.13)	(11.23)	(10.39)	(9.47)
HML	0.37884***	-0.00392	0.24148***	0.40108***	0.25437***
	(14.40)	(-0.16)	(14.33)	(15.20)	(14.64)
UMD			-0.09927***	-0.13460***	-0.116935***
			(-4.76)	(-7.09)	(-5.93)
HDL	0.15324***	0.12965***	0.10237***	0.18102***	0.14157
	(9.19)	(18.27)	(18.30)	(15.20)	(15.24)
Observations	11913	5714	11913	5714	17,627
Adj-R^2	38.19%	53.22%	35.19%	39.14%	41.43%

*significance level of 10%
** significance level of 10%
*** significance level of 1%

CHAPTER 3

Mutual Fund Volatility Decomposition and Manager Skill

Abstract

We construct a volatility decomposition to identify the source of difference in the performance of low and high volatility mutual funds. We find that the source of this difference in performance is associated with the degree to which the returns of the various pairs of constituent stocks covary with one another and that this difference is not explained by stock-level volatility or the *vol* anomaly. Moreover, we find that this phenomenon is fund-specific and is related to, but not explained by, the beta anomaly.

Keywords: mutual funds; volatility; manager skill; anomaly; market efficiency.

JEL codes: G11, G12, G14, G20.

I. Introduction

Jordan and Riley (2015, hereafter JR; p. 289) find that "mutual fund return volatility is a reliable, persistent, and powerful predictor of future abnormal returns." JR connect their results on portfolio-level return volatility to underlying stock volatility by showing that "abnormal returns are eliminated by the addition of a '*vol*' anomaly factor contrasting returns on portfolios of low and high volatility stocks." JR also state that "failure to account for the *vol* anomaly, either directly or indirectly, can lead to substantial mismeasurement of fund manager skill."

While JR examine how a portfolio's volatility is associated with the portfolio's performance, they do not explore the underlying sources of portfolio return volatility. We incorporate the fact that mutual funds' return volatility can be decomposed into terms arising from the constituent securities' volatilities and the covariances between the returns of the constituents (Copeland et al., 2005; Marshal, 2015). The first component, which we designate as ν, represents the volatility of a security in a portfolio. This component is commonly expressed as the diagonal terms in a variance-covariance matrix (Copeland, Weston, and Shastri, 1983; Campbell, Lo, and MacKinlay, 2012). The second component, which we designate as ψ, stems from the constituent holdings' covariances with each other. These are the off-diagonal elements of the variance-covariance matrix. Our goal is to better understand JR's portfolio-level return volatility effect by identifying the underlying variance and covariance components of security-level returns that drive the portfolio effect.

Classical theories, starting with Markowitz (1952, 1959), recognize that total risk, measured by the variance of portfolio returns, can be decomposed into ν (i.e., security-level variance) and ψ (i.e., security-level covariances). Studies following Markowitz acknowledge that the ν component of portfolio returns converges to zero as the degree of diversification increases. For this reason, in the literature, this component of a portfolio's risk is referred to as diversifiable risk or unsystematic risk. The ψ component is not eliminated through diversification and is referred to as nondiversifiable risk or systematic risk. Following the development of the capital asset pricing model (CAPM), a security's systematic risk is commonly measured by the time series regression coefficient estimate of a security's returns on a measure of market returns (Sharpe, 1964; Lintner, 1965). This coefficient estimate is referred to as beta (β).

Although β and ψ both are measures of systematic risk in the literature [β in the CAPM and ψ in the original Markowitz (1952) setting], they differ in construction and, especially, in how they account for a security's variance. β is defined as the covariance of individual security with the market return, scaled by the market variance (Copeland, Weston, and Shastri, 1983). ψ is the weighted average of covariances of portfolio constituent securities' returns with other constituent securities and not with the market return (Marshal, 2015). Marshal (2015) finds that beta, while highly correlated with the ψ measure of systematic risk, is not perfectly correlated and, in general, tends to overestimate risk. Moreover, Jones (2001) uses digital signal processing to demonstrate that portfolio risk can be decomposed into other non-beta systematic and unsystematic components. Jones expresses the systematic part as the cosine component of the random phase of returns and the unsystematic part as the sine.

To illustrate the distinction between β and ψ, assume two extreme cases: a portfolio with one stock and the market portfolio. The portfolio with one stock has a ψ component of variance equal to one, and its β depends on the market return. The market portfolio has a β of one, and its ψ component is not trivial to be calculated and is equal to the total market variance less the value-weighted average of the market constituents' stocks variances. Marshal (2015) explains this distinction further by showing that a stock's beta is not a measure of the stock's systematic risk in any sense but, instead, is a measure of the stock's systematic risk relative to the systematic risk of the market. In our analyses, we confirm the empirical distinction between ψ and β by double-sorting on ψ and β. Intuitively, β is constructed relative to the market with implications for security-level asset pricing, and ψ is constructed relative only to other stocks in a portfolio and chiefly with implications for portfolio management and performance.

JR make a convincing case that their portfolio volatility effect is driven by systematic risk. JR demonstrate that idiosyncratic volatility, as derived from a multi-factor model (Fama and French, 1993), is not causing the inverse association between portfolio past return volatility and future portfolio returns. This suggests that an examination of security-level return volatility generation is essential to understanding portfolio performance, as well as measures of portfolio manager skill. This paper decomposes portfolio risk, proxied by portfolio return variance, into two underlying security-level components and tests how each component is associated with portfolio performance to explain JR's findings.

Liu et al. (2018) study the idiosyncratic volatility (*IVOL*)–return relationship in the context of the beta anomaly. They conclude that the beta anomaly, negative (positive) alphas on stocks with a high (low) beta, arises from beta's positive correlation with *IVOL*. To test whether the JR results are the product of the beta anomaly, we check the beta and beta anomaly for high (low) total and idiosyncratic volatility using the volatility decomposition.

We conclude that JR's finding that "mutual fund return volatility is a reliable, persistent, and powerful predictor of future abnormal returns" (p. 289) is not due to constituent underlying stocks variances (component ν). Instead, portfolio returns are negatively associated with portfolio volatility that is due to the covariances between constituents' stocks in the portfolio (component ψ).

The Fama and French (1993) factor models do not explain this difference in the portfolio return, and the performance of high volatility portfolios (in particular, high ψ portfolios) is significantly lower than low volatility portfolios (in particular, low ψ portfolios). We find that the ψ volatility component is associated with the fund's idiosyncratic volatility and risk-loading factors, and the estimated coefficient is significant regardless of the risk factor model used to estimate the idiosyncratic volatility.

Moreover, the beta anomaly cannot explain the performance difference between the high and low ψ volatility components. We show that the correlation between beta (β) and idiosyncratic volatility (*IVOL*) that Liu et al. (2018) documented at the stock level is not noticeable in mutual funds at the portfolio level. Finally, we show that our results are robust by using the Fama and French five-factor model instead of the three-factor model.

II. Literature Review

This study relies on two strands of literature. The first strand uses the total portfolio volatility and its association with market volatility to study systematic and unsystematic risk (Markowitz 1952, 1959). The second strand focuses on the portfolio return–related components such as alpha, beta, and *IVOL* and their association with each other (Fama and MacBeth, 1973).

The first set of studies starts with Markowitz (1952, 1959), who shows that the total risk, as measured by the variance of return, can be decomposed into two components. Tobin (1958) extends Markowitz's work and shows that including the risk-free asset results in the linearization of the efficient frontier. More recently, Marshal (2015) decomposes the total volatility, measured by the standard deviation, into two new measures of systematic and unsystematic volatility.

In the context of portfolio volatility and mutual funds' volatility, JR study the relation between volatility and portfolio return performance in the US mutual fund industry. They introduce the *vol* anomaly and show that this anomaly can explain part of the volatility-return relationship at the portfolio level. Earlier studies by Novy-Marx (2014) and Fama and French (2014) argue that small, low profitability growth stocks cause the *vol* anomaly. Amihud (2002) and Ang et al. (2006, 2009) show that past volatility is a strong predictor of future cross-sectional stock returns. Baker et al. (2011) show a $58.98 difference between the value of a dollar invested in a portfolio of low volatility stocks and high volatility stocks from 1968 to 2008.

Frazzini and Pedersen (2013) find a *vol* anomaly in stocks, bonds, and other asset classes using many different countries' data. Han and Lesmond (2011) claim that the *vol* anomaly disappears after adjusting for microstructure effects, such as bid-ask bounce. Baker et al. (2011) argue that institutional investors, such as mutual funds, avoid taking advantage of the *vol* anomaly because investments in high alpha, low beta stocks are discouraged by their investment mandates. However, Chen et al. (2012) claim that the *vol* anomaly is robust to many of these investment barriers. Also, Fu (2009) finds the *vol* anomaly is strong only among very small stocks. Garcia-Feijoo, Li, and Sullivan (2012) show that trading on the *vol* anomaly requires frequent rebalancing among stocks with low liquidity.

Marshal (2015) revisits the roots of total volatility in the context of modern portfolio theory. He decomposes the standard deviation of portfolio returns into systematic and unsystematic components, but not the common beta and idiosyncratic risk measures (Goyal and Santa-Clara, 2003). Marshal empirically evaluates the effectiveness of these alternative measures of systematic and unsystematic risk and finds that beta often overestimates a portfolio's risk. Copeland et al. (2005) determine the mathematical derivation of the portfolio volatility decomposition and show how the unsystematic component of the volatility gets smaller as the level of diversification increases, but the covariance component is not affected by the degree of diversification.

Jones (2001) introduces digital portfolio theory by extending modern portfolio theory of Markowitz (1952) and decomposes portfolio variance into two independent components by using the signal processing. He calls the cosine part of the total variance phase the "systematic risk" and the sine part of the phase the "unsystematic risk." Moreover, Campbell et al. (2001) decompose the return at the stock level into three components: the market-wide return, the industry-specific residual, and the firm-specific residual. They report that, over the period of 1962 to 1997, firm-level volatility has significantly increased relative to market volatility. They also find that the market volatility tends to lead the other volatility components.

The second strand of literature considers the impact of idiosyncratic volatility (*IVOL*) on the expected return. This relationship has been studied empirically since almost the inception of classical asset pricing theory. Earlier studies, such as Fama and MacBeth (1973), find inconclusive evidence about the associations between the expected return and stock variance or idiosyncratic volatility. More recent empirical investigations on this topic document an idiosyncratic volatility puzzle, with a consistent and negative relation between idiosyncratic volatility and expected return (Goyal and Santa-Clara, 2003; Bali, Cakici, Yan, and Zhang, 2005; Fu, 2009; Ang, Hodrick, Xing, and Zhang, 2006, 2009). The negative association appears to be more robust to different specification concerns raised by more recent studies (Bali and Cakici, 2008; Chen et al., 2012).

Stambaugh et al. (2015), starting with the principle that idiosyncratic volatility represents a risk that deters arbitrage, find that the *IVOL*-return relation is negative among overpriced stocks and positive among underpriced stocks. They use mispricing as determined by combining 11 return anomalies documented by Stambaugh et al. (2012), constituting a comprehensive list of those that survived adjustment for the Fama and French (1993) three-factor model. Liu et al. (2018) study the *IVOL* in the context of the beta anomaly. They find that the beta anomaly (i.e., a negative alpha on high beta stocks and a positive alpha on low beta stocks) is due to the positive correlation between *IVOL* and beta. Also, according to Stambaugh et al. (2015), *IVOL* and alpha have a positive relationship among underpriced stocks but a negative relationship among overpriced stocks. In other words, they explain the beta anomaly by tying the *IVOL* puzzle to variation in beta and alpha.

