5-2015

The Idiosyncratic Volatility Puzzle: A Behavioral Explanation

Brad Cannon
Utah State University

THE IDIOSYNCRATIC VOLATILITY PUZZLE: A BEHAVIORAL EXPLANATION

by

Brad Cannon

A Plan B paper submitted in partial fulfillment
of the requirements for the degree

of

Master of Science

in

Financial Economics

Approved:

Ben Blau Major Professor	Tyler Brough Committee Member

Ryan Whitby
Committee Member

UTAH STATE UNIVERSITY
Logan, Utah

2015

I. INTRODUCTION

The trade-off between risk and return is a fundamental principle in finance. In any finance class, one will likely hear the phrase, "the greater the risk, the greater the return." The Capital Asset Pricing Model (CAPM), one of the most basic and well-known finance models, estimates the expected return of an asset assuming a positive relation between expected return and a single risk factor. Empirically, risk control variables such as the CAPM beta along with other risk factors associated with market cap, book-to-market ratio, and illiquidity are used when pricing assets. Finance is abundant in theories all supporting positive risk-return relationships. In spite of the general, intuitive risk-return relationship, several studies have empirically observed risk factors, including idiosyncratic volatility, to be negatively related to the future return on a stock (Ang, Hodrick, Xing, and Zhang (2006)). This counterintuitive relationship invokes the question why a risk variable such as idiosyncratic volatility would have a negative effect on expected returns when theory suggests that risk should have a positive relationship with expected return.

The confusing finding in Ang et al. (2006) has led many to refer to the relationship between idiosyncratic volatility and future returns as the idiosyncratic volatility puzzle. As the name would imply, finance theory is opposed to the empirically observed relationship, which has instigated many academics to study the cause of this mysterious relationship. Uncovering this mystery has been the topic for numerous recent papers, all purporting to explain this puzzle. Proposed explanations include those based on idiosyncratic skewness (Boyer, Mitton, and Vorkink (2010)), coskewness (Chabi-Yo and Yang (2009)), maximum daily return (Bali, Cakici, and Whitelaw (2011)), retail trading proportion (Han and Kumar (2013)), one-month return reversal (Fu (2009) and Huang, Liu, Rhee, and Zhang (2009)), illiquidity (Bali and Cakici (2008) and Han and Lesmond (2011)), uncertainty (Johnson (2004)), average variance beta (Chen and Petkova (2012)), and earnings surprises (Jiang, Xu, and Yao (2009) and Wong (2011)). Additionally, several papers show that the negative relationship is stronger among stocks that are short-constrained (Boehme, Danielsen, Kumar, and Sorescu (2009) and George and Hwang (2011)), in financial distress (Avramov, Chorida, Jostova, and Philipov (2013)), have low investor attraction (George and Hwang (2011)), have prices greater than five dollars (George and Hwang (2011)), and in non-January months (George and Hwang (2011) and Doran, Jian, and Peterson (2012)). Despite the ubiquity of papers regarding the idiosyncratic volatility puzzle, the observed relationship remains largely debated and unexplained.

As long as this puzzle persists, there exists essentially a "free lunch" for investors who, holding all else constant, invest in a portfolio of stocks with lower idiosyncratic volatility. In so doing, said investor would be able to expect a greater portfolio return while simultaneously reducing risk.

In this study, I propose an alternative explanation for the idiosyncratic volatility puzzle. I postulate that the negative coefficient observed between idiosyncratic volatility and future returns is driven by investor sentiment. This behavioral explanation is derived from several prominent studies regarding probability assessment. In 1974, Daniel Kahneman and Amos Tversky produced a break-through study indicating the biases inherent in probability assessment. Since its publication, the irrationality of probability assessment has become a popular topic in numerous fields of study. For example, William Wright and Gordon Bower published a paper entitled "Mood Effects on Subjective Probability Assessment" (1992). In this study, moods were induced by having subjects focus on either happy or sad personal experiences. After being subjected to a mood, individuals were subsequently asked to assess the probability of particular events to occur. The group assigned to think of positive experiences tended to be optimistic, estimating higher probabilities for positive events and lower probabilities for negative events. Likewise, the group assigned to think of negative experiences were generally pessimistic, estimating lower probabilities of positive events and higher probabilities of negative events. The results indicated that mood effects were quite significant in probability assessment. I hypothesize that this same phenomenon can be observed in financial markets and may be the underlying cause behind the idiosyncratic volatility puzzle.

Applying this behavioral theory into asset pricing, I assume that investors may be driven by emotion when picking stocks. I believe that emotions may induce investors to making irrational investments by either overestimating or underestimating the probability of an outcome to occur. For example, investors with positive moods would more likely overestimate the probability of any given stock to receive a large return. This incorrect assessment of probabilities could lead investors to invest more money in riskier stock. Said otherwise, the expected return on a risky stock may be lower than what the investor mentally assigns to that stock. Such a behavioral implication would help to explain why we observe a negative relationship between idiosyncratic volatility and future returns.

To test whether investor sentiment provides an explanation to the negative coefficient between idiosyncratic volatility and future returns, I begin by quantifying the emotional state of investors in a given period using the investor sentiment measure introduced by Baker and Wurgler (2007). For much of the study, the data is divided into three quantiles based on the Baker and Wurgler investor sentiment measure. The three quantiles represent periods of low, medium, and high investor sentiment. I assume that each of these quantiles represent the overall mood of investors in a given time period, allowing us to determine if investor risk tolerance is emotionally driven.

I divide each low, medium, and high investor sentiment groups into quintiles based on idiosyncratic volatility and volatility respectively. I then run Fama-French models (1993), estimating the raw returns, adjusted returns, and alphas for three-factor, four-factors, and five-factors models. The data is reported by quintile (Q), with Q I representing a portfolio of stocks with the lowest idiosyncratic volatility within a sentiment group. Differences between the highest and lowest quintiles (Q V – Q I) are reported within each sentiment group. The observed results indicate that the return premium increases as idiosyncratic volatility increases for periods of both low and medium investor sentiment, while decreasing for periods of high investor sentiment.

In other tests, I report coefficients from Fama-Macbeth regressions (1973), controlling for risk factors, using the sentiment terciles mentioned above. I find that after controlling for a variety of other variables, the relationship between idiosyncratic volatility and future returns is mixed and insignificant for periods of low and medium investor sentiment. However, I find the relationship between idiosyncratic volatility and expected returns to be very negative and significant in periods of high investor sentiment.

Finally, I divide investor sentiment into finer quantiles (quintiles and deciles) to assess the robustness of the results. I expect the behavioral effects to become more pronounced as the number of sentiment quantiles increases. As the data is divided into finer quantiles, I find that the coefficient for idiosyncratic volatility becomes increasingly more positive and significant for periods of the lowest investor sentiment. Likewise, the coefficient for idiosyncratic volatility becomes more negative in the highest sentiment quintile and decile.

