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Anchoring bias, idiosyncratic volatility and the cross-section of stock returns

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ANCHORING BIAS, IDIOSYNCRATIC VOLATILITY AND THE CROSS-SECTION OF STOCK RETURNS

by

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ABSTRACT

Ang, Hodrick, Xing and Zhang (2006) document an anomaly in the cross-section of stock returns. They show that high idiosyncratic volatility (IVOL) firms earn lower returns in the following month. Specifically, they find after sorting stocks in quintile portfolios based on the previous month's IVOL that a zero-investment portfolio long the most volatile quintile of stocks and short the least yields about -1% during the subsequent month. The evidence reported in Ang, Hodrick, Xing and Zhang (2006) is primarily puzzling because traditional asset pricing theories suggest that (i) only systematic risk should be priced, (ii) to the extent that markets are complete, frictionless with well diversified investors, idiosyncratic volatility should not matter, and (iii) for incomplete markets with under-diversified investors, idiosyncratic volatility should be positively priced (See Merton (1987)).

In my dissertation, I test the implications of both the anchoring bias and investor sentiments for the idiosyncratic volatility puzzle. I posit that subjecting market participants to such behavioral biases can go a long way in helping us understand this puzzling volatility-return relationship for which the recent empirical evidence is mixed. I consider in this study the possibility that investors are affected by anchoring bias. Employing George and Hwang (2004) measure of Nearness to 52-week high, I form and investigate the two primary hypotheses.

If market participants do anchor on the 52-week high and stocks for which bad news recently reached the market are overpriced (as shown by George and Hwang (2004)) and idiosyncratic volatility is seen as a proxy for uncertainty (Johnson (2004)), short-sale constraints (Nagel (2005) and George and Hwang (2011)) or arbitrage risk (Ali, Hwang and Trombley (2003), then I should expect the negative relationship between idiosyncratic volatility and stock returns to be stronger for stocks that are the farther away from their 52-week high price. Further, I note that Veronesi (1999) proposes a model of overreaction to bad news in good times. He argues and shows that in good times, bad news signals increased uncertainty and greater likelihood negative future performance, both of which lower stock prices and lead to negative returns. I therefore hypothesize that the IVOL puzzle should be stronger when bad news reaches the market in good times.

I report robust empirical evidence consistent with my hypotheses using U.S data from 1965 to 2012. I first investigate the presence of the IVOL puzzle in my sample using a portfolio sorting approach. I find that the choice of data frequency to estimate idiosyncratic volatility, weighing scheme and breakpoints all play an important role in the relationship between IVOL and future returns. After investigating whether anchoring on the 52-week high can explain the IVOL puzzle, I find a strong and robust negative relationship between IVOL and future returns for stocks that are away from their 52-week high. In addition, I also find that my previous results persist up to six months following portfolio formation. I also document that there exist, for stocks that are far from their 52-week high, an even stronger negative volatility-return relationship in period where investors sentiments are at their highest. That is, the negative relationship between

IVOL and future returns is even stronger when bad news reaches the market in good times.

The evidence I present appear to be consistent with the notion that investors are affected by anchoring bias, a behavior that contributes to the overpricing of stocks that move away from their 52-week high prices as shown by George and Hwang (2004). My results are further consistent with the views in the finance literature suggesting that idiosyncratic volatility could serve as a proxy for uncertainty (See Johnson (2004)), short-sale constraints (See Nagel (2005) and George and Hwang (2011)) or arbitrage risk (See Ali, Hwang and Trombley (2003)). Moreover, I find that all my results are even stronger with the arrival of bad news in good times; a piece of evidence consistent with the proposition of Veronesi (1999). Finally, all these results cannot be explained by other known risk factors, momentum, book-to-market, as well as the January effect.

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DEDICATION

I dedicate this work to my family. To Dad, Mum, and my brothers and sisters (Clairine, Nadine, Judith, Fabrice, Badel, Romuald, Doris and Vanessa), distance was never an issue. I would never have made it without your love and unwavering support. To Marie-Louise, my wife and best friend, you have been a calming force and showed patience and understanding during this chaotic time. I hope this work honors you and I love you all.

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CHAPTER ONE

INTRODUCTION

In an influential article, Ang, Hodrick, Xing and Zhang (2006) (hereafter AHXZ) document an anomaly in the cross-section of stock returns: High idiosyncratic volatility (IVOL) firms earn lower subsequent returns. Specifically, they find after sorting stocks in quintile portfolios based on the previous month's IVOL that a zero-investment portfolio long the most volatile quintile of stocks and short the least yields about -1% during the subsequent month. This result is essential and primarily puzzling because traditional asset pricing theories suggest that (i) only systematic risk should be priced, (ii) to the extent that markets are complete, frictionless with well diversified investors, idiosyncratic volatility should not matter, and (iii) for incomplete markets with under-diversified investors, idiosyncratic volatility should be positively priced (See Merton (1987)).

Following this study, several researchers have examined the robustness of their findings. Among others, Huang et al. (2010) argue that this negative relationship between IVOL and future returns is induced by the well-known short-term negative serial correlation that exists in monthly stock returns. However, Peterson and Smedema (2011) show that the findings of AHXZ are particularly robust in Non-January months, even after controlling for the previous month's return.

Tversky and Khaneman (1974) also report in their seminal work, that individuals tend to adopt heuristics to cope with uncertainty. However, adopting such heuristic for decision making can also lead to systematically skewed results. Among such heuristics, is their now well-documented anchoring and adjustment bias,[1] an individual cognitive predisposition whereby, under uncertainty, individuals tend to form numerical estimates through adjustment from an initial (available yet potentially irrelevant) value known as the "anchor."

In a recent study, George and Hwang (2004) demonstrate that traders do anchor on the 52-week high price when evaluating the potential impact of news. They suggest that a stock that moves closer to its 52-week high price is one for which good news recently reached the market, and one that moves away from its 52-week high price is one for which bad news recently arrived. Further, they find that stocks for which bad news recently reached the market are overpriced because traders are unwilling to sell those stocks whereas stocks for which good news recently arrived are underpriced because traders are reluctant to bid the price of those stocks higher.[2]

I posit that subjecting market participants to such behavioral biases can go a long way in helping us understand this puzzling volatility-return[3] relationship for which the recent empirical evidence is mixed. I consider in this study the possibility that investors are affected by anchoring bias. Employing George and Hwang (2004) measure of Nearness to 52-week high, I form and investigate the following hypotheses.

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[1] Several other studies document the robustness of this cognitive predisposition. Among others are Russo and Schoemaker (1989), Qu, Zhou and Luo (2008), Brewer, Chapman, Schartz and Bergus (2007).
[2] See George and Hwang (2004) for more detailed explanation.
[3] As volatility in this study refers to idiosyncratic volatility, volatility-return refers to the IVOL-return relationship.

If market participants do anchor on the 52-week high and stocks for which bad news recently reached the market are overpriced (as shown by George and Hwang (2004)) and idiosyncratic volatility is seen as a proxy for uncertainty (Johnson (2004)), short-sale constraints (Nagel (2005) and George and Hwang (2011)) or arbitrage risk (Ali, Hwang and Trombley (2003), then I should expect the negative relationship between idiosyncratic volatility and stock returns to be stronger for stocks that are the farther away from their 52-week high price. Further, I note that Veronesi (1999) proposes a model of overreaction to bad news in good times. He argues and shows that in good times, bad news signals increased uncertainty and greater likelihood negative future performance, both of which lower stock prices and lead to negative returns. I therefore hypothesize that the IVOL puzzle should be stronger when bad news reaches the market in good times.

I report robust empirical evidence consistent with my hypotheses using U.S data from 1965 to 2012. I first investigate the presence of the IVOL puzzle in my sample using a portfolio sorting approach. I find that the choice of data frequency to estimate idiosyncratic volatility, weighing scheme and breakpoints all play an important role in the relationship between IVOL and future returns. I next examine whether anchoring on the 52-week high can explain the IVOL puzzle. In this case, I perform a double sort on the nearness to the 52-week high first, and then on IVOL. I find a strong and robust negative relationship between IVOL and future returns for stocks that are away from their 52-week high. In addition, my previous results persist up to six months following portfolio formation. I also document that there exist, for stocks that are far from their 52-week high, an even stronger negative volatility-return relationship in period where investors sentiments are at their highest. That is, the negative relationship between IVOL and future returns is even stronger when bad news reaches the market in good times.

To summarize, I find that the arrival of bad news exacerbates the negative relationship between idiosyncratic volatility and future stock returns. The evidence I present appear to be consistent with the notion that investors are affected by anchoring bias, a behavior that contributes to the overpricing of stocks that move away from their 52-week high prices as shown by George and Hwang (2004). My results are further consistent with the views in the finance literature suggesting that idiosyncratic volatility could serve as a proxy for uncertainty (See Johnson (2004)), short-sale constraints (See Nagel (2005) and George and Hwang (2011)) or arbitrage risk (See Ali, Hwang and Trombley (2003)). Moreover, I find that all my results are even stronger with the arrival of bad news in good times; a piece of evidence consistent with the proposition of Veronesi (1999). Finally, all these results cannot be explained by other known risk factors, momentum, book-to-market, as well as the January effect.

While I pursue a goal similar to that of the previous studies attempting to understand the idiosyncratic volatility puzzle, this study adopts a fundamentally different perspective. To the best of my knowledge, this study is the first of its kind attempting to understand the implications of such a cognitive bias for the volatility-return relationship. Ultimately, the results I present in this study shed new lights on the idiosyncratic volatility anomaly, hence contribute in advancing my understanding of financial markets. My findings therefore suggest that inquiries on such issues as the source of the negative volatility-return relationship documented in AHXZ (2006) and potentially other asset pricing anomalies should not ignore the importance of investors' heuristics such as the well-documented anchoring bias and others.

The remainder of this study is organized as follows. Chapter Two reviews the literature and discusses motivation and hypothesis development. Chapter Three describes the sample and discusses the definition of the key variables I use in the various tests. Chapter Four presents and discusses the results of the empirical investigations. In Chapter Five, I summarize the study and conclude with some general observations.

CHAPTER TWO

MOTIVATION AND HYPOTHESIS DEVELOPMENT

Following the influential work of AHXZ (2006) documenting a negative relationship between idiosyncratic volatility and future returns, researchers have been relentless in their efforts to provide possible explanations to this anomaly. Among candidate explanations reported in the finance literature are those based on uncertainty (Johnson (2004)), illiquidity (Bali and Cakici (2008) and Han and Lesmond (2011)), growth options (Cao, Simin, and Zhao (2008) and Chen and Petkova (2012)), coskewness (Chabi-Yo and Yang (2009)), short-sale constraints (Nagel (2005) and George and Hwang (2011)) and one-month return reversal (Fu (2009) and Huang, Liu, Rhee, and Zhang (2010)).

Researchers such as Jiang, Xu, and Yao (2009) and Wong (2011) have also documented the role of earnings shocks, expected idiosyncratic skewness (Boyer, Mitton, and Vorkink (2010)), investor attention (George and Hwang (2011)), maximum daily return (Bali, Cakici, and Whitelaw (2011)), retail trading proportion (Han and Kumar (2013)), financial distress (Avramov, Chordia, Jostova, and Philipov (2013)), average variance beta (Chen and Petkova (2012)), and prospect theory (Bhootra and Hur (2013) in helping us understand better this volatility-return relationship.

While the empirical results reported on this issue are somewhat mixed, what remains clear is that this anomaly persists and is still evident in asset prices today. Nonetheless, a growing body of the literature in finance builds on the evidence reported in the psychology literature to foster our understanding of the behavior of asset prices. Of particular interest to this study are the findings of George and Hwang (2004) who develop a trading strategy based on a stock nearness to its 52-week high. They attribute the success of their investment strategy to the "adjustment and anchoring" bias of Tversky and Khaneman (1974), and argue that this bias causes investors to underreact to positive (negative) information about stocks for which current prices are near (far from) their 52-week high prices. In their view, a stock that is near its 52-week high is a stock for which good news recently arrived in the market whereas a stock that moves away from its 52-week high is one for which bad news recently reached the market. An interesting fact documented in George and Hwang (2004) is that stocks whose current prices are far from their 52-week high are overpriced because investors are unwilling to sell those stocks and those whose current prices are near their 52-week high are underpriced because investors are reluctant to bid the price of those stocks higher.

Putting these two strands of the literature together, I form the following two hypotheses. First, if market participants do in fact anchor on the 52-week high price and stocks for which bad news recently reached the market are overpriced (as shown by George and Hwang (2004)), then I should expect the negative relationship between idiosyncratic volatility and future stock returns to be stronger for stocks that are the farther away from their 52-week high prices. With the arrival of bad news in the market, idiosyncratic volatility could be seen as a proxy for uncertainty as suggested by Johnson

(2004).[4] This would explain the existence of a possible stronger negative volatility-return relationship for the high IVOL stocks that move away from their 52-week highs because uncertainty delays the reflection of bad information into stock price, causing those stocks overpriced. Alternatively, idiosyncratic volatility could also proxy for short-sales constraints as suggested by Nagel (2005) and George and Hwang (2011).[5] In this case, increased idiosyncratic volatility would limit the ability of arbitrageurs to take advantage of these already overpriced stocks, leading to further negative returns for stocks whose current prices are farther away from their 52-week highs. This later view would also be consistent with the notions that idiosyncratic volatility can be seen as a proxy for arbitrage risk (See Ali, Hwang and Trombley (2003)).

Hypothesis 1: The negative relationship between idiosyncratic volatility and future returns documented by Ang et al. (2006) should be concentrated in stocks that are the farther away from their 52-week high prices.

Next, Veronesi (1999) proposes a model of overreaction to bad news in good times. He argues and shows that in good times, bad news signals increased uncertainty and greater likelihood negative future performance, both of which lower stock prices and lead to negative returns. However, in bad times, bad news signals reduced uncertainty (confirming the bad state of the economy), which has the opposite effect on prices. I therefore hypothesize that the negative relationship between idiosyncratic volatility and future returns for stocks that are far from their 52-week high price should be even

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[4] While Johnson (2004) demonstrate that forecast dispersion proxy for idiosyncratic risk, Diether, Malloy and Scherbuna (2002) argue that it is the uncertainty about projected earnings that gives rise to forecast dispersion.

