# High Idiosyncratic Volatility and Low Returns: A Prospect Theory Based Explanation

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## Abstract

The well-documented negative relationship between idiosyncratic volatility and stock returns is puzzling if investors are risk-averse. However, under prospect theory, while investors are risk-averse in the domain of gains, they exhibit risk-seeking behavior in the domain of losses. Consistent with risk-seeking investors' preference for high volatility stocks in the loss domain, we find that the negative relationship between idiosyncratic volatility and stock returns is concentrated in stocks with unrealized capital losses, but is non-existent in stocks with unrealized capital gains. This finding is robust to control for short-term return reversals and maximum daily return, among other variables. Further, the negative volatility-return relationship is stronger among stocks with greater proportional ownership by individual investors.

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## 1. Introduction

According to the standard asset pricing theory, only the systematic risk of securities should be priced and there should be no compensation for the diversifiable idiosyncratic risk. However, according to Merton's (1987) investor recognition hypothesis, if investors invest only in securities with familiar risk-return characteristics and consequently, hold under-diversified portfolios, idiosyncratic risk should be priced in equilibrium. In direct contrast to the implications of Merton's hypothesis, Ang, Hodrick, Xing, and Zhang (2006; AHXZ hereafter) document a puzzling negative cross-sectional relationship between stocks' monthly idiosyncratic volatility and their returns in the following month.

Merton's (1987) implication of a positive volatility-return relationship with suboptimal diversification assumes risk-averse investors with concave utility of wealth functions within the standard expected utility framework. However, Kahneman and Tversky's (1979) descriptive model of decision making under uncertainty, the prospect theory, postulates an S-shaped utility function that is concave in the domain of gains, but convex in the domain of losses. Labeled as the "reflection effect", such non-uniform risk preferences result from the overweighting (underweighting) of certain (probabilistic) outcomes, and suggest risk-aversion over positive prospects, but risk-seeking behavior over negative prospects.

We posit that investors' divergent attitude towards risk over positive and negative prospects is the key to understanding the AHXZ's idiosyncratic volatility anomaly. Specifically, the risk-seeking behavior of investors in the domain of losses suggests a preference for stocks with high idiosyncratic volatility. In conjunction with mental accounting (Thaler, 1980), such a tendency would result in lower returns to high idiosyncratic volatility stocks with unrealized capital losses, if the relevant mental accounts are the paper gains and losses associated with individual stocks.

Note that in the framework of Grinblatt and Han (2005), the demand distortions induced by the presence of prospect theory/mental accounting (PT/MA) investors result in overvaluation (undervaluation) of stocks with unrealized capital losses (gains).[1] We argue that the investors' affinity for high idiosyncratic volatility stocks within the loss domain would lead to greater overpricing among these stocks. Therefore, the PT/MA framework provides a rationale for the existence of negative volatility-return relationship among stocks with unrealized capital losses (and not among stocks with unrealized capital gains).

Based on the foregoing discussion, we hypothesize that the negative relationship between idiosyncratic volatility and subsequent stock returns is concentrated in stocks with unrealized capital losses. In order to empirically test this hypothesis, we construct the capital gains overhang measure in a similar manner as Grinblatt and Han (2005), employing a proxy for the market's aggregate cost basis in a stock as the relevant reference point to determine unrealized gains and losses. In our preliminary tests, we examine the value-weighted and equally-weighted returns of five idiosyncratic volatility portfolios, separately within the subgroup of stocks with unrealized capital losses (CL) and unrealized capital gains (CG). Consistent with our hypothesis, we find that for the stocks in the CL group, the difference in monthly value-weighted (equally-weighted) raw returns of high and low idiosyncratic volatility portfolios is -1.31% (-1.24%) with a *t*-statistic of -4.95 (-5.54). The corresponding alphas from the CAPM (Sharpe, 1964; Lintner, 1965; Mossin, 1966) and Fama and French (1993) models are even larger in magnitude and are

[1]The demand distortions occur because the S-shaped value function from prospect theory, together with mental accounting, leads to disposition effect: the tendency of investors to sell their winning stocks too quickly and hold on to their losing stocks too long (Shefrin and Statman, 1985).

also statistically significant. However, there is no evidence of statistically significant return difference in extreme volatility portfolios of stocks in the CG group, in either value-weighted or equally-weighted returns. We obtain similar results when using the same idiosyncratic volatility cutoffs for CL and CG groups, suggesting that this result is not driven by the presence of extreme idiosyncratic volatility stocks in the CL portfolio.[2]

We perform several tests to ensure the robustness of the above result. Recent evidence in 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).[3] These authors find that in the cross-sectional regressions of stock returns on idiosyncratic volatility that control for previous month's return, the coefficient on idiosyncratic volatility is no longer statistically significant.

In contrast to the evidence in HLRZ, we find that when stocks priced below $5 are excluded from the sample, we obtain a robust negative relationship between idiosyncratic volatility and stock returns in CL stocks, with both value-weighted and equally-weighted portfolio returns as well as in Fama-MacBeth (1973) firm-level cross-sectional regressions that control for the past month's return.[4] Given the high transaction costs as well as the severe short-selling constraints associated with these penny stocks, we believe their exclusion from the sample is justified.

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[2] It is noteworthy that in AHXZ (Table VIII, Panel B; pp. 291), the Fama-French alpha associated with high minus low idiosyncratic volatility portfolio is -2.25% for loser stocks, but only -0.48% for winner stocks, where winners and losers are identified based on past 12-month returns. In accordance with Grinblatt and Han (2005), our focus is on unrealized gains and losses rather than on past returns.

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

[4] Note that while Fink, Fink, and He (2012) find no evidence of a relationship between expected idiosyncratic volatility and expected returns, they rely, in part, on evidence in HLRZ to explain AHXZ finding of negative relationship between lagged idiosyncratic volatility and returns.

Another recent study by 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 for MAX in the cross-sectional regressions of returns on idiosyncratic volatility, the coefficient on volatility is insignificant in some specifications or even significantly positive in others. We document that the negative volatility-return relationship in CL stocks persists after controlling for MAX in our empirical tests.

In addition to the prior month return and MAX variables, we also include other common explanatory variables including size, stock price, book-to-market ratio, illiquidity, past 12-month return, idiosyncratic skewness, and beta in Fama-MacBeth cross-sectional regressions, and find evidence of robust negative volatility-return relationship in CL stocks.

As a further extension of our main hypothesis, we explore the role of individual investor ownership in the negative relationship between idiosyncratic volatility and returns. Given the evidence of stronger behavioral biases among individual investors as well as their tendency to pick stocks with volatilities commensurate with their risk preferences (Dorn and Huberman, 2010) , we hypothesize that the negative relationship between idiosyncratic volatility and returns among CL stocks would be stronger for stocks with relatively higher proportional ownership by individual investors. As a proxy for the fraction of shares owned by individual investors, we use the fraction of outstanding shares of each stock that are not owned by large institutional investors. The portfolio level analysis shows that the difference in monthly returns of high and low volatility portfolios is -2.28% (*t*-statistic = -5.14) for CL stocks with high individual investor ownership, which is significantly lower than the corresponding difference of -0.92% (*t*-statistic = -2.63) for CL stocks with low individual investor ownership. Using firm-level Fama-MacBeth cross-sectional regressions that control for multiple explanatory variables, we confirm that the negative volatility-return relationship in the CL stocks is stronger among stocks with relatively higher level of individual investor ownership. Overall, our results indicate an incremental role of individual investor ownership in the negative volatility-return relationship.

Our study makes several contributions to the literature. This paper is the first to document and provide robust supporting evidence that the negative volatility-return relationship is only observed in stocks with unrealized capital losses. This result lends credence to the significance of prospect theory based risk preferences in understanding the asset pricing anomalies. Additionally, we link this key result of our study to several of the previously documented findings in literature and provide some novel empirical results. We show that in contrast to prior evidence, the short term reversals and maximum daily return do not explain the volatility-return relationship in the sample of capital loss stocks. Further, we report that the previously documented role of penny stocks (George and Hwang, 2011) and January seasonality (Doran, Jiang, and Peterson, 2012) in volatility-return relationship is relevant only for capital loss stocks, and not for capital gains stocks. Moreover, while the role of individual investors in this anomalous relationship is of significance, it is also observed more prominently among capital loss stocks. In sum, our results suggest that whether a stock has unrealized gains or losses is a dominant factor in understanding the idiosyncratic volatility anomaly.

The rest of the paper is organized as follows. Section 2 develops the hypotheses and relates our work to the relevant literature. Section 3 describes the data and methodology. Section 4 presents the results. We conclude in Section 5.

## 2. Hypotheses Development and Related Literature

The negative relationship between idiosyncratic volatility and subsequent stock returns is considered anomalous under the implicit assumption that investors are risk-averse. According to Ang, Hodrick, Xing, and Zhang (2009), "…we do not yet have a theoretical framework to understand why agents have high demand for high-idiosyncratic-volatility stocks, causing these stocks to have low expected returns."

Given that under the expected utility theory, the investors are uniformly risk averse with concave utility of wealth, it has proven challenging to explain the negative volatility-return relationship under this framework. We explore the alternative possibility that investors' risk preferences under Kahneman and Tversky's (1979) prospect theory provide a resolution of this puzzle. The key distinctive element of prospect theory is the S-shaped utility function that is concave in the domain of gains, but convex in the domain of losses. This S-shaped utility function stems from overweighting of certain outcomes over probabilistic outcomes. This certainty effect leads to preference for a sure gain of smaller magnitude over a probable gain of large magnitude. On the other hand, in the domain of losses, the same effect leads to preference for a probable loss of larger magnitude over a certain loss of smaller magnitude. These preferences, which diverge from simple probability weighting under the expected utility framework, imply risk-averse behavior in the domain of gains, but risk-seeking behavior in the domain of losses.

While the negative volatility-return relationship is puzzling under the assumption of risk aversion, a framework that allows for the possibility of investors' risk-seeking behavior can potentially explain the higher demand and subsequent lower returns of high idiosyncratic volatility stocks. And since the investors exhibit risk-seeking behavior in the loss domain under prospect theory, the straightforward implication of prospect theory preferences is that the low returns to high idiosyncratic volatility stocks should be observed in the domain of losses, and not in the domain of gains.

It is clear that an empirical investigation of the role of prospect theory preferences in explaining the negative volatility-return relationship hinges on defining the domain of gains and losses with respect to a reference point. If investors segregate gains and losses on their stocks into separate mental accounts, then the relevant reference point is cost basis of a stock (see Grinblatt and Han, 2005). Further, since prospect theory preferences are relevant when investors face the prospect of a gain or loss, a measure of unrealized gains and losses is appropriate for empirical analysis.

In the model of Grinblatt and Han (2005), the tendency of disposition prone investors to hold on to their loser stocks too long results in overvaluation of these stocks with unrealized capital losses. We expect that due to their risk-seeking behavior, the tendency to hold on to high volatility stocks would be particularly strong, resulting in greater overpricing and subsequent lower returns of these stocks. On the other hand, the tendency of these investors to sell their winners too quickly leads to undervaluation of stocks with unrealized capital gains. However, within the domain of gains, the relationship between volatility and subsequent returns is not clear. On one hand, it is plausible that the risk-averse investors may have greater inclination to liquidate the high volatility stocks, resulting in greater underpricing and higher returns in future. On the other hand, it is also conceivable that the risk-averse investors eliminate the idiosyncratic risk of their portfolios through diversification, as is assumed in standard asset pricing models. In the latter case, we would expect no relationship between idiosyncratic risk and returns for stocks with unrealized gains.

The foregoing discussion forms the basis of our primary hypothesis:

*H1*: *The negative relationship between idiosyncratic volatility and subsequent stock returns is concentrated in stocks with unrealized capital losses.*

Note that in the model of Barberis, Huang, and Santos (2001), investors become risk-averse after realization of a loss. We are interested in prospect theory risk preferences that are relevant when investors are sitting on paper gains/losses, but have not realized them. This distinction is lucidly illustrated in Barberis, Huang, and Santos (1999) using the casino/horse-race betting example. In that example, a gambler at casino sitting on losses (unrealized losses) exhibits risk-seeking behavior in an effort to break-even, consistent with the prospect theory preferences. However, subsequent to the realization of loss, the gambler becomes risk-averse due to fear of accumulating further losses.