III. Empirical Measures: Volatility Decomposition, *IVOL*, and Beta

To understand the source of JR's findings, we use Markowitz's volatility decomposition. Portfolio return volatility can be calculated based on the constituent holding return volatility, i.e., the variance of stocks' return (σ_i^2) and the covariance between the return of constituent stocks (σ_{ij}) (Copeland et al., 2005; Marshal, 2015; Campbell, Lo, and MacKinlay, 2012). Equation (1) shows how the portfolio volatility is connected to the holdings' volatility:

$$\sigma_p^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} \omega_i \omega_j \sigma_{ij}, \tag{1}$$

where σ_p^2 represents the volatility of portfolio returns, $\sigma_{i,j}$ represents the covariance between returns of assets i and j, and ω_i is the weight of asset i in the portfolio.

Because the standard deviation of a portfolio of stocks has two distinct components, we can decompose the right-hand side of Equation (1) into two volatility components:

$$\sum_{i=1}^{N}\sum_{j=1}^{N}\omega_i\omega_j\sigma_{i,j} = \sum_{i=1}^{N}\omega_i^2\,\sigma_i^2 + \sum_{i=1}^{N}\sum_{\substack{j=1\\ i\neq j}}^{N}\omega_i\omega_j\sigma_{i,j}. \tag{2}$$

The first component of Equation (2) is the weighted average of the constituent holdings' volatilities. We designate the first term of Equation (2) as ν and the second term as ψ. Component ν represents the diversifiable portion of the portfolio's variance and can be decreased by increasing the number of holdings (Markowitz, 1952 and 1959). The second component, ψ, is the weighted average of constituent holdings' covariances and represents the nondiversifiable component of a portfolio's variance (Copeland et al., 2005; Marshal, 2015). Increasing the number of holdings does not directly affect this component. However, a fund manager can manage both components by choosing constituent holdings and weights (Copeland et al., 2005).

By mapping each mutual fund to its constituent holdings, we empirically calculate the two components of Equation (2) from the Center for Research in Security Prices (CRSP) mutual fund daily database. The first component of Equation (2) is computed as the monthly weighted constituent holding variance using the daily holding return:

$$\nu_{k,t} = \sum_{i=1}^{N}\omega_{i,t}^2\,\sigma_{i,t}^2, \tag{3a}$$

where $\nu_{k,t}$ is the first volatility component of fund k for month t and $\sigma_{i,t}^2$ is the variance of fund k's constituent security i during month t. We use daily returns to compute monthly variances and covariances. We drop the k and t subscripts when they are unnecessary.

The second component of Equation (2) for fund k at month t, $\psi_{k,t}$, is computed by subtracting the first volatility component from the total portfolio volatility, σ_p^2:

$$\sum_{i=1}^{N} \sum_{\substack{j=1 \\ i \neq j}}^{N} \omega_i \omega_j \sigma_{i,j} = \sum_{i=1}^{N} \sum_{j=1}^{N} \omega_i \omega_j \sigma_{i,j} - \sum_{i=1}^{N} \omega_i^2 \, \sigma_i^2, \tag{3b}$$

so

$$\psi_{k,t} = \sum_{i=1}^{N} \sum_{\substack{j=1 \\ i \neq j}}^{N} \omega_{i,t} \omega_{j,t} \sigma_{i,j,t} = \sigma_{k,t}^2 - \nu_{k,t}, \tag{3c}$$

where $\sigma_{k,t}^2$ is the total volatility, $\nu_{k,t}$ is the diversifiable component, and $\psi_{k,t}$ is the nondiversifiable component of the total volatility.

Which component better explains the relation between portfolio volatility and portfolio return? To answer this question, we replicate JR's study using the above decomposition. The role of the *vol* anomaly in JR can be revisited in light of this decomposition. JR's justification for using a portfolio of high-low volatility stocks to calculate the *vol* anomaly is that an association seems to exist between total volatility and return. However, we find that this difference between the performance of low and high volatility portfolios is not due to the stock-level volatility, ν, but to the pairwise covariances between the constituent holdings, ψ. For this reason, the *vol* anomaly is likely to be insufficient to explain fund managers' skill, α. Furthermore, a fund's covariance component, ψ, likely includes information about the fund manager's skill.

To test this, we estimate idiosyncratic volatility using multi-factor models. We then regress the volatility components, ψ and ν, on idiosyncratic volatility using Equations (4a) and (4b) to test whether idiosyncratic volatility can explain the volatility components:

$$\psi_{k,t} = IVOL_{k,t} + Controls_{k,t} + \varepsilon_{k,t} \tag{4a}$$

and

$$\nu_{k,t} = IVOL_{k,t} + Controls_{k,t} + \varepsilon_{k,t}, \tag{4b}$$

where $IVOL_{k,t}$ is the idiosyncratic standard deviation of daily returns of fund k during month *t* using Fama and French's three-, four-, and five-factor models and $Controls_{i,t}$ includes fund k's fixed effects, the Fama-French four-factor [Mkt (market), SMB (size, small minus big), HML (value, high minus low), and UMD (momentum, up minus down)] exposures estimated from daily returns during month *t*.

We also use double-sorting on ψ and beta to evaluation a connection to the beta anomaly and on idiosyncratic volatility and beta to test for the existence of a more direct association between beta and idiosyncratic volatility. To test whether the stock-level volatility explains the difference in the performance of portfolios formed on volatility components, we reproduce the daily LVH (low volatility versus high volatility) factor of JR and include it alongside the other risk factors. Finally, we add profitability (RMW, robust minus weak) and investment (CMA, conservative minus aggressive) factors to our analysis to test whether they explain the difference between portfolio performances. Our four primary research questions are:

RQ1. Which volatility component (ν or ψ) is causing JR's findings?

RQ2. How are ν and ψ associated with traditional measures of idiosyncratic risk?

RQ3. How are ν and ψ associated with measures (i.e., alphas) of fund manager skill?

RQ4. How are ν and ψ associated with beta and the beta anomaly?

IV. Data and Methods

We use the CRSP mutual fund database from 2006 to 2019 to obtain daily portfolio returns, mutual fund holdings, and other fund characteristics. CRSP began providing reliable mutual funds holdings data in 2006. We use the CRSP stock price database to retrieve the daily return of constituent stock holdings from which we calculate the monthly volatilities of daily returns. We drop funds that CRSP identifies as index funds, exchange-traded funds, or variable annuities and that have a fixed income Lipper asset code. We require that a fund have at least 80% of its assets invested in equity during the current and previous year. We also combine share classes of a single fund using the CRSP portfolio identifier (crsp_portno). The assets of the combined fund are the sum of the assets held across all share classes, and we weigh all other fund attributes (including return) by the lagged assets held in each class.

To investigate RQ1, following JR, we sort mutual funds every month based on total volatility (σ_p^2), unsystematic volatility (ν_k), and systematic covariance volatility (ψ_k) in decile portfolios from January 2006 to December 2019. The volatility and its components are computed monthly using daily returns. We then take the average return of each portfolio to compare the portfolio's return.

To answer RQ2, we compute the traditional measure of idiosyncratic variance using the three-, four-, and five-factor models. We then associate $IVOL$ with our measures of portfolio risk components, ψ and ν, through portfolio sorts and the estimation of Equations (4a) and (4b). We expect that ψ is positively but imperfectly associated with $IVOL$.

To explore RQ4, following JR, Berk and Binsbergen (2015), Fama and French (2015), Stambaugh et al. (2015), Liu et al. (2018), and other similar studies, we use the portfolio-sorting method and estimate the alpha of the risk factor model in the portfolios sorted by covariance risk (ψ). Suppose that the performance of the low and high covariance volatility portfolios could be captured by the risk factors and that it is not idiosyncratic to the fund, i.e., the manager skill. In that case, no significant difference should exist between portfolios in the extreme ends (low covariance volatility versus high covariance volatility). JR find that the *vol* anomaly could eliminate part of the unexplained difference between alphas of decile portfolios. JR make the *vol* anomaly similar to factors that account for the size (SMB), value (HML), and momentum (UMD) effects but slightly different. The *vol* factor is equal to the return on the decile portfolio of low volatility stocks minus the return on the decile portfolio of high volatility stocks. They find that controlling for *vol* makes the difference between alphas of portfolios of low and high volatility funds statistically and economically indistinguishable from zero.

Our results show that, unlike JR's conjecture, the source of differences in the mutual fund's return sorted based on the total volatility is not the stock-level volatility but the covariance volatility (systematic) component. Hence, the *vol* factor (anomaly) has no theoretical foundation to make the difference between alphas of low and high volatility funds insignificant. To test this empirically, we build the *vol* factor using JR's method. If the *vol* anomaly could explain the difference between alphas of low and high covariance volatility funds, this difference could not be attributed to the fund manager's skill. Otherwise, this difference in the performance of low and high volatility portfolios of funds is fund-specific and could be due to the manager's skill in choosing the right combination of stocks that places their portfolios in the low decile covariance volatility.

Regarding idiosyncratic volatility and alpha, another factor comes into the picture: the beta anomaly. Empirical studies show a negative association between beta and alpha. Recent studies, including Asness et al. (2020), Liu et al. (2018), Baker et al. (2018), and Frazzini (2014), investigate the relation between beta, alpha, and *IVOL*. All these studies use stock-level data. According to one of the CAPM propositions, the beta of a portfolio of stocks is the weighted average of the portfolio constituent securities (Copeland et al., 2005). Therefore, beta anomaly findings at the stock level should be applicable to the portfolio level. For this reason, we study the beta characteristics of the decile portfolios in each sorting. Accepting Liu et al. (2018) findings, we expect that high *IVOL* portfolios have high betas and low alphas on average.

V. Results

We primarily examine differences in alphas from the Fama and French four-factor model on portfolios formed by sorting on one of the portfolio volatility measures. Because our portfolio risk measures are derived from models with differing assumptions, we adopt the sorting method widely used in the literature to avoid specifying restrictive parametric relations. The logic of portfolio sorting is similar to that of the random forest technique, a nonparametric analysis, which has been shown to generate robust results (Gu, Kelley, and Xiu, 2021; Bryzgalova et al., 2020; Moritz and Timmerman, 2016).

Table 1 reports the summary statistics of decile portfolios. It shows the average return, as well as other performance measures for decile portfolios sorted based on σ^2, ψ, and ν. We do not report t-statistics for the differences because each is highly statistically significant. Arithmetic average return, geometric average return, and variances are reported as annualized measures, computed from monthly returns. Because a mutual fund cannot be sold short, an investor could not have directly captured the difference in the performance, similar to the analysis of JR. Hence, the difference between the statistics of low and high volatility portfolios represents the opportunity cost of investing in high volatility funds instead of low volatility funds (JR).

>>>Insert Table 1 near here<<<

Consistent with JR's findings, Table 1 shows that the low volatility portfolio has better performance than the high volatility portfolio regardless of the evaluation method. Decomposition of the total risk (volatility) into two components and forming portfolios based on those components shows that the covariance risk component, ψ, is associated with differences in the performance of sorted portfolios. Portfolios formed on the variance of constituent holdings (stock-level variance component), ν, do not follow the same pattern as the portfolios formed on the total volatility or ψ, so we can conclude that ν does not explain the differences between the performance of portfolios of the low and high volatility of return.

Table 2 shows the Pearson correlations of the monthly returns across the portfolios. For the component ν, the correlation between the sorted portfolios does not change going from low to high portfolios. Consistent with JR's findings, the correlation between portfolio returns decreases as the total volatility changes between the portfolios. We find that the covariance component, ψ , does a better job in explaining this pattern once the portfolios are formed based on this component.

We have not reported the significance of the correlation coefficients in this table because all the stated coefficients are highly significant.