The results obtained from these analyses support the idea that the idiosyncratic volatility puzzle can be explained by investor sentiment. In periods of high investor sentiment, investors are optimistic in choosing stocks. Such effects lead investors to flock to assets with high idiosyncratic volatility, creating the negative relationship observed by Ang, Hodrick, Xing, and Zhang (2006). Furthermore, in periods of lowest investor sentiment, results indicate a natural, positive relationship between idiosyncratic volatility and future returns, supporting standard risk-return theory. In all, the results imply that sentiment plays a significant role for investors in picking volatile stocks. In times of high investor sentiment, investors may inappropriately assign higher probabilities of favorable outcomes because of their emotional state. This overconfidence and inflated probability induces riskier stocks to be bought with greater frequency, sustaining the idiosyncratic volatility puzzle. As long as this relationship persists, savvy investors can take advantage of this anomaly, being able to purchase less risky stocks during periods of positive sentiment and receiving a greater return.

II. DATA

The data used in this study are obtained from several different sources. I acquire daily and monthly stock prices, trading volume, shares outstanding, and returns for all traded firms from the Center for Research on Security Prices (CRSP). From Wharton Research Data Services (WRDS), I procure daily and monthly risk factors. I gather the book value used in the book-to-market ratio from Compustat. Lastly, I obtain monthly investor sentiment data from Jeffrey

Wurgler's webpage. After merging the data, I restrict the sample to stocks with prices greater than $2.00.

From the data, several calculations were made to create variables to be used in the analyses. Turnover (*Turn*) is calculated as the ratio of average daily share turnover and shares outstanding, reported as a percent. *Beta* is the beta estimate obtained from the daily Capital Asset Pricing Model over a six-month rolling period. *Size* is the market capitalization on the last day of each month, reported in thousands. *B/M* is the book-to-market ratio, the market value and book value being obtained from CRSP and Compustat respectively. Illiquidity (*Illiq*) is calculated as the absolute value of a daily return scaled by dollar volume (in 100,000s) (Amihud 2002). Idiosyncratic Volatility (*IdioVolt*) is calculated as the standard deviation of the three-factor alpha for daily returns over a six-month rolling period. Lastly, Volatility (*Volt*) is calculated the standard deviation of daily returns over a six-month rolling period.

For much of the analysis, the sample is divided into terciles based on investor sentiment. Low sentiment is defined as the lowest tercile of investor sentiment, while medium sentiment and high sentiment are identified as the middle and highest tercile of investor sentiment respectively.

III. RESULTS

In this section, I begin by presenting statistics that summarize the sample. The statistics, are organized into low, medium, and high investor sentiment, including aggregate totals as well. I then proceed to test whether the relationship between *IdioVolt* and future returns is driven by investor sentiment. I first estimate alpha values from multifactor Fama-French (1993) regressions for each tercile of investor sentiment and report the results across *IdioVolt* quintiles. I then estimate risk-controlled regressions using a Fama-Macbeth (1973) approach. Lastly, I test for robustness by dividing the data into finer investor sentiment quantiles and reporting estimated Fama-Macbeth (1973) regressions for highest and lowest periods of investor sentiment.

III. A. SUMMARY STATISTICS

In Table 1, I report statistics describing the sample. The table includes variables that are used throughout the analysis. The data is presented in four panels, the first panel being totals from the entire sample, while the other three panels report statistics for periods of low, medium, and high investor sentiment respectively. The mean Stock Price (*Price*) from the sample is \$22.28, with means ranging from \$21.30 to \$22.98 in periods of low and medium sentiment respectively. The average *Turn* is 6.0669, with periods of low sentiment averaging the highest average ratio and periods of high sentiment exhibiting the greatest standard deviation. The average *Beta* of the sample is 0.8644 and the average firm size is \$2.385 billion. The mean *B/M* is 0.4465. The average *Illiq* of the sample, as defined by Amihud (2002), is 2.1333, with a high mean of 2.7727 in periods of low sentiment and a low mean of 1.7204 in periods of medium sentiment. The standard deviation of *Illiq* ranges from 15.8279 in periods of medium sentiment to 33.5985 in periods of low investor sentiment. The average *IdioVolt* of the sample is 0.0287 and the average *Volt* is 0.0317, with ranges of 0.0274 to 0.0296 and 0.0300 to 0.0327 respectively.

Table 2 reports summary statistics across levels of investor sentiment, reporting the mean value for each statistic in each sentiment period, as well as the difference in means between periods of high and low investor sentiment. The reported difference in means for *Price* and *Turn* are \$1.24 and -0.6405 respectively, low sentiment having the lower mean *Price* and the higher mean *Turn*. The difference in *Size* is -$.087 billion, with periods of medium sentiment having the highest mean *Size*. The *B/M* difference is -1.0044, with periods of medium sentiment having a lower ratio than either low or high sentiment periods. Lastly, differences between high and low sentiment periods for average *IdioVolt* and *Volt* are 0.0006 and -0.0004 respectively.

III. B. MULTIFACTOR ANALYSIS

I begin the regression analysis by examining the risk-adjusted returns during periods of low, medium, and high investor sentiment. Consistent with the mood effects observed by Wright and Bower (1992), I expect that during periods of high investor sentiment, the risk-adjusted return for a stock with high *IdioVolt* will be more negative than in periods of low investor sentiment. Table 3 reports the alpha values from estimating the following multifactor regression:

$$Excess\ Return_{i,t+1} = \alpha + \beta_1 MRP_{t+1} + \beta_2 SMB_{t+1} + \beta_3 HML_{t+1} + \beta_4 UMD_{t+1} + \beta_5 LIQ_{t+1} + \varepsilon_{i,t+1}$$

The dependent variable is the excess return for stock *i* in month *t+1,* where excess returns are the difference between monthly raw returns and monthly risk-free note (1-month T-bill) yields. The independent variables, measured in month *t+1,* include the market risk premium (*MRP*), the small the small-minus-big risk factor (*SMB*), the high-minus-low risk factor (*HML*), the Carhart (1997) up-minus-down risk factor (*UMD*), and the Pastor-Stambaugh (2003) liquidity risk factor (*LIQ*). *FF3F* is the alpha estimated from the above equation, excluding the last two risk factors (*UMD* and *LIQ*). *FF4F* is the obtained alpha estimated from the above equation, excluding only the liquidity risk factor (*LIQ*). Lastly, *FF5F* is the estimated alpha obtained from the usage of all factors outlined in the above equation. Each of the three sentiment periods are sorted into five quintiles based on *IdioVolt*. Stocks with lowest *IdioVolt* are assigned quintile one (Q I). Each increasing quintile subsequently contains stocks with higher *IdioVolt*, with Q V being the quintile of stocks with the highest *IdioVolt*, within a sentiment period. Alphas are reported across *IdioVolt* quintiles within each of the three sentiment terciles (Low, Medium, and High). The alpha difference between highest and lowest *IdioVolt* stocks is reported at the bottom of each sentiment panel along with its associated p-value.

In Table 3, I observe how the alpha changes within a sentiment period as *IdioVolt* changes. In Panel A, I observe that moving across increasing *IdioVolt* quintiles, the estimated alphas increase as well, creating a natural risk-return relationship. Although the change in alpha is not strictly monotone moving across *IdioVolt* quintiles, there is an apparent increasing relationship, which is significant when differencing the highest and lowest *IdioVolt* quintiles. The alpha differences (p-values) are 0.0185 (<0.0001), 0.0121 (<0.0001), 0.0012 (0.025), 0.0016 (0.002), and 0.0014 (0.015) for Raw Returns, Adjusted Returns, *FF3F* Alphas, *FF4F* Alphas, and *FF5F* Alphas respectively.