In another recent study, Barberis and Xiong (2012) develop a model of realization utility which provides a potential explanation of the negative volatility-return relationship. In their model, investors derive positive (negative) utility from realizing gains (losses) on their investments. This realization utility leads to preference for buying high volatility stocks due to their greater upside potential. The greater downside risk of these stocks is not particularly worrisome for investors since realization of a loss can be postponed to avoid derivation of negative utility. Thus, the risk-seeking behavior of investors with realization utility leads to higher demand and subsequent lower returns of high volatility stocks.

Since hypothesis H1 is based on prospect theory preferences, it differs from the framework of Barberis and Xiong in two important aspects. First, unlike the case of prospect theory preferences, in the framework on Barberis and Xiong, the preference for high volatility stocks does not hinge on whether stocks have unrealized gains or losses. Indeed, in their framework, the investors can be risk-seeking even if their utility is concave. Second, as Barberis and Xiong point out, the idea of realization utility is more relevant for individual rather than institutional investors, suggesting that the negative volatility-return relationship should be observed in stocks with relatively higher individual investor ownership. In contrast, our primary hypothesis H1 postulates negative volatility-return relationship among stocks with unrealized losses, without conditioning on the magnitude of individual investor ownership.

However, within the subgroup of stocks with unrealized losses, we expect the result to be stronger among stocks with greater individual investor ownership. A large body of evidence in the literature suggests that the individual investors are more prone to psychological biases as compared with the more sophisticated institutional investors. For example, using a dataset of individual trades and holdings from a large brokerage house over the 1991 to 1996 period, Odean (1998) documents a strong loss aversion tendency among individual investors. Similarly, Grinblatt and Keloharju (2001) also find that investors in the Finnish stock market are reluctant to realize their losses. Of particular interest is the evidence of volatility specialization in Dorn and Huberman (2010), who find that risk-seeking (risk-averse) individual investors tend to hold high (low) volatility stocks. Further, because of their low price (relative to CG stocks), the CL stocks with high idiosyncratic volatility are likely to appeal to individual investors who have a preference for speculative and lottery-like stocks (Kumar, 2009; Han and Kumar, 2012).[5]

The above evidence forms the basis of secondary hypothesis of this paper:

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[5]On the other hand, Falkenstein (1996) and Gompers and Metrick (2001) document a preference for high priced stocks among institutional investors and mutual funds, respectively.

*H2*: *The negative relationship between idiosyncratic volatility and returns among stocks with unrealized capital losses is stronger for stocks with relatively higher proportional ownership by individual investors*.

The role of individual investors in the negative volatility-return relationship is reported in a recent paper by Han and Kumar (2012). Han and Kumar document stronger negative volatility-return relationship among stocks whose trading is dominated by retail investors. Our analysis differs from Han and Kumar along two dimensions. First, unlike Han and Kumar, we condition on a measure of unrealized capital gains and losses, and propose a stronger role of individual investor ownership within the subgroup of stocks with unrealized losses. Second, our analysis is motivated by prospect theory based preferences which suggest greater affinity among existing shareholders for the high idiosyncratic volatility stocks within the group of "unrealized loss" stocks they currently hold. In contrast, the analysis in Han and Kumar is motivated by the retail investors' attraction to lottery-like stocks; that is, their tendency to invest in stocks *subsequent* to decline in their price and increase in their idiosyncratic volatility.

## 3. Data and Methodology

Our base sample comprises of common stocks listed on NYSE, AMEX, and NASDAQ (shares codes 10 and 11) over the period from July 1963 to December 2007. We obtain daily and monthly stock returns from the CRSP files. Except where necessary to illustrate the impact of low priced stocks on inferences, we exclude firms priced below $5 in the portfolio formation month from the sample to ensure that the results are not driven by these illiquid securities. We also exclude firms with the missing data required for the computation of capital gains overhang and the estimation of monthly idiosyncratic volatility. The final sample comprises of a total of 19,736 unique firms, with an average of 3,567 firms per month.

In the second part of our analysis, we examine the role of individual investor ownership (IIO) in the negative volatility-return relationship. In accordance with Nofsinger and Sias (1999), the IIO in a stock is defined as the fraction of outstanding shares that are not held by large institutional investors. The quarterly holdings of institutional investors are obtained from the Thomson Reuters 13F institutional database, which is constructed from the 13F filings of institutional investors. Institutional investors with \$100 million or more in assets under management are required to disclose their holdings to the Securities and Exchange Commission through quarterly 13F filings. Since the 13F data is not available prior to 1980, our sample period for this part of the analysis is from January 1980 to December 2007. We compute the IIO at the end of each quarter as one minus the ratio of shares held by large institutional investors to the total number of shares outstanding and assume that it remains constant over the subsequent quarter prior to the next update. We merge the 13F data with the returns data from the CRSP files, resulting in 16,665 distinct firms, with an average of 4,008 firms per month over the 1980 to 2007 period.

Following AHXZ, the idiosyncratic volatility of stock *i* is obtained from the following time-series regression of excess daily stock returns during the month on the contemporaneous Fama-French market, size, and book-to-market factors:[6]

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i MKTRF_d + s_i SMB_d + h_i HML_d + e_{i,d} \ , \qquad (1)$$

where $R_{i,d}$ is the return of stock $i$ on day $d$, $R_{f,d}$ is the daily risk-free rate, and $MKTRF_d$, $SMB_d$, and $HML_d$ are the daily Fama-French factors. The daily idiosyncratic volatility is the standard

[6] The Fama-French factors are obtained from Ken French's data library available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

deviation of the residuals from this regression and the monthly idiosyncratic volatility (IVOL) is obtained by multiplying the daily volatility by the square root of the number of trading days in the month. The mean IVOL for the entire sample is 13.07%.

We construct the capital gains overhang variable using CRSP daily returns following the methodology employed in Grinblatt and Han (2005) and Hur, Pritamani, and Sharma (2010). The capital gains overhang of a stock represents the percentage deviation of its price from its current reference price, where the reference price is assumed to be the market's aggregate cost basis for the stock. Specifically, for each stock *i* at the end of each month *t*, the capital gains overhang ($\mathrm{CGO}_{i,t}$) is obtained as:

$$\mathrm{CGO}_{i,t} = (P_{i,t} - RP_{i,t}) / P_{i,t} \ , \tag{2}$$

where $P_{i,t}$ is the price of the stock *i* at the end of month *t* and $RP_{i,t}$ is the reference price for each stock *i* at the end of month *t*. The reference price, $RP_{i,t}$, is estimated as follows:

$$RP_{i,t} = \frac{1}{k}\sum_{n=1}^{T}\left(V_{i,t-n}\prod_{\tau=1}^{n-1}\left[1 - V_{i,t-n+\tau}\right]\right)P_{i,t-n} \ , \tag{3}$$

where $V_{i,t}$ is turnover in the stock *i* on day *t*, *T* is the number of trading days in the previous three years with available daily price and volume information, and $P_{i,t-n}$ is price of security *i* on day *t*-*n*. The term in the parentheses multiplying $P_{i,t-n}$ is a weight that reflects the probability that the shares purchased on date *t*-*n* have not been traded since, the probability being a function of the turnover from *t*-*n* to *t*-1. Intuitively, a higher turnover in any given month (relative to other months) over the past three years would imply a greater likelihood that the stock was bought by the current shareholders in that particular month. The denominator *k* is a constant that makes the weights sum up to one. In computing $RP_{i,t}$, the share price and share turnover variables are adjusted for stock splits and stock dividends.[7]

For empirical tests, we segregate the stocks into groups with unrealized capital losses and unrealized capital gains every month (negative and non-negative values of CGO in equation (2), respectively). We label the stocks with unrealized losses (gains) as CL (CG) stocks. In preliminary tests, we examine the returns of portfolios obtained by employing univariate and multivariate sorts on key variables such as idiosyncratic volatility and capital gains overhang. To control for multiple explanatory variables, we employ the monthly firm-level Fama-MacBeth cross-sectional regressions. To account for any potential impact of autocorrelations on statistical inferences, we use the Newey and West (1987) adjusted standard errors when computing the *t*-statistics in all our tests.

## 4. Results

### *4.1. Idiosyncratic Volatility and Stock Returns*

We begin our analysis by verifying the presence of negative relationship between idiosyncratic volatility and subsequent returns in our sample. Each month, we sort the stocks into 5 portfolios based on their monthly idiosyncratic volatility and examine the returns of these portfolios in the following month. Table 1 reports the value-weighted and equally-weighted returns of these volatility sorted portfolios. To highlight the impact of low-priced stocks on

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[7]In Grinblatt and Han (2005) model, the reference price for a stock is obtained as the turnover weighted average of past stock price and past reference price. That is,

$$RP_{i,t} = V_{i,t-1}P_{i,t-1} + (1 - V_{i,t-1})RP_{i,t-1}$$

The recursive substitution of past reference prices on the right hand side of the above equation leads to equation (3) with the exception that the summation is over infinite periods. For empirical implementation, we sum over the number of trading days in recent 3 years. Grinblatt and Han (2005), however, find robust results using 3, 5, or 7 years of data.

returns, we report the returns for samples that include sub-$5 stocks (in Panel A) and that exclude sub-$5 stocks (in Panel B).

Panel A of Table 1 shows that the difference in value-weighted returns of high and low volatility portfolios is negative, -0.91%, and statistically significant (*t*-statistic = -3.15). The corresponding CAPM and Fama-French alphas are even larger in magnitude at -1.27% and -1.23%, respectively, and are also statistically significant. These results are consistent with AHXZ, who find the raw return differential to be -1.06% per month over the July 1963 - December 2000 period. However, in the sample that includes sub-$5 stocks, the difference in equally-weighted returns of extreme volatility portfolios is a statistically insignificant -0.05%. This finding is consistent with Bali and Cakici (2008) and HLRZ, who document an insignificant difference of 0.02% and -0.005% per month, respectively, for the equally-weighted portfolios over July 1963 - December 2004.[8]

However, when we exclude the sub-$5 penny stocks from the sample in Panel B, we find that the difference in equally-weighted returns of high and low volatility portfolios is -0.63%, which is statistically significant (*t*-statistic = -2.66). The corresponding CAPM and Fama-French alphas are -0.98% (*t*-statistic = -4.75%) and -0.81% (*t*-statistic = -6.03%), respectively. The difference in value-weighted returns and alphas continues to be significant after the exclusion of penny stocks, although the magnitudes are relatively smaller compared with those in Panel A. These findings suggest that the absence of negative volatility-return relationship in equally-weighted portfolios in Bali and Cakici (2008) and HLRZ is driven by the presence of sub-$5 stocks in their sample. The significant impact of penny stocks on equally-weighted portfolio returns coupled with the fact that these stocks are typically associated with high

[8] Note that the inferences based on value-weighted portfolio returns are likely to be more reliable due to potential biases from noisy prices in equally-weighted portfolio returns (Asparouhova, Bessembinder, and Kalcheva, 2011).

illiquidity, high transaction costs, and severe short-selling restrictions justifies their exclusion from the sample.[9]

### *4.2. Summary Statistics of CL and CG Portfolios*

Before we proceed to investigating the role of unrealized gains and losses in the IVOL-return relationship, we present the summary characteristics of stocks in CL and CG portfolios in Table 2. The variable definitions are provided in the Appendix. The numbers in the table represent the averages over sample months of the monthly cross-sectional median values of each characteristic. The magnitude of embedded losses (gains) in CL (CG) stocks is -19.35% (12.64%). The median monthly idiosyncratic volatility of the CL stocks, 9.17%, is significantly higher compared with 7.98% for the CG stocks. Therefore, any evidence of stronger negative IVOL-return relationship must account for the more extreme volatility of stocks in the CL group.

The median price and market capitalization of CL stocks is significantly lower as compared with the CG stocks. This result is not surprising given the significant loss (gain) in value experienced by the CL (CG) stocks. The CL stocks also tend to have smaller book-to-market ratios as compared with the CG stocks. Because of the return premium associated with value stocks, it is important to account for the role of value effect in empirical tests. The CL stocks are also significantly more illiquid, which is expected given their relatively smaller size and much lower median price.

Interestingly, there is no significant difference in the maximum daily return (MAX) for the CL and CG groups. Thus, while the MAX variable is unlikely to explain any differences in

[9] For comparison purposes, we continue to illustrate the results for the sample that includes penny stocks in some of the subsequent tables.

results between the two groups, it can still explain the negative volatility-return relationship *within* the CL or CG groups, in accordance with BCW.