[5] According to Nagel (2005), short sales are difficult for high volatility stocks because of the severe short sale constraints related to the low institutional holdings of these stocks.

stronger when bad news reaches the market in good times (periods of high investors' sentiments).

Hypothesis 2: For stocks that are far from their 52-week high price, there exist an even stronger negative relationship between idiosyncratic volatility and future returns in periods with high investors' sentiments.

CHAPTER THREE

SAMPLE SELECTION AND DATA DESCRIPTION

My sample covers the period from January 1965 to December 2012. I obtain daily and monthly returns, prices and shares outstanding for all the stocks traded on the NYSE, AMEX, and NASDAQ from the Center for Research in Security Prices (CRSP). I limit my sample to firms with common share code 10 and 11 and stocks worth $5 or more each month following Jiang, Xu and Yao (2009).[6] This approach is common in the finance literature and is often used to eliminate the effects of small and illiquid stocks.[7] I obtain monthly Fama-French factors returns, NYSE market capitalization decile breakpoints, and monthly risk-free rates from Kenneth French's website.[8] I follow Brandt et al. (2010) to exclude the stocks with fewer than twelve daily observations in any given month at the end of each portfolio formation month respectively.[9]

For each firm, I also compute the book to market ratio (BTM) using additional information collected from Compustat. Book-to-market is defined as the ratio of fiscal year-end book equity plus the balance sheet deferred taxes in the prior year to market equity in December of that year. As is common in the literature, I define firm size as the

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[6] I find consistent results using a sample without price restriction.
[7] Jiang et al. (2009) argue that eliminating stocks with prices less than $5 helps avoiding market microstructure related issues.
[8] This data can be found at the following address: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.
[9] Brandt et al. (2010) argue in favor of eliminating stocks with less than 12 daily observations in any given month to reduce the noise related to the computation of idiosyncratic volatility.

logarithm of market capitalization. I also follow Amihud (2002) in computing a measure of illiquidity for every stock in my sample and for every month. My illiquidity measure (ILLIQ) is therefore defined as the ratio of a stocks' absolute monthly return to its dollar trading volume.

The 52-week high price of a stock is the highest closing price of the stock during the previous 52 weeks, as reported in the CRSP daily files. I follow George and Hwang (2004) in the identification of the 52-week high prices and the computation of their measure of nearness to the 52-week high price. That is, I first make sure I adjust my price variables for stock splits and dividends using the CRSP price adjustment factor. I then compute the measure of nearness to the 52-week high price (GH Ratio)[10] at the end of every month for every stock in my sample as the ratio of the stock's current price over its 52-week high price. It is given by:

$$GH = \frac{Current\ Price}{52\text{–}Week\ High\ Price} \tag{1}$$

The GH Ratio reaches its maximum at one when a stock's month end price is the 52 week-high price. As suggested in George and Hwang (2004), stocks with high GH are those for which good news recently arrived in the market, and those with low GH are those for which bad news recently arrived in the market.

We follow Bali and Cakici (2008) and use both daily and monthly stock returns to generate my idiosyncratic volatility measures. To obtain my first volatility measure (Ivol^{daily}), I first estimate each individual stock's daily volatility as the standard deviation of the residuals from the regression of the daily excess returns on the daily Fama-French

[10] I refer to the George and Hwang (2004) measure of nearness to 52-week high as the GH ratio or simply GH in the remainder of this study.

three factors (Fama and French, 1993, 1996). That is, for every month t, I estimate the following equation from which I save the standard deviation of the residuals $(\varepsilon_{i,d})$:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i(R_{m,d} - r_{f,d}) + \theta_i SMB_d + \delta_i HML_d + \varepsilon_{i,d} \tag{2}$$

Where $R_{i,d}$ is the rate of return on stock i on day d, $r_{f,d}$ is the risk free rate on day d, $R_{m,d}, SMB_d, HML_d$ are the return of market, Size, Book-to-Market factors on day d, respectively. Finally, $\varepsilon_{i,d}$ is the residual of stock i on day d.

Our stocks' first monthly idiosyncratic volatility measures are then obtained by multiplying the standard deviation of the residuals from the equation (2) above by the square root of the number of trading days for the given month.

$$\text{Ivol}^{\text{daily}} = \sqrt{Var(\varepsilon_{i,d})} \times \sqrt{D_{i,t}} \tag{3}$$

Where $D_{i,t}$ is the number of trading days for stock i in month t. My second volatility measure ($\text{Ivol}^{monthly}$) is obtained using monthly stock returns following Bali and Cakici (2008), Lehmann (1990), and Malkiel and Xu (2002). Every month t, I regress the stocks excess returns on the monthly Fama and French factors. I then compute $\text{Ivol}^{monthly}$ as the standard deviation of the residuals from these monthly regressions over the previous 24 to 60 months as available.

We focus the early discussion of this paper on verifying the existence of the negative relationship between idiosyncratic volatility and future returns for my sample. I then investigate the role of anchoring bias in the idiosyncratic volatility puzzle and finally consider the role of the January effect as well as that of investor sentiments on this volatility-return relationship after controlling for anchoring bias.

CHAPTER FOUR

RESULTS

Idiosyncratic Volatility and Future Returns

We start my analysis with an investigation of the presence of the idiosyncratic volatility puzzle in my sample using both measures of IVOL. Table 1 reports average equal and value weighted monthly returns of quintile portfolios formed on my idiosyncratic volatility measures. In Panel A of this table, I report results from univariate sorts on $Ivol^{daily}$ for my entire sample over the period between 1965 and 2012. V1 (V5) is portfolio of stocks in the bottom (top) quintile of IVOL. I find a strong negative relationship between $Ivol^{daily}$ and equal-weighted returns when portfolios are formed using CRSP breakpoints.

Specifically, the equal-weighted return differential between V5 and V1 is -0.62% per month, a difference that I also find to be statistically significant with a t-statistic of -2.54. Moreover, the corresponding Fama-French alpha (FF-Alpha) is also found to be negative and statistically significant at -0.88% with a t-statistic of -5.60. However, when returns are value-weighted, the return differential between V5 and V1 is -0.51% per month, yet only weakly significant with a t-statistic of -1.76. Although the return differential between V5 and V1 proves weakly significant in this case, I find the FF-Alpha to be negative (-0.74%) and statistically significant (t-statistic = -3.79).

As in Bali and Cakici (2008), I also investigate the effect of the size (market share) distribution of my CRSP-based idiosyncratic volatility portfolios on this volatility-return relationship. I find similar to Bali and Cakici (2008) that although V5 and V1 both contain 20% of the stocks sorted on $Ivol^{daily}$, V5 is mostly made up of extremely small stocks (market share = 2.38%) whereas V1 is made up of large companies (market share = 45.07%).[11]

To eliminate potential concerns about the noteworthy market share differential between V5 and V1, Bali and Cakici (2008) form portfolios based on NYSE breakpoints and "Equal" market share. I follow their approach and find results consistent with their findings. When portfolios are formed based on NYSE breakpoints, the market share spread between V5 and V1 reduces but remains relatively important; V1 contains stocks with a total market share of 32.61% whereas V5 contains stocks with a total market share of 9.19%. The value (equal) weighted return differential between V5 and V1 is found to be -0.14% (-0.33%) per month with a t-statistic of -0.56 (-1.55). Yet, the corresponding FF-Alphas at -0.39% and -0.61% both prove to be negative and statistically significant with a t-statistics of -2.30 and -4.77 respectively.

Forming portfolios based on "Equal" market share, I give up the equal idiosyncratic volatility distribution of my portfolios and allow each portfolio to contain the same fraction of the market share (20%). Doing this eliminates the strong negative equal-weighted return differential between V5 and V1 previously documented in Bali and Cakici (2008), but the corresponding FF-Alpha (-0.40%) is negative and statistically significant (t-statistic = -3.12). I find no negative relationship between return and

[11] Market share is available upon request.

$Ivol^{daily}$ for value-weighted returns. However, I find the FF-Alphas to be negative and statistically significant in five out of the six scenarios in Panel A of Table 1.

Panel B of Table 1 reports the results from a similar exercise using an alternative measure of idiosyncratic volatility ($Ivol^{monthly}$). When portfolios are formed based on CRSP breakpoints, I find negative but insignificant value and equal-weighted return differentials between V5 and V1. The corresponding FF-Alphas in this case are also negative, but only significant for equal-weighted returns (-0.41% with a t-statistic of -2.51). Using NYSE breakpoints, my results mirror those obtained with CRSP breakpoints. Here, the FF-Alphas are also negative and only significant for equal-weighted returns (-0.29% with a t-statistic of -2.47). Finally, results obtained after using "Equal" market share breakpoints suggest no significant relationship between $Ivol^{monthly}$ and future returns (both value and equal weighted), the corresponding FF-Alphas being negative and insignificant as well.

Overall, the results obtained from Table 1 closely replicate the findings of Bali and Cakici (2008).[12] My results confirm their proposition that the choice of data frequency, weighing scheme and breakpoints all play an important role in the relationship between idiosyncratic volatility (however defined) and future returns. I therefore move to provide, in the following sections, evidence of the role of anchoring bias on the idiosyncratic volatility puzzle under these various setups.

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[12] These research findings do not exactly replicate the findings of Bali and Cakici (2008) because of $5 price restriction and sample period.

Table 1

Average Monthly Returns of Portfolio Sorted on Idiosyncratic Volatility

	CRSP Breakpoints		NYSE Breakpoints		20% Market Share	
	Value-weighted Returns	Equal-weighted Returns	Value-weighted Returns	Equal-weighted Returns	Value-weighted Returns	Equal-weighted Returns
			Panel A: Using Daily Data (Ivol^{daily})			
V1	0.82	1.09	0.83	1.08	0.77	1.01
2	0.90	1.29	0.95	1.28	0.95	1.20
3	1.05	1.33	0.96	1.32	0.90	1.26
4	0.93	1.19	1.06	1.35	0.89	1.29
V5	0.32	0.47	0.70	0.75	0.79	0.89
V5-V1	-0.51	-0.62	-0.14	-0.33	0.02	-0.12
	(-1.76)	(-2.54)	(-0.56)	(-1.55)	(0.08)	(-0.56)
FF-Alpha	-0.74	-0.88	-0.39	-0.61	-0.18	-0.40
	(-3.79)	(-5.60)	(-2.30)	(-4.77)	(-1.12)	(-3.12)
			Panel B: Using Monthly Data (Ivol^{monthly})			
V1	0.86	1.10	0.85	1.10	0.77	1.00
2	0.96	1.23	0.94	1.20	0.91	1.08
3	1.03	1.24	0.98	1.26	0.86	1.16
4	1.04	1.24	1.05	1.25	0.94	1.23
V5	0.75	0.92	0.91	1.07	0.94	1.12
V5-V1	-0.11	-0.18	0.06	-0.03	0.17	0.12
	(-0.36)	(-0.76)	(0.25)	(-0.14)	(0.77)	(0.60)
FF-Alpha	-0.28	-0.41	-0.13	-0.29	-0.01	-0.18
	(-1.58)	(-2.51)	(-0.94)	(-2.47)	(-0.01)	(-1.63)

This table reports value and equally-weighted monthly returns of the quintile portfolios formed on idiosyncratic volatility. Quintile portfolios are formed on idiosyncratic volatility every month from January 1965 to December 2012. In Panel A, monthly idiosyncratic volatilities are the square root of the number of trading days times the daily idiosyncratic volatility, the standard deviation of residuals from the regression of excess daily stock returns on the contemporaneous daily Fama-French factors in the month. In Panel B, monthly idiosyncratic volatilities are the standard deviation of residuals from the regression of excess monthly stock returns on the contemporaneous monthly Fama-French factors using the previous 24 to 60 monthly returns (as available) each month. V1 (V5) is portfolio of stocks in the bottom (top) quintile of IVOL. Newey-West (1978) adjusted t-statistics are reported in parenthesis. Alpha reports Fama-French three factor alpha.

The Role of the 52-Week High Price Anchor

The finance literature has struggled with the puzzling findings of Ang, Hodrick, Xing, and Zhang (2006, 2009) that high idiosyncratic volatility stocks earn low future returns. Although this puzzle has been extensively investigated in the literature, an important and widely accepted aspect of the behavior of investors has proven to be absent from this debate. In this section, I investigate the role of anchoring bias as it pertains to the 52-week high price on the idiosyncratic volatility puzzle.

George and Hwang (2004) suggest that stocks whose current prices are close to their 52-week highs are the ones for which good news recently arrived in the market whereas stocks whose current prices are far away from their 52-week high prices are ones for which bad news recently reached the market. They further argue that, because of this anchoring bias, stocks with good news are underpriced while those with bad news are overpriced.

My primary hypothesis is that the high idiosyncratic volatility stocks that are far away from their 52-week high prices are more overpriced; a proposition consistent with the view of high idiosyncratic volatility as a proxy for short sale constraint (See Nagel (2005) for details), arbitrage risk, Ali, Hwang and Trombley (2003), and uncertainty (Johnson (2004)). This implies that I should expect a stronger negative relationship between idiosyncratic volatility and future returns for stocks that move far away from their 52-weeh high. However, stocks close to their 52-week high prices are not affected by idiosyncratic volatility because short sale constraint does not affect underpriced stocks.

To allow variations in IVOL to be unrelated to my measure of nearness to 52-week high price (GH), I employ a double sorting portfolio approach. First, at the end of every month, I rank the stocks in my sample based on their respective GH ratio and form quintile portfolios. I then subdivide each GH quintile into five portfolios on the basis of the stocks' respective idiosyncratic volatilities. I obtain 25 GH-IVOL portfolios. In the spirit of Bali and Cakici (2008), I also set my breakpoints for each IVOL quintile portfolio using CRSP, NYSE and "Equal" Market Share. For robustness, I investigate the relationship between IVOL and future returns for measures of IVOL computed using both daily and monthly data. Table 2 presents results obtained using CRSP breakpoints while Tables 3 and 4 do the same for both NYSE and "Equal" Market Share breakpoints, respectively.

To demonstrate the dispersion of stocks in my GH portfolios, Panel A of Table 2 reports both value and equal weighted GH. While stocks in GH1 group have 0.51 and 0.52 in terms of value and equal weighted average of GH respectively, those in GH5 have 0.96 of GH in both value and equal weighted average. It implies that stocks in GH1 have current price close to half of the 52-week high price, but those in GH5 are currently near their 52-week high price.