In Panel B, I obtain similar results to Panel A, observing near-monotone alpha increases moving across *IdioVolt* quintiles in periods of medium investor sentiment. Additionally, I observe positive and significant differences (at a 0.01 level) between the alphas of the highest *IdioVolt* quintile and the lowest *IdioVolt* quintile for three of the five models. The alpha differences (p-values) are 0.0091 (0.0001), 0.0050 (<0.0001), 0.0005 (0.351), 0.0012 (0.046), and 0.0030 (<0.0001) for Raw Returns, Adjusted Returns, *FF3F* Alphas, *FF4F* Alphas, and *FF5F* Alphas respectively. The results in this panel suggest that in periods of medium consumer sentiment, the risk-return relationship, as pertaining to *IdioVolt,* is positive.

In Panel C, the positive, near-monotone risk premium received by increasing *IdioVolt* reverses and becomes the negative relationship found by Ang, Hodrick, Xing, and Zhang (2006).

In fact, the alpha decreases monotonically moving across increasing *IdioVolt* quintiles and the differences between highest and lowest *IdioVolt* quintiles are negative and significant at a 0.01 level for all five models. The alpha differences (p-values) are -0.0213 (<0.0001), -0.0130 (<0.0001), -0.0070 (<0.0001), -0.0045 (<0.0001), and -0.0040 (<0.0001) for Raw Returns, Adjusted Returns, *FF3F* Alphas, *FF4F* Alphas, and *FF5F* Alphas respectively. This relationship reversal is analogous to the puzzling negative relationship between *IdioVolt* and future returns.

In Table 4, I use the same methodology as used in Table 3 except that the quintiles are sorted by *Volt*, rather than *IdioVolt*. *Volt* is used as a way of ensuring that the behavior implications are robust and can explain a highly correlated risk measure. Furthermore, this helps ensure that the results are not the result of a miscalculation of *IdioVolt*. Although there are mixed results during periods of low investor sentiments, the results are much the same as those obtained in Table 3.

The results yielded in these analyses provide supporting evidence that the negative relationship between *IdioVolt* and expected stock returns is driven by periods of high investor sentiment. The results also indicate that in periods of low and medium investor sentiment, the relationship between *IdioVolt* and future returns becomes "normal" and investors are rewarded for taking on more risk.

III. C. FAMA-MACBETH REGRESSIONS

In Table 5, I report regression results using the following equation:

$$Return_{i,t+1} = \beta_0 + \beta_1 Beta_{i,t} + \beta_2 ln(Size)_{i,t} + \beta_3 ln(B/M)_{i,t} + \beta_4 Mom_{i,t} + \beta_5 ln(Illiq)_{i,t} + \beta_6 IdioVolt_{i,t} + \varepsilon_{i,t+1}$$

The dependent variable is the raw return for stock *i* in month *t+1*. The independent variables, all measured in month *t* for stock *i*, include CAPM betas (*Beta),* the natural log of market capitalization (*Ln(Size)),* the natural log of the book-to-market ratios *(ln(B/M)),* the past six month return *(Mom),* the natural log of Amihud's (2002) Illiquidity measure *(Ln(Illiq)),* and the idiosyncratic volatility *(IdioVolt).* The regressions are estimated using a Fama-MacBeth (1973) method by month. P-values are estimated from Newey-West (1987) standard errors and are reported in parentheses below their corresponding coefficient.

Coefficients on the independent variables listed above are reported in columns [1] through [8]. Fama-MacBeth (1973) regression results are reported for all observations in columns [1] and [2]. Results for Low, Medium, and High Sentiment terciles are reported in columns [3] and [4], [5] and [6], and [7] and [8] respectively. The odd columns ([1], [3], [5], and [7]) estimate coefficients for the above equation excluding the *ln(Illiq)* variable. Even columns estimate coefficients using all variables in the above equation.

The main variable of interest for this analysis is *IdioVolt*, which coefficient I hypothesize changes according to investor sentiment. I expect that in periods of high investor sentiment, the coefficient for *IdioVolt* will be negative and significantly different than zero, while in periods of low and medium investor sentiment, the coefficient will be less negative or flip signs and become positive. A significant difference in the magnitude of the coefficient in sentiment periods, especially a reversal in signs, would support my hypothesis and indicate that investor sentiment influences volatility risk tolerance for investors.

Although I do not observe a positive and significant positive coefficient for *IdioVolt* in periods of low and medium sentiment, a vast difference is apparent in the magnitude of the

IdioVolt coefficients for times of low and medium sentiment compared to periods of high sentiment. In periods of low consumer sentiment, I observe coefficients of -0.0411 and -0.0055, excluding and including *Ln(Illiq)* respectively. For periods of medium investor sentiment, I estimate *IdioVolt* coefficients to be 0.0108 and -0.0062, excluding and including *Ln(Illiq)* respectively. Although these results did not yield positive coefficients, no *IdioVolt* coefficient is significantly different than zero for periods of low and medium investor sentiment. Furthermore, there is a vast difference between the *IdioVolt* coefficients observed during periods of low investor sentiment and the largely negative and significant coefficeients resulting in periods of high investor sentiment -0.5318 and -0.5448.

In Table 6, I use the same methodology as described above except that I include volatility *(Volt)* as an independent variable of interest in lieu of *IdioVolt.* Findings in this table are much the same as those reported from Table 5. The coefficients for *Volt* on future returns have mixed signs during periods of low and medium investor sentiment and do not prove to be significant. During periods of high investor sentiment, I observe an extremely negative and significant coefficient for *Volt.*

The results of these two tables provide further evidence to the hypothesis that periods of high investor sentiment drive the negative relationship between *IdioVolt* and future returns. Although periods of low and medium sentiment do not indicate a positive relationship as in our multifactor analysis, the vast difference between them and periods of high sentiment is indicative that investor sentiment influences risk assessment and drives the idiosyncratic volatility puzzle.

III. D. ROBUSTNESS TESTS

In this section, I divide the data into finer quantiles (quintiles and deciles) based on investor sentiment. I conjecture that when comparing idiosyncratic volatility coefficients at the extremes of investor sentiment, their difference should increase as the number of quantile divisions increases. Such results would indicate that in more extreme periods of investor sentiment, investor emotion would play a more significant role in assessing risk. In Table 7, I report regression results using the following equation:

$$Return_{i,t+1} = \beta_0 + \beta_1 Beta_{i,t} + \beta_2 ln(Size)_{i,t} + \beta_3 ln(B/M)_{i,t} + \beta_4 Mom_{i,t} + \beta_5 ln(Illiq)_{i,t} + \beta_6 IdioVolt_{i,t} + \varepsilon_{i,t+1}$$

The dependent variable is the raw return for stock i in month $t+1$. The independent variables, all measured in month t for stock i, include CAPM betas (*Beta),* the natural log of market capitalization (*Ln(Size)),* the natural log of the book-to-market ratios *(ln(B/M)),* the past six month return *(Mom),* the natural log of Amihud's (2002) Illiquidity measure *(Ln(Illiq)),* and the idiosyncratic volatility *(IdioVolt).* The regressions are estimated using a Fama-MacBeth (1973) method by month. P-values are estimated from Newey-West (1987) standard errors and are reported in parentheses below their corresponding coefficient.

As before, coefficients on the independent variables for sentiment quintiles are reported in columns [1] and [2] and results for deciles are reported in columns [3] and [4]. The lowest quantile for each division is reported in the odd columns [1] and [3] and the highest quantiles are reported in columns [2] and [4].