>>>Insert Table 2 near here<<<

We form portfolios based on their monthly volatility using daily return observations. In Table 3, we extend the decile sorting by basing it on the volatility components, ψ and ν. The last row of the table shows the difference between low and high volatility components portfolios.

>>>Insert Table 3 near here<<<

The first column of Table 3 confirms the JR findings that an inverse association exists between fund volatility and return. In this column, the mutual funds are sorted based on their total volatility. The pattern in the average return is clear: As the volatility goes up, the average return goes down. The decomposition of variance in columns 2 and 3 helps to find the source of this pattern in the returns that JR documented. As column 2 shows, the portfolio returns consistently increase as the total volatility decreases. This pattern in the portfolio deciles sorted based on the ψ component is consistent with the return pattern in the decile portfolio sorted based on the total volatility that is documented by JR.

Column 3 of Table 3 shows that sorting based on the ν component of volatility does not follow the same pattern in the average return resulting from the total volatility sorting. In other words, we can conclude that JR's finding that the total volatility has predictive power in mutual funds returns is driven by the covariance component of volatility, ψ, and not by the stock-level average volatility component, ν. For this reason, following JR and making the *vol* (LVH) anomaly using the stock-level information to control for the volatility anomaly can be misleading because the cause of predictive power of return volatility is not the volatility of constituent holdings but covariance volatility, ψ.

Moreover, to find the source of the differences in the average return of the portfolios, we estimate the Fama and French three-factor model plus momentum factor in each sorted portfolio of Table 3, Panel A. We use the Fama and MacBeth (1973) procedure each month to estimate the alpha in each sorted portfolio decile using daily mutual fund returns to compute volatilities. We then use the time series standard error of average slopes to calculate *t*-statistics using the Newey and West (1987) adjustment for standard errors. The Newey-West method makes the estimation robust by correcting for heteroskedasticity and autocorrelation.

Panel B of Table 3 reports the annualized alpha from the Fama and French four-factor model. As column 2 of this panel shows, as the covariance volatility, Ψ, increases, the alpha decreases. This finding confirms that the commonly known risk factors cannot explain the differences in decile portfolios formed on covariance volatility. Also, as column 3 of Panel B shows, no clear pattern emerges in the alpha of portfolios formed based on the ν component. For this reason, we can conclude that the difference in the return and alpha of decile portfolios formed by total volatility (σ^2) is due to the covariance risk (Ψ) and not the constituent stock volatility component (ν). We also find that the common risk factors cannot explain the differences in the portfolio returns.

Fig. 1 depicts the annualized average risk-adjusted excess return using the Fama and French four-factor model on portfolios formed on total variance in each year in our sample. For clarity, we present only the first (low volatility), fifth, and tenth (high volatility) deciles. Fig. 1 shows the alphas reported in three portfolios of Panel B of Table 3 in different years. The difference between the performance of low and high volatility portfolios is not consistent over time. In 2006, 2008, 2011, 2012, and 2013, performance of the high volatility portfolio is higher than the low volatility portfolio.

>>>Insert Fig. 1 near here<<<

Fig. 2 presents the annualized average risk-adjusted excess return from the Fama and French four-factor model on portfolios formed on the ψ component of total volatility in each year of the sample. The performance of portfolios formed on ψ is consistent over time. Only in 2008 and 2009 does the performance of low ψ portfolios not exceed the performance of low ψ portfolios, as the pattern in the performance of portfolios does not follow the pattern in Panel B of Table 3. Similar figures for the raw returns of the US and selected other countries are displayed in Appendix 2.

>>>Insert Fig. 2 near here<<<

Fig. 3 presents the annualized average risk-adjusted excess return using the Fama and French four-factor model on portfolios formed on the stock-level volatility component of the total volatility (ν). This figure confirms our findings in Panel B of Table 3. That is, no pattern in the performance of portfolios is formed on ν over time. Altogether, with the decomposition of volatility, we can conclude that portfolios formed on ψ and not the ν component of volatility can reveal the performance differences between the high and low volatility portfolios that JR document.

>>>Insert Fig. 3 near here<<<

To investigate the Table 3 results further and control for the market risk factors, following JR, we test whether the alphas of portfolios are following the same pattern as the raw returns. However, we apply the same variance decomposition as Table 3. We use the Fama and French four-factor model using mutual fund daily return to estimate the monthly alphas. We use the Fama and MacBeth (1973) procedure each month to estimate the risk model using daily mutual fund return. We then use the time series standard error of average slopes to calculate *t*-statistics with the Newey and West (1987) standard errors. Suppose the other risk factors cause the difference between the performance of low-high volatility portfolios and not the covariance component. In that case, no significant difference should arise between the alphas of low-high volatility portfolios.

Table 4 shows the Fama-French four-factor alpha and factor exposures for the low and high volatility and Ψ components of volatility portfolios. The difference in alpha between the portfolios sorted based on total volatility and covariance components amounts to about 5% per year. Funds with low volatility and low covariances likely hold larger, low beta, value stocks. Funds with high volatility and high covariances tend to hold smaller, high beta, growth stocks. These exposures do not explain the performance of the funds. As the last three columns of Table 4 show, sorting based on ν does not explain the difference between the performance of low and high volatility portfolios. This confirms that the stock-level return volatility is not the cause of the difference between low and high volatility portfolios.

>>>Insert Table 4 near here<<<

We use JR's estimation equation to test whether past volatility can predict future performance and, in particular, which component of the volatility indicates the performance:

$$Alpha_{k,t+1} = Alpha_{k,t} + Volatility\ Component_{k,t} + IVOL_{k,t} + Fund\ Controls_{k,t} + \varepsilon_{k,t}, \quad (5)$$

where $Alpha_{k,t}$ is the intercept (alpha) of fund k at month t estimated from the Fama and French three- and four-factor models, $Volatility\ Component_{k,t}$ is the volatility components ψ and ν of fund k at time t, $IVOL_{k,t}$ is idiosyncratic volatility of fund k at month t calculated as the standard deviation of the error term from the Fama and French four-factor model estimation, and $Fund\ Controls_{k,t}$ includes funds' fixed effect, the Fama-French four factors estimated from daily returns of fund k during month t.

We estimate Equation (5) by using the Fama and Macbeth (1973) regression procedure and the Newey and West (1987) method to correct for heteroskedasticity and autocorrelation of the error terms. Estimation results are presented in Table 5. All variables are standardized (demeaned and divided by their standard deviation), which controls for the distribution differences across time. The standardization process allows us to compare estimated coefficients with each other and interpret them as the change in the next month's alpha from a one standard deviation change in the variable in the current month. Similar results for unstandardized models are presented in Appendix Table A1.

>>>Insert Table 5 near here<<<

As column 4 of Table 5 shows, a one standard deviation increase in past month return volatility increases the current month fund performance by 25 standardized basis points, controlling for other factors. Our findings are consistent with that of JR. However, here we identify the source of this predictability. Total volatility is composed of ψ and ν. For the estimation results of model (1) and model (2), the ψ component is driving the results. As column 1 shows, a one standard deviation change in the current month's covariance volatility component (ψ) increases the next month's fund performance by 24 basis points per standard deviation. In other words, consistent with JR, we find that past volatility of fund return has an impact on the future fund performance, but only the ψ component of volatility is causing this impact.

In Table 5, column 1 estimates show that this model has the highest explanatory power. Its R^2 is 32.48%, and the estimated coefficient for ν is not significantly different from zero. The ν component of total volatility does not have a predictive power of the fund's future performance. The signs of estimated coefficients of Fama and French risk factors are consistent across the models. Due to the high correlation between σ^2 and its components Ψ and ν, and the high correlation between σ^2 and $IVOL$, we include only one of these variables in the model at a time.

Table 6 shows how the components of volatility, ψ and ν, are related to classical measures of idiosyncratic volatility. In models (1) to (5), we estimate Equation (4a), and the dependent variable is the ψ component or the covariance risk. In models (6) and (7), we estimate Equation (4b), and the dependent variable is the ν component of volatility. We use the Fama and MacBeth (1973) procedure to estimate Equations (4a) and (4b) and the Newey and West (1987) adjustment for standard errors. We use Fama and French three-, four-, and five-factor models to estimate the idiosyncratic volatility, which is the standard deviation of residuals from these models. As Table 6 shows, idiosyncratic volatility is highly correlated with the ψ component but not with the ν component of the total volatility. Also, for the R^2, idiosyncratic volatility has high explanatory power for variation in the ψ component but not the ν component. Similar results for unstandardized models are presented in Appendix Table A2.

>>>Insert Table 6 near here<<<

JR report a significant difference between betas of low and high variance portfolios. As they mentioned in the body of their research, this difference in the betas could not eliminate the differences in the alphas. They did not examine a phenomenon widely used in the literature called the beta anomaly. A negative correlation between beta and alpha has been documented starting as early as Fama and MacBeth (1973). Recent studies, including Stambaugh et al. (2015) and Liu et al. (2018), shed more light on this phenomenon. They involve mispricing as a factor that moderates this relationship and reverses it at some level of mispricing. Because the beta (as well as the alpha) for a portfolio of stocks is a linear combination of constituent stocks' betas, this relationship between beta and alpha can be extended to a portfolio of stocks. For this reason, we examine whether the beta anomaly drives our findings by forming portfolios formed based on beta and ψ.

Table 7 shows the annualized monthly return of portfolios formed based on beta and ψ. As in the third column of Table 3, Table 7 presents the return of portfolios formed on ψ. However, in Table 7, we control for the beta in each column by using the double-sorting technique. The last column of this table shows the difference between low and high portfolios formed on ψ. None of the low-high return portfolios generates a negative return. Because this table repeats Table 3 results by controlling for beta, we can confirm that the beta anomaly is not driving the results that we find about the difference between the performance of portfolios formed on ψ.

>>>Insert Table 7 near here<<<

To further investigate the source of the difference between the performance of low and high Ψ portfolios while controlling for the beta that we document in Table 7, we estimate the alpha from Fama and French four-factor model in each portfolio formed in the table. We use the Fama and MacBeth (1973) regression procedure to estimate alphas and the Newey and West (1987) adjustment. The results of regressions are reported in Table 8. If the beta anomaly is driving our findings, controlling for beta in portfolios formed on Ψ should eliminate the difference between portfolio performance of low and high Ψ volatility.

>>>Insert Table 8 near here<<<

The last column of Table 8 shows the difference between the low and high ψ volatility component controlling for portfolio beta. All the numbers in this column are positive, and most of them are statistically significant. For this reason, we can conclude that the differences in the betas of portfolios formed on the ψ volatility component documented in column 6 of Table 4 cannot explain the difference between the performance of low and high Ψ volatility portfolios.Liu et al. (2018) find that, at the stock level, the beta anomaly is affected by *IVOL*. For this reason, we double-sort funds on *IVOL* and beta each month to reveal the association of *IVOL* with the beta anomaly. For each month, we independently assign stocks to beta deciles and *IVOL* deciles and construct equally weighted portfolios in each intersection. Table 9 reports the alphas on each portfolio and the high-low alpha difference for a given variable within each level of the other variable. As the alphas reported in the last column of this table (lowest-highest) show, controlling for *IVOL* results in only the first *IVOL* decile portfolio having negative alpha on the low-high beta portfolio. However, even this negative alpha is insignificant for this portfolio. For the rest of the portfolios in the last column of Table 9, the beta anomaly is consistently persistent as illustrated by statistically significant positive differences between the alpha of low and high beta portfolios.