Table 2

Average Monthly Returns of Portfolio Sorted on GH and Idiosyncratic Volatility: CRSP Breakpoints

	Value-weighted Returns					Equal-weighted Returns				
	GH1	2	3	4	GH5	GH1	2	3	4	GH5
Panel A: Average GH										
	0.51	0.72	0.82	0.89	0.96	0.52	0.72	0.82	0.89	0.96
Panel B: Using Daily Data ($Ivol^{daily}$)										
V1	1.20	1.12	0.91	0.98	0.74	1.44	1.24	1.11	1.08	1.02
2	1.12	1.03	0.98	0.9	0.75	1.40	1.39	1.32	1.19	1.12
3	0.98	0.92	0.97	0.92	0.90	1.12	1.24	1.35	1.35	1.22
4	0.21	0.54	0.72	1.22	1.07	0.58	0.91	1.26	1.51	1.34
V5	-0.71	0.00	0.67	1.12	1.28	-0.49	0.3	0.92	1.28	1.38
V5-V1	-1.91	-1.12	-0.24	0.15	0.55	-1.93	-0.94	-0.19	0.20	0.36
	(-6.34)	(-4.22)	(-0.96)	(0.56)	(2.05)	(-9.06)	(-4.90)	(-0.93)	(0.96)	(1.75)
FF-	-2.26	-1.31	-0.49	0.04	0.49	-2.11	-1.12	-0.43	-0.03	0.16
Alpha	(-9.71)	(-6.04)	(-2.50)	(0.19)	(1.83)	(-12.93)	(-6.74)	(-2.43)	(-0.16)	(0.86)
Panel C: Using Monthly Data ($Ivol^{monthly}$)										
V1	1.11	0.95	0.91	0.91	0.71	1.4	1.36	1.27	1.07	0.86
2	0.95	0.89	0.83	0.89	0.71	1.28	1.23	1.19	1.15	0.97
3	0.79	0.95	0.77	1.12	0.91	0.98	1.06	1.19	1.2	1.12
4	0.50	0.90	0.91	1.21	1.31	0.66	1.07	1.22	1.34	1.36
V5	0.08	0.45	0.90	1.30	1.46	0.25	0.67	1.18	1.62	1.67
V5-V1	-1.03	-0.50	-0.01	0.39	0.75	-1.15	-0.70	-0.09	0.55	0.81
	(-3.57)	(-1.84)	(-0.05)	(1.40)	(2.99)	(-4.55)	(-3.08)	(-0.38)	(2.38)	(3.80)
FF-	-1.24	-0.65	-0.24	0.25	0.65	-1.25	-0.82	-0.30	0.33	0.64
Alpha	(-5.08)	(-2.92)	(-1.10)	(1.06)	(2.97)	(-7.53)	(-4.73)	(-1.57)	(1.58)	(3.55)

This table reports value and equally-weighted monthly returns of the quintile portfolios formed on GH (George and Hwang Ratio: current price/52-week high price) and idiosyncratic volatility. Quintile portfolios are formed on GH first and then idiosyncratic volatility within each GH portfolio each month from January 1965 to December 2012. In Panel A, monthly idiosyncratic volatilities are the square root of the number of trading days times the daily idiosyncratic volatility, the standard deviation of residuals from the regression of excess daily stock returns on the contemporaneous daily Fama-French factors in the month. In Panel B, monthly idiosyncratic volatilities are the standard deviation of residuals from the regression of excess monthly stock returns on the contemporaneous monthly Fama-French factors using the previous 24 to 60 monthly returns (as available) each month. V1 (V5) is portfolio of stocks in the bottom (top) quintile of IVOL. Newey-West (1978) adjusted t-statistics are reported in parenthesis. Alpha reports Fama-French three factor alpha.

Panel B of Table 2 presents results obtained using a measure of IVOL computed using daily data (Ivol^{daily}). I find that, after controlling for GH, both value and equal weighted return differentials between the V5 and V1 are negative and strongly significant only for stocks that belong to the lowest and the second lowest GH quintiles. Specifically, I find that for stocks that are the farthest away from their 52-week high prices (those that belong to GH1), the value weighted return differential between V5 and V1 is -1.91% per month with a t-statistic of -6.34. Similarly, when returns are equally weighted, I find that for stocks that belong to GH1, the return differential between V5 and V1 is also negative (-1.93% per month) and strongly significant (t-statistic = -9.06). In addition, I also find the corresponding FF-Alphas to be negative and strongly significant in both cases. For value-weighted returns and for the lowest GH quintile (GH1), I find the FF-Alpha to be -2.26% with a t-statistic of -9.71. When equally-weighted, the FF-Alpha for this group of stocks also proves to be negative (-2.11%) and even stronger in significance (t-statistic = -12.93).

However, when I consider stocks that are closer to their 52-week high prices, those that belong to the highest GH quintile (GH5), I find that the value-weighted return differential between V5 and V1 is positive (0.55% per month) and significant as well (t-statistic = 2.05). The corresponding FF-Alpha is also found to be positive (0.49% per month) but only marginally significant (t-statistic = 1.83). Likewise, the equal-weighted return differential between V5 and V1 for GH5 also proves positive (0.36% per month), but only marginally significant (t-statistic = 1.75). I find the FF-Alpha in this case to be positive yet insignificant (0.16% with a t-statistic of 0.86). The results I report so far are consistent with my first hypothesis, suggesting that there is indeed a strong negative relationship between idiosyncratic volatility and future returns only for stocks far away from their 52-week high prices.

Panel C of Table 2 presents results obtained using a measure of IVOL computed using monthly data ($Ivol^{monthly}$). These results are comparable to the ones I obtain in Panel B of Table 2. The negative relationship between IVOL and future returns appears to be concentrated in stocks that belong to the lowest and the second lowest GH portfolio (GH1 and GH2) for both value and equal-weighted returns. For example, when value (equal) weighted, I find the return differential between V5 and V1 for stocks in GH1 to be -1.03% (-1.15%) per month, with a t-statistic of -3.57(-4.55). Similarly, I find the corresponding FF-Alphas to be negative (-1.24% and -1.25%) and strongly significant (t-statistic of -5.08 and -7.53 respectively).

To provide robust evidence for my findings, I further investigate the volatility-return relationship for GH-IVOL portfolios based on NYSE and "Equal" Market Share breakpoints. In Table 3, I present results obtained using NYSE breakpoints. While Panel A of this table reports evidence using $Ivol^{daily}$, Panel B reports results obtained using $Ivol^{monthly}$.

Table 3 shows that forming my IVOL (however defined) quintile portfolios based on NYSE breakpoints does not eliminate my previous findings. In fact, I find strong negative relationship between IVOL and future returns for stocks in the lowest GH quintile (GH1). Using $Ivol^{daily}$ in Panel A of Table 3, I find that the value (equal) weighted return on V1 exceeds that of V5 by an average of 1.41% (1.50%) per month, with a t-statistic of -5.00 (-6.94). I also find the FF-Alphas to be negative and strongly significant in both cases. However, for stocks in GH5, I find that the value (equal)-

weighted return differential between V5 and V1 is positive 0.50% (0.35%) per month and significant as well with a t-statistic of 2.47 (1.99). The corresponding FF-Alpha is found to be positively significant 0.40% per month with a t-statistic of 2.12 for value-weighted return, but it is insignificant 0.14% per month (t-statistic = 0.88).

Table 3

Average Monthly Returns of Portfolio Sorted on GH and Idiosyncratic Volatility: NYSE Breakpoints

	Value-weighted Returns					**Equal-weighted Returns**				
	GH1	2	3	4	GH5	GH1	2	3	4	GH5
	Panel A: Using Daily Data ($Ivol^{daily}$)									
V1	1.24	1.16	0.96	0.87	0.72	1.40	1.24	1.10	1.07	1.02
2	1.23	1.08	0.92	1.00	0.79	1.50	1.38	1.34	1.18	1.13
3	1.27	1.01	1.06	0.88	0.78	1.40	1.42	1.29	1.23	1.17
4	0.96	0.74	0.88	1.10	0.86	1.12	1.11	1.27	1.41	1.13
V5	-0.16	0.40	0.72	1.07	1.22	-0.10	0.52	1.02	1.32	1.36
V5-V1	-1.41	-0.77	-0.24	0.20	0.50	-1.50	-0.72	-0.08	0.25	0.35
	(-5.00)	(-3.38)	(-1.12)	(0.95)	(2.47)	(-6.94)	(-4.25)	(-0.46)	(1.46)	(1.99)
FF-	-1.69	-1.00	-0.46	0.01	0.40	-1.67	-0.91	-0.32	0.01	0.14
Alpha	(-8.07)	(-5.48)	(-2.65)	(0.08)	(2.12)	(-10.50)	(-6.62)	(-2.38)	(0.09)	(0.88)
	Panel B: Using Monthly Data ($Ivol^{monthly}$)									
V1	1.15	1.00	0.90	0.91	0.74	1.43	1.38	1.28	1.08	0.85
2	1.09	0.94	0.96	0.85	0.64	1.44	1.32	1.22	1.11	0.94
3	1.03	0.94	0.74	1.01	0.80	1.25	1.18	1.22	1.18	0.97
4	0.79	0.96	0.75	1.15	0.99	1.06	1.16	1.19	1.20	1.18
V5	0.42	0.68	0.91	1.24	1.36	0.49	0.85	1.21	1.50	1.53
V5-V1	-0.72	-0.32	0.01	0.33	0.62	-0.93	-0.53	-0.08	0.43	0.69
	(-2.65)	(-1.31)	(0.05)	(1.47)	(2.96)	(-4.01)	(-2.78)	(-0.39)	(2.19)	(3.74)
FF-	-0.90	-0.40	-0.17	0.18	0.53	-1.09	-0.69	-0.30	0.20	0.50
Alpha	(-4.08)	(-1.96)	(-0.89)	(0.97)	(2.92)	(-7.54)	(-5.07)	(-1.92)	(1.19)	(3.32)

This table reports value and equally-weighted monthly returns of the quintile portfolios formed on GH (George and Hwang Ratio: current price/52-week high price) and idiosyncratic volatility. Quintile portfolios are formed on GH first and then idiosyncratic volatility within each GH portfolio each month from January 1965 to December 2012. NYSE breakpoints are used to form portfolios. In Panel A, monthly idiosyncratic volatilities are the square root of the number of trading days times the daily idiosyncratic volatility, the standard deviation of residuals from the regression of excess daily stock returns on the contemporaneous daily Fama-French factors in the month. In Panel B, monthly idiosyncratic volatilities are the standard deviation of residuals from the regression of excess monthly stock returns on the contemporaneous monthly Fama-French factors using the previous 24 to 60 monthly returns (as available) each month. V1 (V5) is portfolio of stocks in the bottom (top) quintile of IVOL. Newey-West (1978) adjusted *t*-statistics are reported in parenthesis. Alpha reports Fama-French three factor alpha.

The results reported in panel B of Table 3 using $\mathrm{Ivol}^{monthly}$ are very similar to those I show in Panel A of the same Table. For stocks in GH1, I find a strong negative relationship between IVOL and future returns, both value and equal weighted. Specifically, I find that, when value (equal) weighted, the return differential between V5 and V1 is -0.72% (-0.93%) per month, with a t-statistic of -2.65(-4.01). The corresponding FF-Alphas are also found to be negative (-0.90% and -1.09%) and strongly significant (t-statistics of -4.08 and -7.54 respectively). However, there is a positive relationship between idiosyncratic volatility and future returns for stocks in GH5. These results are also consistent with my first hypothesis such that there is a strong negative relationship between idiosyncratic volatility and future returns only for stocks whose current price move far away from their 52-week high prices.

In Table 4, I employ "Equal" Market Share breakpoints to form my IVOL quintile portfolios. I find, consistent with my previous results and also with Bali and Cakici (2008) that, although the volatility-return relationship vary based on the choice of breakpoint and weighing scheme, there exists a strong negative relationship between IVOL (however defined) and future returns for stocks that belong to the lowest GH portfolio (GH1). Using Ivol^{daily} in Panel A, I find that the value (equally) weighted return differential between V5 and V1 and the corresponding FF-Alpha both prove negative and strongly significant. For example, the value and equal weighted return differential between V5 and V1 for stocks that belong to GH1 are -0.96% per month (t-statistic = -3.72) and -0.94% per month (t-statistic = -4.28) respectively. I find the corresponding FF-Alphas to be negative and significant as well. The results reported in panel B of Table 4 using $\mathrm{Ivol}^{monthly}$ are very similar to those I show in Panel A of the same Table.

