

## **The long and short of the vol anomaly**

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### *Abstract*

On average, stocks with high prior-period volatility underperform those with low prior-period volatility, but that simple comparison paints an incomplete, and potentially misleading, picture. As we show, high volatility is an indicator of both positive and negative future abnormal performance. Among high volatility stocks, those with low short interest actually experience extraordinary positive returns, while those with high short interest experience equally extraordinary negative returns. The fact that publicly available information on aggregate short selling can be used to predict positive and negative abnormal returns of great magnitude points to a large-scale market inefficiency.

## **The long and short of the vol anomaly**

The underperformance of high volatility stocks is well documented and quite striking, at least on the surface. For example, as we subsequently explore in depth, a \$1 investment in an equally weighted portfolio of high volatility stocks in July 1991 is worth \$5.41 at the end of 2012. The same investment made in a portfolio of low volatility stocks is worth \$13.19. This difference in long-run performance, often called the “vol” anomaly, is explored in relatively recent studies such as Amihud (2002) and Ang et al. (2006, 2009), but awareness of it dates back at least four decades (Haugen and Heins (1972, 1975)).

It is also well known that short interest predicts future performance. Studies such as Figlewski (1981) find that heavily shorted stocks subsequently experience poor risk-adjusted performance, though the magnitude and economic significance of the effect is debatable (Asquith, Pathak, and Ritter (2005)). More recently, Boehmer, Huszár, and Jordan (2010) document that lightly shorted stocks have significant positive abnormal returns. Taken together, the performance of heavily and lightly shorted stocks is known as the short interest, or “SI,” anomaly.

As we show in this paper, there is a surprisingly strong connection between the vol and SI anomalies, and studying the two together yields new and sharper insights into both. For example, we find that high volatility is not necessarily a bad thing. In fact, stocks with high volatility and low short interest experience huge positive returns. A \$1 investment in an equally weighted portfolio of high volatility stocks with low short interest in July 1991 is worth \$37.70 at the end of 2012. The annualized compound return for this high vol/low SI portfolio is 7% per year greater than that of the CRSP value weighted index. In a Fama-French-Carhart (1993, 1997) four-factor framework, this portfolio has an *alpha* of 11% per year. In addition, the portfolio

greatly outperforms low volatility portfolios (on a raw and risk-adjusted basis) regardless of their short interest levels. Thus, both the vol and SI anomalies are more complex than earlier studies would suggest.

Our long-only strategy of buying high volatility stocks with low short interest avoids the limits to arbitrage arguments of Shleifer and Vishny (1997). However, our results are stronger when contrasted against high volatility stocks with high short interest. A \$1 investment in an equally weighted portfolio of high volatility stocks with high short interest in July 1991 is worth only \$0.44 at the end of 2012. This portfolio has a four-factor alpha of about -9% per year. A long/short portfolio that contrasts high volatility stocks with low and high SI has a four-factor alpha in excess of 20% per year. Further, it has no exposure to any of the Fama-French-Carhart factors (the four-factor  $R^2$  is essentially zero).

Our results are quite robust. High volatility stocks with low short interest are less liquid than the average stock, so execution costs could prevent realizing the returns. However, we find no significant difference in performance between those stocks in the group with high or low liquidity. Further, because high volatility stocks with low short interest have better prior year performance than the average stock in our sample, a momentum strategy may explain the returns. But counter to that possibility, we find that the best performing stocks in the group are those with the worst prior year performance.

We also show that the high vol/low SI portfolio performs well during turbulent markets by studying performance during the “dot-com” bubble (1998-2000) and the recent financial crisis (2007-2009). We find that in both instances the high vol/low SI portfolio outperforms the market. During the “dot-com” bubble, the equally weighted high vol/low SI portfolio had an annualized compound return 3.5% greater than that of the CRSP value weighted index. During

the financial crisis, that same gap was 10.8%. In addition, the high vol/low SI portfolio had larger Sharpe and Treynor ratios in both instances.

We additionally perform a battery of tests involving alternative factors, including the Pastor-Stambaugh (2003) liquidity factor, multiple factors suggested in Cremers et al. (2012), the “betting against beta” factor in Frazzini and Pedersen (2014), and the investment/profitability effects in Fama and French (2013). In some instances, these alternative factors are useful in modeling the returns on high volatility stocks, but they never explain the enormous difference in abnormal returns.

So, as a formal matter, we will always have the “joint hypothesis” issue, but the abnormal returns we document here are so large that attributing them to an omitted, systematic risk factor strains credulity.<sup>1</sup> We can always posit the existence of a “black swan” risk that we never observe, but to put these numbers in perspective, the 11% alpha on the long-only, high vol/low SI portfolio is roughly *double* the overall historic market risk premium.

Instead, a simpler, more plausible explanation is that misvaluation, both positive and negative, exists among hard-to-value, highly volatile stocks, and short sellers are capable of, at least on average, identifying and exploiting valuation errors. Whether they do so using only publicly available information is not knowable to us. However, the fact that publicly available information on their aggregate holdings, even with a time lag, can be used to predict future winners and losers points to a large-scale market efficiency failure, one that can be partially exploited through long-only positions.

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<sup>1</sup> Per Fama (1970, 1991), market efficiency can only be tested jointly with an asset pricing model. Put differently, any apparent inefficiency of any size could, at least in principle, be due to a misspecified model.

## I. Literature review

Haugen and Heins (1972, 1975) first showed that stocks with low volatility past returns subsequently outperformed those with high volatility. More recently, Amihud (2002) and Ang, Hodrick, Xing, and Zhang (2006, 2009) find that past volatility has a large, negative effect in the cross-section of stock returns.

This “vol” anomaly has led to many comparisons of the relative performance of low and high volatility stocks. Baker, Bradley, and Wurgler (2011) show a \$1 investment in portfolio of low volatility stocks in 1968 is worth \$59.55 in 2008. The matching high volatility portfolio is worth only \$0.58. Blitz and Vliet (2007) find that a global portfolio of low volatility stocks outperforms a matching high volatility portfolio by about 12% per year. Garcia-Feijoo, Li, and Sullivan (2012), among others, argue that trading costs may prevent investors from realizing such returns. However, Jordan and Riley (2014) show that actual, realized mutual fund returns are strongly affected by the vol anomaly, so it plainly impacts investors.