>>>Insert Table 9 near here<<<

To explore whether the *vol* anomaly can explain (or at least reduce) the difference between the performance of decile portfolios sorted on the volatility of return, JR constructed the *vol* anomaly based on the difference between the volatility of stocks traded in the US markets. Following JR, we construct the LVH factor as equal to the return on a value-weighted portfolio of the stocks in the lowest decile of the standard deviation of daily returns during the previous calendar month less the return on a value-weighted portfolio of stocks in the highest decile. We use only the US equities commonly held by mutual funds that trade on the NYSE, Nasdaq, or Amex (CRSP share codes 10 and 11 and CRSP exchange codes 1, 2, and 3). We also drop penny stocks, with prices below $5 at the end of the previous month, from the sample.

JR find that LVH explains the difference between the performance of low and high volatility portfolios. We form decile portfolios on covariance volatility, Ψ, and add LVH to the four-factor model. Table 10 reports the results of this estimation. As columns 5 and 6 show, LVH not only does not explain the difference in the performance of portfolios but also inflates the difference between average alphas of high and low covariance volatility portfolios. Unlike JR, we find that LVH cannot explain the difference between performances once the portfolios are formed based on the covariance volatility, Ψ.

>>>Insert Table 10 near here<<<

While LVH could not explain fund performance, the profitability (RMW) and investment (CMA) factors could provide an explanation for the results. In Table 11, we use the Fama-French five-factor model by including RMW and CMA in addition to the market, size, and value factors. As the last two right columns of Table 11 present, there is a positive loading on RMW and CMA for the low and high, indicating that the low volatility funds hold stocks in companies that are more profitable and invest more conservatively than companies whose stock is held by high volatility funds. The difference in loading on beta, SMB, and HML all decrease once we add the new factors.

>>>Insert Table 11 near here<<<

VI. Conclusion

Mutual funds with high (low) volatility have lower (higher) performance compared with low (high) volatility mutual funds. In the context of the Fama-French four-factor model, a portfolio of low volatility funds has an alpha of about 0.4% per year more than a portfolio of high volatility funds. Furthermore, after controlling for the fund's fixed effects and fund's risk loadings, we show that a 1% increase in fund volatility in a month decreases the fund's alpha in the same month by about 0.03%. We decompose the volatility into two components, the covariance volatility (ψ) and the constituent's stocks volatility (v), to find which component is causing the difference in the portfolio's return. Unlike JR, we find that the source of performance differences is not the volatility of the constituent stocks and that the *vol* anomaly cannot explain this difference once the mutual funds' portfolios are formed on the covariance volatility. After controlling for fund fixed effects and fund's risk loadings, we show that a 1% increase in the fund covariance volatility in a month decreases the fund's alpha in the same month by about 0.15%. The v component cannot explain the variation in the funds' return.

We explore the reason for this relation between fund covariance volatility and performance by controlling for the stock market volatility constructed as an anomaly (LVH) based on using JR's method. We also add the profitability (RMW) and investment (CMA) factors to the Fama and French three-factor model and find that the difference in portfolio performance persists.

We test whether the beta anomaly drives the difference between the performance of low and high volatility portfolios. We find that controlling for portfolio beta reduces the effect of volatility on performance, but the difference between the alpha of portfolios of low and high volatility remains significant. To address the inverse relation between alpha and beta at the stock level (Stambaugh et al., 2015; Liu et al., 2018), we also test for this relation at the fund level and do not find significant evidence of this phenomenon.

Overall, our results have three essential takeaways. First, JR's finding of the inverse relationship between fund's volatility and performance is due to the covariance component (ψ) of portfolio volatility. Second, the covariance component (ψ) has a significant relationship with idiosyncratic volatility. Third, although the factor loadings and, in particular, the beta of low and high volatility portfolios are significantly different from each other, the beta anomaly is not driving our results. We could not find any significant evidence of inverse relation between beta and idiosyncratic volatility at the fund level.

References

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. Journal of financial markets, 5(1), 31-56.

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.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2009). High idiosyncratic volatility and low returns: International and further US evidence. Journal of Financial Economics, 91(1), 1-23.

Asness, C., Frazzini, A., Gormsen, N. J., & Pedersen, L. H. (2020). Betting against correlation: Testing theories of the low-risk effect. Journal of Financial Economics, 135(3), 629-652.

Baker, M., Bradley, B., & Wurgler, J. (2011). Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly. Financial Analysts Journal, 67(1), 40-54.

Bali, T., Cakici, N., Yan, X., & Zhang, Z. (2005). Does Idiosyncratic Risk Really Matter? The Journal of Finance, 60(2), 905-929.

Bali, T. G., & Cakici, N. (2008). Idiosyncratic volatility and the cross section of expected returns. Journal of Financial and Quantitative Analysis, 43(1), 29-58.

Bryzgalova, S., Pelger, M., & Zhu, J. (2020). Forest through the trees: Building cross-sections of stock returns. Available at SSRN 3493458.

Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (2012). The econometrics of financial markets. princeton University press.

Carhart, M. M. (1997). On persistence in mutual fund performance. The Journal of finance, 52(1), 57-82.

Chen, L. H., Jiang, G. J., Xu, D., & Yao, T. (2012). Dissecting the idiosyncratic volatility anomaly. Available at SSRN 2023883.

Copeland, T. E., Weston, J. F., Shastri, K., & Education, P. (1983). Financial theory and corporate policy (Vol. 3). Massachusetts: Addison-Wesley.

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.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. The Journal of Political Economy, 607–636.

Fama, E. F., & French, K. R. (2016). Dissecting anomalies with a five-factor model. The Review of Financial Studies, 29(1), 69-103.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. Journal of financial economics, 116(1), 1-22.

Fama, E. F., & MacBeth, J. D. (2021). Risk, Return, and Equilibrium Empirical Tests. In The Fama Portfolio (pp. 315-348). University of Chicago Press.

Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. Journal of Financial Economics, 111(1), 1-25.

Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. Journal of financial Economics, 91(1), 24-37.

Li, X., Sullivan, R. N., & Garcia-Feijóo, L. (2014). The limits to arbitrage and the low-volatility anomaly. Financial Analysts Journal, 70(1), 52-63.

Giambona, E., & Golec, J. (2009). Mutual fund volatility timing and management fees. Journal of Banking & Finance, 33(4), 589-599.

Goyal, A., & Santa-Clara, P. (2003). Idiosyncratic risk matters!. The journal of finance, 58(3), 975-1007.

Gu, S., Kelly, B., & Xiu, D. (2021). Autoencoder asset pricing models. Journal of Econometrics, 222(1), 429-450.

Han, Y., & Lesmond, D. (2011). Liquidity biases and the pricing of cross-sectional idiosyncratic volatility. The Review of Financial Studies, 24(5), 1590-1629.

Jones, C. K. (2001). Digital portfolio theory. Computational Economics, 18(3), 287-316.

Jordan, B. D., & Riley, T. B. (2015). Volatility and mutual fund manager skill. Journal of Financial Economics, 118(2), 289-298.

Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. The journal of finance, 20(4), 587-615.

Lintner, J. (1969). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets: A reply. The review of economics and statistics, 222-224.

Markowitz, H. M. (1952) Portfolio selection, Journal of Finance, 7, 77–91.

Markowitz, H. M. (1959) Portfolio Selection: Efficient Diversification of Investments, John Wiley & Sons, New York, NY.

Marshall, C. M. (2015). Isolating the systematic and unsystematic components of a single stock's (or portfolio's) standard deviation. Applied Economics, 47(1), 1-11.

Moritz, B., & Zimmermann, T. (2016). Tree-based conditional portfolio sorts: The relation between past and future stock returns. Available at SSRN 2740751.

Newey, W. K., & West, K. D. (1986). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix (No. t0055). National Bureau of Economic Research. Novy-Marx, R., 2014. Understanding defensive equity. Unpublished working paper. University of Rochester, Rochester, NY.

Pontiff, J. (2006). Costly arbitrage and the myth of idiosyncratic risk. Journal of Accounting and Economics, 42(1-2), 35-52.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. The Journal of Finance, 19(3), 425–442.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. Journal of Financial Economics, 104(2), 288-302.

Tobin, J. (1958) Liquidity preference as behavior towards risk, The Review of Economic Studies, 25, 65–86.

Table 1: The returns on portfolios of mutual funds are sorted on return volatility components

The table shows the returns on five equally weighted portfolios of US equity mutual funds. The low volatility portfolio has the 10% of mutual funds in the sample with the lowest monthly standard deviation of daily returns. In contrast, the high volatility portfolio has the 10% of mutual funds in the sample with the highest monthly standard deviation of daily returns. We present only the first (low volatility), third, fifth, seventh, and tenth (high volatility) deciles to save space. Average and geometric returns are the annualized average of monthly simple and geometric returns for the portfolio. Sharpe ratio is the annualized average of the monthly returns less the risk-free rate divided by the annualized portfolio standard deviation. Treynor ratio is the annualized average of the monthly returns less the risk-free rate divided by the portfolio's beta.

Portfolio Returns							
Variance Component							
	Performance measure	Low	3	5	7	High	Low-High
	Average return	14.34%	14.00%	13.30%	12.80%	9.05%	5.29%
	Geometric return	14.43%	13.10%	12.30%	11.70%	6.73%	7.70%
σ^2	Variance	10.40%	13.90%	15.20%	16.80%	25.90%	-15.50%
	Sharpe ratio	0.48	0.36	0.25	0.18	0.09	0.39
	Treynor ratio	0.07	0.06	0.04	0.03	0.02	0.05
	Average return	14.47%	14.10%	13.50%	12.90%	8.87%	5.60%
	Geometric return	14.60%	13.20%	12.50%	11.70%	6.60%	8.00%
ψ	Variance	10.50%	14.00%	15.20%	16.80%	25.80%	-15.30%
	Sharpe ratio	0.49	0.36	0.24	0.19	0.08	0.41
	Treynor ratio	0.07	0.06	0.04	0.03	0.02	0.05
	Average return	12.40%	13.80%	13.40%	12.60%	11.10%	1.30%
	Geometric return	11.20%	12.40%	12.20%	11.60%	9.50%	1.70%
ν	Variance	15.70%	16.60%	16.40%	16.50%	20.10%	-4.40%
	Sharpe ratio	0.3	0.28	0.28	0.26	0.15	0.15
	Treynor ratio	0.04	0.04	0.04	0.04	0.03	0.01

Table 2: Portfolio return correlations

This table shows the Pearson correlation of the monthly returns across the portfolios. The low volatility portfolio has the 10% of mutual funds in the sample with the lowest monthly standard deviation of daily returns. Conversely, the high volatility portfolio has the 10% of mutual funds in the sample with the highest monthly standard deviation of daily returns. We present only the first (low volatility), third, fifth, seventh, and tenth (high volatility) deciles to save space. All the correlation coefficients reported are highly significant.

Component	Portfolio	Low	3	5	7	High
σ^2	Low	1				
	3	0.951	1			
	5	0.943	0.986	1		
	7	0.925	0.97	0.986	1	
	High	0.814	0.87	0.879	0.902	1
ψ	Low	1				
	3	0.952	1			
	5	0.937	0.988	1		
	7	0.919	0.97	0.986	1	
	High	0.799	0.866	0.87	0.894	1
ν	Low	1				
	3	0.988	1			
	5	0.989	0.989	1		
	7	0.971	0.973	0.979	1	
	High	0.947	0.941	0.946	0.966	1

Table 3: Average annualized portfolios' returns and alphas

Average annualized portfolios' returns, and annualized alphas sorted by the variance component in decile portfolios. Numbers in the table are reported as percentages, and numbers between parentheses are t-statistics. All the alphas and returns reported for each portfolio are significantly different from zero.