Similar to Tables 5 and 6, the main variable of interest is *IdioVolt.* I anticipate that the coefficients for *IdioVolt* will become more extreme while increasing the number of divisions for investor sentiment. Significant, and increasingly positive coefficients across finer quantiles of lowest investor sentiment would support my hypothesis, implying that in periods of low investor sentiment investors would be rewarded for assuming *IdioVolt* risk. I likewise expect the *IdioVolt* coefficients for periods of highest investor sentiment to be negative and significant, becoming more negative as sentiment quantiles become finer.

The results observed in Table 7 provide significant support for the hypothesis that the relationship between *IdioVolt* and stock returns is driven by investor sentiment. As I divide the data into finer sentiment quantiles, I observe a greater difference between periods of highest and lowest investor sentiment. In column [1], I find the *IdioVolt* coefficient to be 0.2222 and significant at the 0.10 level. This result becomes even more valuable when noting the coefficient corresponding to the highest sentiment quintile to be -0.5043 and significant at the 0.01 level (difference of 0.7265). Furthermore, splitting the data into deciles based on investor sentiment, I observe these coefficients to become even more extreme. The lowest sentiment decile yields a coefficient of 0.3886 for *IdioVolt* and the highest sentiment decile -0.5785, being significant at 0.10 and 0.05 levels respectively (difference of 0.9671).

In Table 8, I use the same methodology as described above except that I include total volatility *(Volt)* as an independent variable in lieu of *IdioVolt.* Findings in this table are much the same as those reported from Table 7. Splitting the data into quintiles, I observe *Volt* coefficients to be 0.2283 and -0.4542 for lowest and highest quintiles respectively (difference of 0.6825). As I further divide the data into deciles, I find these coefficients to become more extreme, being 0.4011 and -0.5354 for lowest and highest sentiment periods respectively (difference of 0.9365).

The results from these robustness tests provide substantial evidence to the claim that the negative effect of *IdioVolt* on stock returns is driven by periods of high investor sentiment. I observe the *IdioVolt* coefficient to become increasingly positive in periods of lowest investor sentiment as I increase quantile divisions, while becoming increasingly negative in periods of highest investor sentiment. The increased separation of these coefficients with finer quantiles implies that the emotional effect is greater in extreme sentiment periods.

IV. CONCLUSIONS

Many explanations have been offered, but none universally accepted explaining the idiosyncratic volatility puzzle. Applying the effect of mood on probability assessment observed by Wright and Bower (1992) and others, I conjecture that investor sentiment plays a significant role in the ability of an investor to correctly assess risk, and consequently select stocks. Following Wright and Bower's observations, I expect that in periods of high investor sentiment, investors will irrationally overestimate stock returns (favorable outcomes) and underestimate stock risk, acting optimistically. As a result, stocks with higher idiosyncratic volatility will yield a lower return than stocks with lower idiosyncratic volatility during high sentiment periods.

By first using multifactor regressions, I test whether investor sentiment plays a significant role in the relationship between the idiosyncratic volatility of a stock and its future return. Sorting by idiosyncratic volatility, results indicate that an increase in idiosyncratic volatility, during periods of low or medium investor sentiment, results in a higher estimated alpha from multifactor regressions. Likewise, an increase in idiosyncratic volatility in periods of high investor sentiment results in a lower estimated alpha.

To further support the hypothesis that the relationship between idiosyncratic volatility and stock returns is driven by investor sentiment, I estimate risk-controlled regressions using a Fama-Macbeth (1973) method for each tercile of investor sentiment. The estimated coefficients for idiosyncratic volatility vary greatly in periods of high investor sentiment compared to periods of low and medium investor sentiment, with the coefficients being much more negative in periods of high investor sentiment.

Lastly, as a test of robustness, I divide the data into finer investor sentiment quantiles and estimate Fama-Macbeth (1973) regressions for the lowest and highest quantiles. To the extent that idiosyncratic volatility coefficients are explained by periods of investor sentiment, I expect that finer quantiles will yield more extreme coefficients for periods of lowest and highest investor sentiment, creating a larger gap between the two idiosyncratic volatility coefficients. Consistent with this belief, I observe the idiosyncratic volatility coefficients to become more positive in periods of lowest investor sentiment increasing the number of quantile divisions. Similarly, I find in periods of highest investor sentiment that the idiosyncratic volatility coefficient becomes more negative as quantiles are more finely divided.

Combined, these analyses provide empirical evidence supporting the idea that the idiosyncratic volatility puzzle is driven primarily by periods of high investor sentiment. I observe that in periods of high investor sentiment, investors may underestimate the risk of a stock and overestimate its expected return. To the extent that investors inaccurately assess risk and flock to stocks with high idiosyncratic volatility during periods of high investor sentiment, we will continue to observe the idiosyncratic volatility puzzle.

REFERENCES

Amihud, Y. “Illiquidity and Stock Returns: Cross-Section and Time-Series Effects.” *Journal of Financial Markets,* 5 (2002), 31-56.

Ang, A., R. Hodrick, Y. Xing, and X. Zhang. “The Cross-Section of Volatility and Expected Returns.” *The Journal of Finance,* 61 (2006), 259-299.

Avramov, D., T. Chordia, G. Jostova, and A. Philipov, “Anomalies and Financial Distress.” *Journal of Financial Economics,* 108 (2013), 139-159.

Baker, M., and J. Wurgler, “Investor Sentiment in the Stock Market.” *Journal of Economic Perspectives,* 21 (2007), 129-152.

Bali, Turan G. and Nusret Cakici, “Idiosyncratic Volatility and the Cross Section of Expected Returns.” *Journal of Financial and Quantitative Analysis,* 43 (2008), 29-58.

Bali, T., N. Cakici, and R. Whitelaw, 2011, “Maxing out: Stocks as lotteries and The Cross-Section of Expected Returns.” *Journal of Financial Economics,* 99 (2011), 427-446.

Boehme, R., B. Danielsen, P. Kumar, and S. Sorescu, “Idiosyncratic Risk and the Cross-Section of Stock Returns: Merton (1987) meets Miller (1977).” *Journal of Financial Markets,* 12 (2009), 438-468.

Boyer, B., T. Mitton, and K. Vorkink, “Expected Idiosyncratic Skewness.” *Review of Financial Studies*, 23 (2010), 169-202.

Carhart, M., “On Persistence in Mutual Fund Performance.” *Journal of Finance,* 52 (1997), 57-82.

Chabi-Yo, F. and J. Yang, "Default Risk, Idiosyncratic Coskewness and Equity Returns." Working paper (2009), Ohio State University.

Chen, Z. and R. Petkova, "Does Idiosyncratic Volatility Proxy for Risk Exposure?" *Review of Financial Studies,* 25 (2012), 2745-2787.

Doran, J., D. Jiang, and D. Peterson, "Gambling Preference and the New Year Effect of Assets with Lottery Features." *Review of Finance,* 16 (2012), 685-731.

Fama, E. and K. French, "Common Risk Factors in the Returns of Stocks and Bonds." *Journal of Financial Economics,* 33 (1993), 3-56.

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

Fu, F., "Idiosyncratic Risk and the Cross-Section of Expected Stock Returns." *Journal of Financial Economics,* 91 (2009), 24-37.