There are many competing explanations for the vol anomaly.<sup>2</sup> Some argue that the anomaly is driven by investor preference for lottery-type payoffs.<sup>3</sup> Fu (2009) and Huang, Liu, Rhee, and Zhang (2010) claim the anomaly is related to short-term return reversals. Wong (2011) finds that at least 42% of the anomaly can be explained by earnings momentum and earnings shocks. Avramov, Chordia, Jostova, and Philipov (2013) show that much of the profit from investing in the anomaly results from short positions in financial distressed firms. Hou and Loh (2012) test these claims and many others simultaneously and find that 60% to 80% of the vol anomaly can be explained by a combination of lottery preferences, short-term return reversals, and earnings shocks.

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<sup>2</sup> See Hou and Loh (2012) for a more thorough analysis of potential explanations for the vol anomaly.

<sup>3</sup> For instance, Barberis and Huang (2008); Bali, Cakici, and Whitelaw (2011); Boyer, Mitton, and Vornick (2010); and Chichernea, Kassa, and Slezak (2014).

In another, seemingly unrelated strand of research, information on aggregate short selling activity has been consistently shown to be useful in predicting subsequent performance.<sup>4</sup> The conventional Wall Street wisdom has been that high short interest is a bullish signal because it predicts future buying due to short covering (e.g., Epstein (1995)). When tested empirically, however, stocks with high short interest perform poorly on average. Desai, Ramesh, Thiagarajan, and Balachandran (2002), for example, find abnormal returns of -0.76% to -1.13% per month for NASDAQ stocks with high short interest. At the same time, stocks with low short interest typically perform well. Boehmer, Huszár, and Jordan (2010) show that stocks with low short interest outperform both stocks with high short interest (in absolute value) and the overall market. This short interest, or “SI,” anomaly is particularly striking because it can be exploited through long-only strategies involving the purchase of low SI stocks.

Our study appears to be the first to simultaneously consider the vol and SI anomalies. As we begin to explore next, conditioning on vol brings the SI anomaly into much clearer focus, and, at the same, conditioning on SI shows that the vol anomaly is much more complex (and interesting) than previous studies would suggest.

## **II. Data and methods**

We start with the CRSP monthly stock file to form our sample. We use only ordinary common share classes (CRSP share codes 10 and 11) that trade on the NYSE, AMEX, or NASDAQ (CRSP exchange codes 1, 2, and 3). We eliminate penny stocks by excluding a stock until the month after its price first exceeds \$5 per share. Once included in the sample, a stock remains regardless of future price movement. We remove microcaps by only using stocks with a

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<sup>4</sup> For instance, Dechow, Hutton, Meulbroek, and Sloan (2001); Karpoff and Lou (2010); and Engelberg, Reed, and Ruggenberg (2012).

market capitalization greater than the 10% NYSE breakpoint.<sup>5</sup> We replace any missing returns or prices with delisting returns and prices when possible.

We determine the level of short interest in a stock using data from Compustat augmented with data supplied by NASDAQ.<sup>6</sup> We only use short interest values reported in the middle of each month to insure public availability by the start of the next month.<sup>7</sup> We convert the level of short interest into a measure called Days to Cover (DTC). We calculate DTC as the level of short interest in month  $t$  divided by the average daily trading volume in month  $t$ . DTC indicates the number of days it would take all short sellers to cover their positions under normal trading conditions (assuming they were the only buyers).

Another common measure of short interest is the Short Interest Ratio (SIR), calculated as the short interest level divided by shares outstanding. SIR indicates the percentage of shares outstanding for a stock that are currently sold short. We replicate our key tests using SIR in Appendix A and find similar, albeit weaker, results. Our results suggest that DTC may be more informative about short seller conviction than SIR. With a high DTC stock, short sellers cannot collectively close their positions quickly, thus a short squeeze is a significant risk. In contrast, for at least some high SIR stocks, trading volume is also high, so this risk is lessened.

In addition to short interest data, we require stocks to have data for the following variables as of month  $t - 1$  to be part of the sample in month  $t$ :

1. Idiosyncratic volatility – Measured following Ang, Hodrick, Xing, and Zhang (2006)<sup>8</sup>
2. Beta – Measured following Fama and French (1992)<sup>9</sup>

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<sup>5</sup> We re-screen for microcaps once per year (in June). If we include microcap stocks in our sample, the portfolios we test have similar, if not stronger, performance.

<sup>6</sup> We only use the NASDAQ data when the Compustat data is missing.

<sup>7</sup> Short interest data is made public eight business days after the mid-month reporting settlement date.

<sup>8</sup> The authors measure idiosyncratic volatility as the standard deviation of the residuals from regressing one month of daily returns against the Fama-French four-factor model. If we substitute total volatility (measured over the past month using daily returns) or beta (measured over the past year using monthly returns and the Fama-French-Carhart (1993, 1997) four-factor model augmented with the Pastor and Stambaugh (2003) liquidity factor) for idiosyncratic volatility in our sorts, our results are similar, albeit slightly weaker.

3. Size – Measured following Fama and French (1992)
4. Book-to-market – Measured following Fama and French (1992)
5. 12-month return – Raw return over the previous twelve months
6. Amihud illiquidity – Measured following Amihud (2002)<sup>10</sup>
7. Share turnover – Average daily share volume divided by shares outstanding
8. Institutional holding percentage – From Thomson Reuters Institutional (13F) Holdings

We identify our sample of low and high volatility stocks with low or high short interest by first sorting stocks into quintiles in month  $t$  based on their idiosyncratic volatility in month  $t - 1$ . If a stock falls within the lowest (highest) quintile of volatility, then we consider it low (high) volatility. We then conditionally sort our sample based on short interest. If a stock falls within the lowest (highest) quintile of DTC within its volatility quintile in month  $t - 1$ , we consider it low (high) short interest in month  $t$ . After imposing our data requirements and sorting, we limit our sample to July 1991 through December 2012 to insure a large number of stocks in both groups.