Panel A: Average portfolio return			
Portfolio	σ^2	ψ	ν
Low	14.34	14.47	12.34
2	13.88	14.11	13.10
3	13.30	13.85	13.73
4	13.88	13.44	13.25
5	13.21	13.10	13.34
6	12.80	12.92	12.70
7	12.60	12.34	12.64
8	12.18	12.01	12.59
9	11.63	11.74	12.24
High	9.05	8.87	11.01
Low-High	5.29***	5.60***	1.33***
	(3.63)	(3.66)	(2.19)
Panel B: Average portfolio alpha			
Portfolio	σ^2	ψ	ν
Low	0.13	0.13	-0.17
2	0.05	0.06	-0.12
3	0.00	0.00	0.01
4	-0.03	-0.03	-0.09
5	-0.05	-0.05	-0.07
6	-0.05	-0.06	-0.05
7	-0.07	-0.07	0.00
8	-0.07	-0.08	-0.01
9	-0.12	-0.11	-0.01
High	-0.26	-0.27	0.03
Low-High	0.39***	0.40***	-0.20***
	(5.46)	(5.53)	(-2.38)

* Significance level of 10%
** Significance level of 10%
*** Significance level of 1%

Table 4: Can the Fama-French four-factor model explain the performance sorted portfolios?

This table shows the Fama-French four-factor regression results for daily returns on portfolios of low and high volatility components of mutual funds from January 2006 through December 2019. Volatility portfolios are all monthly equally weighted portfolios of US mutual funds.
Numbers between parentheses are t-statistics.

	σ^2			ψ			ν		
	Low	High	Low - High	Low	High	Low - High	Low	High	Low - High
Factor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Beta	0.635***	1.139***	-0.504***	0.632***	1.137***	-0.505***	0.898***	1.035***	-0.137***
	(28.81)	(23.05)	(-6.90)	(21.62)	(22.33)	(-7.43)	(17.85)	(18.46)	(-2.75)
SMB	-0.033***	0.561***	-0.594***	-0.023*	0.578***	-0.601***	0.224***	0.358***	-0.134
	(-3.94)	(7.28)	(-5.87)	(1.88)	(5.39)	(-5.05)	(2.62)	(5.73)	(-1.44)
HML	0.004***	-0.050***	0.054***	-0.003***	-0.037***	0.034***	0.105***	-0.039***	0.144***
	(5.51)	(-4.43)	(2.90)	(-3.76)	(-2.93)	(4.45)	(3.60)	(-2.69)	(3.01)
UMD	-0.012	0.029	-0.040	-0.012	0.034	-0.045	0.007	-0.026	0.033
	(0.87)	(0.55)	(-0.24)	(0.21)	(0.16)	(-0.15)	(1.31)	(1.55)	(0.36)
Alpha	0.129%**	-0.265%**	0.393%***	0.126%**	-0.266%***	0.392%***	0.013%	-0.173%**	0.186%
	(2.24)	(-2.26)	(2.73)	(2.47)	(-3.37)	(3.51)	(1.52)	(2.08)	(1.61)
Observations	28,803	28,803		28,803	28,803		28,803	28,803	
Average R^2	84%	85%		83%	86%		94%	83%	

* Significance level of 10%
** Significance level of 10%
*** Significance level of 1%

Table 5: Can fund volatility predict future performance?

$$Alpha_{i,t+1} = Alpha_{i,t} + Volatility\ Component_{i,t} + IVOL_{i,t} + Fund\ Controls_{i,t} + \varepsilon_{i,t}$$

Here we use the Fama-Macbeth regression procedure to estimate the above equation. The dependent variable is the alpha for fund i in month t estimated using the Fama-French four-factor model using daily returns. For the $Volatility\ Component$ variable, we use σ^2, ψ, and ν in different estimation equations. σ^2 is the variance of returns during month t using daily observations. Psi is the covariance component (ψ), and Nu is the variance component (ν) of the σ^2. $IVOL$ is the idiosyncratic standard deviation of daily returns during month t. Fund controls include funds' fixed effect, the Fama-French four-factor Mkt (market), SMB (size), HML (value), and UMD (momentum) exposures estimated from daily returns during month t. All variables are standardized (demeaned and divided by their standard deviations).

Numbers between parentheses are t-statistics.

Characteristic	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.026***			0.026***	0.007***	0.027***
	(8.91)			(9.10)	(3.09)	(9.16)
σ^2		-0.049***		-0.0247***		
		(-2.61)		(-8.59)		
ψ	-0.0241***					-0.0222***
	(-8.35)					(-7.63)
ν	-0.002				-0.004	-0.002
	(-1.15)				(-1.23)	(-1.28)
IVOL			-0.004***			
			(-2.08)			
Mkt	0.032***	0.030***	0.031***	0.031***	0.031***	
	(3.78)	(3.65)	(3.70)	(3.75)	(3.56)	
SMB	0.091***	0.092***	0.092***	0.091***	0.090***	
	(12.41)	(12.67)	(22.64)	(22.45)	(22.43)	
HML	0.065***	0.071***	0.070***	0.066***	0.066***	
	(4.14)	(4.47)	(4.43)	(4.19)	(7.15)	
UMD	0.028***	0.031***	0.031***	0.028**	0.028**	
	(2.44)	(2.77)	(2.75)	(2.48)	(2.50)	
Observations	281,782	281,782	281,782	281,782	281,782	281,782
Average R^2	32.48%	28.70%	28.45%	31.65%	24.14%	17.44%

* Significance level of 10%
** Significance level of 10%
*** Significance level of 1%

Table 6: How are portfolio unsystematic and covariance risks associated with traditional measures of idiosyncratic risk?

$$\psi_{i,t} = IVOL_{i,t} + Controls_{i,t} + \varepsilon_{i,t}$$
$$\upsilon_{i,t} = IVOL_{i,t} + Controls_{i,t} + \varepsilon_{i,t}$$

Here we use the Fama-Macbeth regression procedure to estimate the above equations. The dependent variable in models (1) to (5) is the covariance component (ψ), and in models (6) and (7) is the stock level average volatility component (ν) of total return volatility for fund i in month t. $IVOL$s are the idiosyncratic standard deviation of daily returns during month t using Fama and French's three, four, and five-factor models. Fund controls include funds' fixed effect, the Fama-French four-factor Mkt (market), SMB (size), HML (value), and UMD (momentum) exposures estimated from daily returns during month *t*. All variables are standardized (demeaned and divided by their standard deviations).

Numbers between parentheses are t-statistics.

	Dependent Variable						
	ψ					ν	
Characteristic	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IVOL (3)	0.938***	0.891***			0.931***	0.114	0.012
	(23.02)	(18.25)			(21.19)	(1.24)	(0.73)
IVOL (4)			0.947***				
			(19.29)				
IVOL (5)				0.926***			
				(21.23)			
ν					-0.035		
					(-1.46)		
Risk Loading Controls	No	Yes	Yes	Yes	Yes	No	Yes
Observations	287,021	287,021	287,021	287,021	287,021	287,021	287,021
Average R^2	88%	89%	93%	94%	94%	1%	2%

* Significance level of 10%
** Significance level of 10%
*** Significance level of 1%

Table 7: The annualized return of decile portfolios formed by sorting on Beta and Ψ

The table reports the average annualized return for portfolios formed by sorting independently on monthly Betas and Ψ using daily observation of US mutual funds.
Numbers in the table are reported as percentages, and numbers between parentheses are t-statistics.

Beta decile	Ψ decile										Lowest-Highest
	Lowest	2	3	4	5	6	7	8	9	Highest	
Lowest	0.11	0.19	0.18	0.13	0.12	0.12	0.19	0.16	0.16	0.09	0.015 (1.40)
2	0.14	0.10	0.13	0.12	0.17	0.16	0.14	0.22	0.22	0.13	0.008 (0.54)
3	0.16	0.14	0.11	0.10	0.10	0.13	0.16	0.18	0.21	0.13	0.035** (2.01)
4	0.20	0.17	0.11	0.13	0.12	0.10	0.13	0.17	0.18	0.13	0.065*** (2.99)
5	0.20	0.18	0.15	0.14	0.11	0.11	0.10	0.15	0.18	0.14	0.068** (2.31)
6	0.23	0.20	0.19	0.13	0.13	0.12	0.10	0.10	0.14	0.16	0.065** (2.41)
7	0.20	0.23	0.19	0.17	0.15	0.13	0.11	0.09	0.13	0.12	0.072** (2.19)
8	0.14	0.24	0.20	0.19	0.16	0.16	0.11	0.10	0.10	0.12	0.020 (0.54)
9	0.15	0.24	0.25	0.22	0.19	0.17	0.17	0.10	0.07	0.07	0.081* (1.90)
Highest	0.14	0.12	0.23	0.27	0.24	0.19	0.20	0.16	0.10	0.06	0.081* (1.90)

* Significance level of 10%
** Significance level of 10%
*** Significance level of 1%

Table 8: Annualized Alpha of decile portfolios formed by sorting on Beta and Ψ

The table reports the average annualized alpha from the Fama and French four-factor model (mkt, smb, hml, and umd) for portfolios formed by sorting independently on monthly Betas and Ψ using daily observation of US mutual funds. Numbers in the table are reported as percentages, and numbers between parentheses are t-statistics.

Beta decile	Ψ decile										Lowest-Highest
	Lowest	2	3	4	5	6	7	8	9	Highest	
Lowest	0.20%	0.45%	0.27%	0.14%	0.23%	0.32%	0.34%	0.26%	0.23%	-0.03%	0.23%***
											(3.45)
2	0.07%	0.10%	0.14%	0.07%	0.13%	0.14%	0.09%	0.13%	0.09%	-0.16%	0.23%***
											(5.10)
3	0.00%	0.04%	0.05%	0.05%	0.02%	0.04%	0.04%	0.06%	0.04%	-0.22%	0.22%***
											(6.65)
4	-0.03%	0.00%	-0.02%	0.01%	0.01%	0.01%	0.02%	0.00%	0.01%	-0.16%	0.13%***
											(3.12)
5	-0.04%	-0.02%	-0.03%	-0.01%	-0.03%	-0.03%	0.00%	-0.02%	-0.04%	-0.05%	0.01%
											(0.10)
6	-0.02%	-0.04%	-0.05%	-0.09%	-0.06%	-0.05%	-0.03%	-0.04%	-0.06%	-0.12%	0.10%**
											(2.21)
7	-0.10%	-0.04%	-0.06%	-0.09%	-0.09%	-0.10%	-0.06%	-0.07%	-0.07%	-0.22%	0.12%**
											(2.35)
8	-0.03%	-0.05%	-0.08%	-0.11%	-0.13%	-0.14%	-0.14%	-0.12%	-0.09%	-0.20%	0.17%**
											(2.39)
9	-0.09%	-0.07%	-0.07%	-0.12%	-0.16%	-0.17%	-0.19%	-0.19%	-0.17%	-0.27%	0.18%*
											(1.75)
Highest	0.04%	-0.05%	-0.11%	-0.19%	-0.16%	-0.27%	-0.29%	-0.27%	-0.33%	-0.41%	0.45%***
											(2.65)

* Significance level of 10%
** Significance level of 10%
*** Significance level of 1%

Table 9: Annualized Alpha of decile portfolios formed by sorting on *IVOL* and Beta

The table reports the average annualized alpha from the Fama and French four-factor model (mkt, smb, hml, and umd) for portfolios formed by sorting independently on monthly *IVOL* and Beta using daily observation of US mutual funds.
Numbers in the table are reported as percentages, and numbers between parentheses are t-statistics.