The next two rows in the table show the median values of prior 12-month return and REV variables for the CL and CG groups. As expected, the prior 12-month returns are negative for CL stocks and positive for CG stocks, with the corresponding magnitudes being -2.72% and 30.51%, respectively. Similarly, the REV is negative, -1.73%, for CL stocks and positive, 3.44%, for CG stocks. As previously mentioned, the REV variable is of particular interest due to the finding of HLRZ that short-term reversals can explain the negative IVOL-return relationship. However, because CL stocks have significantly lower return as compared with CG stocks in the month of portfolio formation, the short-term reversals would suggest a higher, not lower, return for the CL stocks in the subsequent month. Again, similar to the MAX variable, the REV variable might be positively associated with IVOL *within* the CL and CG groups, and can potentially explain the low returns to high volatility stocks within the groups.

The next row in the table shows the median idiosyncratic skewness of the stocks in the two groups. Recent theories and empirical evidence suggest that idiosyncratic skewness is a priced variable in the cross-section of stocks returns (e.g., Brunnermeier, Gollier, and Parker, 2007; Mitton and Vorkink, 2007; Barberis and Huang, 2008). In our sample, we find that the median idiosyncratic skewness is significantly lower for the CL stocks as compared with the CG stocks. Lastly, the table shows the median betas for the two groups, and we do not find any evidence of significant difference in betas across the CL and CG stocks.

### *4.3. Preliminary Tests of the Hypothesis*

We next begin preliminary investigation of our main hypothesis that the negative relationship between idiosyncratic volatility and stock returns is concentrated among stocks with unrealized capital losses. Within each of the CL and CG groups, we sort the stocks into quintile portfolios based on idiosyncratic volatility. Panel A of Table 3 reports the returns in the following month of the portfolios thus obtained, along with the difference in returns of extreme volatility portfolios and the corresponding CAPM and Fama-French alphas.

Consistent with our hypothesis, we find that the difference in the value-weighted (equally-weighted) raw returns of high and low idiosyncratic volatility portfolios within the CL portfolio is negative, -1.31% (-1.24%), and statistically significant with a *t*-statistic of -4.95 (-5.54). On the other hand, the difference in value-weighted (equally-weighted) returns is a statistically insignificant 0.05% (0.16%) for the CG portfolio with an associated *t*-statistic of 0.19 (0.72). The corresponding alphas from the CAPM and three-factor models are also highly significant for the CL portfolio, but are insignificant for the CG portfolio. Finally, the difference in high minus low IVOL returns between CL and CG stocks as well as the corresponding differences in CAPM and three-factor alphas are all negative and statistically significant.[10]

As documented in Table 2, the average idiosyncratic volatility of stocks in the CL portfolio is relatively higher as compared with the stocks in the CG portfolio. Since the results in Panel A of Table 3 employ sequential sorting, a potential explanation of the findings in Panel A is that the cutoffs for the high and low volatility portfolios within the CL portfolio are more extreme as compared with the CG portfolio, and therefore the return predictability is stronger.

[10]In Grinblatt and Han (2005) model, the loser (winner) stocks are overpriced (underpriced) despite recent inferior (superior) performance and overpricing (underpricing) is evidenced by their continued inferior (superior) performance. Along the same lines, we infer presence of mispricing in this paper based on subsequent risk-adjusted performance.

To ensure that these more extreme cutoffs are not driving the results, we repeat the analysis with independent sorting instead of sequential sorting, so that the same IVOL cutoffs are employed for both CL and CG portfolios. The returns with independent sorting are presented in Panel B of Table 3. The results are qualitatively similar to those in Panel A. The value-weighted (equally-weighted) return spread between high and low volatility stocks for CL portfolio is a statistically significant -1.20% (-1.16%), but is an insignificant 0.13% (0.02%) for the CG portfolio. The alphas also exhibit a pattern similar to the case of sequential sorting. Therefore, the concentration of negative volatility-return relationship in the CL portfolio does not seem to be attributable to the presence of stocks with relatively higher volatility in this portfolio.[11]

In unreported results, we also examine the market capitalization of quintile volatility portfolios across CL and CG groups. We find a monotonic decline in market cap as the volatility increases, for both CL and CG groups. Given the negative volatility-return relationship is only observed among CL stocks, it does not appear that the results can be attributable to small size or illiquidity of high volatility portfolios. Note that through the exclusion of sub-$5 stocks, we have already eliminated the smallest, most illiquid stocks. Further, we explicitly control for size and illiquidity in our cross-sectional regression tests later in the paper.

### *4.4. Are the Results Robust to Control for MAX and REV variables?*

Having documented the preliminary evidence supporting our main hypothesis, we next turn our attention to examining the robustness of our findings. To begin with, we focus on two variables that have been found to explain away the negative volatility-return relationship in

[11]A potential concern with independent sorting is the possibility of disproportionately small number of firms in some portfolios during certain months. We found that the minimum number of stocks in any given month during the sample period is 31, so we have sufficient observations to draw reliable inferences. Our results are also robust to exclusion of months with relatively small number of firms.

recent literature: the prior month's maximum daily return (MAX) and the prior month's stock return (REV). As previously mentioned, BCW find that the maximum daily return of a stock in a given month is negatively related with subsequent month's stock return. Of particular interest, these authors find that after controlling for MAX, the relationship between IVOL and subsequent returns is insignificant in some regression specifications or even becomes positive in other specifications. HLRZ find that the negative volatility-return relationship is due an omitted variable bias, the omitted variable being the previous month's stock return (REV). Owing to the short-term return reversals, the inclusion of previous month's return in regression specifications renders the relationship between volatility and subsequent returns insignificant.

Using firm-level Fama-MacBeth cross-sectional regressions, we first verify that the results of BCW and HLRZ are obtained in our sample. The results from the first set of regressions, with the stock return as the dependent variable and various combinations of IVOL, MAX, and REV as explanatory variables, are reported in Panel A of Table 4.[12] Panel A.1 shows the results for the sample that includes sub-$5 stocks (to be consistent with BCW and HLRZ), while the results in Panel A.2 are obtained after excluding these penny stocks.

For the sample that includes penny stocks, the mean coefficient on IVOL in univariate regression is negative, -0.012, but is statistically insignificant with a *t*-statistic of -0.92. On the other hand, the coefficient on MAX variable in univariate regression is negative, -0.037, and statistically significant with a *t*-statistic of -2.50. Moreover, controlling for MAX in specification (3) of Panel A.1 reverses the sign of slope coefficient on IVOL, which is now positive, 0.074, with a *t*-statistic of 4.74. These findings are consistent with those reported in BCW (see Table 10 on pp. 441). Also, consistent with HLRZ, we find that the average

[12] In addition to Fama-MacBeth regressions, we also examined returns of portfolios obtained using bivariate sorts on IVOL and MAX as well as on IVOL and REV. Our conclusions are similar to those with regressions; hence, we report only the regression results for brevity. The results from sorts are available upon request.

coefficient on REV variable in univariate regression is negative, -0.051, and statistically significant (*t*-statistic = -10.03). After controlling for REV, the coefficient on IVOL turns positive, 0.001, but is still insignificant. When we control for both MAX and REV in specification (6), the coefficients on IVOL and MAX turn out to be statistically insignificant, but the coefficient on REV continues to be negative and highly statistically significant.

Turning to the results for the sample without penny stocks in Panel A.2, the coefficient on IVOL in univariate regression is now negative, -0.057, and statistically significant (*t* –statistic = -4.20). This result mirrors the result obtained in Table 1 for equally-weighted portfolios without including penny stocks. The MAX variable continues to be negative and statistically significant in the univariate regression. However, the coefficient on IVOL, after controlling for MAX, is no longer positive as in Panel A.1, but is rather negative, -0.022, albeit statistically insignificant (*t*-statistic = -1.25). The REV variable, on the other hand, does not explain away the negative-volatility return relationship: the coefficient on IVOL, after controlling for REV, is -0.046 with a *t*-statistic of -3.09. In contrast to results in Panel A.1, the IVOL is negative and significant when controlling for both MAX and REV, although similar to Panel A.1, the coefficient on MAX variable is not statistically significant.

In addition to excluding penny stocks, the well-documented January seasonality in stocks returns provides motivation for examining the IVOL-return relationship after excluding January returns as well. Peterson and Smedema (2011) document a robust negative volatility-return relationship outside of January. In particular, these authors find that once the January months are excluded, the REV variable is no longer able to explain the AHXZ result. Doran, Jiang, and Peterson (2012) find that the investors' preference for lottery-like stocks at the turn of the year due to their gambling mentality results in superior performance of these stocks in January and subsequent underperformance during the rest of the year. Note that the evidence of investors' preference for lottery-like stocks was the primary motivation behind examining the relationship between MAX and subsequent returns in BCW.

In light of the above evidence, we repeat the analysis in Panel A of Table 4 after excluding the January returns from the sample. The results are reported in Panel B. In contrast to the results in Panel A.1, Panel B.1 shows that the coefficient on IVOL is negative, -0.041, and statistically significant (*t*-statistic = -3.01) in univariate regressions, even with penny stocks included in the sample. Consistent with Doran, Jiang, and Peterson (2012), this finding suggests that the high IVOL stocks earn positive returns in January and exhibit poor performance over the remainder of the year. Also in contrast with Panel A.1 results, we find that (a) IVOL is no longer significantly positive after controlling for MAX, and (b) IVOL is negative and statistically significant at 5% (10%) level after controlling for REV (MAX and REV). In Panel B.2, we exclude penny stocks in addition to excluding the January returns. The most noticeable conclusion from Panel B.2 is that the coefficient on IVOL is negative and significant in univariate regression, as well as in regressions that control for MAX and REV, individually or both at the same time.

The preceding evidence suggests that after accounting for the presence of low-priced stocks and January seasonality, the negative relationship between IVOL and subsequent returns is robust to control for MAX and REV. Thus, while the AHXZ result cannot be dismissed yet, we still need to rule out the possibility that the concentration of negative volatility-return relationship in CL stocks is attributable to MAX and/or REV measures. Therefore, we re-examine the results in Table 3 after controlling for MAX and REV.

We employ a three-way sorting procedure for this test. As before, stocks are first segregated into CL and CG groups each month. Then, within each of the CL and CG groups, 5 portfolios are formed by sorting stocks on MAX (REV) in Table 5 (Table 6), and then within each of these 5 portfolios, 5 additional portfolios are formed by sorting stocks on their IVOL. For each of the CL and CG portfolios, we average the returns across the 5 MAX (REV) portfolios within each of the IVOL portfolios. Such a procedure ensures similar levels of MAX (REV) variable across each of the IVOL portfolios, thereby providing a convenient method to control for MAX (REV). BCW adopt a similar scheme in their tests. Tables 5 and 6 report both value-weighted and equally-weighted returns as before. We exclude the penny stocks from the sample in these tests, and report the results with and without January returns, in Panels A and B, respectively.

Focusing first on the results in Panel A of Table 5, we find that the after controlling for MAX, the difference in value-weighted returns of high and low IVOL portfolios is negative, -0.66%, and statistically significant (*t*-statistic = -4.13) for CL stocks. On the other hand, the value-weighted return difference of -0.01% (*t*-statistic = -0.12) for CG stocks is insignificant. Similar patterns are observed in the differences of CAPM and Fama-French alphas as well, both of which are again higher in magnitude as compared with the raw returns. The difference in equally-weighted raw returns of extreme IVOL portfolios for CL (CG) stocks is -0.13% (0.35%), which is statistically insignificant (significant) with a *t*-statistic of -1.03 (2.91). However, the differences in CAPM and Fama-French alphas, -0.27% and -0.31%, are statistically significant for CL stocks with corresponding *t*-statistics of -2.41 and -3.96, respectively.

When January returns are excluded in Panel B, the results are qualitatively similar for the value-weighted portfolios: the differences in returns and alphas are negative and statistically significant for the CL stocks, but insignificant for the CG stocks. The important differences in Panel A and Panel B results are for the equally-weighted portfolios. Here, we find that for the CL stocks, the raw return difference between high and low IVOL portfolio is -0.40%, which is significant with a *t*-statistic of -3.17. The corresponding differences in CAPM and Fama-French alphas are -0.52% (*t*-statistic = -4.45) and -0.44% (*t*-statistic = -5.33). On the other hand, for the CG stocks, the raw return difference is positive, 0.21%, but statistically insignificant (*t*-statistic = 1.54), and the corresponding differences in alphas are also insignificant. The takeaway from these results is that after excluding penny stocks and January returns, the negative relationship between IVOL and returns in stocks with unrealized capital losses is robust to control for the MAX variable.