### **III. The performance of low and high volatility stocks**

Figure 1 shows the value of a \$1 investment in equally weighted portfolios of all low and high volatility stocks in our sample starting in July 1991 and ending in December 2012. For comparison to overall market, we present the value of a \$1 investment in the CRSP value weighted index. The high volatility portfolio has a larger value than the low volatility portfolio during the first year, but a smaller value in every other month (except February 2000, the height of the “dot-com” bubble). At the end of 2012, the high volatility portfolio has a value of \$5.41,

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<sup>9</sup> Calculating beta following Fama and French (1992) requires that a stock has at least 24 months of monthly returns available, so all stocks are in CRSP for at least two years before entering our sample. If we relax this constraint, our results are similar.

<sup>10</sup> Amihud (2002) measures illiquidity as the average ratio of the daily absolute return to dollar trading volume.

compared to \$13.19 for the low volatility portfolio.<sup>11</sup> The CRSP index has a value of \$6.29 at that same time.

[Figure 1 about here]

Table 1 shows annualized performance measures for those same portfolios. The high volatility portfolio has an average return of 12.8% per year with a standard deviation of 31.9%. The low volatility portfolio has an average return of 12.8% per year with a standard deviation of 12.2%. While the average annual returns are the same, the difference in volatility creates a gap of 4.2% per year between their annualized compound returns. In addition, the Sharpe and Treynor ratios for the low volatility portfolio are about 2.5 times those of the high volatility portfolio. These results are similar if both portfolios are value weighted. Despite their increased risk, the average high volatility stock underperforms the average low volatility stock over the long-term.

[Table 1 about here]

As Figure 1 and Table 1 show, the average high volatility stock clearly underperforms. As we explore next, however, not all high volatility stocks are poor performers. In fact, short sellers are able to reliably identify (and avoid) high volatility stocks that perform extremely well in the future. To illustrate, Figure 2 shows the value of a \$1 investment in equally weighted portfolios of low and high volatility stocks with varying levels of short interest from July 1991 through December 2012. The low vol/low SI and high vol/low SI portfolios hold the stocks with the lowest 20% of DTC within their respective volatility quintiles. The low vol/high SI and high

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<sup>11</sup> In looking at Figure 1 (and some subsequent figures), there is potentially something of an optical illusion. At a glance, it looks as though the low volatility portfolio has a much larger drop than the other portfolios in 2008-09, indicating that it is perhaps much riskier. However, that appearance is just due to the linear, dollar-denominated scale of the vertical axis; on closer examination, the percentage change for the low volatility portfolio is the smallest of the portfolios presented in Figure 1.

vol/high SI portfolios hold the stocks with the highest 20% of DTC within their respective volatility quintiles.

[Figure 2 about here]

In Figure 2, the low SI portions of both vol portfolios perform well, but the high vol/low SI portfolio significantly outperforms all others. At the end of 2012, the high vol/low SI portfolio is worth \$37.70. In comparison, the low vol/low SI portfolio is worth \$27.24. Conversely, the high SI portions of both vol portfolios perform poorly. The high vol/high SI portfolio significantly underperforms all other portfolios with a maximum value of \$1.34 and a final value of \$0.44. The low vol/high SI portfolio has a final value of \$6.83, about equivalent to the overall market and significantly less than the unconditional low vol portfolio.

Table 2, Panel A, shows annualized performance measures for those same portfolios. The high vol/low SI portfolio has an average return of 22.0% per year with a standard deviation of 32.5%, while the low vol/low SI portfolio has an average return of 16.1% per year with a standard deviation of 11.4%. The returns are larger for the high vol/low SI portfolio, but the Sharpe and Treynor ratios are larger for the low vol/low SI portfolio. Regardless of measure, both portfolios perform well compared to the high SI portfolios.

The high vol/high SI portfolio has an average return of 1.3% per year with a standard deviation of 32.0%. Its Sharpe and Treynor ratios are both negative. The low vol/high SI portfolio has an average return of 9.9% with a standard deviation of 13.6%. The Sharpe and Treynor ratios of the low vol/high SI portfolio are both less than those of the high vol/low SI portfolio. Despite the average performance of low volatility stocks, the low vol/high SI portfolio offers worse performance than the low SI portfolios regardless of volatility. We value weight our portfolios in Panel B and find similar, but weaker, results.

[Table 2 about here]

Our results thus far cannot contest that the average low volatility stocks outperforms the average high volatility stock; however, they do show that comparison to be misleading. There are large, identifiable portions of the high volatility portfolio that outperform large, identifiable portions of the low volatility portfolio by a significant margin. Moving forward, we focus on the performance of high volatility stocks rather than low volatility stocks. The results for the low vol/low SI are what we would expect from “stacking” anomalies. If low volatility stocks outperform and low short interest stocks outperform, it is not surprising that the combination performs even better. However, there is no such obvious expectation when combining high volatility and low short interest.

We continue analyzing the performance of low volatility stocks with low and high short interest in Appendix B. We find that the low vol/low SI portfolio has smaller risk-adjusted returns and performs worse in turbulent markets than the high vol/low SI portfolio. We also confirm that there is no performance benefit to being both low vol and low SI. Combining the anomalies together actually leads to worse performance than would be expected based on the individual anomalies.

#### **IV. The performance of high volatility stocks with low and high short interest**

The results for the high vol portfolios in Table 2 are suggestive of extraordinary performance, but they do not control for other well-known market anomalies. The difference in performance between the high vol/low SI and high vol/high SI portfolios may be driven by significant differences in small cap, value, or other exposures. We test that possibility by regressing the returns on both portfolios against the Fama-French-Carhart (1993, 1997) four-

factor model augmented with the Pastor and Stambaugh (2003) liquidity factor (FF-PS five-factor model). We present results from those regressions for both equally and value weighted portfolios in Table 3.