IVOL decile	Beta decile										Lowest-Highest
	Lowest	2	3	4	5	6	7	8	9	Highest	
Lowest	0.047%	0.061%	0.012%	-0.001%	-0.025%	-0.053%	-0.073%	-0.092%	-0.120%	0.083%	-0.04% (-0.72)
2	0.033%	0.068%	0.027%	-0.002%	-0.027%	-0.064%	-0.086%	-0.088%	-0.147%	-0.096%	0.13%*** (3.11)
3	0.065%	0.086%	0.025%	0.002%	-0.011%	-0.068%	-0.081%	-0.112%	-0.148%	-0.214%	0.28%*** (11.89)
4	0.074%	0.065%	0.032%	0.005%	-0.033%	-0.067%	-0.078%	-0.137%	-0.168%	-0.238%	0.31%*** (4.09)
5	0.145%	0.090%	0.045%	-0.015%	-0.031%	-0.059%	-0.093%	-0.142%	-0.170%	-0.240%	0.39%*** (4.73)
6	0.149%	0.123%	0.038%	-0.002%	-0.026%	-0.045%	-0.099%	-0.142%	-0.170%	-0.227%	0.38%*** (5.94)
7	0.192%	0.120%	0.060%	-0.019%	-0.034%	-0.040%	-0.084%	-0.137%	-0.191%	-0.224%	0.42%*** (6.93)
8	0.190%	0.130%	0.066%	-0.002%	0.001%	-0.059%	-0.073%	-0.114%	-0.200%	-0.305%	0.50%*** (8.83)
9	0.302%	0.123%	0.053%	0.050%	0.011%	-0.036%	-0.100%	-0.099%	-0.162%	-0.335%	0.64%*** (14.44)
Highest	0.421%	0.074%	-0.018%	-0.067%	0.008%	-0.019%	-0.135%	-0.228%	-0.398%	-0.471%	0.89%*** (6.33)
Lowest-Highest	-0.374%*** (-5.60)	-0.013% (-0.29)	0.030% (0.82)	0.066%** (2.11)	-0.033% (-1.19)	-0.034% (-1.19)	0.062%** (2.05)	0.136%*** (2.65)	0.278%*** (5.48)	0.554%*** (2.98)	-0.928%*** (4.77)

* Significance level of 10%
** Significance level of 10%
*** Significance level of 1%

Table 10: Can the *vol* anomaly explain the performance of the mutual funds?

This table repeats the estimation results of Table 4 by adds a new factor to the Fama-French four-factor model specification. Following Jordan and Riley (2015), the LVH factor is equal to the monthly return on a value-weighted portfolio of all stocks in the lowest decile of the standard deviation of daily returns during the less the return on a value weighted portfolio of all stocks the highest decile.
Numbers between parentheses are t-statistics.

	Low ψ		High ψ		Low - High ψ	
Factor	(1)	(2)	(3)	(4)	(5)	(6)
Beta	0.6320***	0.6599***	1.1371***	1.1723***	-0.5051***	-0.5124***
	(21.62)	(24.28)	(22.33)	(23.92)	(-7.43)	(-7.71)
SMB	-0.0227*	0.0024***	0.5783***	0.3597***	-0.6010***	-0.3572***
	(1.88)	(2.62)	(5.39)	(3.20)	(-5.05)	(-5.15)
HML	-0.0030***	-0.0003***	-0.0373***	-0.4465***	0.0343***	0.4461***
	(-3.76)	(-2.72)	(-2.93)	(-3.36)	(4.45)	(3.69)
UMD	-0.0115	-0.0037	0.0337	0.7568	-0.0452	-0.7604***
	(0.21)	(0.52)	(0.16)	(0.20)	(-0.15)	(-2.14)
LVH		0.0181		0.0045		0.0136
		(1.13)		(0.21)		(1.00)
Alpha	0.126%**	0.16%***	-0.266%***	-0.97%***	0.392%***	1.128%***
	(2.47)	(3.72)	(-3.37)	(-4.26)	(3.51)	(4.35)
Observations	28,803	28,803	28,803	28,803	28,803	28,803
Average R^2	83%	85%	86%	88%		

* Significance level of 10%
** Significance level of 10%
*** Significance level of 1%

Table 11: Can profitability and investment factors, RMW and CMA, explain the performance of the mutual funds?

This table shows the Fama-French five-factor regression results for daily returns on portfolios of low and high volatility components of mutual funds from January 2006 through December 2019. The new factors added to the specification are the profitability (RMW) and investment (CMA) factors of Fama and French (2015).
Numbers between parentheses are t-statistics.

	Low		High		Low - High	
Factor	σ^2	ψ	σ^2	ψ	σ^2	ψ
Beta	0.66***	0.65***	1.08***	1.08***	-0.42***	-0.42***
	(20.60)	(22.61)	(19.78)	(21.77)	(-5.99)	(-6.17)
SMB	-0.02***	-0.01**	0.52***	0.54***	-0.54***	-0.55***
	(3.17)	(2.32)	(2.64)	(2.90)	(-4.37)***	(-4.57)
HML	-0.02**	-0.03*	-0.13***	-0.12*	0.11***	0.09***
	(2.57)	(1.87)	(3.18)	(1.76)	(3.46)	(3.18)
RMW	0.07***	0.07***	-0.26***	-0.24***	0.34**	0.31**
	(3.43)	(3.39)	(4.29)	3.91	(2.30)	(2.11)
CMA	0.12***	0.11***	-0.05**	-0.04***	0.17***	0.15***
	(4.11)	(4.15)	(2.23)	(3.11)	(6.13)	(5.46)
Alpha	0.09%***	0.10%***	-0.17%***	-0.18%***	0.26%***	0.27%***
	(3.18)	(3.64)	(-4.57)	(4.67)	(3.86)	(3.89)
Observations	28,803	28,803	28,803	28,803	28,803	28,803
Average R^2	83%	85%	86%	88%		

* Significance level of 10%
** Significance level of 10%
*** Significance level of 1%

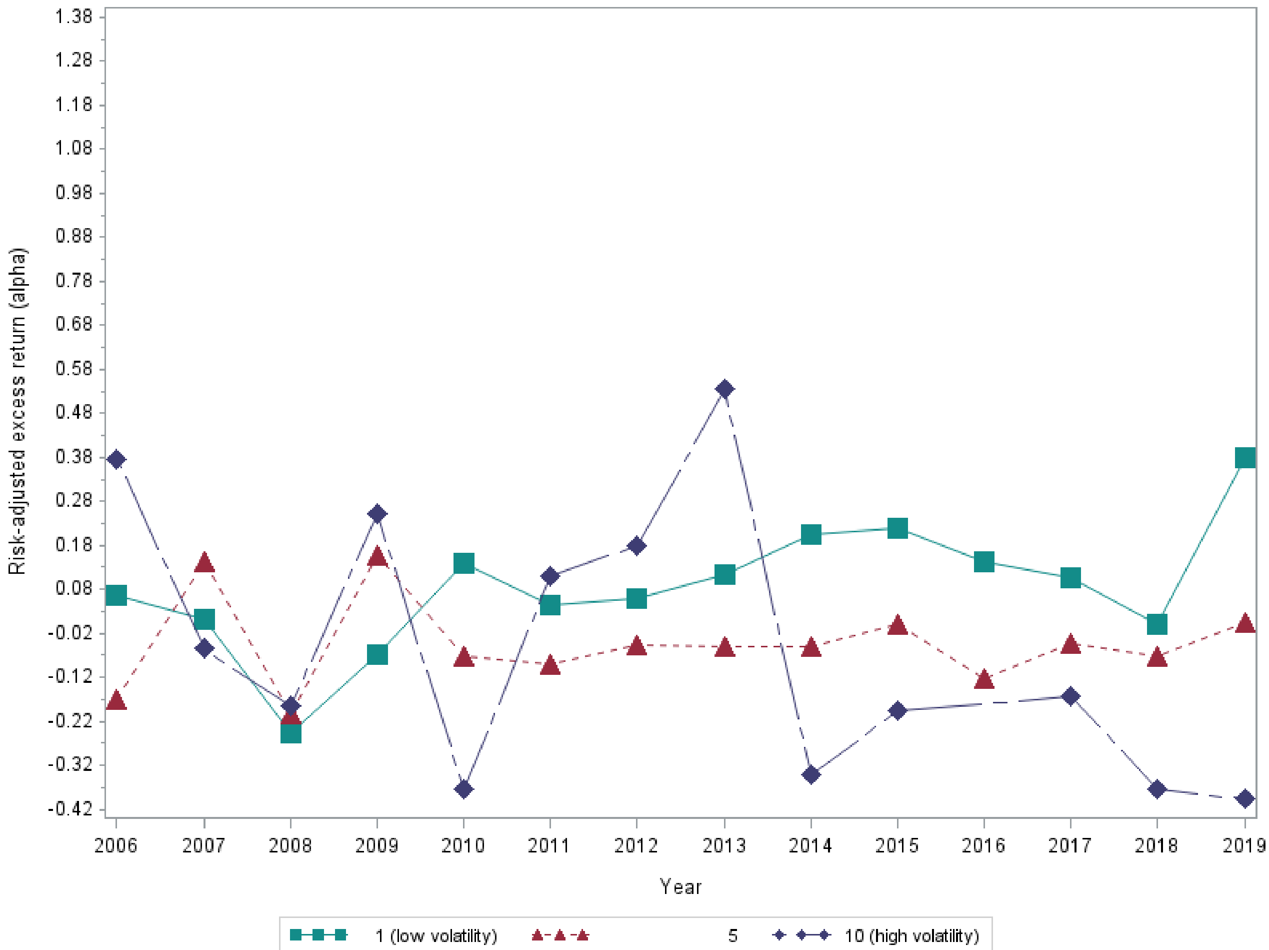

Fig. 1. The annualized average risk-adjusted excess return (alpha) on portfolios formed on variance (σ^2)

This figure shows the average alpha from Fama and French four-factor model from January 2006 through December 2019 in three equal weighted portfolios of active US equity mutual funds. The low volatility portfolio buys the 10% of mutual funds in the sample with the lowest monthly variance of daily returns. The high volatility portfolio buys the 10% of mutual funds in the sample with the highest monthly variance of daily returns.