Turning to results in Panel A of Table 6, we find a statistically significant return difference between extreme IVOL portfolios in CL stocks after controlling for REV, for both value-weighted and equally-weighted portfolios. The difference in value-weighted (equally-weighted) raw returns is -1.14% (-1.01%) with a *t*-statistic of -4.50 (-4.86). The corresponding difference in CAPM alphas is -1.45% (-1.28%) with a *t*-statistic of -6.37 (-6.89), and in Fama-French alphas is -1.36% (-1.20%) with a *t*-statistic of -7.68 (-8.95). For the CG stocks, the differences in returns and alphas are statistically insignificant, for both value-weighted and equally-weighted portfolios. The results in Panel B, obtained after excluding January returns, are qualitatively similar: the differences in raw returns and alphas are negative (and larger in magnitude compared with those in Panel A) and statistically significant for the CL stocks, but insignificant (at 5% level) for the CG stocks. Thus, the negative IVOL-return relationship in CL stocks persists after controlling for REV, with and without inclusion of January returns.

### *4.5. Fama-MacBeth Cross-Sectional Regressions*

The results so far lend support to our primary hypothesis that the negative volatility-return relationship is concentrated in stocks with paper losses. In terms of robustness, our focus has been on MAX and REV variables, which have been shown to play an important role in explaining the idiosyncratic volatility puzzle in the recent literature. We now examine the IVOL-return relationship using firm-level Fama-MacBeth cross-sectional regressions that allow us to control for additional variables along with MAX and REV. The full cross-sectional regression specification takes the following form:

$$R_{i,t+1} = \alpha_t + \beta_1 \mathrm{IVOL}_{i,t} + \beta_2 \mathrm{IVOL}_{i,t}\mathrm{Ind1}_{i,t} + \beta_3 \mathrm{Ind1}_{i,t} + \beta_4 \mathrm{MAX}_{i,t} + \beta_5 \mathrm{REV}_{i,t} + \beta_6 \mathrm{Prc}_{i,t} + \beta_7 \mathrm{Size}_{i,t} + \beta_8 \mathrm{BTM}_{i,t} + \beta_9 \mathrm{Illiq}_{i,t} + \beta_{10} \mathrm{Pre12Ret}_{i,t} + \beta_{11} \mathrm{Skw}_{i,t} + \beta_{12} \mathrm{Beta}_{i,t} + e_{i,t+1}, \quad (4)$$

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), maximum daily return (MAX), stock return (REV), natural log of stock price (Prc), natural log of market capitalization (Size), book-to-market ratio (BTM), illiquidity (Illiq), cumulative return over 12-month period ending in month *t* (Pre12Ret), idiosyncratic skewness (Skw), and stock's beta (Beta). The details of computation of these control variables are included in the Appendix. $\mathrm{Ind1}_{i,t}$ is an indicator variable that takes a value of 1 if stock *i* is a CL stock in month *t*, and is 0, otherwise. The role of unrealized gains and losses on IVOL-return relationship is captured through the interaction term, $\mathrm{IVOL}_{i,t} * \mathrm{Ind1}_{i,t}$.

We estimate various versions of equation (4) with different subsets of explanatory variables. The average slope coefficients are reported in Table 7. The first specification is simply the univariate regression on IVOL and confirms the negative IVOL-return relationship.[13] Next, we include the interaction term and Ind1 along with IVOL as the explanatory variables. We find that while the coefficient on interaction term is negative, -0.084, and statistically significant (*t*-statistic = -10.47), the coefficient on IVOL is no longer significant.[14] This evidence provides further confirmation that the negative volatility-return relationship is concentrated among stocks with unrealized losses, but is non-existent among stocks with unrealized gains. After controlling for MAX or REV, the coefficient on interaction term continues to be negative and highly statistically significant, as shown in specifications (3) and (4) of Table 7. The coefficient on IVOL is positive and statistically significant in these specifications, suggesting that the evidence of sign reversal on IVOL coefficient after controlling for MAX, documented in BCW, applies only to the CG stocks, but not to the CL stocks. Controlling for both MAX and REV simultaneously yields similar results as shown in specification (5), although the MAX variable loses its statistical significance.

In the full specification that includes all the control variables, the coefficient on interaction term is again negative, -0.109, and statistically significant (*t*-statistic = -10.15), but the coefficient on IVOL is insignificant. Most of the control variables have expected signs: coefficients on REV and firm size are negative and statistically significant, while coefficients on book-to-market, prior 12-month return, and idiosyncratic skewness are positive and statistically significant.[15] The coefficient on MAX variable is insignificant, as in specification (5).[16] The

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[13] This result is same as the one previously reported in Panel A.2 of Table 4.

[14] Note that in univariate regression of returns on indicator variable Ind1 (not reported), the coefficient is a negative -0.563 with a *t*-statistic of -5.28. In the presence of interaction term IVOL*Ind1, the coefficient on Ind1 itself is positive, while the coefficient on interaction term is negative.

[15]The significantly positive coefficient on lagged idiosyncratic skewness is consistent with the evidence in BCW. Note that Boyer, Mitton, and Vorkink (2010) find a negative relationship between expected (not lagged) idiosyncratic skewness and returns, so our results do not contradict their finding.

beta coefficient is also insignificant, perhaps due to inclusion of size and book-to-market ratio as control variables (see Fama and French (1993)). Given the previously documented implications of January seasonality for our results, we also run the regressions separately for January and non-January months.[17] Consistent with Doran, Jiang, and Peterson (2012), the results indicate that the negative volatility-return relationship is a non-January phenomenon; we do not find evidence of significant IVOL-return relationship in January. Similar to the all-month case, for the non-January months, the coefficient on interaction term is negative, -0.114, and statistically significant (*t*-statistic = -9.73), but the coefficient on IVOL is insignificant.

### *4.6. Time-Series Regressions*

In addition to the above cross-sectional tests, we also examine the IVOL-return relationship in monthly time series regressions. These tests examine the returns to a strategy that takes a long position in stocks in the highest volatility quintile and a short position in stocks in the lowest volatility quintile each month, after controlling for various factors. These factors include the monthly Fama-French factors (MKTRF, SMB, and HML) and the Carhart's (1997) momentum factor (UMD). Additionally, to account for the role of short-term reversals and maximum daily return, we include two factors based on REV (the WML factor) and MAX (the MMM factor) variables. Following HLRZ, the WML factor represents the return on a portfolio that takes a long position in stocks in the highest REV decile and a short position in stocks in the lowest REV decile in the month of portfolio formation. The monthly MMM factor is constructed

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[16] It is worth emphasizing that our sample differs from BCW in that we exclude stocks priced below $5. With this price restriction, the coefficient on MAX is rendered insignificant in presence of other control variables. Without the price restriction, we obtain a significantly negative coefficient on MAX, similar to BCW.

[17] For January regressions, the dependent variable is the January stock return and lagged control variables are computed in December.

similarly as the difference in return of a portfolio long in stocks in the top decile of maximum daily return and short in stocks in the bottom decile of maximum daily return.

Finally, we also incorporate a monthly sentiment index (SENT) in these time-series tests. This sentiment index, based on Baker and Wurgler (2006, 2007), represents the first principal component of commonly employed proxies for investor sentiment including the closed-end fund discount, the NYSE share turnover, the number and first-day returns of initial public offerings, the equity share in new issue of debt and equity, and the dividend premium.[18] The motivation for including sentiment index in our analysis stems from Baker and Wurgler's (2006) finding that the high volatility stocks earn relatively lower (higher) returns when the sentiment index is positive (negative), suggesting a potential role of investor sentiment in the volatility-return relationship.[19]

The results of time-series regressions are reported in Table 8, for the entire sample, as well as separately for the CL and CG groups. For the entire sample, we first note that when only the standard Fama-French and momentum factors are included as explanatory variables, the intercept from the time-series regression is negative, -0.727, and statistically significant (*t*-statistic = -6.23). This result confirms the existence of negative IVOL-return relationship. The coefficient on size factor is positive and significant, while that on book-to-market factor is negative and significant, consistent with high (low) IVOL firms being small, growth (large, value) firms. The coefficient on the market factor is positive and significant; the coefficient on momentum factor, however, is insignificant.

[18] The sentiment index is obtained from Jeff Wurgler's website at http://pages.stern.nyu.edu/~jwurgler.

[19] However, note that Baker and Wurgler's (2006) result is based on total volatility (measured as the standard deviation of monthly returns over the past year), and not idiosyncratic volatility. Nonetheless, AHXZ and others document negative relationship between total volatility and subsequent returns as well.

When we also include WML, MMM, and SENT factors in time-series regression, we find that the intercept is no longer statistically significant. In contrast to HLRZ, the coefficient on WML factor is insignificant, due to the exclusion of the penny stocks. The coefficient on MMM factor is positive, 0.749, and highly significant (*t*-statistic = 14.70), confirming a strong positive correlation between MAX and IVOL, as documented in BCW. The MMM factor is responsible for the insignificance of the intercept in these time-series regressions.[20] The coefficient on SENT is negative, but not statistically significant. After controlling for these additional factors, the coefficients on market and HML factors lose their significance, while the SMB factor continues to be positive and significant.

Turning to the results for CL and CG groups, the most significant finding is that the intercept is negative and statistically significant for CL stocks, after controlling for Fama-French and momentum factors, as well as after including the other three factors as control variables in the regression. The intercept from the four-factor model is -1.293 (*t*-statistic = -9.43) and declines to – 0.732 (*t*-statistic = -8.28) when all the seven factors are included. For the CG stocks, the intercept from the four-factor model is insignificant, but turns positive, 0.762, and significant (*t*-statistic = 5.52) with all the seven factors included.[21] The coefficient on UMD is negative for CL stocks, but positive for CG stocks, suggesting that the high IVOL stocks in the CL (CG) group have relatively lower (higher) past returns compared with the low IVOL stocks, as expected.

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[20] We verified this result by including the WML, MMM, and SENT factors, one at a time, along with Fama-French and momentum factors. The intercept is significant with WML and SENT factors, but insignificant with MMM factor.

[21]The positive intercept for CG socks reflects the evidence of sign reversal in presence of MAX in our cross-sectional tests as well in BCW. The WML and MMM factors have average monthly returns of -0.99% and -1.13%, respectively. Since the CG stocks have significantly positive loadings on these factors, the alpha for CG stocks turns positive when these factors are included as explanatory variables. Note, however, that this positive IVOL-return relationship occurs only among CG stocks and not CL stocks.

Overall, the results from time-series regressions corroborate the evidence from portfolio level analysis and cross-sectional regressions. Our findings support the hypothesis that attractiveness of high idiosyncratic volatility stocks to the risk seeking investors with unrealized capital losses drives the observed negative relationship between idiosyncratic volatility and subsequent returns.

### *4.7. Individual Investor Ownership and the Volatility-Return Relationship*

In this section, we test the hypothesis that negative relationship between volatility and returns in the CL group is stronger among stocks with greater fractional ownership by individual investors. While it has been well-documented that individual investors are more prone to behavioral biases, a growing body of literature suggests that the affinity for high idiosyncratic stocks is particularly stronger among these investors. Dorn and Huberman (2010) introduce the preferred risk habitat hypothesis, which suggests that the individual investors tend to focus on the idiosyncratic risk rather than the systematic risk of securities. Using stock holdings of German individual investors over 1995-2000, these authors find that risk-averse (risk-seeking) investors hold less (more) volatile stocks. Since PT/MA investors are risk-seeking in the domain of losses, the preferred risk habitat hypothesis suggests that these individual investors will find the high idiosyncratic volatility stocks particularly desirable.

High volatility stocks may also be preferred by individual investors with gambling tendencies (Barberis and Huang, 2008; Kumar, 2009). On the other hand, the prudent man laws may restrict the ability of institutional investors to trade in high volatility stocks. Recent evidence in Han and Kumar (2012) is consistent with the notion that it is the individual investors, rather than institutional investors, that predominantly hold and trade in high idiosyncratic volatility stocks.

As explained in Section 2, we measure the individual investor ownership (IIO) in a stock as the proportion of outstanding shares that are not held by large institutional investors. For our tests, each month, we sort the stocks into CL and CG groups as before, and within each of these portfolios, we further sort the stocks into tercile portfolios based on IIO to obtain high, medium, and low IIO portfolios. Table 9 summarizes the characteristics of portfolios thus obtained. The numbers in the table are the time-series averages of cross-sectional median values computed each month.

We find that for stocks with high IIO, the absolute magnitudes of both unrealized losses and gains are significantly higher as compared with the low IIO stocks. Further, while the average idiosyncratic volatility of CL stocks is higher compared with the CG stocks as shown in Table 2, we also find an interesting variation in idiosyncratic volatility across the ownership portfolios. The stocks with higher IIO tend to have higher volatility within the CL and CG groups. For the CL group, this finding is consistent with the stronger risk-seeking tendencies among individual investors as compared with the institutional investors. Moreover, the stocks with higher IIO tend to have smaller price and higher skewness as compared with low IIO stocks.