We find no statistically significant difference in risk exposure between the high vol/low SI and high vol/high SI portfolios. Both portfolios are high beta with significant small cap and growth exposures. Momentum exposure is large and negative for both, but neither has a significant liquidity exposure.<sup>12</sup> The only difference between the portfolios appears to be their risk-adjusted performance, or alpha. Looking at the equally weighted results, the high vol/low SI portfolio has an alpha of 0.95% per month, compared to -0.71% per month for the high vol/high SI portfolio. This difference of 1.67% per month (20.0% per year) covers nearly the entire 20.7% gap in average annual return between the portfolios found in Table 2. A similar gap in alpha of 0.96% per month (11.5% per year) exists between the value weighted portfolios, covering nearly the entire 11.7% gap in average annual return.<sup>13</sup>

[Table 3 about here]

In Appendix C, we measure the alpha on the high vol/low SI and high vol/high SI portfolios using different models and methods. We test our results using various permutations of the Fama-French four-factor model and use the Cremers, Petajisto, and Zitzewitz (2012) four- and seven-factor models.<sup>14</sup> Regardless of model, we find a large, positive alpha for the high vol/low SI portfolio, and a large, negative alpha for the high vol/high SI portfolio. Because we find the risk exposures on both portfolios vary over time, we also estimate month-by-month

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<sup>12</sup> Both the high vol/low SI and the high vol/high SI portfolio have a large, negative exposure to the Frazzini and Pedersen (2014) betting against beta (BAB) factor. However, the exposures are economically and statistically similar, and including the factor in the model has little effect on alpha.

<sup>13</sup> We control for differences in tax treatment by removing all dividend paying stocks from both portfolios. 25.4% (17.1%) of stocks in the high vol/low SI (high vol/high SI) portfolio paid an ordinary cash dividend greater than or equal to \$0.01 in the prior year, compared to 51.1% of the stocks in the full sample. Our results are similar without stocks that paid such dividends.

<sup>14</sup> We thank the authors for making their factors available at <http://www.petajisto.net/data.html>

alphas using daily returns. Using that method, we find the average alpha for the high vol/low SI portfolio is large and positive, and the average alpha for the high vol/high SI portfolio is negative or zero.

While all of our tests so far indicate that short sellers are able to predict the future performance of high volatility stocks, it is possible that other differences between high volatility stocks with low and high short interest are actually driving our results. Table 4 presents summary statistics for both groups and for the full sample of stocks.<sup>15</sup> As expected, the high vol/low SI stocks have very low short interest. The average DTC is only 0.82 days and the average SIR is only 2.0%. The high vol/high SI stocks, of course, have very high short interest. The average DTC is 13.2 days and the average SIR is 9.3%. Unexpectedly, the high vol/low SI stocks are more volatile than the high vol/high SI stocks. The high vol/low SI stocks have an average daily idiosyncratic volatility of 4.2%, compared to 3.8% for the high vol/high SI stocks.

[Table 4 about here]

High vol/low SI and high vol/high SI stocks are both small in size. The median size of a stock in the full sample is \$712 million. The median size is \$301 million for high vol/low SI stocks and \$338 million for high vol/high SI stocks. Size is less skewed for high vol/high SI stocks than for the high vol/low SI stocks. High vol/high SI stocks have an average size of \$556 million, compared to about \$2 billion for the high vol/low SI stocks. High vol/low SI stocks have book-to-market values similar to the full sample, but high vol/high SI stocks have lower book-to-market values than both. The average book-to-market value for a stock in the full sample is 0.50, while the average book-to-market value is 0.53 for high vol/low SI stocks and 0.41 for high vol/high SI stocks.

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<sup>15</sup> We winsorize all variables, except beta and size decile, at the 1% and 99% levels.

High vol/low SI stocks differ greatly from high vol/high SI stocks in prior year performance. The average return during the prior year for the full sample is 18.6%. The average return during the prior year for high vol/low SI stocks is 29.8%, but only 0.6% for high vol/high SI stocks. The median return during the prior year for the full sample is 10.7%. The median return during the prior year is 10.5% for high vol/low SI stocks and -14.0% for high vol/high SI stocks. Thus, the difference in prior year performance between high vol/low SI and high vol/high SI stocks is not driven by skewness, but the difference between high vol/low SI stocks and the full sample is.

We find mixed results with respect to measures of portfolio execution cost for high vol/low SI and high vol/high SI stocks. High vol/low SI stocks have greater Amihud illiquidity than high vol/high SI stocks and the full sample, but also about twice the share turnover. High vol/low SI and high vol/high SI stocks have similar levels of institutional holdings, and while both have a lower level than the full sample, neither has an average or median institutional holdings level low enough to create short sale constraints.<sup>16</sup> Overall, it is unclear whether high vol/low SI and high vol/high SI stocks face different execution costs and whether those costs significantly exceed those of the average stock.

We test the predictive ability of volatility and short interest on future stock performance using the following model:

$$\text{Return}_{i,t} = \text{FF Controls}_{i,t-1} + \text{Idio Vars}_{i,t-1} + \text{Short Interest Vars}_{i,t-1} + \text{Time FE} + \varepsilon_{i,t} \quad (1)$$

The dependent variable is the percentage stock return for stock  $i$  in month  $t$ . The FF Controls <sub>$i,t-1$</sub>  include typical Fama-French style controls: Beta, ln(size), book-to-market, and 12-month return.