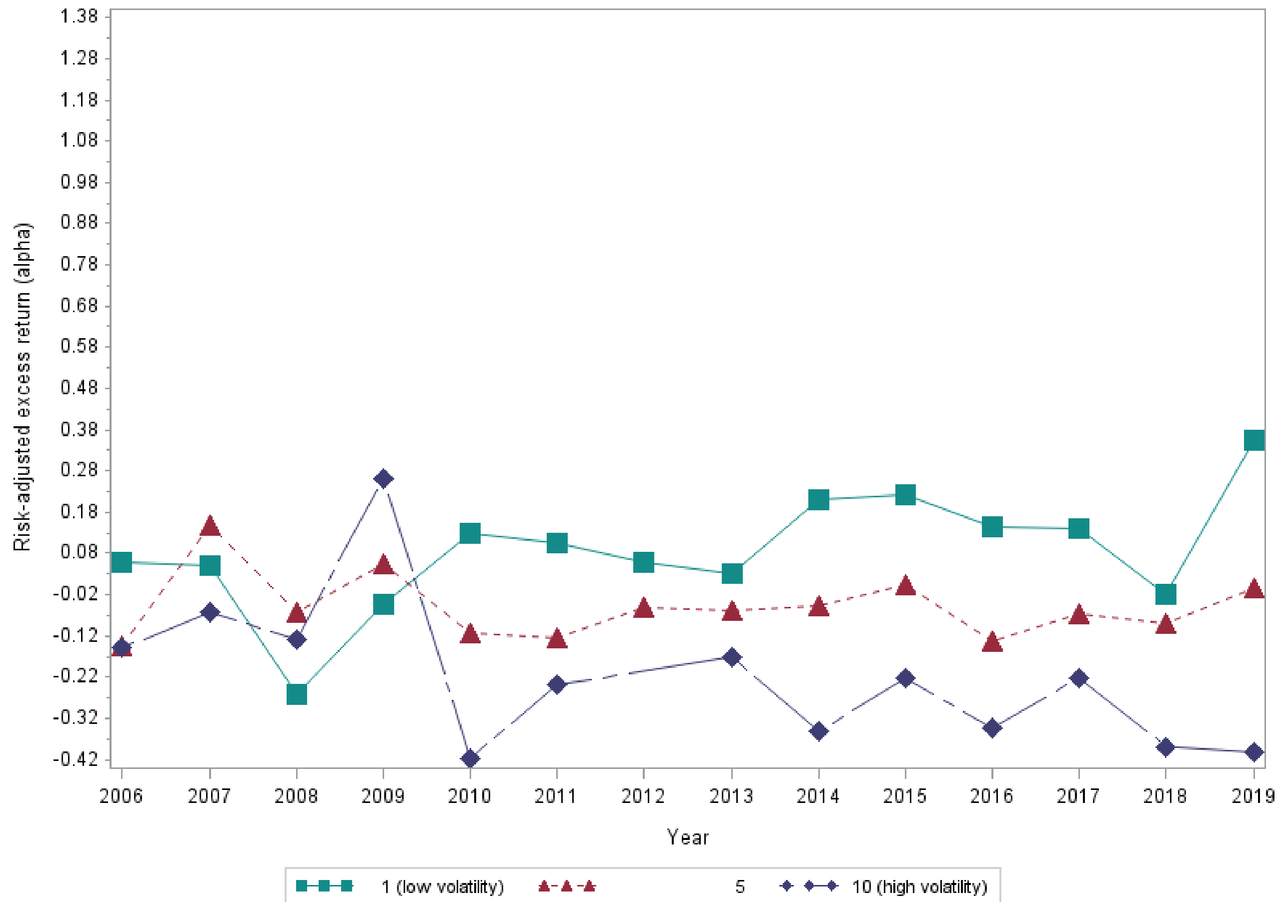

Fig. 2 The annualized average risk-adjusted excess return (alpha) on portfolios formed on the ψ component

This figure shows the average alpha from Fama and French four-factor model from January 2006 through December 2019 in three equal weighted portfolios of active US equity mutual funds. The low ψ portfolio buys the 10% of mutual funds in the sample with the lowest monthly covariance component of the total variance of daily returns. The high ψ portfolio buys the 10% of mutual funds in the sample with the highest monthly covariance component of the total variance daily returns.

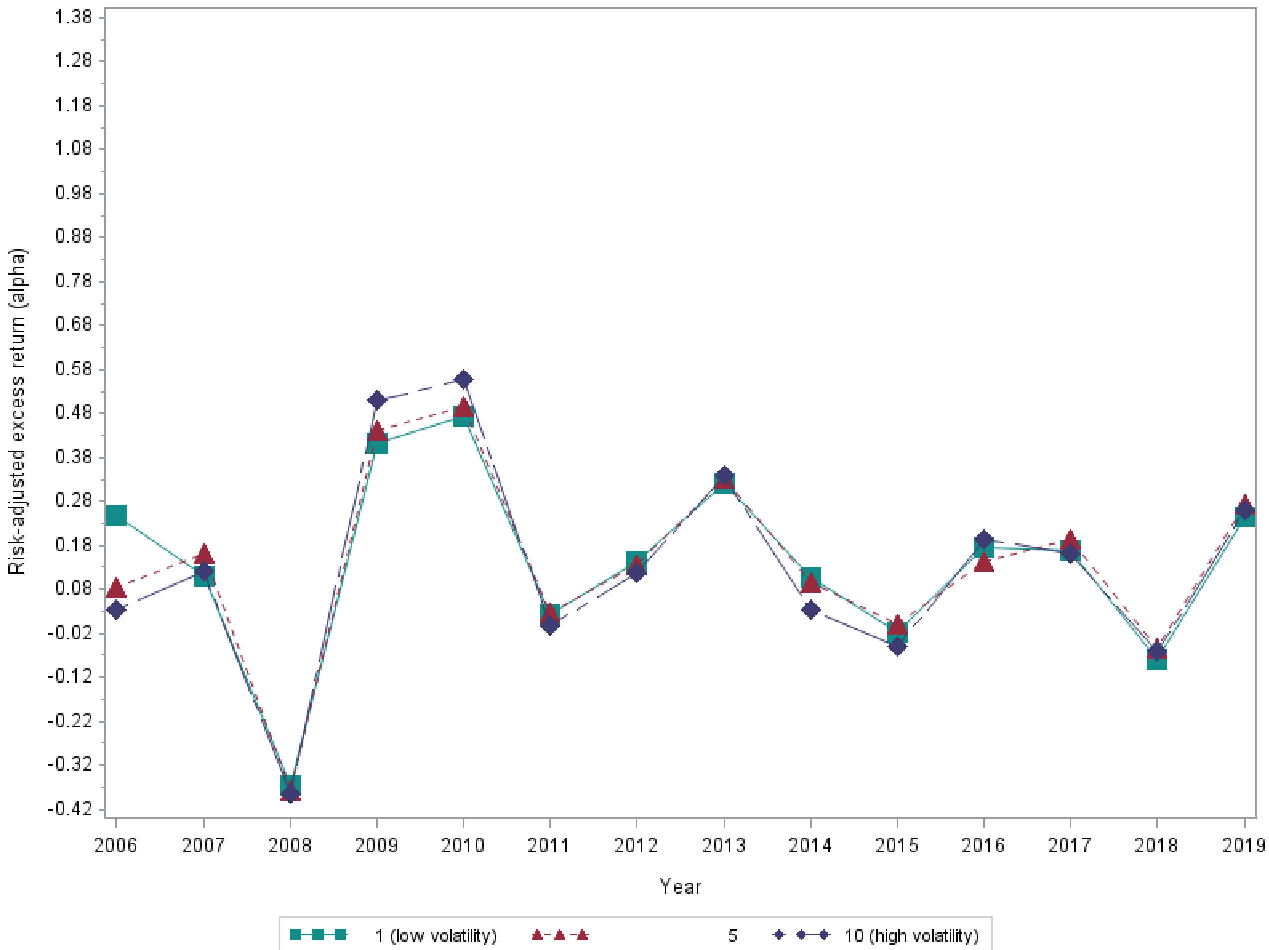

Fig. 3 The annualized average risk-adjusted excess return (alpha) on portfolios formed on the ν component

This figure shows the average alpha from Fama and French four-factor model from January 2006 through December 2019 in three equal weighted portfolios of active US equity mutual funds. The low ν portfolio buys the 10% of mutual funds in the sample with the lowest monthly stock-level variance component of the total variance of daily returns. The high ν portfolio buys the 10% of mutual funds in the sample with the highest monthly stock-level variance component of the total variance daily returns.

Appendix 1

Table A- 1: Can fund volatility predict future performance?

$$Alpha_{i,t+1} = Alpha_{i,t} + Volatility\ Component_{i,t} + IVOL_{i,t} + Fund\ Controls_{i,t} + \varepsilon_{i,t}$$

Here we use the Fama-Macbeth regression procedure to estimate the above Equation. The dependent variable is the alpha for fund i in month t estimated using the Fama-French four-factor model using daily returns. For the $Volatility\ Component$ variable, we use σ^2, ψ, and ν in different estimation equations. σ^2 is the variance of returns during month t using daily observations. Psi is the covariance component (ψ) and Nu is the variance component (ν) of the σ^2. $IVOL$ is the idiosyncratic standard deviation of daily returns during month t. Fund controls include funds' fixed effect, the Fama-French four-factor Mkt (market), SMB (size), HML (value), and UMD (momentum) exposures estimated from daily returns during month t.

Numbers between parentheses are t-statistics.

Characteristic	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.076***			0.077***	0.022***	0.078***
	(8.91)			(9.10)	(3.09)	(9.16)
σ^2		-0.031***		-0.154***		
		(-2.61)		(-8.59)		
ψ	-0.151***				***	-0.138***
	(-8.35)					(-7.63)
ν	-1.440				-2.636	-1.611
	(-1.15)				(-1.23)	(-1.28)
IVOL			-0.033***			
			(-2.08)			
Mkt	0.060***	0.058***	0.059***	0.059***	0.057***	
	(3.78)	(3.65)	(3.70)	(3.75)	(3.56)	
SMB	0.150***	0.152***	0.151***	0.150***	0.150***	
	(12.41)	(12.67)	(22.64)	(22.45)	(22.43)	
HML	0.064***	0.070***	0.069***	0.065***	0.095***	
	(4.14)	(4.47)	(4.43)	(4.19)	(7.15)	
UMD	0.009***	0.010***	0.010***	0.009**	0.009**	
	(2.44)	(2.77)	(2.75)	(2.48)	(2.47)	
Observations	281,782	281,782	281,782	281,782	281,782	281,782
Average R^2	32.48%	28.70%	28.45%	31.65%	24.14%	17.44%

Table A- 2: How are portfolio unsystematic and covariance risks associated with traditional measures of idiosyncratic risk?

$\psi_{i,t} = IVOL_{i,t} + Controls_{i,t} + \varepsilon_{i,t}$
$\nu_{i,t} = IVOL_{i,t} + Controls_{i,t} + \varepsilon_{i,t}$
Here we use the Fama-Macbeth regression procedure to estimate the above equations. The dependent variable in models (1) to (5) is the covariance component (ψ), and in models (6) and (7) is the stock level average volatility component (Nu) of total return volatility for fund i in month t. σ^2 is the variance of returns during month t using daily observations. *IVOL*s are the idiosyncratic standard deviation of daily returns during month t using Fama and French's three, four, and five-factor models. Fund controls include funds' fixed effect, the Fama-French four-factor Mkt (market), SMB (size), HML (value), and UMD (momentum) exposures estimated from daily returns during month t.
Numbers between parentheses are t-statistics.