Consistent with Kumar (2009), the lower price, higher volatility, and higher skewness of stocks with high IIO suggest a stronger preference among individual investors for stocks with lottery-like features. The fact that high IIO stocks also have higher maximum daily returns further corroborates this affinity for lottery-like stocks among individual investors.[22] Across both CL and CG groups, we find that in comparison with low IIO stocks, the stocks with high IIO are smaller in size, have higher book-to-market ratios, have higher absolute values of past 12-month returns, and are significantly more illiquid. We do not observe a highly significant difference in REV across ownership portfolios. The average beta of high IIO stocks is much lower. Consistent with the institutional investors' tendency to hold diversified portfolios that do not deviate significantly from the market portfolio (Cohen, Gompers, Vuolteenaho, 2002), we find that the betas of low IIO portfolios are close to 1.

The higher idiosyncratic volatility of high IIO stocks within the CL group provides preliminary indication that the negative volatility-return relationship is likely to be stronger among this group of stocks. We formally test this hypothesis using portfolio sorts as well as Fama-MacBeth cross-sectional regressions. For the portfolio level analysis, we adopt a three-way sorting procedure: we first sort the stocks into CL and CG groups, then obtain three individual ownership portfolios within each of CL and CG portfolios, and finally sort the 6 resulting portfolios further into 5 portfolios based on idiosyncratic volatility.

The difference in value-weighted and equally-weighted returns of the high and low volatility portfolios within the gain/loss and ownership portfolios are reported in Table 10. The results in Panel A are obtained with returns from all calendar months included in the analysis. We find that within the CL group, the difference in high and low volatility portfolio returns is significantly lower for the high IIO stocks. The difference in value-weighted (equally-weighted) returns of the extreme IVOL portfolios for high IIO stocks is a statistically significant -2.28% (-1.95%) per month, while the corresponding difference for the low IIO portfolios is -0.92% (-

[22] Note that as a group, there is no statistically significant difference in maximum daily returns between CL and CG stocks, as shown in Table 2. But as Table 9 shows, within each of these groups, there is a strong positive relationship between MAX and IIO.

1.00%). The difference of -1.35% (-0.95%) in the value-weighted (equally-weighted) IVOL return spread between high and low IIO portfolios is statistically significant with a *t*-statistic of -3.87 (-4.37), and the corresponding CAPM and three-factor alphas are also statistically significant. On the other hand, for the CG stocks, the IVOL return spread is not statistically significant for any of the IIO portfolios, albeit the spread is larger in magnitude for the high IIO portfolios. We obtain qualitatively similar results after excluding January months from the analysis, as shown in Panel B of Table 10. In this case, the difference in value-weighted returns of extreme IVOL portfolios is a statistically significant -2.40% for CL/high IIO stocks, and -0.98% the CL/low IIO stocks. The corresponding equally-weighted return differences are -2.23% and -1.03%, respectively, and are also statistically significant. Again, the return spreads are not significant for CG stocks, for both value-weighted and equally-weighted portfolios.

Lastly, we examine the role of ownership in IVOL-return relationship using monthly firm-level Fama-MacBeth cross-sectional regressions that control for additional variables. To investigate the role of IIO, we introduce a new indicator variable, ind2, which equals 1 for stocks in high and medium IIO groups, and is 0 for stocks in low IIO group. The choice of pooling together high and medium IIO portfolios stems from the observation in Table 10 that the difference in returns of extreme volatility portfolios for these two groups is very similar, and much larger in magnitude as compared with the low IIO portfolio.[23] The complete regression specification, shown below, is similar in form to equation (4), except for the additional terms associated with ind2:

[23]In unreported statistical tests, we find that the difference in IVOL return spread between high and medium IIO portfolios is insignificant, while the difference in IVOL return spread between medium and low IIO portfolio is negative and statistically significant.

$$R_{i,t+1} = \alpha_t + \beta_1 \text{IVOL}_{i,t} + \beta_2 \text{IVOL}_{i,t}\text{Ind1}_{i,t} + \beta_3 \text{IVOL}_{i,t}\text{Ind2}_{i,t} + \beta_4 \text{IVOL}_{i,t}\text{Ind1}_{i,t}\text{Ind2}_{i,t}$$
$$+ \beta_5 \text{Ind1}_{i,t} + \beta_6 \text{Ind2}_{i,t} + \beta_7 \text{Ind1}_{i,t}\text{Ind2}_{i,t} + \beta_8 \text{MAX}_{i,t} + \beta_9 \text{REV}_{i,t} + \beta_{10} \text{Prc}_{i,t}$$
$$+ \beta_{11} \text{Size}_{i,t} + \beta_{12} \text{BTM}_{i,t} + \beta_{13} \text{Illiq}_{i,t} + \beta_{14} \text{Pre12Ret}_{i,t} + \beta_{15} \text{Skw}_{i,t} + \beta_{16} \text{Beta}_{i,t} + e_{i,t+1} \quad (5)$$

The results of the regression analysis are presented in Table 11. As before, we find evidence that the negative volatility-return relationship is concentrated in CL stocks, but non-existent among CG stocks: the coefficient $\beta 1$ is insignificant, but $\beta 2$ is negative, -0.078, and statistically significant (*t*-statistic = -6.60). Our main focus in this analysis is on $\beta 4$, the coefficient on interaction between IVOL and the two indicator variables. In the sample that includes returns from all calendar months, we find that $\beta 4$ is negative, -0.026, and statistically significant (*t*-statistic = -2.02). This result confirms the incremental role of individual investor ownership in IVOL-return relationship. Specifically, the findings suggest that the negative relationship between idiosyncratic volatility and stock returns, while pervasive across the CL stocks, is relatively stronger among stocks with moderate to high level of individual investor ownership. Further, we note that this effect is observed only in non-January months, but is non-existent in January. This result in not surprising given that the negative IVOL-return relationship itself is observed only in non-January months, as shown in Table 7.

## 5. Concluding Remarks

The negative relationship between idiosyncratic volatility and subsequent stock returns is considered a significant anomaly in the finance literature. In this paper, we propose a prospect theory based explanation of this anomalous relationship. Prospect theory, in conjunction with mental accounting, suggests that the stocks with unrealized capital losses would be overpriced due to the tendency of disposition-prone investors to hold on to these stocks too long. Further, the investors in loss domain are risk seeking, implying a greater affinity for high idiosyncratic volatility stocks, and resulting in greater overpricing of these stocks in equilibrium. Therefore, we hypothesize that the observed low average returns to high idiosyncratic volatility stocks would be concentrated in stocks with unrealized capital losses. Our results support this hypothesis: we find evidence of a robust negative relationship between idiosyncratic volatility and subsequent returns among stocks with unrealized losses, but no such relationship among stocks with unrealized gains.

We further argue that this result would be stronger among stocks with greater ownership by individual investors, who are known to have a stronger tendency to trade in and hold high volatility stocks. Consistent with this conjecture, we find that negative relationship between idiosyncratic volatility and returns in stocks with unrealized capital losses is relatively stronger among stocks with higher proportional ownership by individual investors.

Alternative rational explanations, such as those based on limits to arbitrage, are also possible. For example, it is possible that high idiosyncratic risk deters arbitrage (Pontiff, 2006), causing greater overpricing and subsequent lower returns among these high volatility stocks. This argument by itself, however, does not explain why the anomaly is observed only in stocks with unrealized losses, and not in stocks with unrealized gains; it is predicated on the existence of overpricing only among unrealized loss stocks. Similar to Grinblatt and Han (2005), the overpricing of unrealized loss stocks in our framework stems from risk-seeking behavior in the loss domain, as postulated in the prospect theory. On the other hand, high idiosyncratic risk deters arbitrage due to arbitrageurs' risk aversion, as pointed out in Pontiff (2006). Therefore, an alternative explanation of overpricing of unrealized loss stocks that does not rely on the assumption of risk-seeking behavior is necessary for a limits to arbitrage based explanation.

It is also possible that short sale constraints deter correction of overpricing among high volatility stocks with unrealized losses. However, the impact of short sale constraints is mitigated due to exclusion of stocks priced below $5. Diether, Lee and Werner (2009) document higher short-selling in stocks priced at or above $5 as compared with those priced below $5, due to higher collateral costs associated with stocks priced below $5. Nonetheless, we believe that these limits to arbitrage based explanations deserve detailed exploration and offer a fruitful area for future research.

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**Appendix: Variable Definitions**

**IVOL:** During month *t*, we run the following regression of excess daily returns of each stock *i* on contemporaneous daily Fama-French factors:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i MKT_d + s_i SMB_d + h_i HML_d + e_{i,d},$$

where $R_{i,d}$ is the return of stock *i* on day *d*, $R_{f,d}$ is the T-Bill return on day *d*, and $MKTRF_d$, $SMB_d$, and $HML_d$ are the daily Fama-French market, size, and book-to-market factors. The monthly idiosyncratic volatility of stock *i* in month *t* is defined as standard deviation of the residuals from this regression times the square root of the number of trading days in the month:

$$IVOL_{i,t} = \sqrt{\text{var}(e_{i,d})} \times \sqrt{D_t},$$

where $D_t$ is the number of trading days for stock *i* in month *t*.

**CGO:** Similar to Grinblatt and Han (2005) and Hur, Pritamani, and Sharma (2010), for each stock *i* at the end of each month *t*, the capital gains overhang ($\text{CGO}_{i,t}$) is obtained as:

$$\text{CGO}_{i,t} = (P_{i,t} - RP_{i,t}) / P_{i,t} \ ,$$

where $P_{i,t}$ is the price of the stock *i* at the end of month *t* and $RP_{i,t}$ is the reference price for each stock *i* at the end of month *t*. The reference price, $RP_{i,t}$, is estimated as follows:

$$RP_{i,t} = \frac{1}{k}\sum_{n=1}^{T}\left(V_{i,t-n}\prod_{\tau=1}^{n-1}\left[1 - V_{i,t-n+\tau}\right]\right)P_{i,t-n} \ ,$$

where $V_{i,t}$ is turnover in the stock *i* on day *t*, *T* is the number of trading days in the previous three years with available daily price and volume information, and $P_{i,t-n}$ is price of security *i* on day *t-n*

**MAX**: MAX is the maximum daily return of a stock in a given month. If $D_t$ is the number of trading days for stock *i* in month *t*, then $MAX_{i,t}$ is given by:

$$MAX_{i,t} = \max(R_{i,1}, R_{i,2}, ..., R_{i,D_t}),$$

where $R_{i,d}$ ($d$ = 1, 2, …, $D_t$) is the return on stock *i* on day *d*.

**REV**: REV variable is used to capture short-term reversals in stock returns and equals the return of stock $i$ in month $t$; that is, $REV_{i,t} = R_{i,t}$ .

**Skw**: Skw is daily idiosyncratic skewness of a stock, which is skewness of the residuals from the following regression:

$$R_{i,d} - R_{f,d} = a_i + \beta_i \, (R_{m,d} - R_{f,d}) + \gamma_i \, (R_{m,d} - R_{f,d})^2 + e_{i,d} \, ,$$

where $R_{i,d}$, $R_{f,d}$, and $R_{m,d}$ are the return on stock $i$ on day $d$, the T-Bill return on day $d$, and the return on CRSP value-weighted market index on day $d$, respectively.

**Size**: Size is the natural logarithm of the stock's month-end market capitalization (price times shares outstanding).

**BTM**: BTM is firm's book-to-market ratio. Following Fama and French (1993), we compute BTM in month $t$ of a year as the ratio of book value of equity for the fiscal year ending in prior calendar year and market equity at the end of December of the prior calendar year. Book value of equity, computed using Compustat data, is the stockholders' equity (DATA 216), plus balance sheet deferred taxes and investment tax credit (DATA 35), minus the book value of preferred stock (DATA56 or DATA10 or DATA 130, in that order) at the fiscal year end.

**Pre12Ret**: Pre12Ret is the momentum variable. Following Jegadeesh and Titman (1993), the momentum variable for each stock in a given month is defined as its buy and hold return over the past 12 months.

**Illiq**: Illiq is the measure of illiquidity for a stock in a given month. Following Amihud (2002), Illiq is measured as the ratio of stock's absolute monthly return to its dollar trading volume:

$$ILLIQ_{i,t} = \left| R_{i,t} \right| \; / \; VOLD_{i,t}$$

where $R_{i,t}$ and $VOLD_{i,t}$ are the return and dollar volume, respectively, of stock $i$ in month $t$.