The Idio Vars <sub>$i,t-1$</sub>  include idiosyncratic volatility and a dummy variable. High vol dummy is

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<sup>16</sup> Asquith, Pathak, and Ritter (2005) use institutional holdings as a proxy for lending supply and find that of the 5,500 domestic companies trading on the NYSE, AMEX, and NASDAQ National Market System in a typical year, only 21 are short sale constrained in a given month.

equal to one if the idiosyncratic volatility of stock  $i$  in month  $t - 1$  falls within the highest 20% among stocks in the sample, zero otherwise. The Short Interest Vars $_{i,t-1}$  include DTC and two dummy variables. Low (high) DTC dummy is equal to one if the DTC for stock  $i$  in month  $t - 1$  falls within the lowest (highest) 20% within that stock's month  $t - 1$  volatility quintile, zero otherwise.<sup>17</sup> We test the dual effect of volatility and short interest by interacting our dummy variables in some models. We also include monthly time fixed effects in all models.<sup>18</sup> All right-hand-side variables, except beta and the dummy variables, are  $z$ -scored (demeaned and divided by their standard deviations) within each month to control for differences in distributions across time and to ease interpretability.<sup>19</sup>

We present results for our model in Table 5. In Column 1, we use only the Fama-French style controls and find typical results. We add idiosyncratic volatility to the model in Column 2 and find having an idiosyncratic volatility one standard deviation above the mean in the prior month predicts an expected return 0.26% lower in the next month. We remove idiosyncratic volatility from the model and add DTC in Column 3. As shown, having a DTC one standard deviation above the mean in the prior month predicts an expected return 0.23% lower in the next month. In Column 4, we test idiosyncratic volatility and DTC simultaneously and find results similar to those in Columns 2 and 3, so the two variable appear to have separate effects.

[Table 5 about here]

We add our dummy variables to the model in Column 5. High vol dummy has a statistically insignificant effect of -0.13% per month ( $p$ -value = 0.159). Low DTC dummy has a large, highly statistically significant effect of 0.31% per month, and high DTC dummy has a

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<sup>17</sup> Our results are similar if we calculate the DTC dummy variables using unconditional quintiles. The correlation between the unconditional rankings is -0.093.

<sup>18</sup> We find similar results if we re-specify the model into a standard Fama-Macbeth (1973) framework.

<sup>19</sup> Before  $z$ -scoring, we winsorize all variables, except beta and the dummy variables, at the 1% and 99% levels. We find similar results using the unwinsorized variables.

similarly large effect of -0.20% per month. The large effect of DTC dummy variables suggests a nonlinear relationship between expected returns and short interest.

We interact our dummy variables in Column 6. We find a significant, distinct impact on expected returns from being both high volatility and low/high short interest. A stock that is both high volatility and high short interest has the previously discussed effects of being high volatility and high interest and also an additional -0.62% per month effect from being both simultaneously. Further, a stock that is both high volatility and low short interest benefits from (1) the previously discussed effects of being low short interest and (2) a 0.28% per month increase in subsequent return from being both high volatility and low short interest simultaneously.

## **V. Alternative explanations**

### *5.1 Do execution costs prevent the realizations of these returns?*

Execution costs are a primary concern for both the high vol/low SI and the high vol/high SI portfolio. The average stock in both portfolios is smaller and arguably less liquid than the average stock in the full sample. Significant trading costs may prevent investors from taking advantage of the performance of either portfolio, and short sale constraints may prevent investors from taking a short position in the high vol/high SI portfolio (recall, however, that penny stocks and microcaps have already been eliminated).

We evaluate these issues by sorting the stocks in each portfolio into terciles based on three indicators of execution costs: Amihud (2002) illiquidity, share turnover, and institutional holdings. As illiquidity increases and share turnover decreases the cost of buying and selling the

stocks may increase. As institutional holdings decrease, the lendable supply of the stock decreases, which in turn may raise the cost of shorting.<sup>20</sup>

There is significant variation in our execution cost measures within the high vol/low SI and high vol/high SI portfolios. For example, within the high vol/low SI portfolio, the highest tercile of share turnover has an average turnover of 3.57%. The lowest tercile has an average share turnover of only 0.54%. Within the high vol/high SI portfolio, the highest tercile of share turnover has an average share turnover of 1.70%, compared to only 0.25% for the lowest tercile. The highest (lowest) tercile of each portfolio has an average share turnover higher (lower) than the full sample average of 0.77%.

In Table 6, we present the FF-PS five-factor alphas for equally weighted portfolios of high vol/low SI and high vol/high SI stocks sorted on measures of execution costs. Looking first at the Amihud illiquidity results in Panel A, we find the high vol/low SI portfolio has a large, positive alpha regardless of liquidity level. We find no statistically significant difference in alpha between high vol/low SI portfolios with higher and lower liquidity.

[Table 6 about here]

On the other hand, the high vol/high SI portfolio has a large, negative alpha regardless of liquidity level, but the highest illiquidity tercile has an alpha about -0.87% per month lower than the lowest illiquidity tercile. The high vol/low SI portfolio outperforms the similar liquidity high vol/high SI portfolio in all three instances, with the difference in alpha being 0.98% per month greater in the highest illiquidity tercile than in the lowest. So while we do see a larger difference in alpha in the most illiquid tercile, the difference in alpha is still 1.02% per month within the most liquid tercile.

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<sup>20</sup> Asquith, Pathak, and Ritter (2005) and Nagel (2005), among others, use institutional ownership as a proxy for lending supply.

The differences in performance across the other measures of execution costs are smaller. We sort by share turnover in Panel B. Regardless of share turnover, we find a large, positive alpha for the high vol/low SI portfolio and a large, negative alpha for the high vol/high SI portfolio, with no statistically significant difference in alpha between the highest and lowest terciles of each. The difference in alpha between the high vol/low SI and high vol/high SI portfolios is similar within the highest and lowest share turnover terciles. We sort by institutional holdings in Panel C, and we find similar results.<sup>21</sup>

We further test the investability of both the high vol/low SI and the high vol/high SI portfolio in Appendix D. We first show that our results are driven by levels of short interest, not changes. Short interest is highly persistent, and dropping stocks with large changes in short interest has no effect on our results. We then test the effect of a delay in information about short interest. We find that skipping an additional month (about six weeks total) between measuring and using short interest does weaken our results, but the equally weighted high vol/low SI and high vol/high SI portfolios still have a difference in FF-PS five-factor alpha of 1.03% per month. Finally, we test whether reducing the portfolio turnover changes our results. If we only update measures of short interest and idiosyncratic volatility once per quarter, the difference in FF-PS five-factor alpha between the equally weighted high vol/low SI and high vol/high SI portfolios is still 1.12% per month.