	Dependent Variable						
	ψ					ν	
Characteristic	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	-0.002***	-0.004***	-0.002***	-0.003***	-0.003***	0.001***	0.000***
	(-32.97)	(-13.63)	(-14.03)	(19.79)	(13.89)	(21.74)	(20.02)
IVOL (3)	0.128***	0.122***				0.000	0.000
	(23.02)	(18.25)				(1.24)	(0.73)
IVOL (4)			0.129***				
			(19.29)				
IVOL (5)				0.122***	0.127***		
				(21.23)	(21.19)		
ν					-0.035		
					(-1.46)		
Risk Loading Controls	No	Yes	Yes	Yes	Yes	No	Yes
Observations	287,021	287,021	287,021	287,021	287,021	287,021	287,021
Average R^2	88%	89%	93%	94%	94%	1%	2%

Appendix 2

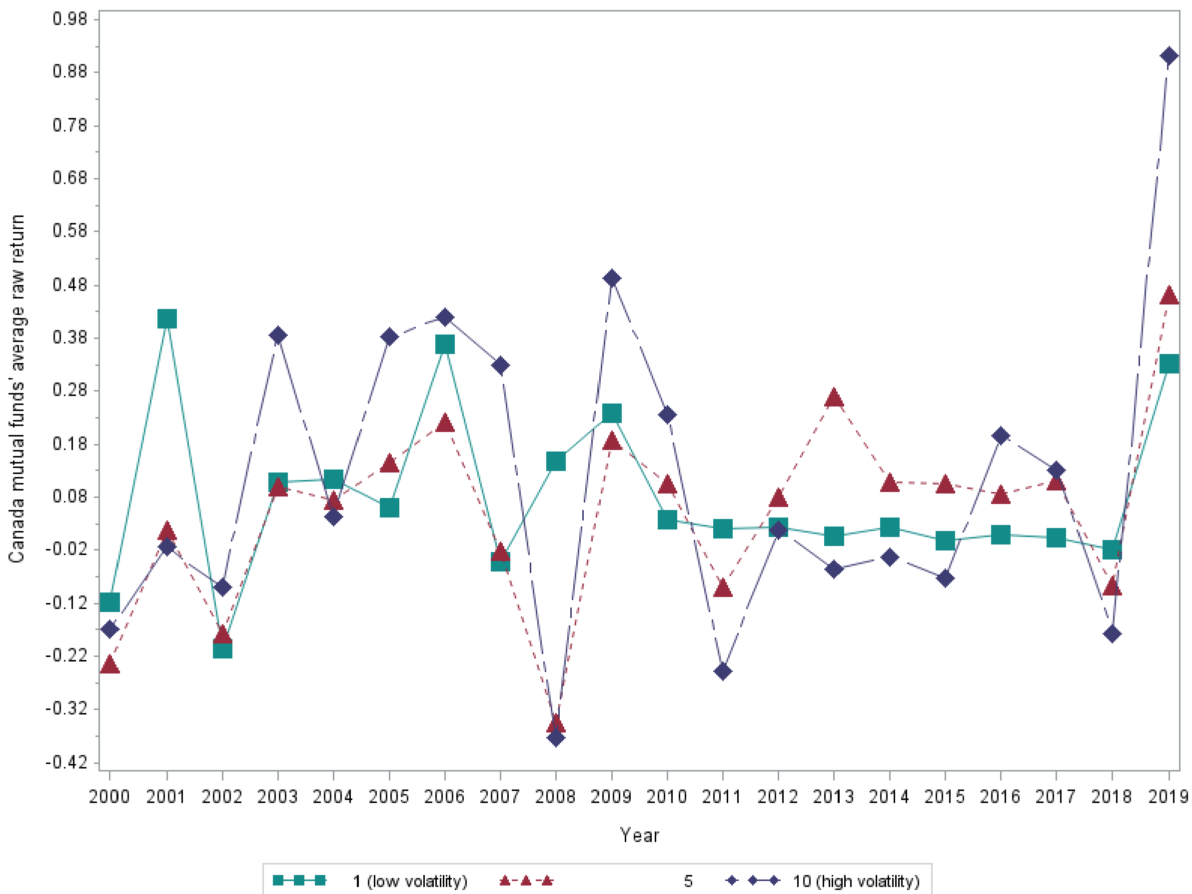

Fig. A- 1: The annualized raw return of Canada on portfolios formed on annual variance (σ^2) using monthly return

This figure shows the annualized average return of from January 2000 through December 2019 in three equal weighted portfolios of mutual funds in Canada. The low volatility portfolio buys the 10% of mutual funds in the sample with the lowest annual variance of monthly returns. The high volatility portfolio buys the 10% of mutual funds in the sample with the highest annual variance of monthly returns.

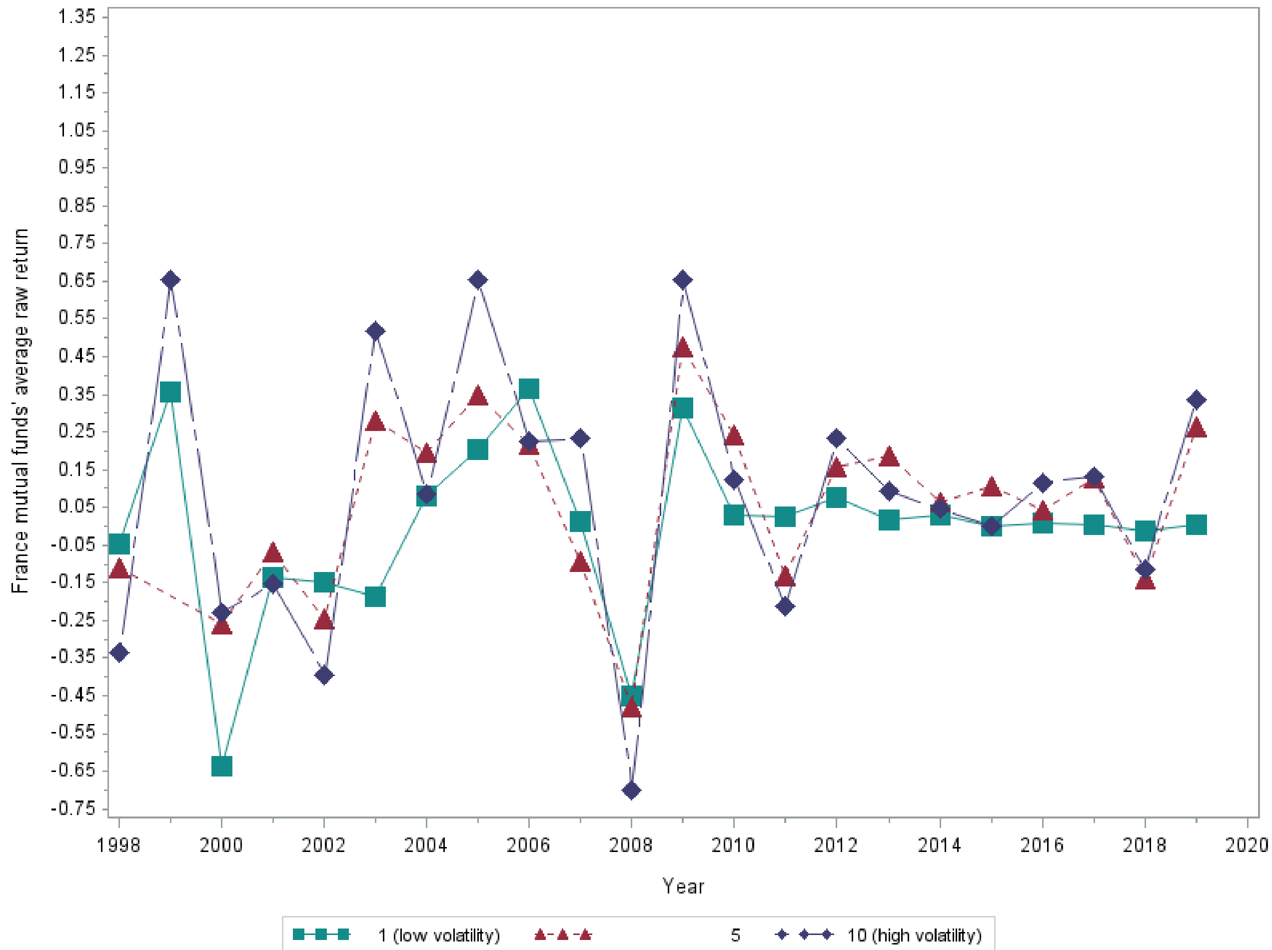

Fig. A- 2: The annualized raw return of France mutual funds on portfolios formed on annual variance (σ^2) using monthly return

This figure shows the annualized average return of from January 1998 through December 2019 in three equal weighted portfolios of mutual funds in France. The low volatility portfolio buys the 10% of mutual funds in the sample with the lowest annual variance of monthly returns. The high volatility portfolio buys the 10% of mutual funds in the sample with the highest annual variance of monthly returns.

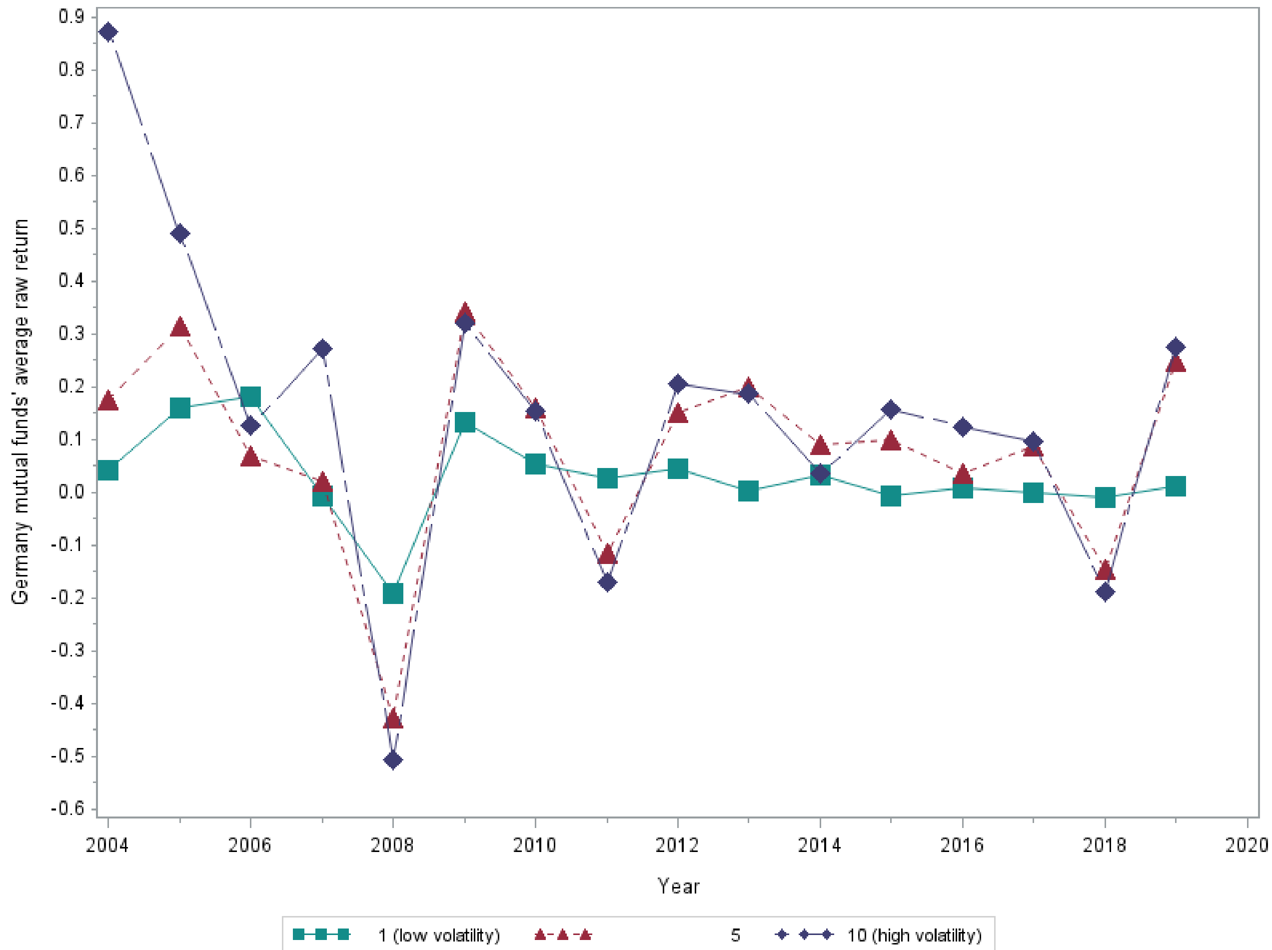

Fig. A- 3: The annualized raw return of Germany's mutual funds on portfolios formed on annual variance (σ^2) using monthly return

This figure shows the annualized average return of from January 2004 through December 2019 in three equal weighted portfolios of mutual funds in Germany. The low volatility portfolio buys the 10% of mutual funds in the sample with the lowest annual variance of monthly returns. The high volatility portfolio buys the 10% of mutual funds in the sample with the highest annual variance of monthly returns.