Table 4

Average Monthly Returns of Portfolio Sorted on GH and Idiosyncratic Volatility: "Equal" Market Share Breakpoints

	Value-weighted Returns					Equal-weighted Returns				
	GH1	2	3	4	GH5	GH1	2	3	4	GH5
Panel A: Using Daily Data ($Ivol^{daily}$)										
V1	1.19	1.40	0.91	1.01	0.69	1.18	1.21	0.97	0.95	1.06
2	1.18	0.87	0.80	0.85	0.70	1.46	1.15	1.07	1.17	1.06
3	1.15	0.81	0.88	1.01	0.71	1.33	1.29	1.17	1.22	1.04
4	0.93	0.67	0.94	0.97	0.62	1.18	1.11	1.30	1.30	1.08
V5	0.23	0.50	0.87	1.16	1.05	0.24	0.8	1.32	1.49	1.35
V5-V1	-0.96	-0.91	-0.05	0.15	0.37	-0.94	-0.42	0.35	0.54	0.30
	(-3.72)	(-4.29)	(-0.25)	(0.72)	(1.87)	(-4.28)	(-2.54)	(2.09)	(3.02)	(1.76)
FF-	-1.21	-1.00	-0.14	0.06	0.31	-1.14	-0.6	0.15	0.33	0.12
Alpha	(-6.24)	(-5.57)	(-0.88)	(0.31)	(1.67)	(-7.78)	(-4.91)	(1.20)	(1.91)	(0.75)
Panel B: Using Monthly Data ($Ivol^{monthly}$)										
V1	1.15	1.08	0.88	0.92	0.72	1.33	1.31	1.13	0.82	0.88
2	1.05	0.95	0.73	0.81	0.57	1.25	1.28	0.98	0.72	0.93
3	1.06	0.76	0.88	0.92	0.50	1.33	1.30	1.10	0.87	1.04
4	0.98	0.82	0.88	1.01	0.66	1.23	1.17	1.14	0.93	1.10
V5	0.61	0.65	1.01	1.14	1.32	0.67	0.96	1.37	1.40	1.55
V5-V1	-0.53	-0.42	0.13	0.22	0.60	-0.66	-0.36	0.23	0.58	0.67
	(-2.15)	(-1.93)	(0.57)	(1.84)	(2.51)	(-2.59)	(-1.98)	(1.08)	(3.02)	(3.38)
FF-	-0.62	-0.53	-0.02	0.01	0.40	-0.89	-0.56	-0.02	0.35	0.41
Alpha	(-2.91)	(-2.77)	(-0.10)	(0.04)	(1.92)	(-6.57)	(-3.98)	(-0.12)	(2.09)	(2.55)

This table reports value and equally-weighted monthly returns of the quintile portfolios formed on GH (George and Hwang Ratio: current price/52-week high price) and idiosyncratic volatility. Quintile portfolios are formed on GH first and then idiosyncratic volatility within each GH portfolio each month from January 1965 to December 2012. Equal market share breakpoints are used to form portfolios. In Panel A, monthly idiosyncratic volatilities are the square root of the number of trading days times the daily idiosyncratic volatility, the standard deviation of residuals from the regression of excess daily stock returns on the contemporaneous daily Fama-French factors in the month. In Panel B, monthly idiosyncratic volatilities are the standard deviation of residuals from the regression of excess monthly stock returns on the contemporaneous monthly Fama-French factors using the previous 24 to 60 monthly returns (as available) each month. V1 (V5) is portfolio of stocks in the bottom (top) quintile of IVOL. Newey-West (1978) adjusted *t*-statistics are reported in parenthesis. Alpha reports Fama-French three factor alpha.

The results so far lend support to my primary hypothesis that the negative volatility-return relationship is concentrated in stocks that are farther away from their 52-

week high prices and are shown to be robust to the propositions of Bali and Cakici (2008). Figure 1 summarizes the results obtained in Tables 2, 3 and 4.

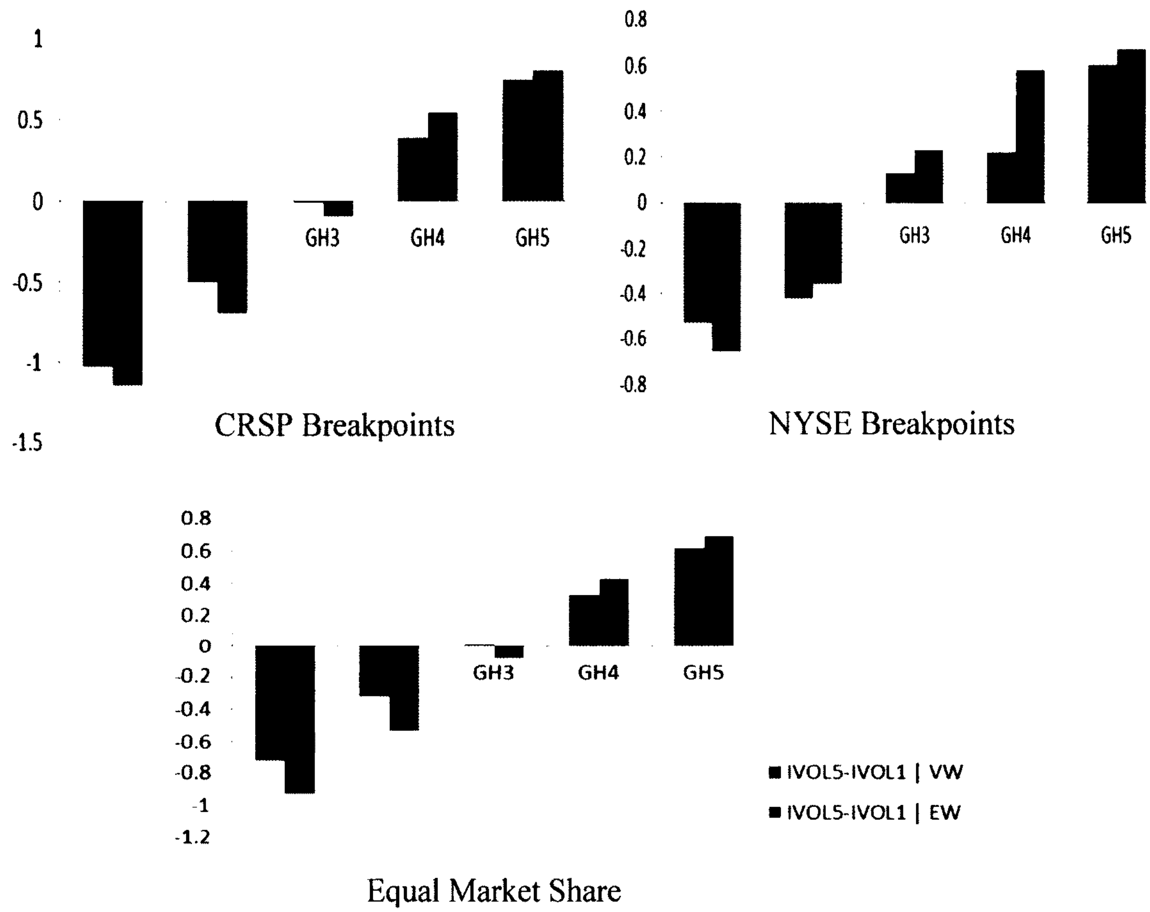

Figure 1 *Value and Equal Weighted Return Differential Between Ivol5 and Ivol1 Under the Various Scenarios*

I now turn my attention to the investigation of the robustness of my results after controlling for other known drivers of the volatility-return relationship. To provide such evidence, I perform a series of firm-level Fama-MacBeth cross-sectional regression tests that allow us to control for other variables. Each month from January 1965 to December 2012, I run firm-level Fama-MacBeth cross-sectional regressions of stock returns in month t+1 on the lagged explanatory variables in month t. The full cross-sectional regression specification takes the following form:

$$R_{i,t+1} = \alpha_t + \beta_1 \mathrm{IVOL}_{i,t} + \beta_2 \mathrm{IVOL}_{i,t} * \mathrm{GH}_{i,t} + \beta_3 \mathrm{GH}_{i,t} + \beta_4 \mathrm{REV}_{i,t} + \beta_5 \mathrm{MAX}_{i,t} + \beta_6 \mathrm{BETA}_{i,t} + \beta_7 \mathrm{BTM}_{i,t} + \beta_8 \mathrm{SIZE}_{i,t} + \beta_9 \mathrm{MOM}_{i,t} + \beta_{10} \mathrm{SKW}_{i,t} + \beta_{11} \mathrm{ILLIQ} + e_{i,t+1}, \quad (4)$$

Where the dependent variable, $R_{i,t+1}$, is the return of stock i in month t+1. The lagged explanatory variables, computed in month t, include idiosyncratic volatility (IVOL), current price/52-week high price (GH: George and Hwang Ratio), the interaction term (IVOL*GH), monthly stock return (REV), maximum daily return (MAX), stock's beta (Beta), book-to-market ratio (BTM), the natural log of market capitalization (Size), the holding period return from month t-12 to month t-2 (MOM), the idiosyncratic skewness (Skw) and illiquidity (ILLIQ).

Huang, Liu, Rhee, and Zhang (2010; HLRZ hereafter) suggests that the idiosyncratic volatility puzzle is attributable to the short-term reversals in returns documented in Jegadeesh (1990), Lehmann (1990), and Lo and MacKinlay (1990).[13] They find that in the cross-sectional regressions of future returns of stocks on idiosyncratic volatility that control for previous month's return, the coefficient on idiosyncratic volatility is no longer statistically significant. We, therefore, control for the short-term reversal by monthly stock return (REV). I also control for maximum daily return (MAX) because Bali, Cakici, and Whitelaw (2011; BCW hereafter) finds a significant negative relationship between stocks' maximum daily return (MAX) in a month and their returns in the following month. These authors find that after controlling

[13]Fu (2009) also documents a similar role of return reversals in the negative volatility-return relationship.

for MAX in the cross-sectional regressions of future returns on idiosyncratic volatility, the coefficient on volatility is insignificant in some specifications or even significantly positive in others.

Table 5 reports Fama-MacBeth cross-sectional regression results. In Models (1) through (3), IVOL is estimated using daily observations, and in Models (4) through (6), monthly estimates of IVOL are employed. Models (1) and (4) investigate the existence of the IVOL puzzle in my sample in univariate regression settings. Model (1) confirms the negative volatility-return relationship documented in Ang et al. (2006). I find in Model (1) that the mean coefficient estimate on my IVOL measure is negative (-0.047) and highly significant (t-statistic = -3.81). However, using my monthly estimate of IVOL, I find in Model (4) that there exists no significant relationship between IVOL and future returns (coefficient estimate = -0.024, t-statistic = -1.24). These results in Model (1) and (4) are consistent with my previous findings in Table 1 and with those of Bali and Cakici (2008).

In Models (2) and (5), I include my measure of nearness to the 52-week high (GH) as well as an interaction term (IVOL*GH) along with IVOL. I find in Model (2) that while the coefficient estimate on IVOL becomes -0.212 with a t-statistic of -11.41, the coefficient on the interaction term is positive, 0.214, and statistically significant with a t-statistic of 8.84. Given that IVOL is non-negative and GH is between zero and one, this evidence implies that the negative relationship between IVOL and next month's return is stronger for stocks that are farther away from their 52-week high prices.

Table 5

Fama-MacBeth Cross-Sectional Regressions

	$Ivol^{daily}$			$Ivol^{monthly}$		
	(1)	(2)	(3)	(4)	(5)	(6)
IVOL	-0.047	-0.212	-0.284	-0.024	-0.257	-0.321
	(-3.81)	(-11.41)	(-12.19)	(-1.24)	(-9.95)	(-10.28)
IVOL*GH		0.214	0.319		0.296	0.378
		(8.84)	(10.10)		(6.93)	(7.91)
GH		-2.037	-2.606		-2.334	-2.836
		(-4.65)	(-5.84)		(-4.37)	(-5.82)
REV			-0.049			-0.046
			(-11.60)			(-11.01)
MAX			-0.007			-0.052
			(-0.45)			(-5.97)
BETA			0.049			0.033
			(1.92)			(1.24)
BTM			0.114			0.098
			(2.12)			(2.02)
SIZE			-0.128			-0.146
			(-3.19)			(-4.01)
MOM			0.701			0.758
			(6.32)			(7.24)
SKW			0.099			0.165
			(3.67)			(6.78)
ILLIQ			-0.011			-0.008
			(-1.64)			(-1.24)

Each month from January 1965 to December 2012, I run a firm-level Fama-MacBeth cross-sectional regressions of stock return in month t+1 on the lagged explanatory variables in month t. The explanatory variables include stock's monthly idiosyncratic volatility (IVOL), current price/52-week high price (GH: George and Hwang Ratio), the interaction term (IVOL*GH), monthly stock return (REV), maximum daily return (MAX), BETA, the book-to-market ratio (BTM), the log of market capitalization (Size), the holding period return from month t-12 to month t-2 (MOM), the idiosyncratic skewness (Skw), and the illiquidity measure (ILLIQ). Common stocks with price greater than or equal to $5 from the NYSE/AMEX/NASDAQ are included in the sample. Newey-West (1978) adjusted t-statistics are reported in parenthesis.

In Model (5) with IVOL computed using monthly data, I find consistent with the result reported in Model (2) that the negative return predictive power of IVOL on future returns increases for stocks that move farther away from their 52-week high price (coefficient estimate for IVOL = -0.257 with t-statistic = -9.95 and coefficient estimate for IVOL*GH = 0.296 with t-statistic = 6.93).

Next, I control in Models (3) and (6) for other variables known in the recent literature for their ability to help explain the negative volatility-return relationship. Using my first measure of IVOL in the full specification of Equation (4), I find in Model (3) that controlling for REV and for other variables such as MAX, MOM, ILLIQ and SKW as well does not change the negative relationship between the volatility and the return in the following month for stocks that are far away from their 52-week high. Specifically, the coefficient on IVOL is -0.284 with a t-statistic of -12.19. The interaction term has a coefficient of 0.319 with a t-statistic of 10.10. Similarly, when I consider a measure of IVOL computed using monthly data in the full specification of Model (6), I find the coefficient on IVOL to equal -0.321 with a t-statistic of -10.28 and the interaction term has a coefficient of 0.378 with a t-statistic of 7.91. Further, most of the control variables have expected signs: the coefficients on REV and firm size (SIZE) are negative and statistically significant, while coefficients on book-to-market (BTM), MOM, and idiosyncratic skewness are positive and statistically significant.

To summarize, the results obtained from my regression tests suggest that even after accounting for other important variables, it remains clear, as suggested by my previous findings, that the negative volatility-return relationship documented by Ang et al. (2006) is concentrated in stocks with low GH ratio, those stocks that are the farther away from their 52-week high prices. In addition to the preceding evidence on the robustness of my findings, I also investigate in the following section the role of the January effect in the volatility-return relationship after controlling for a stock's nearness to its 52-week high price. Investigating this issue is particularly important given the findings of Peterson and Smedema (2011) who provide robust evidence to the fact that the negative volatility-return relationship is particular to every month of the year other than the month of January. Doran, Jiang, and Peterson (2012) and Bhootra and Hur (2014) provide supporting evidence to their results. I turn to this investigation in the following section.

Controlling for the January Effect

In view of the evidence presented by Peterson and Smedema (2011) and Bhootra and Hur (2014) among others on the role of the January effect on the IVOL puzzle, it is important to ensure that my findings are not a simple artifact of the well documented January seasonality in stock returns. I start with an investigation of the existence of the January effect in my sample. In Table 6, I report average value and equal weighted monthly returns of quintile portfolios formed on IVOL for January and Non-January months. In Panel A, I present results from univariate sorts using my first idiosyncratic volatility measure ($\text{Ivol}^{\text{daily}}$). For the month of January, I find the value (equal) weighted return differential between V5 and V1 to be positive 1.19% (2.12%) per month with a t-statistic of 1.13 (2.57); the corresponding FF-Alphas being -1.26% (0.11%) with t-statistic of -1.67 (0.20). For Non-January months on the other hand, I find the value (equal) weighted return differential between V5 and V1 to be negative -0.66% (-0.87%) per month and statistically significant with a t-statistic of -2.20 (-3.41); the corresponding FF-Alphas being negative -0.79% (-1.02%) and highly significant with t-statistic of -4.00 (-6.39).