## *5.2 Is this really a momentum strategy?*

We have included a momentum factor, UMD, in all of our measurements of portfolio alpha and also included prior year return in our predictive model. However, those controls alone

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<sup>21</sup> If we include Amihud (2002) illiquidity, share turnover, and institutional holdings in our panel model tested in Table 5, our conclusions are unchanged.

may not capture the effect of prior performance on either the high vol/low SI or high vol/high SI portfolio. Table 4 showed that high vol/low SI stocks had an average return of 29.8% during the prior year, compared to 0.6% for high vol/high SI stocks. The full sample average was 18.6%, so the high vol/low SI portfolio appears to follow a momentum strategy while the high vol/high SI portfolio appears to follow a contrarian strategy.<sup>22</sup> We test whether prior performance is driving our results by dividing the stocks in each portfolio into terciles based on either prior year return or prior year FF-PS five-factor alpha.

There is significant variation in prior return within the high vol/low SI and the high vol/high SI portfolio. For example, within the high vol/low SI portfolio, the highest tercile of prior year return has an average prior year return of 137.3%. The lowest tercile has an average prior year return of -35.3%. Within the high vol/high SI portfolio, the highest tercile of prior year return has an average prior year return of 69.5%, compared to -49.3% for the lowest tercile. The highest (lowest) tercile of each portfolio has an average prior year return higher (lower) than the full sample average of 18.6%, so the highest (lowest) prior return terciles of both portfolios appears to follow a momentum (contrarian) strategy.

In Table 7, we present the FF-PS five-factor alphas for equally weighted portfolios of high vol/low SI and high vol/high SI stocks sorted into terciles based on prior year performance.<sup>23</sup> Looking first at the prior return results in Panel A, we find the high vol/low SI portfolio has a large, positive alpha regardless of prior return. Counter to expectations, the stocks in the high vol/low SI portfolio in the lowest prior return tercile have an alpha 0.78% per month greater than those in the highest prior return tercile. The high vol/high SI portfolios have a large,

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<sup>22</sup> This statement appears inconsistent with the UMD factor loading for the high vol/low SI portfolio shown in Table 3. However, Appendix C shows that the UMD factor loading for the high vol/low SI portfolio is highly variable across time.

<sup>23</sup> In untabulated results, we performed the same sort using prior month return. The results were similar to those using the prior year return.

negative alpha regardless of prior return, and we find no statistically significant difference in alpha between the high vol/high SI stocks in the lowest and highest prior return terciles. Again counter to expectations, the difference in alpha between the high vol/low SI and high vol/high SI portfolios is 1.18% per month larger within the lowest prior return tercile compared to the highest prior return tercile.

[Table 7 about here]

In Panel B, we perform the same sort using prior year FF-PS five-factor alpha. We again find a large, positive alpha for each high vol/low SI portfolio, and a large, negative alpha for each high vol/high SI portfolio. The difference in alpha between the stocks in high vol/low SI portfolio in the highest and lowest terciles of prior alpha is only -0.26% per month, but, among the high vol/high SI portfolios, the highest prior alpha tercile has an alpha 0.61% per month ( $p$ -value = 0.145) larger than the lowest prior alpha tercile. The difference in alpha between the high vol/low SI and high vol/high SI portfolios is 0.87% per month larger in the lowest prior alpha tercile compared to the highest prior alpha tercile. So again counter to expectations, the performance of the long/short portfolio is best when not investing in stocks with high prior performance.

### *5.3 What happens during turbulent markets?*

Another potential concern with the high vol/low SI portfolio is its performance during significant market events. We first explore the performance of the high vol/low SI portfolio from 1998 through 2000 to see the portfolio's reaction to the buildup of the "dot-com" bubble and the subsequent crash. We then explore the performance of the high vol/low SI portfolio from 2007

through 2009 to see the portfolio's performance before, during, and after the recent financial crisis.

The performance of the high vol/low SI portfolio during the “dot-com” bubble is illustrated in Figure 3. We show the value of a \$1 investment in the equally weighted high vol/low SI portfolio from January 1998 through December 2000. For comparison, we also show the value of a \$1 investment in the CRSP value weighted index. The high vol/low SI portfolio peaks in value at the end of February 2000 at \$2.55. At that same time, the CRSP index has a value of \$1.52. Between that date and end of 2000, the high vol/low SI portfolio loses 41% of its value and drops to \$1.51. The CRSP value weighted index loses only 10% of its value during that time and drops to \$1.36. So while the high vol/low SI portfolio did have a higher peak and subsequent fall during the “dot-com” bubble, it still ends 2000 worth 11% more than the CRSP index.

[Figure 3 about here]

We further study the performance of the high vol/low SI portfolio during this period in Panel A of Table 8. Looking first at the equally weighted portfolio, the annualized compound return of the high vol/low SI portfolio was 3.5% per year greater than that of the CRSP index. The high vol/low SI portfolio has an annualized standard deviation of returns of 40.2%, compared to only 19.1% for the CRSP index, but the Sharpe and Treynor ratios for both are similar. Looking next at the value weighted portfolio, the return on the high vol/low SI portfolio is larger than before, as are the Sharpe and Treynor ratios. Overall, the high vol/low SI portfolio was riskier during the “dot-com” bubble, but it offered a higher return and more return per unit of risk than the CRSP index.

[Table 8 about here]

We examine the recent financial crisis in Figure 4. We present the value of a \$1 investment in an equally weighted high vol/low SI portfolio from January 2007 through December 2009. As before, we show the value of a \$1 investment in the CRSP value weighted index over the same period for comparison. The high vol/low SI portfolio underperforms the CRSP index early in this period, but both experience large losses from August 2008 through February 2009. The high vol/low SI portfolio decreases in value from \$0.85 to \$0.38, while the CRSP index decreases in value from \$0.96 to \$0.55. But, the primary difference in their performance occurs after that point. The CRSP value weighted index has a return of 58% between February 2009 and the end of that year, but the high vol/low SI portfolio has a return of 213% over that same period. The CRSP value weighted index has a final value of only \$0.87, while the high vol/low SI portfolio has a final value of \$1.21.