George, T. and C. Hwang, "Analyst Coverage and the Cross-Sectional Relation Between Returns and Volatility." Working Paper (2011), Nanyang Technological University.

Han, B. and A. Kumar, "Speculative Trading and Asset Prices." *Journal of Financial & Quantitative Analysis*, 48 (2013), 377-404.

Han, Y. and D. Lesmond, "Liquidity Biases and the Pricing of Cross-Sectional Idiosyncratic Volatility." *Review of Financial Studies,* 24 (2011), 1590-1629.

Huang, W., Q. Liu, S. Rhee, and L. Zhang, "Return Reversals, Idiosyncratic Risk, and Expected Returns." *Review of Financial Studies,* 23 (2009), 147-168.

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

Johnson, T., "Forecast Dispersion and the Cross-Section of Stock Returns." *Journal of Finance,* 59 (2004), 1957-1978.

Newey, W. and K. West, "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica,* 55 (1987), 703-708.

Pastor, L. and R. Stambaugh, "Liquidity Risk and Expected Stock Returns." *Journal of Political Economy,* 11 (2003), 642-685.

Tversky, A., and D. Kahneman, "Judgment under Uncertainty: Heuristics and Biases." *Science*, 185 (1974), 1124-1131.

Wong, P., "Earnings Shocks and the Idiosyncratic Volatility Discount in the Cross-Section of Expected Returns." Working Paper (2011), University of South Carolina.

Wright, W., and G. Bower. "Mood Effects on Subjective Probability Assessment." *Organizational Behavior and Human Decision Processes,* 52 (1992), 276-291.

Table 1
Summary Statistics

The table reports statistics describing the sample. The sample is divided into terciles based on investor sentiment. Low Sentiment is defined as the lowest tercile of investor sentiment, while Medium Sentiment and High Sentiment are the middle and highest tercile of investor sentiment respectively. Panel A reports the summary statistics for all sentiments (Low, Medium, and High). Panels B, C, and D report the summary statistics for Low Sentiment, Medium Sentiment, and High Sentiment respectively. *Price* is the closing month price obtained from CRSP. *Turn* is the ratio of average daily share turnover and shares outstanding, reported as a percent. *Beta* is the beta estimate obtained from the daily Capital Asset Pricing Model over a six-month rolling period. *Size* is the market capitalization on the last day of each month, reported in thousands. *B/M* is the book-to-market ratio, the market value and book value being obtained from CRSP and Compustat respectively. *Illiq* is a measure of illiquidity and is the ratio of the absolute value of a daily return scaled by dollar volume (in 100,000s). *IdioVolt* is the standard deviation of the three-factor alpha for daily returns over a six-month rolling period. *Volt* is the standard deviation of daily returns over a six-month rolling period.

	Mean	*Std. Deviation*	*25^{th} Percentile*	*Median*	*75^{th} Percentile*
	[1]	[2]	[3]	[4]	[5]
Panel A. All Observations					
Price	22.28	27.34	8.00	16.44	29.00
Turn	6.0669	20.9660	1.2692	3.0814	7.0584
Beta	0.8644	3.7319	0.3806	0.8450	1.2894
Size	2,385,073	12,520,909	58,515	223,799	949,113
B/M	0.4465	10.1917	0.3387	0.5923	0.9617
Illiq	2.1333	25.5419	0.0037	0.0398	0.4848
IdioVolt	0.0287	0.0186	0.0161	0.0240	0.0312
Volt	0.0317	0.0197	0.0184	0.0269	0.0396
Panel B. Low Sentiment					
Price	21.30	25.98	7.50	18.81	28.02
Turn	6.2953	15.0009	1.2885	3.2310	7.4054
Beta	0.8545	1.8812	0.3791	0.8391	1.2644
Size	2,322,694	11,451,071	61,504	233,544	985,189
B/M	0.5460	9.9040	0.3591	0.6222	1.0083
Illiq	2.7727	33.5985	0.0032	0.0351	0.4787
IdioVolt	0.0290	0.0187	0.0163	0.0245	0.0367
Volt	0.0327	0.0201	0.0188	0.0280	0.0413
Panel C. Medium Sentiment					
Price	22.98	29.21	8.25	16.95	29.92
Turn	6.2489	12.1473	1.4054	3.3980	7.4538
Beta	0.8475	5.9623	0.3962	0.8501	1.2751
Size	2,596,055	12,965,791	66,944	251,023	1,061,522
B/M	0.3478	6.8231	0.3266	0.5599	0.8887
Illiq	1.7204	15.8279	0.0029	0.0304	0.4044
IdioVolt	0.0274	0.0183	0.0155	0.0228	0.0343
Volt	0.0300	0.0188	0.0179	0.0256	0.0372
Panel D. High Sentiment					
Price	22.54	26.70	8.15	16.5	29.25
Turn	5.6548	30.7860	1.1473	2.6769	6.2450
Beta	0.8914	1.6262	0.3676	0.8456	1.3320
Size	2,235,998	13,079,650	48,810	189,718	810,196
B/M	0.44560	12.9295	0.3314	0.5984	0.9953
Illiq	1.9056	24.0122	0.0056	0.0576	0.5701
IdioVolt	0.0296	0.0188	0.0167	0.0247	0.0373
Volt	0.0323	0.0200	0.0187	0.0273	0.0402

Table 2
Summary Statistics Across Levels of Sentiment

The table reports the mean of several statistics from each sentiment tercile of the sample. The sample is divided into terciles based on investor sentiment. Low Sentiment is defined as the lowest tercile of investor sentiment, while Medium Sentiment and High Sentiment are the middle and highest tercile of investor sentiment respectively. Columns [1], [2], and [3] report the means from the summary statistics of Low Sentiment, Medium Sentiment, and High Sentiment respectively. Column [4] reports the difference in mean statistics of columns [3] and [1], subtracting column [1] from column [3]. *Price* is the closing month price obtained from CRSP. *Turn* is the ratio of average daily share turnover and shares outstanding, reported as a percent. *Beta* is the beta estimate obtained from the daily Capital Asset Pricing Model over a six-month rolling period. *Size* is the market capitalization on the last day of each month, reported in thousands. *B/M* is the book-to-market ratio, the market value and book value being obtained from CRSP and Compustat respectively. *Illiq* is a measure of illiquidity and is the ratio of the absolute value of a daily return scaled by dollar volume (in 100,000s). *IdioVolt* is the standard deviation of the three-factor alpha for daily returns over a six-month rolling period. *Volt* is the standard deviation of daily returns over a six-month rolling period.