Employing an alternative measure of IVOL, computed using monthly data, the results in Panel B show that the value (equal) weighted return differential between V5 and V1 is positive 2.38% (3.18%) per month and significant with a t-statistic of 2.58 (3.82) in January; the corresponding FF-Alphas being equally positive 0.94% (1.56%) and significant with t-statistic of 2.36 (2.42). For Non-January months, both value and equal weighted return differentials between V5 and V1 are negative -0.32% and -0.49% respectively, yet only marginally significant when returns are equally weighted (t-statistic = -1.86). However, I also find the corresponding FF-Alphas to be equally negative -0.42% and -0.60%, and significant with t-statistics of -2.26 and -3.81 respectively.

Overall, my results are generally consistent with prior studies. I find a positive or flat relationship between IVOL and future returns in the month of January. However, for Non-January months, I find a strong negative relationship between IVOL and future returns, irrespective of the weighing scheme employed and/or the frequency used in the computation of my measures of IVOL. I now turn my attention to the examination of the role of the nearness to the 52-week high on the volatility-return relationship for January versus Non-January months. I repeat the analysis in Table 6 for January versus Non-January months. The results are presented in Tables 7 for my first measure of IVOL ($Ivol^{daily}$), and Table 8 for the second measure of IVOL ($Ivol^{monthly}$).

Table 6

Average Monthly Returns of Portfolio Sorted on Idiosyncratic Volatility: January versus Non-January

	January		Non-January	
	Value-weighted Returns	Equal-weighted Returns	Value-weighted Returns	Equal-weighted Returns
		Panel A: Ivol^{daily}		
V1	0.86	2.28	0.82	0.98
2	1.20	2.89	0.87	1.15
3	2.08	3.69	0.96	1.12
4	2.94	4.42	0.76	0.90
V5	2.05	4.39	0.16	0.12
V5-V1	1.19	2.12	-0.66	-0.87
	(1.13)	(2.57)	(-2.20)	(-3.41)
FF-Alpha	-1.26	0.11	-0.79	-1.02
	(-1.67)	(0.20)	(-4.00)	(-6.39)
		Panel B: Ivol^{monthly}		
V1	0.85	1.93	0.84	1.02
2	1.36	2.61	0.90	1.09
3	2.24	3.30	0.89	1.03
4	2.84	4.37	0.86	0.95
V5	3.23	5.11	0.52	0.54
V5-V1	2.38	3.18	-0.32	-0.49
	(2.58)	(3.82)	(-1.11)	(-1.86)
FF-Alpha	0.94	1.56	-0.42	-0.60
	(2.36)	(2.42)	(-2.26)	(-3.81)

This table reports value and equally-weighted monthly returns of the quintile portfolios formed on idiosyncratic volatility for January and Non-January months. Quintile portfolios are formed on idiosyncratic volatility each month from January 1965 to December 2012. For panel A, monthly idiosyncratic volatilities are the square root of the number of trading days times the daily idiosyncratic volatility, the standard deviation of residuals from the regression of excess daily stock returns on the contemporaneous daily Fama-French factors in the month. For panel B, monthly idiosyncratic volatilities are the standard deviation of residuals from the regression of excess monthly stock returns on the contemporaneous monthly Fama-French factors using the previous 24 to 60 monthly returns (as available) each month. V1 (V5) is portfolio of stocks in the bottom (top) quintile of IVOL. Newey-West (1978) adjusted t-statistics are reported in parenthesis. Alpha reports Fama-French three factor alpha.

Looking at both value and equal weighted return differentials between V5 and V1, my results in Panel A of Table 7 are generally consistent with the findings of George and Hwang (2008). I find that there exists a flat volatility-return relationship in the month of January. However, I also find the FF-Alpha of my lowest GH group (GH1) to be negative and highly significant, irrespective of the weighing scheme employed. Specifically, I find that when returns are value-weighted, the FF-Alpha of my lowest GH group is -2.66 with a t-statistic of -4.74. When returns are equally weighted, the FF-Alpha of this group of stocks (GH1) is also negative (-1.64) and significant (t-statistic = - 2.97).

In panel B of Table 7, my focus is turned to Non-January months. Consistent with my earlier findings, I show, for my lowest GH quintile, that the value (equal) weighted return differential between V5 and V1 is negative, -2.07% (-2.08%) per month, and highly significant, with a t-statistic of -6.57 (-9.34). Conversely, this return differential between V5 and V1 for my highest GH quintile (GH5) appears to be positive, 0.55% (0.29%) per month, yet only marginally significant or flat, with a t-statistic of 1.95(1.37). I also find the corresponding FF-Alphas to follow a similar pattern. When returns are value (equal) weighted, the FF-Alpha for my lowest GH quintile (GH1) is negative, -2.28% (-2.18%), and strongly significant, with a t-statistic of -8.25 (-12.44). For my highest GH quintile, the FF-Alphas are found to be positive yet insignificant.

Table 7

Average Monthly Returns of Portfolio Sorted on Idiosyncratic Volatility: January versus Non-January

Panel A : January										
	Value-weighted Returns					**Equal-weighted Returns**				
	GH1	2	3	4	GH5	GH1	2	3	4	GH5
V1	1.70	2.49	1.73	1.62	0.46	4.49	4.15	3.10	2.18	1.11
2	2.97	2.70	1.96	1.37	0.39	5.12	4.57	3.21	2.35	1.29
3	3.18	2.50	2.15	1.69	0.25	5.96	4.9	3.50	2.46	1.32
4	2.43	2.97	2.66	2.02	0.98	5.55	4.77	4.05	2.78	1.59
V5	1.61	2.80	2.66	1.83	1.01	4.27	4.48	4.03	3.56	2.21
V5-V1	-0.09	0.31	0.92	0.22	0.55	-0.23	0.33	0.93	1.38	1.1
	(-0.10)	(0.31)	(1.04)	(0.19)	(0.62)	(-0.33)	(0.47)	(1.40)	(1.77)	(1.46)
FF-Alpha	-2.66	-2.01	-0.19	-0.58	-0.85	-1.64	-1.12	-0.45	0.02	-0.28
	(-4.74)	(-2.09)	(-0.16)	(-0.33)	(-1.11)	(-2.97)	(-1.50)	(-0.64)	(0.03)	(-0.39)
Panel B : Non-January										
V1	1.15	0.99	0.84	0.92	0.76	1.17	0.98	0.93	0.99	1.01
2	0.96	0.88	0.89	0.86	0.78	1.07	1.11	1.15	1.09	1.11
3	0.79	0.78	0.86	0.86	0.96	0.69	0.92	1.16	1.25	1.21
4	0.02	0.33	0.54	1.15	1.07	0.14	0.57	1.02	1.40	1.32
V5	-0.91	-0.25	0.49	1.06	1.31	-0.92	-0.07	0.64	1.08	1.31
V5-V1	-2.07	-1.24	-0.34	0.14	0.55	-2.08	-1.05	-0.29	0.09	0.29
	(-6.57)	(-4.54)	(-1.32)	(0.53)	(1.95)	(-9.34)	(-5.29)	(-1.35)	(0.43)	(1.37)
FF-Alpha	-2.28	-1.43	-0.52	0.06	0.47	-2.18	-1.17	-0.45	-0.07	0.17
	(-8.25)	(-6.94)	(-2.59)	(0.39)	(1.69)	(-12.44)	(-7.60)	(-2.62)	(-0.49)	(1.08)

This table shows value and equally-weighted monthly returns of the quintile portfolios formed on GH (George and Hwang Ratio: current price/52-week high price) and idiosyncratic volatility. Quintile portfolios are formed on GH first and then idiosyncratic volatility within each GH portfolio each month from January 1965 to December 2012. Monthly idiosyncratic volatilities are the square root of the number of trading days times the daily idiosyncratic volatility, the standard deviation of residuals from the regression of excess daily stock returns on the contemporaneous daily Fama-French factors. V1 (V5) is portfolio of stocks in the bottom (top) quintile of IVOL. Newey-West (1978) adjusted *t*-statistics are reported in parenthesis. Alpha reports Fama-French three factor alpha.

Table 8 reports results obtained after using a measure of IVOL computed with monthly data. As in Table 7, Panel A of this table focuses on the month of January while Panel B reports results for Non-January months. In Panel A, I find a positive and generally significant volatility-return relationship for all my GH quintiles, irrespective of the weighing scheme employed for the computation of returns. However, the corresponding FF-Alphas in this case are found to be significant when returns are equally-weighted and only for my highest GH groups (GH4 and GH5). In Panel B, the results confirm my previous findings that for Non-January months, the volatility-return relationship is negative and strongly significant only for stocks that are far away from their 52-week high prices.

With value (equal) weighted returns, I find that the return differential between V5 and V1 for my lowest GH quintile (GH1) is negative, -1.33% (-1.46%) per month and highly significant, with a t-statistic of -4.49 (-5.59). On the contrary, the return differential between V5 and V1 for my highest GH quintile (GH5) appears to be positive, 0.62% (0.69%) per month and significant, with a t-statistic of 2.37(3.12). Similarly, the FF-Alpha for my lowest GH quintile (GH1) is negative, -1.41% (-1.49%), and strongly significant, with a t-statistic of -6.05 (-8.40). For my highest GH quintile, the FF-Alphas (using both value and equal weighted returns) are found to be positive and significant.

The evidence I present in Tables 7 and 8 suggest that the findings I document in this study on the role of anchoring bias on the IVOL puzzle are indeed robust to the well documented January seasonality in stock returns. Figure 2 shows a graphical summary of the results I report in Tables 7 and 8.

Table 8

Average Monthly Returns of Portfolio Sorted on GH and $Ivol^{monthly}$: January versus Non-January

	Value-weighted Returns					Equal-weighted Returns				
Panel A : January										
	GH1	2	3	4	GH5	GH1	2	3	4	GH5
V1	1.40	2.09	1.73	1.47	0.00	3.67	3.67	2.86	2.08	0.71
2	3.42	2.53	2.15	1.31	0.25	4.99	3.97	3.07	1.98	0.73
3	3.60	3.74	1.8	1.67	0.27	5.63	4.57	3.16	2.24	1.12
4	2.96	4.27	2.67	1.28	0.55	5.46	5.19	3.95	2.86	1.78
V5	3.57	3.48	3.17	2.84	2.04	5.91	5.3	4.73	4.16	2.76
V5-V1	2.17	1.39	1.44	1.37	2.03	2.24	1.62	1.87	2.08	2.05
	(1.95)	(1.52)	(1.54)	(1.49)	(2.50)	(2.64)	(2.07)	(2.43)	(2.86)	(2.97)
FF-Alpha	0.65	0.41	0.47	0.64	1.04	0.97	0.82	0.86	1.14	0.89
	(1.01)	(0.63)	(0.66)	(0.81)	(1.45)	(1.36)	(0.92)	(1.34)	(2.22)	(2.00)
Panel B : Non-January										
V1	1.08	0.85	0.83	0.86	0.78	1.20	1.16	1.13	0.98	0.87
2	0.74	0.74	0.71	0.86	0.75	0.94	0.98	1.02	1.08	0.99
3	0.53	0.69	0.70	1.07	0.96	0.57	0.75	1.03	1.11	1.13
4	0.28	0.62	0.75	1.19	1.39	0.23	0.71	0.97	1.20	1.33
V5	-0.25	0.19	0.69	1.18	1.40	-0.26	0.27	0.87	1.40	1.57
V5-V1	-1.33	-0.67	-0.14	0.32	0.62	-1.46	-0.89	-0.26	0.42	0.69
	(-4.49)	(-2.35)	(-0.48)	(1.08)	(2.37)	(-5.59)	(-3.82)	(-1.09)	(1.73)	(3.12)
FF-Alpha	-1.41	-0.73	-0.31	0.20	0.57	-1.49	-0.95	-0.40	0.28	0.60
	(-6.05)	(-3.48)	(-1.39)	(0.88)	(2.63)	(-8.40)	(-5.75)	(-2.16)	(1.43)	(3.46)

This table shows value and equally-weighted monthly returns of the quintile portfolios formed on GH (George and Hwang Ratio: current price/52-week high price) and idiosyncratic volatility for January and Non-January months. Quintile portfolios are formed on GH first and then idiosyncratic volatility within each GH portfolio each month from January 1965 to December 2012. Monthly idiosyncratic volatilities are the standard deviation of residuals from the regression of excess monthly stock returns on the contemporaneous monthly Fama-French factors using the previous 24 to 60 monthly returns (as available) each month. V1 (V5) is portfolio of stocks in the bottom (top) quintile of IVOL. Newey-West (1978) adjusted t-statistics are reported in parenthesis. Alpha reports Fama-French three factor alpha.