[Figure 4 about here]

We further study the performance of the high vol/low SI portfolio over this period in Panel B of Table 8. Looking first at the equally weighted portfolio, the annualized compound return of the high vol/low SI portfolio is 10.8% per year greater than that of the CRSP index. The high vol/low SI portfolio has an annualized standard deviation of returns of 47.4%, compared to 21.1% for the CRSP index, but the high vol/low SI portfolio has positive Sharpe and Treynor ratios, while the CRSP index has negative values for both. Looking next at the value weighted portfolio, the high vol/low SI portfolio has an annualized compound return 2.9% lower than the CRSP index, but the Sharpe and Treynor ratios are negative for both. Overall, it does not appear that the high vol/low SI portfolio experienced exceptionally poor performance during the financial crisis.

#### 5.4 Additional tests

We perform two sets of additional tests in Appendix E. First, we account for industry clustering within the high vol/low SI and high vol/high SI portfolios. Using the Fama-French (1997) 49 industry specification, the high vol/low SI portfolio has much higher concentrations of stocks that operate in the electronic equipment, computer software, and petroleum and natural gas industries than does the high vol/high SI portfolio. The high vol/high SI portfolio has much higher concentrations of stocks that operate in the pharmaceutical products, business services, and banking industries.<sup>24</sup> If we drop these industries from our portfolios, returns and alphas are similar to those in Table 2 and 3. Likewise, if we drop these industries from our panel regression or include industry fixed effects in the model, the regression coefficients are similar to those in Table 5.

We then account for the profitability and investment anomalies described in Fama and French (2013). We find that stocks in the high vol/low SI portfolio have higher average profitability and lower average investment than stocks in the high vol/high SI portfolio. As in our execution cost and momentum tests, we test whether profitability and investment drive our results by dividing the stocks in each portfolio into terciles based on those measures. Regardless of the level of profitability or investment, we find that the high vol/low SI portfolio has a large, positive alpha and the high vol/high SI portfolio has a large, negative alpha. The difference in alpha between the portfolios is greatest among stocks in the lowest tercile of profitability and investment, but the difference in alpha is large in all instances.

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<sup>24</sup> We thank the authors for making their SIC industry code to FF-49 industry code mapping available at [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\\_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

## **VI. Conclusions**

The average underperformance of stocks with high volatility relative to those with low volatility is well documented (though perhaps not widely appreciated). For instance, a \$1 investment in an equally weighted portfolio of high volatility stocks in July 1991 is worth \$5.41 at the end of 2012. The same investment made in a portfolio of low volatility stocks is worth \$13.19. Taken at face value, it appears investors would be well-served to avoid high volatility stocks, but a key takeaway from this study is that matters are more complex than that.

In particular, we show that high volatility is not necessarily a bad thing. A \$1 investment in an equally weighted portfolio of high volatility stocks with low short interest in July 1991 is worth \$37.70 at the end of 2012. The same investment made in a portfolio of high volatility stocks with high short interest is worth only \$0.44. The high vol/low SI portfolio has an alpha of 11% per year, compared to about -9% per year for the high vol/high SI portfolio. Thus, it is not the case that high volatility stocks, in general, underperform.

The “joint hypothesis problem” prevents us from conclusively declaring these results a major market inefficiency, but an argument for efficiency here requires a significant logical leap. Short sellers generally attempt to profit from firm-specific misvaluations. If our results are driven by an omitted systematic risk factor, then it must be the case that short sellers, for some reason, choose to load heavily on that factor in some cases and avoid it in others.

Instead, a simpler explanation is that (1) both positive and negative misvaluation exists among hard-to-value, highly volatile stocks and (2) short sellers are adept at identifying and exploiting those valuation errors. We do not know how short sellers identify stock misvaluations, but the fact that publically available information on their aggregate holdings predicts future winners and losers points to a large-scale market efficiency failure.