	Investor Sentiment			
	Low	*Medium*	*High*	*High-Low*
	[1]	[2]	[3]	[4]
Price	21.30	22.98	22.54	1.24
Turn	6.2953	6.2489	5.6548	-0.6405
Beta	0.8545	0.8475	0.8914	0.0369
Size	2,322,694	2,596,055	2,235,998	-86,695
B/M	0.5460	0.3478	0.4456	-0.1004
Illiq	2.7727	1.7204	1.9056	-0.8671
IdioVolt	0.0290	0.0274	0.0296	0.0006
Volt	0.0327	0.0300	0.0323	-0.0004

Table 3
Returns across Idiosyncratic Volatility Portfolios by Investor Sentiment

The table reports several measures of next-month returns across quintiles sorted by idiosyncratic volatility in month *t.* The sample is divided into terciles based on investor sentiment. Low sentiment is defined as the lowest tercile of investor sentiment, while medium sentiment and high sentiment are the middle and highest tercile of investor sentiment respectively. Panel A reports return measures for periods of low investor sentiment. Panels B and C report return measures for periods of medium and high investor sentiment respectively. Column [1] details CRSP raw returns. Column [2] reports the excess returns, the difference between raw returns and monthly risk-free rates. Column [3] shows the results from adjusted returns, meaning the difference between raw returns and value-weighted market returns. Columns [4] through [6] report the estimated alpha from variations of the following equation.

$$Excess\ Return_{i,t+1} = \alpha + \beta_1 MRP_{t+1} + \beta_2 SMB_{t+1} + \beta_3 HML_{t+1} + \beta_4 UMD_{t+1} + \beta_5 LIQ_{t+1} + \varepsilon_{i,t+1}$$

The dependent variable is the excess return for stock *i* in month *t+1*. The independent variables include the market risk premium (MRP), the small the small-minus-big risk factor (*SMB*), the high-minus-low risk factor (*HML*), the Carhart (1997) up-minus-down risk factor (*UMD*), and the Pastor-Stambaugh (2003) liquidity risk factor (*LIQ*). *FF3F* is the alpha estimated from the above equation, excluding the last two risk factors (UMD and LIQ). FF4F is the obtained alpha estimated from the above equation, excluding only the liquidity risk factor (LIQ). Lastly, FF5F is the estimated alpha obtained from the usage of all factors outlined in the above equation. These measures are subsequently reported across quintiles sorted by idiosyncratic volatility within each of the three sentiment terciles (Low, Medium, and High). Additionally, differences between the extreme quintiles are reported along with their corresponding p-values. *, **, and *** represent statistical significance at 0.10, 0.05, and 0.01 levels respectively.

Panel A. Low Investor Sentiment					
	Raw Returns [1]	*Adj. Returns* [2]	*FF3F Alphas* [3]	*FF4F Alphas* [4]	*FF5F Alphas* [5]
Q I	0.0109	0.0014	0.0029	0.0027	0.0031
Q II	0.0121	0.0018	0.0020	0.0016	0.0016
Q III	0.0159	0.0040	0.0024	0.0023	0.0021
Q IV	0.0200	0.0068	0.0022	0.0023	0.0016
Q V	0.0295	0.0135	0.0041	0.0043	0.0045
Q V – Q I	0.0185***	0.0121***	0.0012**	0.0016***	0.0014**
	(<0.0001)	(<0.0001)	(0.025)	(0.002)	(0.015)
Panel B. Med Investor Sentiment					
Q I	0.0121	-0.0010	0.0006	0.0012	0.0009
Q II	0.0119	-0.0014	-0.0009	-0.0004	-0.0008
Q III	0.0120	-0.0022	-0.0021	-0.0019	-0.0015
Q IV	0.0127	-0.0022	-0.0026	-0.0016	-0.0011
Q V	0.0212	0.0039	0.0011	0.0023	0.0038
Q V – Q I	0.0091***	0.0050***	0.0005	0.0012**	0.0030***
	(<0.0001)	(<0.0001)	(0.351)	(0.046)	(<0.0001)
Panel C. High Investor Sentiment					
Q I	0.0122	0.0054	0.0047	0.0041	0.0045
Q II	0.0078	0.0055	0.0020	0.0020	0.0032
Q III	0.0039	0.0044	-0.0004	0.0005	0.0019
Q IV	0.0007	0.0019	-0.0023	-0.0003	0.0006
Q V	-0.0091	-0.0076	-0.0023	-0.0004	0.0005
Q V – Q I	-0.0213***	-0.0130***	-0.0070***	-0.0045***	-0.0040***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)

Table 4
Returns across Volatility Portfolios by Investor Sentiment

The table reports several measures of next-month returns across quintiles sorted by volatility in month *t.* The sample is divided into terciles based on investor sentiment. Low sentiment is defined as the lowest tercile of investor sentiment, while medium sentiment and high sentiment are the middle and highest tercile of investor sentiment respectively. Panel A reports return measures for periods of low investor sentiment. Panels B and C report return measures for periods of medium and high investor sentiment respectively. Column [1] details CRSP raw returns. Column [2] reports the excess returns, the difference between raw returns and monthly risk-free rates. Column [3] shows the results from adjusted returns, meaning the difference between raw returns and value-weighted market returns. Columns [4] through [6] report the estimated alpha from variations of the following equation.

$$Excess\ Return_{i,t+1} = \alpha + \beta_1 MRP_{t+1} + \beta_2 SMB_{t+1} + \beta_3 HML_{t+1} + \beta_4 UMD_{t+1} + \beta_5 LIQ_{t+1} + \varepsilon_{i,t+1}$$

The dependent variable is the excess return for stock *i* in month *t+1*. The independent variables include the market risk premium (MRP), the small the small-minus-big risk factor (*SMB*), the high-minus-low risk factor (*HML*), the Carhart (1997) up-minus-down risk factor (*UMD*), and the Pastor-Stambaugh (2003) liquidity risk factor (*LIQ*). *FF3F* is the alpha estimated from the above equation, excluding the last two risk factors (UMD and LIQ). FF4F is the obtained alpha estimated from the above equation, excluding only the liquidity risk factor (LIQ). Lastly, FF5F is the estimated alpha obtained from the usage of all factors outlined in the above equation. These measures are subsequently reported across quintiles sorted by idiosyncratic volatility within each of the three sentiment terciles (Low, Medium, and High). Additionally, differences between the extreme quintiles are reported along with their corresponding p-values. *, **, and *** represent statistical significance at 0.10, 0.05, and 0.01 levels respectively.

	Raw Returns	*Adj. Returns*	*FF3F Alphas*	*FF4F Alphas*	*FF5F Alphas*
	[1]	[2]	[3]	[4]	[5]
Panel A. Low Investor Sentiment					
Q I	0.0101	0.0012	0.0029	0.0027	0.0028
Q II	0.0105	0.0010	0.0013	0.0010	0.0010
Q III	0.0146	0.0040	0.0025	0.0021	0.0024
Q IV	0.0186	0.0055	0.0015	0.0014	0.0017
Q V	0.0345	0.0156	0.0027	0.0018	0.0018
Q V – Q I	0.0262***	0.0145***	-0.0003	-0.0010*	-0.0010*
	(<0.0001)	(<0.0001)	(0.633)	(0.077)	(0.095)
Panel B. Med Investor Sentiment					
Q I	0.0103	-0.0025	-0.0003	0.0007	0.0005
Q II	0.0113	-0.0017	-0.0007	0.0000	0.0002
Q III	0.0126	-0.0018	-0.0015	-0.0013	-0.0013
Q IV	0.0129	-0.0021	-0.0032	-0.0022	-0.0020
Q V	0.0229	0.0052	0.0013	0.0024	0.0038
Q V – Q I	0.0126***	0.0077***	0.0016***	0.0017***	0.0033***
	(<0.0001)	(<0.0001)	(0.004)	(0.003)	(<0.0001)
Panel C. High Investor Sentiment					
Q I	0.0144	0.0060	0.0058	0.0053	0.0057
Q II	0.0094	0.0058	0.0024	0.0022	0.0033
Q III	0.0035	0.0044	-0.0005	0.0002	0.0022
Q IV	-0.0009	0.0017	-0.0024	-0.0003	0.0007
Q V	-0.0107	-0.0082	-0.0029	-0.0007	-0.0002
Q V – Q I	-0.0251***	-0.0142***	-0.0088***	-0.0060***	-0.0059***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)