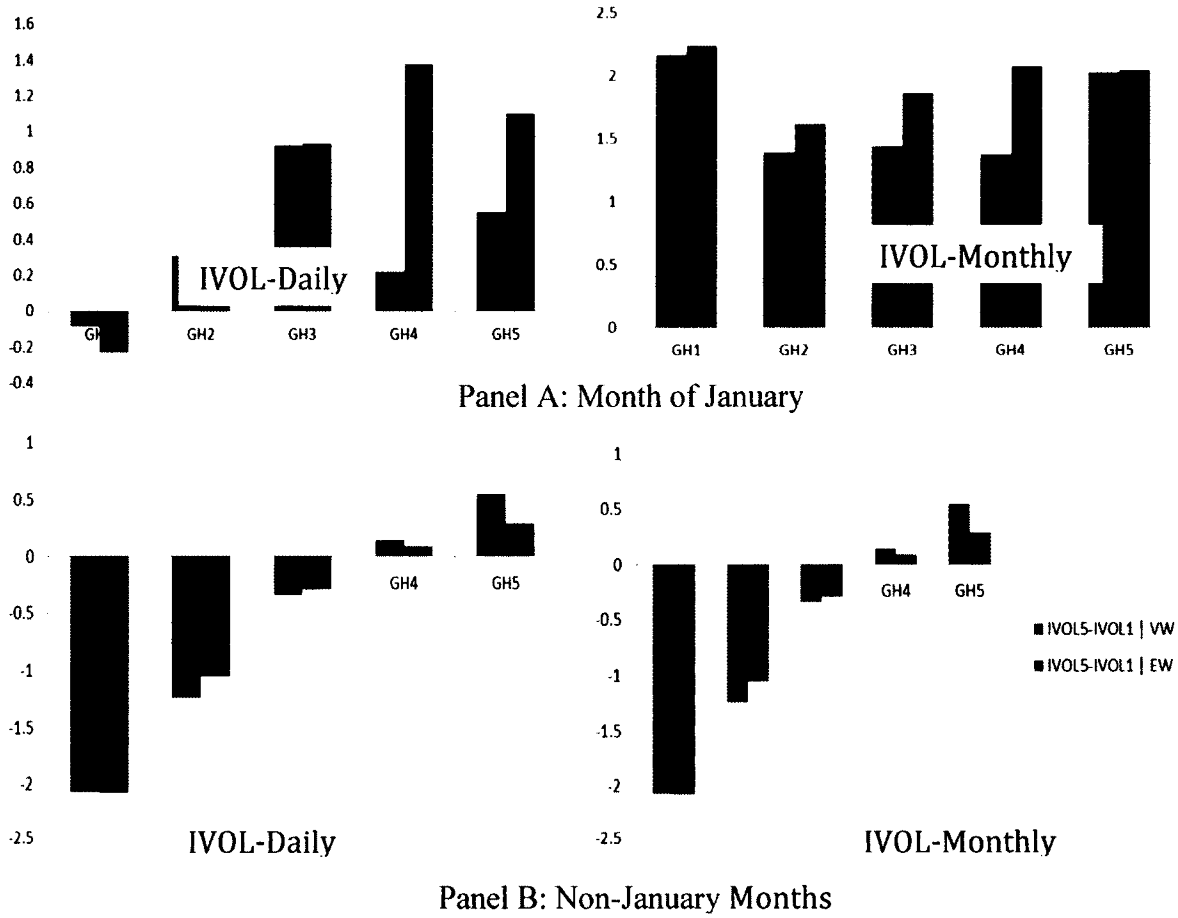

Figure 2 *Value and Equal Weighted Return Differential Between Ivol5 and Ivol1 for January vs. Non-January Months*

To further support this evidence, I perform regression tests for which I present the results in Table 9. Specifically, I run cross-sectional firm-level Fama-MacBeth regressions of stock returns on lagged explanatory variables, differentiating between January and Non-January months. In Models (1) through (3), IVOL is estimated using daily observations, and in Models (4) through (6), monthly return estimates of IVOL are employed. As stated earlier, for each one of my Model specifications, I differentiate between January and Non-January months.

Table 9

Fama-MacBeth Cross-Sectional Regressions: January Versus Non-January

	$\mathbf{Ivol}^{daily}$						$\mathbf{Ivol}^{monthly}$					
	(1)		(2)		(3)		(4)		(5)		(6)	
	Jan	Non-Jan	Jan	Non-Jan	Jan	Non-Jan	Jan	Non-Jan	Jan	Non-Jan	Jan	Non-Jan
IVOL	0.084	-0.058	-0.187	-0.215	-0.329	-0.279	0.236	-0.047	-0.094	-0.271	-0.274	-0.335
	(1.88)	(-4.46)	(-4.63)	(-10.57)	(-5.01)	(-11.10)	(3.44)	(-2.32)	(-1.18)	(-9.66)	(-2.01)	(-10.09)
IVOL*GH			0.290	0.207	0.419	0.310			0.330	0.293	0.375	0.380
			(4.54)	(8.06)	(7.00)	(9.13)			(2.74)	(6.57)	(5.00)	(7.50)
GH			-9.601	-1.349	-7.537	-2.158			-8.912	-1.736	-5.933	-2.555
			(-5.35)	(-3.12)	(-8.32)	(-4.86)			(-3.90)	(-3.38)	(-5.99)	(-5.31)
REV					-0.104	-0.045					-0.098	-0.041
					(-7.51)	(-10.71)					(-7.99)	(-10.01)
MAX					0.040	-0.011					-0.008	-0.056
					(0.82)	(-0.71)					(-0.32)	(-5.96)
BETA					-0.039	0.058					-0.083	0.044
					(-0.69)	(2.07)					(-1.27)	(1.55)
BTM					0.613	0.068					0.754	0.039
					(2.20)	(1.28)					(2.64)	(0.79)
SIZE					-0.915	-0.057					-0.788	-0.088
					(-3.84)	(-1.41)					(-3.01)	(-2.44)
MOM					-0.437	0.804					-0.874	0.906
					(-0.92)	(7.02)					(-1.75)	(8.53)
SKW					0.165	0.093					0.190	0.163
					(1.60)	(3.50)					(2.73)	(6.56)
ILLIQ					0.001	-0.012					0.018	-0.010
					(0.06)	(-2.29)					(0.69)	(-1.86)

Each month from January 1965 to December 2012, I run a firm-level Fama-MacBeth cross-sectional regressions of stock return in month $t+1$ on the explanatory variables in month t. The explanatory variables include stock's monthly idiosyncratic volatility (IVOL), current price/52-week high price (GH: George and Hwang Ratio), the interaction term (IVOL*GH), monthly stock return (REV), maximum daily return (MAX), BETA, the book-to-market ratio (BTM), the log of market capitalization (Size), the holding period return from month t-12 to month t-2 (MOM), the idiosyncratic skewness (Skw), and the illiquidity measure (ILLIQ).Common stocks with price greater than or equal to $5 from the NYSE/AMEX/NASDAQ are included in the sample. Newey-West (1978) adjusted t-statistics are reported in parenthesis.

Models (1) and (4) investigate the existence of the IVOL puzzle for my sample in univariate regression settings. Consistent with previous studies, the results in both Models (1 & 4) confirm the existence of a negative volatility-return relationship for Non-January months only. In the month of January, the mean coefficient estimate on my IVOL measure in Model (1) is positive (0.084) and only marginally significant (t-statistic = 1.88). However, for Non-January months, I find the coefficient estimate on my IVOL measure to be negative (-0.058) and strongly significant with a t-statistic of -4.46. Using a measure of IVOL obtained with monthly data, I find in Model (4) that for the month of January, there exist a strong positive volatility-return relationship; the coefficient estimate on IVOL in this case is 0.236 with a t-statistic of 3.44. For Non-January months, the volatility-return relationship proves negative (coefficient estimate = -0.047) and significant (t-statistic = -2.32). These results are consistent with my previous findings and also with those of Peterson and Smedema (2011) and Bhootra and Hur (2014).

In Models (2) and (5), I include GH as well as an interaction term (IVOL*GH). Interestingly, I find in Model (2) that controlling for GH in the month of January changes the nature of the volatility-return relationship; the coefficient estimates on my IVOL measures become negative (-0.187) and significant (t-statistic = -4.63). It seems inconsistent with Panel A of Table 7 that shows no volatility-return relationship even for stocks in GH1. However, using 0.50 as a reasonable number of GH in GH1 group (See Panel A of Table 2), the net effect of IVOL on future return will be -0.032 (=-0.187 + 0.290*0.5) which is negative and seems potentially insignificant, and thus is consistent with Panel A of Table 7.

For Non-January months, I find a strong negative relationship between volatility and returns for those stocks that move away from their 52-week high prices; the coefficient on my IVOL measure in this case is negative, -0.215 and highly significant (t-statistic = -10.57) and the coefficient on interaction term is positive, 0.207 and highly significant (t-statistic = 8.06). As stock prices move away from their respective 52-week highs as in stocks in GH1, the net effect of IVOL on future returns remains negative at -0.112 (= -0.215 + 0.207*0.50) and potentially significant. I obtain similar results in Model (5). These findings are consistent with Panel B of Table 7 and 8.

Next, similar to the analysis performed in Table 5, I control in Models (3) and (6) for other variables known in the recent literature for their ability to help explain the negative volatility-return relationship, differentiating this time between January and Non-January months. In Model (3), I find for Non-January months that, controlling for REV, MAX, MOM, ILLIQ and SKW does not change the nature of the volatility-return relationship that I document for stocks that are far away from their 52-week high. Specifically, the coefficient on my IVOL measure is -0.279 and highly significant (t-statistic = -11.10) and the coefficient on interaction term is 0.310 and highly significant (t-statistic = 9.13) for Non-January months. This finding is confirmed in Model (6) with IVOL estimated using monthly data.

Examining the Persistence of Results

The results I report up to this point suggest a systematic overpricing of high IVOL stocks that move away from their 52-week high prices. George and Hwang (2011) argue that while pricing errors are just as likely to generate overpricing as they are to generate underpricing, only the overpricing is likely to persist due to short sale constraints. If this is true, I should expect the overpricing I document in this paper for high IVOL stocks that move away from their 52-week prices to persist. To provide such evidence, I perform the following analysis. Every month t, I form quintile portfolios based on my measure of nearness to the 52-week high price (GH). Within each of these quintile portfolios formed based on GH, I also form another quintile portfolios based on my various measures of IVOL. For each of the 25 portfolios I obtain, I then compute average value (equal) weighted returns during each of the six months following my portfolio formation month (i.e., from t+1 to t+6).

Tables 10 and 11 present the average monthly return difference between V5 and V1 for the post-formation months from t+2 to t+6 as my previous results focus on the post-formation month t+1. In Table 10, I employ $\mathrm{Ivol}^{\mathrm{daily}}$ while Table 11 reports results obtained using $\mathrm{Ivol}^{\mathrm{monthly}}$. Panel A.1 (B.1) of Table 10 reports the post-formation average value (equal) weighted return differentials between my highest (V5) and lowest (V1) portfolios formed on my measure of IVOL estimated using daily return only. Here, I find that although my lowest IVOL portfolios (V1) generally outperform my highest IVOL portfolios (V5) over the subsequent months, the return differentials between both groups of stocks (V5-V1) are only marginally significant when returns are equally-weighted (See Panel B.1).

Table 10

Average Monthly Returns in Post Holding Period Months ($Ivol^{daily}$)

	t+2	t+3	t+4	t+5	t+6
Panel A: Value-weighted Returns					
Panel A.1: Portfolio Sorted on $Ivol^{daily}$					
	-0.38	-0.22	-0.27	-0.26	-0.28
	(-1.37)	(-0.78)	(-0.97)	(-0.95)	(-1.03)
Panel A.2: Portfolio Sorted on GH and $Ivol^{daily}$					
GH1	-1.36	-1.12	-1.11	-0.86	-0.59
	(-4.20)	(-3.43)	(-3.46)	(-2.71)	(-1.99)
2	-0.24	0.04	-0.27	-0.17	0.07
	(-0.81)	(0.15)	(-0.90)	(-0.56)	(0.21)
3	0.03	0.50	0.04	0.19	0.32
	(0.11)	(1.65)	(0.15)	(0.67)	(1.10)
4	0.31	0.50	-0.02	0.37	0.35
	(1.14)	(1.69)	(-0.05)	(1.26)	(1.23)
GH5	0.77	0.81	0.47	0.28	0.50
	(2.77)	(2.89)	(1.57)	(0.95)	(1.61)
Panel B: Equal-weighted Returns					
Panel B.1: Portfolio Sorted on $Ivol^{daily}$					
	-0.43	-0.39	-0.38	-0.41	-0.36
	(-1.82)	(-1.66)	(-1.63)	(-1.73)	(-1.53)
Panel B.2: Portfolio Sorted on GH and $Ivol^{daily}$					
GH1	-1.31	-0.99	-0.92	-0.71	-0.70
	(-5.28)	(-4.02)	(-3.81)	(-2.76)	(-2.91)
2	-0.32	-0.06	0.00	-0.09	0.04
	(-1.47)	(-0.28)	(0.01)	(-0.41)	(0.21)
3	0.17	0.29	-0.01	0.10	0.24
	(0.81)	(1.37)	(-0.03)	(0.47)	(1.13)
4	0.49	0.55	0.31	0.25	0.46
	(2.16)	(2.56)	(1.48)	(1.18)	(2.15)
GH5	0.73	0.89	0.44	0.35	0.59
	(2.90)	(3.88)	(1.85)	(1.49)	(2.40)

This table reports the average monthly returns of the V5 (firms with high idiosyncratic volatility) – the V1 (firms with low idiosyncratic volatility) portfolios during the post-holding period from month t+2 to month t+6 from January 1965 until June 2012. For Panel A.1 and B.1, quintile portfolios are formed on idiosyncratic volatility each month. For Panel A.2 and B.2, quintile portfolios are formed on GH (George and Hwang Ratio: current price/52-week high price) first and then idiosyncratic volatility within each GH portfolio each month t. Monthly idiosyncratic volatilities are the square root of the number of trading days times the daily idiosyncratic volatility, the standard deviation of residuals from the regression of excess daily stock returns on the contemporaneous daily Fama-French factors in the month. Newey-West (1978) adjusted t-statistics are reported in parenthesis.