**Beta**: We use the daily returns within a month to estimate stocks' beta and therefore employ the adjustment procedure of Scholes and Williams (1977) and Dimson (1979) to mitigate the impact of non-synchronous trading. Beta is estimated using following regression model:

$$R_{i,d} - R_{f,d} = a_i + \beta_{1,i}\,(R_{m,d-1} - R_{f,d-1}) + \beta_{2,i}\,(R_{m,d} - R_{f,d}) + \beta_{3,i}\,(R_{m,d+1} - R_{f,d+1}) + e_{i,d}\,,$$

where $R_{i,d}$, $R_{f,d}$, and $R_{m,d}$ are the return on stock *i* on day *d*, the T-Bill return on day *d*, and the return on CRSP value-weighted market index on day *d*, respectively. The estimate of stock's beta is given by $\widehat{\beta}_i = \widehat{\beta}_{1,i} + \widehat{\beta}_{2,i} + \widehat{\beta}_{3,i}$ .

**IIO**: We compute the individual investors ownership in a stock (IIO) at the end of each quarter as one minus the ratio of shares held by large institutional investors to the total number of shares outstanding and assume that it remains constant over the subsequent quarter prior to the next update. The quarterly holdings of institutional investors are obtained from the Thomson Reuters 13F institutional database, which is constructed from the 13F filings of large institutional investors with $100 million or more in assets under management.

## Table 1
## Idiosyncratic Volatility and Stock Returns

During each month, we run time-series regression of excess daily stock returns on the contemporaneous daily Fama-French factors. Daily idiosyncratic volatility is the standard deviation of residuals from the regression. Monthly idiosyncratic volatility (IVOL) is the daily idiosyncratic volatility times the square root of the number of trading days in the month. We sort the stocks into quintile portfolios based on their IVOL each month and compute the value-weighted (VW) and equally-weighted (EW) returns of these portfolios in the following month. V1 (V5) is portfolio of stocks in the bottom (top) quintile of IVOL. Panel A (Panel B) reports the returns of IVOL portfolios for the sample that includes (excludes) stocks priced below $5 at the end of portfolio formation month. The table also shows the difference in returns of extreme IVOL portfolios, V5-V1, along with the corresponding CAPM and Fama-French (FF) alphas. The returns are in percent per month. The *t*-statistics, reported in parentheses, are adjusted for autocorrelation using the Newey-West method. The sample covers the period from July 1963 to December 2007.

**Panel A: Average Returns of IVOL Portfolios (No Price Filter)**

| | VW Return | EW Return |
|---|---|---|
| V1(Low) | 0.93 | 1.16 |
| V2 | 1.02 | 1.39 |
| V3 | 1.06 | 1.40 |
| V4 | 0.74 | 1.26 |
| V5(High) | 0.02 | 1.11 |
| V5-V1 | -0.91 | -0.05 |
| | (-3.15) | (-0.15) |
| CAPM Alpha | -1.27 | -0.38 |
| | (-4.62) | (-1.40) |
| FF Alpha | -1.23 | -0.40 |
| | (-6.39) | (-1.89) |

**Panel B: Average Returns of IVOL Portfolios (Price ≥ $5)**

| | VW Return | EW Return |
|---|---|---|
| V1(Low) | 0.93 | 1.15 |
| V2 | 0.98 | 1.36 |
| V3 | 1.06 | 1.43 |
| V4 | 0.94 | 1.26 |
| V5(High) | 0.36 | 0.51 |
| V5-V1 | -0.57 | -0.63 |
| | (-2.12) | (-2.66) |
| CAPM Alpha | -0.92 | -0.98 |
| | (-3.91) | (-4.75) |
| FF Alpha | -0.75 | -0.81 |
| | (-4.58) | (-6.03) |

## Table 2
## Summary Statistics for Capital Gains Overhang Portfolios

At the end of each month, we divide the sample stocks into two groups based on their capital gains overhang. CL (CG) is portfolio of stocks with negative (non-negative) capital gains overhang. For each group, the Table reports the time-series averages of monthly median cross-sectional values of the following firm characteristics – the magnitude of capital gains overhang (CGO), monthly idiosyncratic volatility (IVOL), stock price, log of market capitalization (Size), the book-to-market ratio (BTM), the illiquidity measure (Illiq), the maximum daily return in month *t* (MAX), the buy and hold return over the previous 12 months (Pre12Ret), the return in month *t* (REV), idiosyncratic skewness (Skw), and beta of the stock. The last column shows the differences in these variables across the CL and CG groups. The returns are in percent per month. The *t*-statistics, reported in parentheses, are adjusted for autocorrelation using the Newey-West method. Stocks with price less than $5 at the end of portfolio formation month are excluded from the sample. The sample covers the period from July 1963 to December 2007.

| | CL | CG | CL - CG |
|---|---|---|---|
| | | | -32.99 |
| CGO | -19.35 | 12.64 | (-24.32) |
| | | | 1.19 |
| IVOL | 9.17 | 7.98 | (6.18) |
| | | | -8.07 |
| Price | 15.54 | 23.62 | (-13.70) |
| | | | -0.32 |
| Size | 11.54 | 11.87 | (-5.04) |
| | | | -0.09 |
| BTM | 0.69 | 0.77 | (-3.82) |
| | | | 0.11 |
| Illiq($\times 10^5$) | 0.26 | 0.15 | (3.88) |
| | | | 0.15 |
| Max | 4.72 | 4.57 | (1.34) |
| | | | -33.23 |
| Pre12Ret | -2.72 | 30.51 | (-33.27) |
| | | | -5.17 |
| Rev | -1.73 | 3.44 | (-22.66) |
| | | | -0.13 |
| Skw | 0.14 | 0.26 | (-16.52) |
| | | | 0.02 |
| Beta | 0.84 | 0.82 | (0.81) |

## Table 3
## Idiosyncratic Volatility and Stock Returns Conditional on Capital Gains Overhang

At the end of each month, we divide the sample stocks into two groups based on their capital gains overhang. CL (CG) is the portfolio of stocks with negative (non-negative) capital gains overhang. For results in Panel A, the stocks within CL and CG stocks are further sorted into quintile portfolios based on their monthly idiosyncratic volatility (IVOL). For results in Panel B, the sample stocks are independently sorted into quintile portfolios based on their IVOL. The table shows the value-weighted (VW) and equally-weighted (EW) returns of the quintile IVOL portfolios. V1 (V5) is portfolio of stocks in the bottom (top) quintile of IVOL. The table also shows the difference in returns of extreme IVOL portfolios, V5-V1, the corresponding CAPM and Fama-French (FF) alphas, and the difference of IVOL spread between CL and CG groups, ((V5-V1|CL) – (V5-V1|CG)) . The returns are in percent per month. The *t*-statistics, reported in parentheses, are adjusted for autocorrelation using the Newey-West method. Stocks with price less than $5 at the end of portfolio formation month are excluded from the sample. The sample covers the period from July 1963 to December 2007.

**Panel A: Sequential Sorting**

| | VW Return | | EW Return | |
|---|---|---|---|---|
| | CL | CG | CL | CG |
| V1(Low) | 0.90 | 0.96 | 1.06 | 1.12 |
| V2 | 0.97 | 0.96 | 1.28 | 1.40 |
| V3 | 0.86 | 1.17 | 1.21 | 1.58 |
| V4 | 0.56 | 1.21 | 0.83 | 1.63 |
| V5(High) | -0.41 | 1.01 | -0.18 | 1.28 |
| V5-V1 | -1.31 | 0.05 | -1.24 | 0.16 |
| | (-4.95) | (0.19) | (-5.54) | (0.72) |
| CAPM Alpha | -1.66 | -0.22 | -1.56 | -0.11 |
| | (-6.93) | (-0.89) | (-7.52) | (-0.50) |
| FF Alpha | -1.54 | -0.09 | -1.43 | 0.03 |
| | (-8.99) | (-0.45) | (-10.80) | (0.13) |

| | Raw Return | CAPM Alpha | FF Alpha | Raw Return | CAPM Alpha | FF Alpha |
|---|---|---|---|---|---|---|
| (V5-V1\|CL) – | -1.36 | -1.44 | -1.46 | -1.41 | -1.45 | -1.46 |
| (V5-V1\|CG) | (-7.66) | (-8.68) | (-7.95) | (-9.87) | (-9.52) | (-8.19) |

**Panel B: Independent Sorting**

| | VW Return | | EW Return | |
|---|---|---|---|---|
| | CL | CG | CL | CG |
| V1(Low) | 0.91 | 0.93 | 1.05 | 1.15 |
| V2 | 0.98 | 1.02 | 1.29 | 1.38 |
| V3 | 0.93 | 1.16 | 1.26 | 1.57 |
| V4 | 0.68 | 1.15 | 0.96 | 1.61 |
| V5(High) | -0.29 | 1.06 | -0.11 | 1.18 |
| V5-V1 | -1.20 | 0.13 | -1.16 | 0.02 |
| | (-4.50) | (0.50) | (-5.09) | (0.11) |
| CAPM Alpha | -1.54 | -0.15 | -1.49 | -0.24 |
| | (-6.40) | (-0.60) | (-7.35) | (-1.02) |
| FF Alpha | -1.44 | -0.02 | -1.37 | -0.11 |
| | (-8.16) | (-0.13) | (-10.39) | (-0.58) |

| | Raw Return | CAPM Alpha | FF Alpha | Raw Return | CAPM Alpha | FF Alpha |
|---|---|---|---|---|---|---|
| (V5-V1\|CL) – | -1.33 | -1.40 | -1.41 | -1.18 | -1.25 | -1.26 |
| (V5-V1\|CG) | (-7.64) | (-8.26) | (-7.38) | (-8.52) | (-8.50) | (-7.09) |

## Table 4
## Role of MAX and REV Variables in IVOL-Return Relationship

We run monthly firm-level Fama-MacBeth cross-sectional regressions of month *t* individual stock returns on the lagged explanatory variables, computed in month *t*-1. The various specifications include subsets of stock's monthly idiosyncratic volatility (IVOL), maximum daily return (MAX), and monthly stock return (REV) as explanatory variables. The table reports the time-series means of coefficient estimates from cross-sectional regressions. Results with and without January returns are shown, in Panels A and B, respectively. For results in Panels A.1 and B.1 (A.2 and B.2), the stocks priced below \$5 at the end of month *t*-1 are included in (excluded from) the sample. The *t*-statistics, reported in parentheses, are adjusted for autocorrelation using the Newey-West method. The sample covers the period from July 1963 to December 2007.

**Panel A: All Months**

| | **Panel A.1: No Price Filter** | | | **Panel A.2: Price ≥ \$5** | | |
|---|---|---|---|---|---|---|
| | IVOL | MAX | REV | IVOL | MAX | REV |
| (1) | -0.012<br>(-0.92) | | | -0.057<br>(-4.20) | | |
| (2) | | -0.037<br>(-2.50) | | | -0.078<br>(-5.00) | |
| (3) | 0.074<br>(4.12) | -0.128<br>(-8.40) | | -0.022<br>(-1.25) | -0.052<br>(-4.18) | |
| (4) | | | -0.051<br>(-10.03) | | | -0.027<br>(-6.25) |
| (5) | 0.001<br>(0.06) | | -0.058<br>(-11.15) | -0.046<br>(-3.09) | | -0.028<br>(-6.02) |
| (6) | 0.011<br>(0.65) | -0.016<br>(-1.26) | -0.057<br>(-11.26) | -0.053<br>(-3.20) | 0.011<br>(0.95) | -0.029<br>(-6.20) |

**Panel B: Non-January Months**

| | **Panel B.1: No Price Filter** | | | **Panel B.2: Price ≥ \$5** | | |
|---|---|---|---|---|---|---|
| | IVOL | MAX | REV | IVOL | MAX | REV |
| (7) | -0.041<br>(-3.01) | | | -0.073<br>(-4.99) | | |
| (8) | | -0.066<br>(-3.99) | | | -0.091<br>(-5.35) | |
| (9) | 0.018<br>(1.00) | -0.898<br>(-6.38) | | -0.052<br>(-3.04) | -0.030<br>(-2.51) | |
| (10) | | | -0.039<br>(-8.64) | | | -0.021<br>(-5.00) |
| (11) | -0.029<br>(-1.99) | | -0.045<br>(- 9.49) | -0.066<br>(-4.29) | | -0.019<br>(-4.55) |
| (12) | -0.033<br>(-1.92) | 0.005<br>( 0.39) | -0.046<br>(-9.68) | -0.075<br>(-4.44) | 0.015<br>( 1.18) | -0.022<br>(-4.77) |

## Table 5
## Idiosyncratic Volatility and Stock Returns Conditional on Capital Gains Overhang - Controlling for MAX

At the end of each month, we divide the sample stocks into two groups based on their capital gains overhang. CL (CG) is the portfolio of stocks with negative (non-negative) capital gains overhang. Within CL and CG portfolios, stocks are further sorted into quintile portfolios based on maximum daily return (MAX), and within each of the MAX portfolios, another 5 portfolios are formed by sorting stocks on their monthly idiosyncratic volatility (IVOL). We compute the value-weighted (VW) and equally-weighted (EW) returns of the IVOL portfolios thus obtained in the following month. To control for MAX, we average the returns across 5 MAX portfolios for each of the IVOL portfolios, for both CL and CG groups. The numbers in the table are averages of value-weighted (VW) and equally-weighted (EW) returns across 5 MAX portfolios for each of the IVOL portfolios. Results with and without January returns are shown, in Panels A and B, respectively. V1 (V5) is portfolio of stocks in the bottom (top) quintile of IVOL. The table also shows the difference in returns of extreme IVOL portfolios, V5-V1, the corresponding CAPM and Fama-French (FF) alphas, and the difference of IVOL spread between CL and CG groups, ((V5-V1|CL) – (V5-V1|CG)) . The returns are in percent per month. The *t*-statistics, reported in parentheses, are adjusted for autocorrelation using the Newey-West method. Stocks with price less than $5 at the end of portfolio formation month are excluded from the sample. The sample covers the period from July 1963 to December 2007.