Table 5
Fama-MacBeth (1973) Regressions – Idiosyncratic Volatility

The table reports estimates from variations of the following equation using pooled stock-month observation.

$$Return_{i,t+1} = \beta_0 + \beta_1 Beta_{i,t} + \beta_2 ln(Size)_{i,t} + \beta_3 ln(B/M)_{i,t} + \beta_4 Mom_{i,t} + \beta_5 ln(Illiq)_{i,t} + \beta_6 IdioVolt_{i,t} + \varepsilon_{i,t+1}$$

The dependent variable is the raw return for stock *i* in month *t+1*. The independent variables, all measured at month *t* for stock *i*, will be described in turn. *Beta* is the beta estimate obtained from the daily Capital Asset Pricing Model over a six-month rolling period. *Ln(Size)* is the natural log of market capitalization on the last day of each month (in $ thousands). *Ln(B/M)* is the natural log of the book-to-market ratio, the market value and book value being obtained from CRSP and Compustat respectively. *Mom* is the cumulative return for stock *i* during months *t-12* to *t-2*. *Ln(Illiq)* is the natural log of illiquidity, which is the ratio of the absolute value of a daily return scaled by dollar volume (in 100,000s). *IdioVolt* is the standard deviation of the three-factor alpha for daily returns over a six-month rolling period. The above equation is estimated via the Fama-MacBeth (1973) method. Coefficients corresponding to the independent variables listed above are reported in columns [1] through [8]. P-values are estimated from Newey-West (1987) standard errors and are reported in parentheses below their corresponding coefficient. The sample is divided into terciles based on investor sentiment. Low sentiment is defined as the lowest tercile of investor sentiment, while medium sentiment and high sentiment are the middle and highest tercile of investor sentiment respectively. Fama-MacBeth (1973) regression results are reported for all sentiment periods in columns [1] and [2], while results obtained from low sentiment, medium sentiment, and high sentiment are reported in columns [3] and [4], columns [5] and [6], and columns [7] and [8] respectively. The odd columns ([1], [3], [5], and [7]) estimate coefficients for the above equation excluding the *ln(Illiq)* variable. Their complements, the even columns, estimate coefficients using all variables in the above equation. Significance is indicated by *, **, and *** representing statistical significance at 0.10, 0.05, and 0.01 levels respectively.

	All Observations		*Low Sentiment*		*Medium Sentiment*		*High Sentiment*	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Intercept	0.0226***	0.0498***	0.0198***	0.0544***	0.0078	0.0513***	0.0355***	0.0452***
	(<0.0001)	(<0.0001)	(0.006)	(<0.0001)	(0.289)	(<0.0001)	(<0.0001)	(0.0001)
$Beta_{i,t}$	0.0009	0.0002	0.0005	-0.0006***	0.0016	0.0010	0.0008	0.0004
	(0.173)	(0.696)	(0.686)	(<0.0001)	(0.130)	(0.253)	(0.503)	(0.724)
$Ln(Size)_{i,t}$	-0.0006	-0.0031***	-0.0006	-0.0039***	0.0003	-0.0038***	-0.0012*	-0.0020*
	(0.115)	(<0.0001)	(0.297)	(0.0001)	(0.626)	(0.0006)	(0.082)	(0.059)
$Ln(B/M)_{i,t}$	0.0028***	0.0027***	0.0019***	0.0018***	0.0031***	0.0029***	0.0032***	0.0032***
	(<0.0001)	(<0.0001)	(0.004)	(0.005)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
$Mom_{i,t}$	0.0123***	0.0125***	0.0069	0.0066	0.0114***	0.0113***	0.0174***	0.0181***
	(<0.0001)	(<0.0001)	(0.135)	(0.136)	(0.001)	(0.001)	(<0.0001)	(<0.0001)
$Ln(Illiq)_{i,t}$		-0.0018***		-0.0023***		-0.0028***		-0.0006
		(0.0002)		(0.003)		(0.002)		(0.470)
$IdioVolt_{i,t}$	-0.2211***	-0.2198***	-0.0411	-0.0055	0.0108	-0.0062	-0.5318***	-0.5448***
	(0.001)	(0.001)	(0.673)	(0.956)	(0.917)	(0.950)	(<0.0001)	(<0.0001)

Table 6
Fama-MacBeth (1973) Regressions - Volatitlity

The table reports estimates from variations of the following equation using pooled stock-month observation.

$$Return_{i,t+1} = \beta_0 + \beta_1 Beta_{i,t} + \beta_2 ln(Size)_{i,t} + \beta_3 ln(B/M)_{i,t} + \beta_4 Mom_{i,t} + \beta_5 ln(Illiq)_{i,t} + \beta_6 Volt_{i,t} + \varepsilon_{i,t+1}$$

The dependent variable is the raw return for stock *i* in month *t+1*. The independent variables, all measured at month *t* for stock *i*, will be described in turn. *Beta* is the beta estimate obtained from the daily Capital Asset Pricing Model over a six-month rolling period. *Ln(Size)* is the natural log of market capitalization on the last day of each month (in $thousands). *Ln(B/M)* is the natural log of the book-to-market ratio, the market value and book value being obtained from CRSP and Compustat respectively. *Mom* is the cumulative return for stock *i* during months *t-12* to *t-2*. *Ln(Illiq)* is the natural log of illiquidity, which is the ratio of the absolute value of a daily return scaled by dollar volume (in 100,000s). *Volt* is the standard deviation of daily returns over a six-month rolling period. The above equation is estimated via the Fama-MacBeth (1973) method. Coefficients corresponding to the independent variables listed above are reported in columns [1] through [8]. P-values are estimated from Newey-West (1987) standard errors and are reported in parentheses below their corresponding coefficient. The sample is divided into terciles based on investor sentiment. Low sentiment is defined as the lowest tercile of investor sentiment, while medium sentiment and high sentiment are the middle and highest tercile of investor sentiment respectively. Fama-MacBeth (1973) regression results are reported for all sentiment periods in columns [1] and [2], while results obtained from low sentiment, medium sentiment, and high sentiment are reported in columns [3] and [4], columns [5] and [6], and columns [7] and [8] respectively. The odd columns ([1], [3], [5], and [7]) estimate coefficients for the above equation excluding the *ln(Illiq)* variable. Their complements, the even columns, estimate coefficients using all variables in the above equation. Significance is indicated by *, **, and *** representing statistical significance at 0.10, 0.05, and 0.01 levels respectively.