Table 11

Average Monthly Returns in Post Holding Period Months ($Ivol^{monthly}$)

	t+2	t+3	t+4	t+5	t+6
Panel A: Value-weighted Returns					
Panel A.1: Portfolio Sorted on $\mathbf{Ivol^{monthly}}$					
	-0.06	-0.05	-0.02	-0.04	-0.02
	(-0.23)	(-0.18)	(-0.09)	(-0.15)	(-0.06)
Panel A.2: Portfolio Sorted on GH and $\mathbf{Ivol^{monthly}}$					
GH1	-1.10	-0.79	-0.95	-0.66	-0.60
	(-3.43)	(-2.51)	(-3.01)	(-2.10)	(-1.96)
2	-0.08	0.19	0.12	-0.06	-0.35
	(-0.26)	(0.58)	(0.39)	(-0.17)	(-1.07)
3	0.13	0.52	0.29	0.49	0.64
	(0.40)	(1.61)	(0.93)	(1.60)	(2.06)
4	0.62	0.70	0.36	0.58	0.72
	(2.11)	(2.13)	(1.08)	(1.89)	(2.36)
GH5	0.94	0.76	0.77	0.43	0.76
	(3.15)	(2.54)	(2.63)	(1.43)	(2.41)
Panel B: Equal-weighted Returns					
Panel B.1: Portfolio Sorted on $\mathbf{Ivol^{monthly}}$					
	-0.10	-0.10	-0.09	-0.15	-0.15
	(-0.42)	(-0.41)	(-0.38)	(-0.60)	(-0.59)
Panel B.2: Portfolio Sorted on GH and $\mathbf{Ivol^{monthly}}$					
GH1	-1.00	-0.73	-0.64	-0.60	-0.64
	(-3.54)	(-2.57)	(-2.23)	(-2.02)	(-2.31)
2	-0.15	0.12	0.16	-0.06	-0.11
	(-0.57)	(0.48)	(0.60)	(-0.22)	(-0.44)
3	0.29	0.52	0.25	0.26	0.38
	(1.15)	(2.08)	(0.99)	(1.05)	(1.53)
4	0.68	0.71	0.50	0.47	0.55
	(2.64)	(2.79)	(1.98)	(1.89)	(2.16)
GH5	0.81	0.91	0.66	0.43	0.74
	(3.06)	(3.63)	(2.55)	(1.69)	(2.80)

This table reports the average monthly returns of the V5 (firms with high idiosyncratic volatility) – the V1 (firms with low idiosyncratic volatility) portfolios during the post-holding period from month t+2 to month t+6 from January 1965 until June 2012. For Panel A.1 and B.1, quintile portfolios are formed on idiosyncratic volatility each month. For Panel A.2 and B.2, quintile portfolios are formed on GH (George and Hwang Ratio: current price/52-week high price) first and then idiosyncratic volatility within each GH portfolio each month t. Monthly idiosyncratic volatilities are the standard deviation of residuals from the regression of excess monthly stock returns on the contemporaneous monthly Fama-French factors using the previous 24 to 60 monthly returns (as available) each month. Newey-West (1978) adjusted t-statistics are reported in parenthesis

In Panels A.2 and B.2, I employ a double sort approach. Here, portfolios are formed based on GH first and then IVOL within each GH quintile. For each of my GH portfolios, I then report in Panel A.2 (B.2) the post-formation average value (equal) weighted return differentials between my highest and lowest IVOL portfolios. I find in Panel A.2 (B.2) that for my lowest GH portfolio (GH1), the value (equal) weighted return differentials between my highest and lowest IVOL portfolios (V5-V1) are significantly negative for up to six months following the portfolios formation months. I find similar results with idiosyncratic volatilities estimated using monthly data in Table 11.

Controlling for Investor Sentiments

In this section, I investigate the behavior of the volatility-return relationship of stocks that are far away from their 52-week high prices in periods of high and low investor sentiments. Veronesi (1999) shows that in good times, bad news signals increased uncertainty and greater likelihood negative future performance. Building on the propositions of Veronesi (1999), it follows that if nearness to the 52-week high serves as a proxy for a firm's idiosyncratic information "quality" (good vs. bad news) as in George and Hwang (2004) and periods of high (low) investor sentiments are understood to be good (bad) times, I should expect, all else equal, that the negative relationship between IVOL and future returns of stocks that are farther away from their 52-week high prices be stronger in periods of high investor sentiments.

We start with the investigation of the behavior of the volatility-return relationship in periods of low, medium, and high investor sentiments. As stated earlier, I obtain the investor sentiment data is from Baker and Wurgler (2006). This data is only available for the period from July 1965 to December 2010, which limits my sample for the following analyses. The results of this preliminary analysis are presented in Table 12 where I form quintile portfolios solely on idiosyncratic volatility. Panel B (C) of Table 12 reports the results using idiosyncratic volatility estimated with daily (monthly) data. After assigning the various months to the sentiment categories (low, medium, high), I obtain 182 months for each sentiment category.

In Panel A of Table 12, I report the average factor (market, size, and book-to-market) returns for my entire sample. While for low sentiments periods, market, size, and book-to-market factors have average monthly returns of 0.65, 0.73, and 0.38% respectively, they are -0.06, -0.17, and 1.22% for high sentiments periods, respectively. In Panel B and C, I report for each of my IVOL measures the value and equal weighted returns for quintile portfolios formed on IVOL only. I find in Panel B and C that, in periods of low investor sentiments, there generally exists a strong positive relationship between IVOL and future returns.

However, in periods of medium investor sentiments, I find that irrespective of my definition of IVOL, the volatility-return relationship is generally flat. Finally, for my highest investor sentiments periods, I find strong negative relationship between IVOL and future returns. Specifically, I find in Panel B that for my highest investor sentiments periods, the value (equal) weighted return differential between V5 and V1, my highest and lowest IVOL portfolios, is negative, -1.75% (-1.83%) per month and statistically significant with a t-statistic of -2.91 (-3.48). Here, I also find the FF-Alphas to be significantly negative. Similarly, the results in Panel C show that the value (equal) weighted return differential between V5 and V1 is negative, -1.53% (-1.62%) per month and statistically significant with a t-statistic of -2.55 (-2.90).

Table 12

Average Monthly Returns of Portfolio Sorted on Idiosyncratic Volatility Across Investor Sentiments

	LOW SENTIMENT			MEDIUM SENTIMENT			HIGH SENTIMENT		
Panel A: Average Returns of Factors									
	MKT	SMB	HML	MKT	SMB	HML	MKT	SMB	HML
	0.65	0.73	0.38	0.65	0.08	-0.18	-0.06	-0.17	1.22

	LOW SENTIMENT		MEDIUM SENTIMENT		HIGH SENTIMENT	
Panel B: ($Ivol^{daily}$)						
	Value-weighted Returns	Equal-weighted Returns	Value-weighted Returns	Equal-weighted Returns	Value-weighted Returns	Equal-weighted Returns
V1	0.64	1.17	0.55	0.62	1.25	1.55
2	1.09	1.68	0.58	0.69	1.12	1.58
3	1.53	2.03	0.70	0.79	0.92	1.31
4	1.77	2.16	0.85	0.74	0.42	0.88
V5	1.66	1.79	0.08	0.22	-0.50	-0.28
V5-V1	1.02 (2.46)	0.63 (1.75)	-0.47 (-1.04)	-0.40 (-1.15)	-1.75 (-2.91)	-1.83 (-3.48)
FF-Alpha	-0.08 (-0.32)	-0.35 (-1.65)	-0.75 (-2.43)	-0.62 (-3.36)	-1.19 (-3.01)	-1.56 (-4.72)
Panel C: ($Ivol^{monthly}$)						
V1	0.86	1.13	0.54	0.56	1.19	1.66
2	1.28	1.60	0.62	0.57	0.96	1.53
3	1.58	1.87	0.73	0.58	0.77	1.27
4	1.86	2.11	0.95	0.74	0.31	0.90
V5	1.97	2.17	0.69	0.64	-0.34	0.04
V5-V1	1.12 (2.76)	1.04 (2.86)	0.16 (0.34)	0.08 (0.19)	-1.53 (-2.55)	-1.62 (-2.90)
FF-Alpha	0.04 (0.16)	0.04 (0.23)	-0.12 (-0.46)	-0.17 (-0.87)	-1.06 (-2.85)	-1.37 (-3.98)

This table shows value and equally-weighted monthly returns of the quintile portfolios formed on idiosyncratic volatility. Quintile portfolios are formed on idiosyncratic volatility each month from January 1965 to December 2010. For panel B, monthly idiosyncratic volatilities are the square root of the number of trading days times the daily idiosyncratic volatility, the standard deviation of residuals from the regression of excess daily stock returns on the contemporaneous daily Fama-French factors in the month. For panel C, monthly idiosyncratic volatilities are the standard deviation of residuals from the regression of excess monthly stock returns on the contemporaneous monthly Fama-French factors using the previous 24 to 60 monthly returns (as available) each month. The investor sentiment data is from Baker and Wurgler (2006) and downloaded from Wurgler's website from July 1965 to December 2010. There are 182 months for each Low, Medium, and High sentiments. V1 (V5) is portfolio of stocks in the bottom (top) quintile of IVOL. Newey-West (1978) adjusted t-statistics are reported in parenthesis. Alpha reports Fama-French three factor alpha.

Next, I control for the stocks' nearness to their respective 52-week high price using a double portfolio sorting approach. In Tables 13 and 14, I report the results of this exercise using $Ivol^{daily}$ and $Ivol^{monthly}$, respectively. In Panel A of Table 13, I focus on periods of low investor sentiments (or bad times). During periods of low investor sentiments, the value (equal) weighted return differential between V5 and V1 for stocks in GH1 is negative, -0.56% (-0.93%) per month. Nonetheless, I find these negative value and equal weighted return differentials between V5 and V1 for stocks that belong to GH1 to be significant only when returns are equally weighted; t-statistics of -1.19 and -2.96 for value and equal weighted returns, respectively.

In Panel C of Table 13, I present similar results for periods of high investor sentiments. In this case, I find consistent with my second hypothesis that, the already strong negative volatility-return relationship I document in this paper for stocks that move away from their 52-week highs is even stronger in periods of high investor sentiments. Precisely, I find that for stocks that belong to GH1, the value (equal) weighted return differential between V5 and V1 is negative, -3.50% (-3.29%) per month and highly significant with a t-statistic of -5.63 (-6.83). I also find that the FF-Alphas in this case are negative and strongly significant. I obtain similar results in Table 14 using idiosyncratic volatility estimated with monthly returns ($Ivol^{monthly}$).

Table 13

Average Monthly Returns of Portfolio Sorted on GH and Idiosyncratic Volatility Across Investor Sentiments : ($Ivol^{daily}$)

	GH1	2	3	4	GH5	GH1	2	3	4	GH5
	Value-weighted Returns					**Equal-weighted Returns**				
					Panel A: LOW SENTIMENT					
V1	1.57	1.24	0.73	0.78	0.60	2.13	1.59	1.29	1.12	0.87
2	1.82	1.52	0.88	0.99	0.82	2.41	2.15	1.70	1.40	1.21
3	2.26	1.79	1.32	1.22	1.18	2.57	2.10	1.94	1.64	1.57
4	1.84	1.68	1.20	1.50	1.58	2.21	2.12	2.05	1.96	1.74
V5	1.01	1.37	1.61	1.58	1.81	1.20	1.72	1.92	1.77	1.76
V5-V1	-0.56	0.12	0.87	0.80	1.21	-0.93	0.13	0.63	0.64	0.90
	(-1.19)	(0.31)	(2.15)	(2.13)	(3.45)	(-2.96)	(0.42)	(1.94)	(2.02)	(2.87)
FF-Alpha	-1.29	-0.35	0.33	0.17	0.48	-0.87	-0.17	0.22	0.23	0.62
	(-4.26)	(-1.10)	(0.90)	(0.57)	(1.59)	(-4.33)	(-0.69)	(0.78)	(0.94)	(2.61)
					Panel B: MEDIUM SENTIMENT					
V1	0.70	0.67	0.57	0.65	0.42	0.75	0.58	0.50	0.60	0.71
2	1.30	0.59	0.72	0.52	0.55	0.76	0.67	0.61	0.63	0.79
3	0.71	0.26	0.44	0.54	0.60	0.53	0.58	0.70	0.76	0.82
4	-0.38	0.12	0.64	1.07	1.10	-0.08	0.24	0.66	1.10	1.16
V5	-1.05	-0.23	0.32	1.06	1.54	-0.88	-0.17	0.50	1.22	1.58
V5-V1	-1.74	-0.90	-0.25	0.41	1.11	-1.63	-0.75	0.01	0.62	0.87
	(-3.46)	(-2.24)	(-0.60)	(0.88)	(1.92)	(-5.23)	(-2.57)	(0.02)	(1.72)	(2.26)
FF-Alpha	-0.89	-0.23	-0.16	0.39	1.33	-0.99	-0.71	0.05	0.85	1.17
	(-2.40)	(-0.66)	(-0.48)	(1.22)	(4.14)	(-4.47)	(-3.09)	(0.20)	(3.05)	(4.36)
					Panel C: HIGH SENTIMENT					
V1	1.44	1.48	1.48	1.47	1.18	1.54	1.59	1.60	1.57	1.54
2	0.39	1.08	1.45	1.28	0.92	1.19	1.43	1.69	1.60	1.44
3	0.07	0.72	1.23	1.06	0.95	0.41	1.09	1.49	1.69	1.38
4	-0.54	-0.11	0.33	1.28	0.64	-0.25	0.39	1.13	1.57	1.27
V5	-2.06	-1.12	0.10	0.85	0.65	-1.75	-0.68	0.40	0.95	0.95
V5-V1	-3.50	-2.60	-1.38	-0.62	-0.53	-3.29	-2.26	-1.20	-0.62	-0.59
	(-5.63)	(-4.43)	(-2.72)	(-1.13)	(-1.12)	(-6.83)	(-5.61)	(-2.68)	(-1.47)	(-1.52)
FF-Alpha	-1.99	-1.73	-1.50	-0.45	-0.40	-2.10	-1.90	-1.73	-0.62	-0.16
	(-4.89)	(-4.70)	(-3.89)	(-1.08)	(-1.21)	(-5.51)	(-5.85)	(-5.04)	(-1.86)	(-0.57)

This table shows value and equally-weighted monthly returns of the quintile portfolios formed on GH (George and Hwang Ratio: current price/52-week high price) and idiosyncratic volatility. Quintile portfolios are formed on GH first and then another quintile portfolios are formed on idiosyncratic volatility within each GH portfolio each month *t* from January 1965 to December 2010. Monthly idiosyncratic volatilities are the square root of the number of trading days times the daily idiosyncratic volatility, the standard deviation of residuals from the regression of excess daily stock returns on the contemporaneous daily Fama-French factors in the month. The investor sentiment data is from Baker and Wurgler (2006) and downloaded from Wurgler's website from July 1965 to December 2010. There are 182 months for each Low, Medium, and High sentiments. V1 (V5) is portfolio of stocks in the bottom (top) quintile of IVOL. Newey-West (1978) adjusted *t*-statistics are reported in parenthesis. Alpha reports Fama-French three factor alpha.