**Panel A: All Months**

| | VW Return | | EW Return | |
|---|---|---|---|---|
| | CL | CG | CL | CG |
| V1(Low) | 0.82 | 1.05 | 0.84 | 1.16 |
| V2 | 0.80 | 1.08 | 0.90 | 1.40 |
| V3 | 0.61 | 1.18 | 0.88 | 1.45 |
| V4 | 0.56 | 1.04 | 0.87 | 1.48 |
| V5(High) | 0.16 | 1.04 | 0.71 | 1.52 |
| V5-V1 | -0.66 | -0.01 | -0.13 | 0.35 |
| | (-4.13) | (-0.12) | (-1.03) | (2.91) |
| CAPM Alpha | -0.82 | -0.12 | -0.27 | 0.24 |
| | (-5.59) | (-0.98) | (-2.41) | ( 1.84) |
| FF Alpha | -0.87 | -0.14 | -0.31 | 0.22 |
| | (-7.35) | (-1.17) | (-3.96) | (1.96) |

| | Raw Return | CAPM Alpha | FF Alpha | Raw Return | CAPM Alpha | FF Alpha |
|---|---|---|---|---|---|---|
| (V5-V1\|CL) – | -0.65 | -0.69 | -0.73 | -0.48 | -0.52 | -0.53 |
| (V5-V1\|CG) | (-4.73) | (-5.17) | (-5.03) | (-5.02) | (-5.13) | (-5.01) |

**Panel B: Non-January Months**

| | VW Return | | EW Return | |
|---|---|---|---|---|
| | CL | CG | CL | CG |
| V1(Low) | 0.69 | 1.07 | 0.62 | 1.13 |
| V2 | 0.66 | 1.07 | 0.60 | 1.31 |
| V3 | 0.42 | 1.12 | 0.53 | 1.34 |
| V4 | 0.38 | 1.02 | 0.51 | 1.37 |
| V5(High) | -0.13 | 1.00 | 0.22 | 1.34 |
| V5-V1 | -0.82 | -0.06 | -0.40 | 0.21 |
| | (-5.06) | (-0.47) | (-3.17) | (1.54) |
| CAPM Alpha | -0.94 | -0.15 | -0.52 | 0.12 |
| | (-6.38) | (-1.22) | (-4.45) | ( 0.92) |
| FF Alpha | -0.89 | -0.10 | -0.44 | 0.19 |
| | (-7.66) | (-0.89) | (-5.33) | (1.60) |

| | Raw Return | CAPM Alpha | FF Alpha | Raw Return | CAPM Alpha | FF Alpha |
|---|---|---|---|---|---|---|
| (V5-V1\|CL) – | -0.75 | -0.79 | -0.79 | -0.61 | -0.64 | -0.63 |
| (V5-V1\|CG) | (-5.53) | (-5.99) | (-5.86) | (-6.25) | (-6.03) | (-5.58) |

## Table 6
## Idiosyncratic Volatility and Stock Returns Conditional on Capital Gains Overhang - Controlling for REV

At the end of each month, we divide the sample stocks into two groups based on their capital gains overhang. CL (CG) is the portfolio of stocks with negative (non-negative) capital gains overhang. Within CL and CG portfolios, stocks are further sorted into quintile portfolios based on their monthly return (REV), and within each of the REV portfolios, another 5 portfolios are formed by sorting stocks on their monthly idiosyncratic volatility (IVOL). We compute the value-weighted (VW) and equally-weighted (EW) returns of the IVOL portfolios thus obtained in the following month. To control for short-term reversals, we average the returns across 5 REV portfolios for each of the IVOL portfolios, for both CL and CG groups. The numbers in the table are averages of value-weighted (VW) and equally-weighted (EW) returns across 5 REV portfolios for each of the IVOL portfolios. Results with and without January returns are shown, in Panels A and B, respectively. V1 (V5) is portfolio of stocks in the bottom (top) quintile of IVOL. The table also shows the difference in returns of extreme IVOL portfolios, V5-V1, the corresponding CAPM and Fama-French (FF) alphas, and the difference of IVOL spread between CL and CG groups, ((V5-V1|CL) – (V5-V1|CG)) . The returns are in percent per month. The *t*-statistics, reported in parentheses, are adjusted for autocorrelation using the Newey-West method. Stocks with price less than $5 at the end of portfolio formation month are excluded from the sample. The sample covers the period from July 1963 to December 2007.

**Panel A: All Months**

| | VW Return | | EW Return | |
|---|---|---|---|---|
| | CL | CG | CL | CG |
| V1(Low) | 0.92 | 1.05 | 1.00 | 1.18 |
| V2 | 1.10 | 1.25 | 1.23 | 1.50 |
| V3 | 0.83 | 1.28 | 1.04 | 1.63 |
| V4 | 0.52 | 1.22 | 0.70 | 1.58 |
| V5(High) | -0.22 | 1.07 | -0.01 | 1.44 |
| V5-V1 | -1.14 | 0.02 | -1.01 | 0.26 |
| | (-4.50) | (0.07) | (-4.86) | (1.15) |
| CAPM Alpha | -1.45 | -0.25 | -1.28 | 0.01 |
| | (-6.37) | (-1.00) | (-6.89) | ( 0.05) |
| FF Alpha | -1.36 | -0.14 | -1.20 | 0.09 |
| | (-7.68) | (-0.64) | (-8.95) | (0.46) |

| | Raw Return | CAPM Alpha | FF Alpha | Raw Return | CAPM Alpha | FF Alpha |
|---|---|---|---|---|---|---|
| (V5-V1\|CL) – | -1.15 | -1.20 | -1.23 | -1.27 | -1.29 | -1.28 |
| (V5-V1\|CG) | (-5.67) | (-5.40) | (-5.07) | (-7.33) | (-6.98) | (-6.49) |

**Panel B: Non-January Months**

| | VW Return | | EW Return | |
|---|---|---|---|---|
| | CL | CG | CL | CG |
| V1(Low) | 0.83 | 1.08 | 0.79 | 1.15 |
| V2 | 0.97 | 1.23 | 0.96 | 1.42 |
| V3 | 0.61 | 1.26 | 0.68 | 1.53 |
| V4 | 0.26 | 1.09 | 0.28 | 1.40 |
| V5(High) | -0.52 | 0.90 | -0.52 | 1.16 |
| V5-V1 | -1.35 | -0.18 | -1.30 | 0.01 |
| | (-5.18) | (-0.73) | (-5.72) | (0.05) |
| CAPM Alpha | -1.60 | -0.41 | -1.52 | -0.19 |
| | (-6.54) | (-1.69) | (-7.64) | (-0.83) |
| FF Alpha | -1.38 | -0.20 | -1.33 | -0.02 |
| | (-7.51) | (-1.01) | (-9.34) | (-0.11) |

| | Raw Return | CAPM Alpha | FF Alpha | Raw Return | CAPM Alpha | FF Alpha |
|---|---|---|---|---|---|---|
| (V5-V1\|CL) – | -1.16 | -1.19 | -1.18 | -1.31 | -1.33 | -1.31 |
| (V5-V1\|CG) | (-5.62) | (-5.34) | (-5.02) | (-7.37) | (-7.03) | (-6.55) |

## Table 7
## Fama-MacBeth Cross-Sectional Regressions

We run monthly firm-level Fama-MacBeth cross-sectional regressions of month *t* individual stock returns on the lagged explanatory variables, computed in month *t*-1. Ind1 is an indicator variable that equals 1 for stocks with unrealized capital losses and equals 0, otherwise. The explanatory variables in various specifications include stock's monthly idiosyncratic volatility (IVOL), the interaction term (IVOL*Ind1), ind1, maximum daily return (MAX), monthly stock return (REV), log of stock price, log of market capitalization (Size), the book-to-market ratio (BTM), the illiquidity measure (Illiq), the buy and hold return over the previous 12 months (Pre12Ret), idiosyncratic skewness (Skw), and beta of the stock. The table reports the time-series means of coefficient estimates from cross-sectional regressions. Results for January and non-January months are shown separately in specifications (7) and (8), respectively. The *t*-statistics, reported in parentheses, are adjusted for autocorrelation using the Newey-West method. Stocks with price less than $5 at the end month *t*-1 are excluded from the sample. The sample covers the period from July 1963 to December 2007.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | All Months | | | | | | January | Non –January Months |
| IVOL | -0.057 | -0.013 | 0.058 | 0.028 | 0.034 | 0.007 | -0.018 | 0.009 |
| | (-4.20) | (-1.06) | (3.38) | (2.09) | (1.95) | ( 0.43) | (-0.43) | (0.59) |
| IVOL*Ind1 | | -0.084 | -0.094 | -0.121 | -0.120 | -0.109 | -0.049 | -0.114 |
| | | (-10.47) | (-11.44) | (-14.32) | (-14.16) | (-10.15) | (-1.24) | (-9.73) |
| Ind1 | | 0.367 | 0.404 | 0.421 | 0.416 | 0.661 | 0.939 | 0.635 |
| | | (3.27) | (3.55) | (3.81) | (3.71) | (5.87) | (2.94) | (5.64) |
| MAX | | | -0.096 | | -0.007 | -0.011 | 0.040 | -0.016 |
| | | | (-10.74) | | (-0.65) | (-0.85) | ( 0.82) | ( -1.22) |
| REV | | | | -0.045 | -0.046 | -0.047 | -0.099 | -0.042 |
| | | | | (-10.83) | (-10.91) | (-10.52) | (-9.57) | (-9.42) |
| Log(Price) | | | | | | -0.175 | -2.133 | 0.005 |
| | | | | | | (-2.04) | (-6.32) | ( 0.06) |
| Size | | | | | | -0.099 | -0.387 | -0.073 |
| | | | | | | (-2.72) | (-1.99) | (-1.98) |
| BTM | | | | | | 0.122 | 0.436 | 0.094 |
| | | | | | | (2.20) | (1.85) | (1.64) |
| Illiq | | | | | | -0.014 | -0.013 | -0.015 |
| | | | | | | (-2.17) | (-0.62) | (-2.64) |
| Pre12Ret | | | | | | 0.707 | -0.129 | 0.784 |
| | | | | | | (6.22) | (-0.38) | (6.71) |
| Skw | | | | | | 0.089 | 0.171 | 0.082 |
| | | | | | | (3.85) | (1.60) | (3.44) |
| Beta | | | | | | -0.010 | -0.119 | -0.001 |
| | | | | | | (-0.34) | (-1.34) | (-0.02) |