	All Observations		*Low Sentiment*		*Medium Sentiment*		*High Sentiment*	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Intercept	0.0203***	0.0484***	0.0192***	0.0538***	0.0067	0.0497***	0.0310***	0.0430***
	(<0.0001)	(<0.0001)	(0.007)	(<0.0001)	(0.364)	(<0.0001)	(0.0004)	(0.0002)
Beta	0.0010	0.0003	0.0002	-0.0010	0.0017*	0.0011	0.0010	0.0007
	(0.133)	(0.6383)	(0.861)	(0.320)	(0.092)	(0.182)	(0.338)	(0.506)
Ln(Size)	-0.0004	-0.0030***	-0.0006	-0.0038***	0.0003	-0.0037***	-0.0008	-0.0019*
	(0.239)	(<0.0001)	(0.293)	(0.0001)	(0.587)	(0.001)	(0.217)	(0.067)
Ln(B/M)	0.0028***	0.0027***	0.0019***	0.0018***	0.0032***	0.0029***	0.0032***	0.0032***
	(<0.0001)	(<0.0001)	(0.003)	(0.004)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Mom	0.0121***	0.0123***	0.0069	0.0067	0.0111***	0.0111***	0.0170***	0.0177***
	(<0.0001)	(<0.0001)	(0.116)	(0.119)	(0.002)	(0.002)	(<0.0001)	(<0.0001)
Ln(Illiq)		-0.0018***		-0.0023***		-0.0028***		-0.0007
		(<0.0001)		(0.003)		(0.002)		(0.328)
Volt	-0.1908***	-0.1948***	-0.0211	0.0043	0.0268	0.0045	-0.4830***	-0.4975***
	(0.005)	(0.0042)	(0.836)	(0.967)	(0.800)	(0.964)	(0.0002)	(0.0001)

Table 7
Fama-MacBeth (1973) Regressions – Finer Idiosyncratic Volatility Quantiles

The table reports estimates from the following equation using pooled stock-month observation.

$$Return_{i,t+1} = \beta_0 + \beta_1 Beta_{i,t} + \beta_2 ln(Size)_{i,t} + \beta_3 ln(B/M)_{i,t} + \beta_4 Mom_{i,t} + \beta_5 ln(Illiq)_{i,t} + \beta_6 IdioVolt_{i,t} + \varepsilon_{i,t+1}$$

The dependent variable is the raw return for stock *i* in month *t+1*. The independent variables, all measured at month *t* for stock *i*, will be described in turn. *Beta* is the beta estimate obtained from the daily Capital Asset Pricing Model over a six-month rolling period. *Ln(Size)* is the natural log of market capitalization on the last day of each month (in $ thousands). *Ln(B/M)* is the natural log of the book-to-market ratio, the market value and book value being obtained from CRSP and Compustat respectively. *Mom* is the cumulative return for stock *i* during months *t-12* to *t-2*. *Ln(Illiq)* is the natural log of illiquidity, which is the ratio of the absolute value of a daily return scaled by dollar volume (in 100,000s). *IdioVolt* is the standard deviation of the three-factor alpha for daily returns over a six-month rolling period. The above equation is estimated via the Fama-MacBeth (1973) method. Coefficients corresponding to the independent variables listed above are reported in columns [1] through [4]. Associated p-values are estimated from Newey-West (1987) standard errors and are reported in parentheses below their corresponding coefficient. For this set of regressions, the sample is divided into both quintiles and deciles based on investor sentiment. Fama-Macbeth (1973) regression results are reported for the lowest and highest quintiles in columns [1] and [2]. Results from the lowest and highest deciles are reported in columns [3] and [4]. Significance is represented by *, **, and *** indicating statistical significance at 0.10, 0.05, and 0.01 levels respectively.

	Sentiment in lowest QUINTILE	Sentiment in highest QUINTILE	Sentiment in lowest DECILE	Sentiment in highest DECILE
	[1]	[2]	[3]	[4]
Intercept	0.0592***	0.0640***	0.0683***	0.0811***
	(0.0002)	(<0.0001)	(0.0002)	(0.0002)
Beta	0.0001	0.0017	0.0012	0.0038**
	(0.960)	(0.173)	(0.553)	(0.030)
Ln(Size)	-0.0047***	-0.0031**	-0.0051***	-0.0044**
	(0.001)	(0.018)	(0.0003)	(0.035)
Ln(B/M)	0.0022***	0.0035***	0.0020	0.0025***
	(0.008)	(<0.0001)	(0.134)	(0.003)
Mom	0.0021	0.0151***	0.0068	0.0174**
	(0.724)	(0.003)	(0.215)	(0.017)
Ln(Illiq)	-0.0032***	-0.0011	-0.0033***	-0.0011
	(0.002)	(0.291)	(0.005)	(0.468)
IdioVolt	0.2222*	-0.5043***	0.3886*	-0.5785**
	(0.088)	(0.003)	(0.0657)	(0.024)

Table 8
Fama-MacBeth (1973) Regressions – Finer Volatility Quantiles

The table reports estimates from the following equation using pooled stock-month observation.

$$Return_{i,t+1} = \beta_0 + \beta_1 Beta_{i,t} + \beta_2 ln(Size)_{i,t} + \beta_3 ln(B/M)_{i,t} + \beta_4 Mom_{i,t} + \beta_5 ln(Illiq)_{i,t} + \beta_6 Volt_{i,t} + \varepsilon_{i,t+1}$$

The dependent variable is the raw return for stock *i* in month *t+1*. The independent variables, all measured at month *t* for stock *i*, will be described in turn. *Beta* is the beta estimate obtained from the daily Capital Asset Pricing Model over a six-month rolling period. *Ln(Size)* is the natural log of market capitalization on the last day of each month (in $ thousands). *Ln(B/M)* is the natural log of the book-to-market ratio, the market value and book value being obtained from CRSP and Compustat respectively. *Mom* is the cumulative return for stock *i* during months *t-12* to *t-2*. *Ln(Illiq)* is the natural log of illiquidity, which is the ratio of the absolute value of a daily return scaled by dollar volume (in 100,000s). *Volt* is the standard deviation of daily returns over a six-month rolling period. The above equation is estimated via the Fama-MacBeth (1973) method. Coefficients corresponding to the independent variables listed above are reported in columns [1] through [4]. Associated p-values are estimated from Newey-West (1987) standard errors and are reported in parentheses below their corresponding coefficient. For this set of regressions, the sample is divided into both quintiles and deciles based on investor sentiment. Fama-Macbeth (1973) regression results are reported for the lowest and highest quintiles in columns [1] and [2]. Results from the lowest and highest deciles are reported in columns [3] and [4]. Significance is represented by *, **, and *** indicating statistical significance at 0.10, 0.05, and 0.01 levels respectively.

	Sentiment in lowest QUINTILE	Sentiment in highest QUINTILE	Sentiment in lowest DECILE	Sentiment in highest DECILE
	[1]	[2]	[3]	[4]
Intercept	0.0591***	0.0617***	0.0693***	0.0807***
	(0.0001)	(<0.0001)	(0.0002)	(0.0001)
Beta	-0.0011	0.0018	-0.0005	0.0040**
	(0.430)	(0.1565)	(0.823)	(0.015)
Ln(Size)	-0.0047***	-0.0030**	-0.0052***	-0.0045**
	(0.0004)	(0.018)	(0.0003)	(0.027)
Ln(B/M)	0.0021***	0.0035***	0.0020	0.0023***
	(0.007)	(<0.0001)	(0.122)	(0.004)
Mom	0.0028	0.0147***	0.0069	0.0171**
	(0.627)	(0.002)	(0.196)	(0.014)
Ln(Illiq)	-0.0031***	-0.0012	-0.0032***	-0.0014
	(0.002)	(0.193)	(0.005)	(0.328)
Volt	0.2283*	-0.4542***	0.4011*	-0.5354**
	(0.081)	(0.008)	(0.053)	(0.036)