Table 14

Average Monthly Returns of Portfolio Sorted on GH and Idiosyncratic Volatility Across Investor Sentiments: ($Ivol^{monthly}$)

	GH1	2	3	4	GH5	GH1	2	3	4	GH5
	Value-weighted Returns					**Equal-weighted Returns**				
Panel A: LOW SENTIMENT										
V1	1.76	1.37	0.71	0.82	0.74	1.99	1.68	1.36	1.07	0.74
2	1.98	1.45	1.03	0.92	0.72	2.27	1.71	1.56	1.32	1.05
3	1.78	1.72	1.18	1.36	1.31	2.35	1.99	1.74	1.55	1.49
4	1.91	2.05	1.56	1.71	1.74	2.14	2.24	1.93	1.74	1.80
V5	1.62	2.03	1.92	1.90	1.90	1.91	2.22	2.39	2.16	2.07
V5-V1	-0.15	0.66	1.20	1.08	1.17	-0.08	0.54	1.04	1.09	1.33
	(-0.31)	(1.49)	(2.84)	(2.67)	(3.36)	(-0.22)	(1.60)	(2.88)	(3.04)	(4.30)
FF-Alpha	-1.29	-0.35	0.33	0.17	0.48	-0.87	-0.17	0.22	0.23	0.62
	(-4.26)	(-1.10)	(0.90)	(0.57)	(1.59)	(-4.33)	(-0.69)	(0.78)	(0.94)	(2.61)
Panel B: MEDIUM SENTIMENT										
V1	0.76	0.37	0.60	0.59	0.41	0.69	0.67	0.58	0.50	0.45
2	0.77	0.46	0.46	0.63	0.49	0.55	0.53	0.52	0.51	0.56
3	0.39	0.48	0.44	0.49	0.64	0.22	0.27	0.58	0.60	0.73
4	0.31	0.50	0.74	0.95	1.44	-0.04	0.46	0.54	0.99	1.26
V5	0.07	0.34	0.68	1.21	1.97	-0.11	0.16	0.82	1.57	1.85
V5-V1	-0.68	-0.03	0.08	0.62	1.55	-0.80	-0.51	0.25	1.07	1.39
	(-1.34)	(-0.07)	(0.17)	(1.32)	(3.35)	(-2.07)	(-1.34)	(0.65)	(2.61)	(3.52)
FF-Alpha	-0.89	-0.23	-0.16	0.39	1.34	-0.99	-0.71	0.05	0.85	1.17
	(-2.40)	(-0.66)	(-0.48)	(1.22)	(4.14)	(-4.47)	(-3.09)	(0.20)	(3.05)	(4.36)
Panel C: HIGH SENTIMENT										
V1	0.95	1.17	1.48	1.36	1.04	1.61	1.78	1.96	1.71	1.43
2	0.27	0.81	1.07	1.25	0.93	1.11	1.48	1.54	1.68	1.37
3	0.26	0.67	0.80	1.52	0.77	0.45	0.97	1.32	1.48	1.26
4	-0.57	0.30	0.41	1.03	0.90	0.02	0.56	1.16	1.34	1.20
V5	-1.39	-0.83	0.16	0.95	0.58	-0.93	-0.29	0.47	1.25	1.20
V5-V1	-2.34	-2.00	-1.33	-0.41	-0.47	-2.54	-2.07	-1.49	-0.46	-0.23
	(-4.15)	(-3.72)	(-2.35)	(-0.66)	(-0.91)	(-4.40)	(-4.42)	(-3.17)	(-0.96)	(-0.55)
FF-Alpha	-1.99	-1.73	-1.50	-0.45	-0.40	-2.10	-1.89	-1.73	-0.62	-0.16
	(-4.89)	(-4.70)	(-3.89)	(-1.08)	(-1.21)	(-5.51)	(-5.85)	(-5.04)	(-1.86)	(-0.57)

This table shows value and equally-weighted monthly returns of the quintile portfolios formed on GH (George and Hwang Ratio: current price/52-week high price) and idiosyncratic volatility. Quintile portfolios are formed on GH first and then another quintile portfolios are formed on idiosyncratic volatility within each GH portfolio each month *t* from January 1965 to December 2010. Monthly idiosyncratic volatilities are the standard deviation of residuals from the regression of excess monthly stock returns on the contemporaneous monthly Fama-French factors using the previous 24 to 60 monthly returns (as available) each month. The investor sentiment data is from Baker and Wurgler (2006) and downloaded from Wurgler's website from July 1965 to December 2010. There are 182 months for each Low, Medium, and High sentiments. V1 (V5) is portfolio of stocks in the bottom (top) quintile of IVOL. Newey-West (1978) adjusted *t*-statistics are reported in parenthesis. Alpha reports Fama-French three factor alpha.

To provide further evidence in support of the findings reported in Tables 13 and 14, I perform a series of regression tests. The results are presented in Tables 15 and 16 using $Ivol^{daily}$ and $Ivol^{monthly}$, respectively. Specifically, I run cross-sectional firm-level Fama-MacBeth regressions of stock returns on lagged explanatory variables, differentiating between periods of low, medium and high investor sentiments. In Models (1) through (3), the focus is on low investor sentiments periods whereas Models (7) through (9) focus on periods of high investor sentiments. In both Tables (15 and 16), Models (1) and (7) investigate the existence of the IVOL puzzle for my sample in univariate regression settings.

In summary, the negative relationship between IVOL and future returns are stronger during period of high investor sentiments for stocks that are far away from their 52-week high prices. That is, the negative relationship between IVOL and future returns is even stronger when bad news reaches the market in good times.

Table 15

Fama-MacBeth Cross-Sectional Regressions Across Investor Sentiments: $(Ivol^{daily})$

	LOW SENTIMENT			MEDIUM SENTIMENT			HIGH SENTIMENT		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IVOL	0.001	-0.186	-0.292	-0.032	-0.189	-0.241	-0.109	-0.256	-0.295
	(0.05)	(-5.01)	(-7.24)	(-2.31)	(-6.63)	(-6.63)	(-6.07)	(-7.70)	(-7.22)
IVOL*GH		0.221	0.407		0.217	0.264		0.199	0.271
		(5.23)	(8.64)		(6.22)	(5.76)		(4.40)	(5.02)
GH		-3.038	-3.922		-1.643	-2.163		-1.469	-1.726
		(-4.59)	(-6.49)		(-2.37)	(-2.70)		(-1.93)	(-2.30)
REV			-0.064			-0.032			-0.052
			(-7.45)			(-6.55)			(-10.20)
MAX			-0.072			0.019			0.025
			(-2.86)			(0.83)			(1.21)
BETA			0.081			0.047			0.025
			(2.71)			(1.33)			(0.40)
BTM			0.045			0.026			0.261
			(0.50)			(0.43)			(2.63)
SIZE			-0.234			-0.077			-0.072
			(-3.45)			(-1.45)			(-1.04)
MOM			1.052			0.745			0.339
			(5.54)			(4.61)			(1.79)
SKW			0.169			0.100			0.042
			(4.11)			(2.57)			(0.80)
ILLIQ			-0.027			-0.006			-0.002
			(-2.80)			(0.40)			(-0.16)

Each month from January 1965 to December 2010, we run a firm-level Fama-MacBeth cross-sectional regressions of stock return in month *t+1* on the lagged explanatory variables in month *t*. The explanatory variables include stock's monthly idiosyncratic volatility (IVOL), current price/52-week high price (GH: George and Hwang Ratio), the interaction term (IVOL*GH), monthly stock return (REV), maximum daily return (MAX), BETA, the book-to-market ratio (BTM), the log of market capitalization (Size), the holding period return from month *t-12* to month *t*-2 (MOM), the idiosyncratic skewness (Skw), and the illiquidity measure (ILLIQ). The investor sentiment data is from Baker and Wurgler (2006) and downloaded from Wurgler's website from July 1965 to December 2010. There are 182 months for each Low, Medium, and High sentiments. Common stocks with price greater than or equal to $5 from the NYSE/AMEX/NASDAQ are included in the sample. Newey-West (1978) adjusted *t*-statistics are reported in parenthesis.

Table 16

Fama-MacBeth Cross-Sectional Regressions Across Investor Sentiments: ($Ivol^{monthly}$)

	LOW SENTIMENT			MEDIUM SENTIMENT			HIGH SENTIMENT		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IVOL	0.053	-0.288	-0.400	-0.011	-0.207	-0.257	-0.111	-0.264	-0.687
	(1.41)	(-4.72)	(-6.67)	(-0.48)	(-5.72)	(-5.94)	(-4.33)	(-7.92)	(-6.27)
IVOL*GH		0.428	0.563		0.270	0.315		0.185	0.248
		(5.35)	(6.48)		(5.68)	(6.03)		(2.98)	(3.60)
GH		-4.342	-4.687		-1.634	-2.331		-1.055	-1.489
		(-5.22)	(-6.44)		(-2.19)	(-3.33)		(-1.37)	(-1.98)
REV			-0.063			-0.027			-0.046
			(-8.18)			(-6.90)			(-8.37)
MAX			-0.057			-0.034			-0.066
			(-3.14)			(-3.03)			(-4.58)
BETA			0.050			0.023			0.001
			(2.52)			(0.61)			(0.01)
BTM			0.103			0.035			0.156
			(1.21)			(0.61)			(1.74)
SIZE			-0.209			-0.077			-0.149
			(-3.53)			(-0.51)			(-2.32)
MOM			0.983			0.808			0.507
			(4.99)			(4.98)			(2.62)
SKW			0.166			0.185			0.153
			(4.53)			(4.66)			(4.46)
ILLIQ			-0.024			-0.004			0.001
			(-2.34)			(-0.32)			(0.09)

Each month from January 1965 to December 2010, we run a firm-level Fama-MacBeth cross-sectional regressions of stock return in month *t+1* on the lagged explanatory variables in month *t*. The explanatory variables include stock's monthly idiosyncratic volatility (IVOL), current price/52-week high price (GH: George and Hwang Ratio), the interaction term (IVOL*GH), monthly stock return (REV), maximum daily return (MAX), BETA, the book-to-market ratio (BTM), the log of market capitalization (Size), the holding period return from month *t-12* to month *t*-2 (MOM), the idiosyncratic skewness (Skw), and the illiquidity measure (ILLIQ). The investor sentiment data is from Baker and Wurgler (2006) and downloaded from Wurgler's website from July 1965 to December 2010. There are 182 months for each Low, Medium, and High sentiments. Common stocks with price greater than or equal to $5 from the NYSE/AMEX/NASDAQ are included in the sample. Newey-West (1978) adjusted *t*-statistics are reported in parenthesis.

CHAPTER FIVE

CONCLUSIONS

The finance literature has struggled with the puzzling findings of Ang, Hodrick, Xing, and Zhang (2006, 2009) that high idiosyncratic volatility stocks earn low future returns. This puzzling relationship between idiosyncratic volatility and expected returns has been widely documented in international data, and continues to exist in the U.S data. Several theories both rational and behavioral have been suggested to explain this phenomenon. However, important and widely accepted aspect of the behavior of investors has proven to be absent from this debate.

The main contribution of this study is to provide evidence of the role of anchoring bias on the relationship between idiosyncratic volatility and future returns. I posit that idiosyncratic volatility puzzle should be concentrated in stocks that move away from their 52-week high prices. In other word, I argue that the limits of arbitrage, short sale constraint, and uncertainty of high idiosyncratic volatility combined with the anchoring bias of the 52-week high price can explain the low returns of high idiosyncratic volatility stocks. The empirical results are consistent with this hypothesis. I find that the negative relationship between idiosyncratic volatility and expected returns documented by Ang et al. (2006) primarily exists in stocks for which bad news recently arrived in the market.

In addition, I find that the idiosyncratic volatility discount documented in Ang et al. (2006) is even stronger for stocks for which bad news arrives in the market when investor sentiments are high. This finding is consistent with Veronesi (1999), showing that in good times, bad news signals increased uncertainty and greater likelihood negative future performance. Furthermore, I find that the negative relationship between idiosyncratic volatility and future returns for stocks that move away from their 52 Week-High prices persists up to six months following the portfolio formation.

Overall, the results presented in this paper are very robust to data frequency, the length of time series used in the computation of idiosyncratic volatility, and January seasonality. Ultimately, I contribute to the extensive literature on the idiosyncratic volatility puzzle by suggesting that attempts to understand the low returns of high idiosyncratic volatility stocks can leverage on the growing strand of the literature that identifies the role of reference points and anchors in the decision making of investors. Specifically, I argue in this paper in favor of a focus on specific behavioral biases such as the tendency to anchor on publicly available information such as the 52 Week-High prices as possible explanations of the idiosyncratic volatility puzzle.

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APPENDIX

VITA

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To obtain a tenure-track position as an Assistant Professor in Finance with a balanced teaching and research focus.

Areas of Interest

- My research at this point focuses on Empirical Asset Pricing, Excess Volatility, Behavioral Finance and Macroeconomics.
- I look forward to teaching Financial Economics, Investments, Empirical Asset Pricing,
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Education

D.B.A – Finance — Expected May 2015
The College of Business, Louisiana Tech University
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M.B.A – Management and Finance — 2007 - 2009
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Job Market Paper

"52-Week High, Idiosyncratic Volatility and the Cross-Section of Stock Returns"
With Jungshik Hur

Publications

"The Impact of Monetary and Fiscal Policies on Real Output: A Re-examination"
With Ali Darrat and Kenneth Tah. Forthcoming at the
Journal of Business and Economics (2014)

"Integration in Star-Ups: Realizing and Understanding Differences"
With Nina Krey. ***Journal of Business and Entrepreneurship (2013)***

1. *Presented at the Small Business and Entrepreneurship Conference in New Orleans (2013)*
2. *Won the Students' Best Paper Award*

Working Papers

"Fiscal Policy and the U.S Stock Market" *With Ali Darrat. 2nd Round Revise and Resubmit at the **Review of Quantitative Finance and Accounting Journal***

"Idiosyncratic Volatility, Dynamic Aspects of Loss Aversion, and Narrow Framing" *With Jungshik Hur. Submitted*

"Investors' Sentiments and the Ostrich Effect" *With Badel Mbanga*

"Investors' Attention and Sentiments in the Cross-Section of Stock Returns"

Teaching Experience

Lecturer:

- Introduction to Business Finance (FINC 318) – Summer 2014
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- Investments (FINC 414) for Dr. J. Hur
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