## Table 8
## Time-Series Regressions

The table reports the results from time-series regression. At the end of each month, we divide the sample stocks into two groups based on their capital gains overhang. CL (CG) is the portfolio of stocks with negative (non-negative) capital gains overhang. The stocks within CL and CG stocks are further sorted into quintile portfolios based on their monthly idiosyncratic volatility (IVOL). The dependent variable is the monthly return of a portfolio that takes a long position in the highest IVOL portfolio and a short position in the lowest IVOL portfolio. The independent variables include the Fama-French market, size, and book-to-market factors (MKTRF, SMB, and HML, respectively), the momentum factor (UMD), the return on a portfolio that takes a long position in the highest decile and a short position in the lowest decile of previous month's maximum daily return (MMM), the return on a portfolio that takes a long position in the highest decile and a short position in the lowest decile of past one-month return (WML), and the Baker and Wurgler's (2006) sentiment index (SENT). The *t*-statistics, reported in parentheses, are adjusted for autocorrelation using the Newey-West method. Stocks with price less than $5 at the end of previous month are excluded from the sample. The sample covers the period from July 1963 to December 2007.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | All Stocks | | CL | | CG | |
| Intercept | -0.727 | 0.015 | -1.293 | -0.732 | -0.161 | 0.762 |
| | (-6.23) | (0.10) | (-9.43) | (-8.28) | (-1.02) | (5.52) |
| MKTRF | 0.319 | 0.004 | 0.358 | -0.025 | 0.279 | 0.032 |
| | ( 8.46) | (0.11) | (-7.92) | (-1.08) | (-5.44) | (0.73) |
| SMB | 0.916 | 0.190 | 0.872 | 0.075 | 0.961 | 0.308 |
| | (12.65) | (3.02) | (13.67) | (1.68) | (9.71) | (6.96) |
| HML | -0.447 | -0.003 | -0.461 | 0.015 | -0.432 | -0.019 |
| | (-5.17) | (-0.06) | (-4.18) | (0.43) | (-4.33) | (-0.46) |
| UMD | 0.021 | 0.052 | -0.148 | -0.048 | 0.189 | 0.151 |
| | ( 0.37) | (1.39) | (-2.24) | (-2.03) | ( 2.89) | (3.71) |
| WML | | -0.091 | | -0.281 | | 0.098 |
| | | (-1.51) | | (-8.62) | | (2.30) |
| MMM | | 0.749 | | 0.809 | | 0.691 |
| | | (14.70) | | (25.14) | | (14.85) |
| SENT | | -0.143 | | -0.242 | | -0.044 |
| | | (-1.58) | | (-3.43) | | (-0.35) |

## Table 9
## Summary Statistics for Individual Investor Ownership Portfolios

At the end of each month, we divide the sample stocks into two groups based on their capital gains overhang. CL (CG) is portfolio of stocks with negative (non-negative) capital gains overhang. Within CL and CG groups, stocks are further sorted into tercile portfolios (High, Med, and Low) based on their individual investor ownership (IIO). IIO in a stock is defined as the fraction of shares outstanding that are not held by large institutional investors. For each portfolio, the table reports the time-series averages of monthly median cross-sectional values of the following firm characteristics – the magnitude of capital gains overhang (CGO), idiosyncratic volatility (IVOL), stock price, log of market capitalization (Size), the book-to-market ratio (BTM), the illiquidity measure (Illiq), the maximum daily return in month *t* (MAX), the buy and hold return over the previous 12 months (Pre12Ret), the return in month *t* (REV), idiosyncratic skewness (Skw), and beta of the stock. The column labeled H-L shows the differences in these variables across the High and Low IIO portfolios. The returns are in percent per month. The *t*-statistics, reported in parentheses, are adjusted for autocorrelation using the Newey-West method. Stocks with price less than $5 at the end of portfolio formation month are excluded from the sample. The sample covers the period from January 1980 to December 2007.

| | CL | | | | CG | | | |
|---|---|---|---|---|---|---|---|---|
| | High IIO | Med IIO | Low IIO | H-L | High IIO | Med IIO | Low IIO | H-L |
| CGO | -18.57 | -18.15 | -15.42 | -3.15 | 14.37 | 12.66 | 11.96 | 2.41 |
| | | | | (-9.02) | | | | (5.18) |
| IVOL | 11.21 | 10.09 | 8.69 | 2.51 | 9.89 | 8.29 | 7.31 | 2.58 |
| | | | | (7.86) | | | | (8.25) |
| Price | 10.40 | 13.57 | 21.04 | -10.64 | 14.83 | 22.03 | 32.37 | -17.54 |
| | | | | (-32.98) | | | | (-29.77) |
| Size | 10.98 | 11.92 | 13.12 | -2.13 | 11.03 | 12.32 | 13.56 | -2.53 |
| | | | | (-59.78) | | | | (-88.65) |
| BTM | 0.61 | 0.61 | 0.55 | 0.06 | 0.78 | 0.73 | 0.60 | 0.18 |
| | | | | (3.06) | | | | (7.44) |
| Illiq($\times 10^5$) | 0.38 | 0.10 | 0.02 | 0.36 | 0.31 | 0.06 | 0.01 | 0.29 |
| | | | | (8.91) | | | | (10.35) |
| MAX | 5.55 | 5.12 | 4.58 | 0.97 | 5.38 | 4.70 | 4.29 | 1.09 |
| | | | | (6.48) | | | | (6.46) |
| Pre12Ret | -2.92 | -4.50 | -0.39 | -2.52 | 33.66 | 30.34 | 28.58 | 5.08 |
| | | | | (-3.22) | | | | (4.54) |
| REV | -1.81 | -2.16 | -2.23 | 0.42 | 3.41 | 3.71 | 3.68 | -0.28 |
| | | | | (1.82) | | | | (-1.49) |
| Skw | 0.14 | 0.13 | 0.10 | 0.04 | 0.27 | 0.26 | 0.23 | 0.04 |
| | | | | (3.69) | | | | (2.26) |
| Beta | 0.58 | 0.86 | 1.03 | -0.45 | 0.51 | 0.81 | 1.01 | -0.51 |
| | | | | (-15.50) | | | | (-16.48) |

## Table 10
## The IVOL-Return Relationship Conditional on Capital Gains Overhang and Individual Investor Ownership

At the end of each month, we divide the sample stocks into two groups based on their capital gains overhang. CL (CG) is portfolio of stocks with negative (non-negative) capital gains overhang. Within CL and CG groups, stocks are further sorted into tercile portfolios (High, Med, and Low) based on their individual investor ownership (IIO). IIO in a stock is defined as the fraction of shares outstanding that are not held by large institutional investors. The table reports the difference in value-weighted (VW) and equally-weighted (EW) returns of stocks in the top and bottom quintile of IVOL within the IIO portfolios, for the CL and CG groups. Results with and without January returns are shown, in Panels A and B, respectively. The column labeled H-L shows the differences in returns across the High and Low IIO portfolios, and the last two columns report the corresponding CAPM and Fama-French (FF) alphas, respectively. The *t*-statistics, reported in parentheses, are adjusted for autocorrelation using the Newey-West method. Stocks with price less than $5 at the end of portfolio formation month are excluded from the sample. The sample covers the period from January 1980 to December 2007.

**Panel A: All Months**

**Panel A.1: VW Returns**

| | High IIO | Med IIO | Low IIO | H-L | CAPM Alpha | FF Alpha |
|---|---|---|---|---|---|---|
| CL | -2.28 | -2.21 | -0.92 | -1.35 | -1.48 | -1.34 |
| | (-5.14) | (-5.22) | (-2.63) | (-3.87) | (-3.84) | (-3.56) |
| CG | -0.56 | -0.06 | 0.02 | -0.58 | -0.73 | -0.58 |
| | (-1.35) | (-0.13) | (0.07) | (-1.80) | (-2.32) | (-1.83) |

**Panel A.2: EW Returns**

| | High IIO | Med IIO | Low IIO | H-L | CAPM Alpha | FF Alpha |
|---|---|---|---|---|---|---|
| CL | -1.95 | -1.82 | -1.00 | -0.95 | -1.00 | -1.03 |
| | (-6.29) | (-5.50) | (-3.42) | (-4.37) | (-3.82) | (-3.95) |
| CG | -0.28 | 0.03 | -0.03 | -0.25 | -0.31 | -0.30 |
| | (-0.84) | (0.09) | (-0.11) | (-1.32) | (-1.65) | (-1.60) |

**Panel B: Non-January Months**

**Panel B.1: VW Returns**

| | High IIO | Med IIO | Low IIO | H-L | CAPM Alpha | FF Alpha |
|---|---|---|---|---|---|---|
| CL | -2.40 | -2.32 | -0.98 | -1.43 | -1.55 | -1.41 |
| | (-5.19) | (-5.11) | (-2.71) | (-3.93) | (-3.98) | (-3.89) |
| CG | -0.60 | -0.12 | -0.04 | -0.56 | -0.68 | -0.55 |
| | (-1.38) | (-0.27) | (-0.12) | (-1.64) | (-2.10) | (-1.67) |

**Panel B.2: EW Returns**

| | High IIO | Med IIO | Low IIO | H-L | CAPM Alpha | FF Alpha |
|---|---|---|---|---|---|---|
| CL | -2.23 | -1.98 | -1.03 | -1.20 | -1.23 | -1.25 |
| | (-6.99) | (-5.69) | (-3.33) | (-5.59) | (-4.82) | (-5.11) |
| CG | -0.43 | -0.10 | -0.06 | -0.37 | -0.43 | -0.41 |
| | (-1.25) | (-0.28) | (-0.20) | (-1.90) | (-2.13) | (-2.04) |

## Table 11
## Fama-MacBeth Cross-Sectional Regressions: The Role of Individual Investors

We run monthly firm-level Fama-MacBeth cross-sectional regressions of month *t* individual stock returns on the lagged explanatory variables, computed in month *t*-1. Ind1 is an indicator variable that equals 1 for stocks with unrealized capital losses and equals 0, otherwise. Ind2 is an indicator variable that equals 1for stocks with high and medium level of individual investor ownership (IIO), and equals 0, otherwise. The explanatory variables in various specifications include stock's monthly idiosyncratic volatility (IVOL), the interaction terms (IVOL*Ind1, IVOL*ind2, IVOL*ind1*ind2, and ind1*ind2), ind1, ind2, maximum daily return (MAX), monthly stock return (REV), log of stock price, log of market capitalization (Size), the book-to-market ratio (BTM), the illiquidity measure (Illiq), the buy and hold return over the previous 12 months (Pre12Ret), idiosyncratic skewness (Skw), and beta of the stock. The table reports the time-series means of coefficient estimates from cross-sectional regressions. Results for January and non-January months are shown separately. The *t*-statistics, reported in parentheses, are adjusted for autocorrelation using the Newey-West method. Stocks with price less than $5 at the end month *t*-1 are excluded from the sample. The sample covers the period from January 1980 to December 2007.

| | All Months | January | Non-January Months |
|---|---|---|---|
| IVOL | -0.018 | -0.092 | -0.011 |
| | (-0.97) | (-1.14) | (-0.63) |
| IVOL*Ind1 | -0.078 | -0.116 | -0.075 |
| | (-6.60) | (-2.95) | (-5.53) |
| IVOL*Ind2 | 0.010 | 0.095 | 0.002 |
| | ( 0.82) | ( 2.17) | ( 0.17) |
| IVOL*Ind1*Ind2 | -0.026 | 0.015 | -0.030 |
| | (-2.02) | ( 0.46) | (-2.23) |
| Ind1 | 0.663 | 1.143 | 0.619 |
| | (5.30) | (4.75) | (4.69) |
| Ind2 | 0.015 | -0.885 | 0.096 |
| | (0.09) | (-2.01) | (0.59) |
| Ind1*Ind2 | -0.188 | 0.382 | -0.240 |
| | (-1.28) | ( 1.79) | (-1.62) |
| MAX | 0.011 | 0.068 | 0.006 |
| | (0.80) | (1.01) | (0.40) |
| REV | -0.035 | -0.088 | -0.030 |
| | (-8.15) | (-10.40) | (-6.75) |
| Log(Price) | -0.082 | -1.859 | 0.080 |
| | (-0.82) | (-7.38) | (0.81) |
| Size | -0.087 | -0.064 | -0.089 |
| | (-2.08) | (-0.90) | (-2.07) |

| | | | |
|---|---|---|---|
| BTM | 0.113 | 0.157 | 0.109 |
| | (1.94) | (1.53) | (1.80) |
| Illiq | -0.011 | 0.016 | -0.013 |
| | (-0.89) | ( 0.39) | (-1.53) |
| Pre12Ret | 0.627 | -0.065 | 0.689 |
| | (5.51) | (-0.27) | (5.70) |
| Skw | 0.103 | 0.102 | 0.103 |
| | (3.27) | (0.66) | (3.26) |
| Beta | -0.072 | -0.219 | -0.058 |
| | (-2.00) | (-2.92) | (-1.55) |