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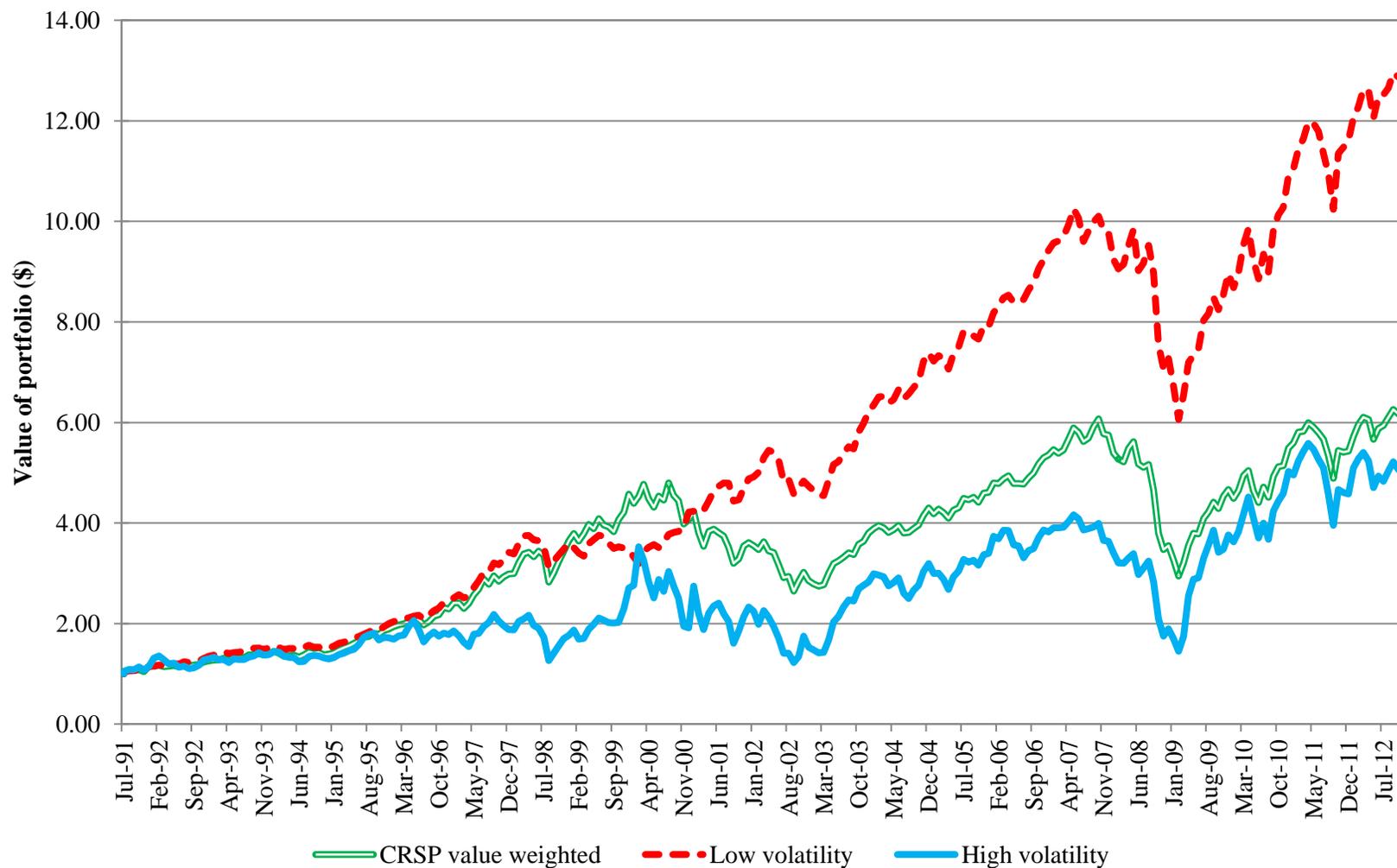
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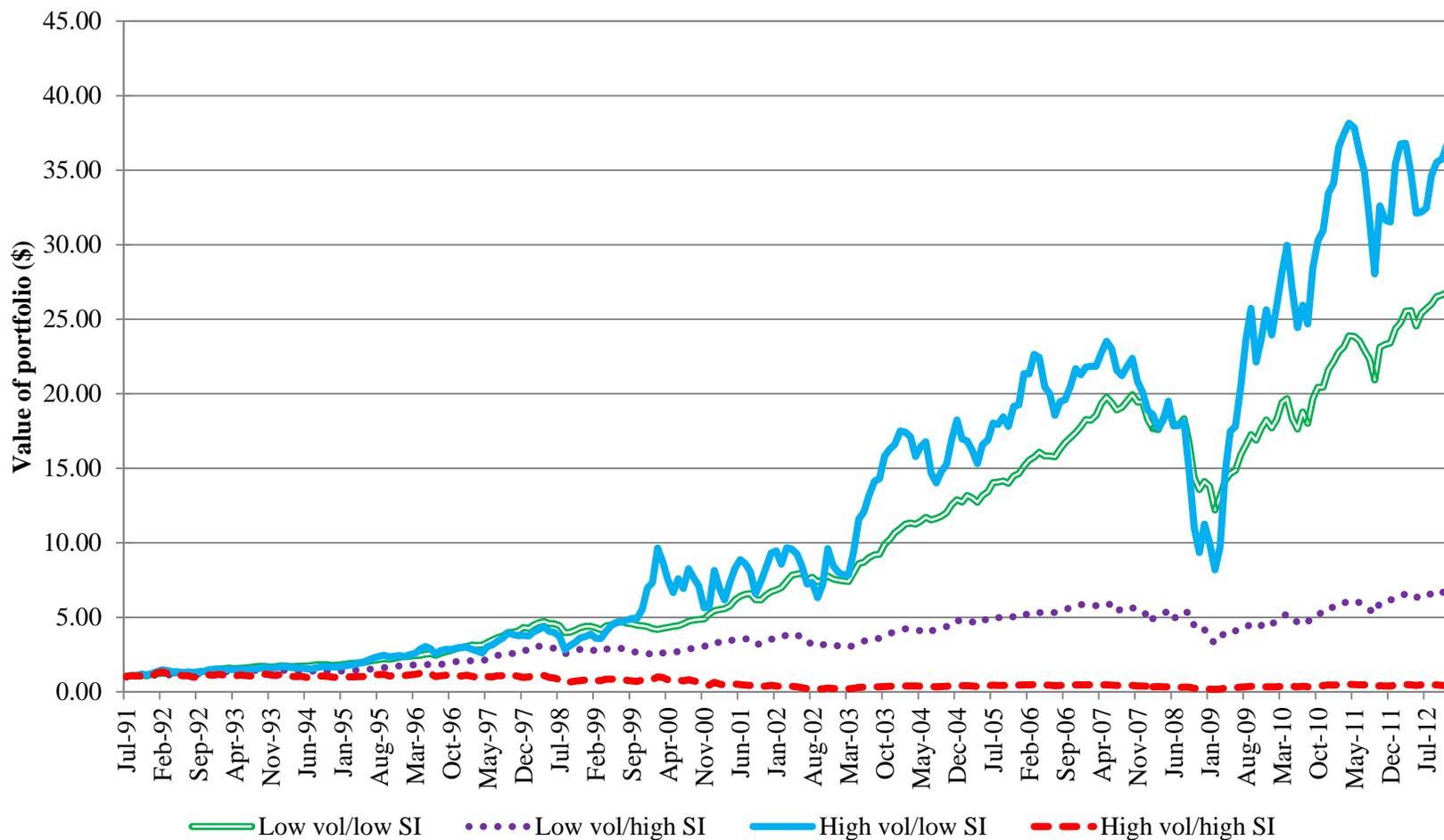
**Figure 1: The return on one dollar invested in low and high volatility stocks**

This figure shows the value of a \$1 investment in equally weighted portfolios of low and high volatility stocks from July 1991 through December 2012. A stock is considered low (high) volatility in month  $t$  if its idiosyncratic volatility in month  $t - 1$  falls within the lowest (highest) 20% among stocks in the sample. The value of the CRSP value weighted index is presented for comparison.



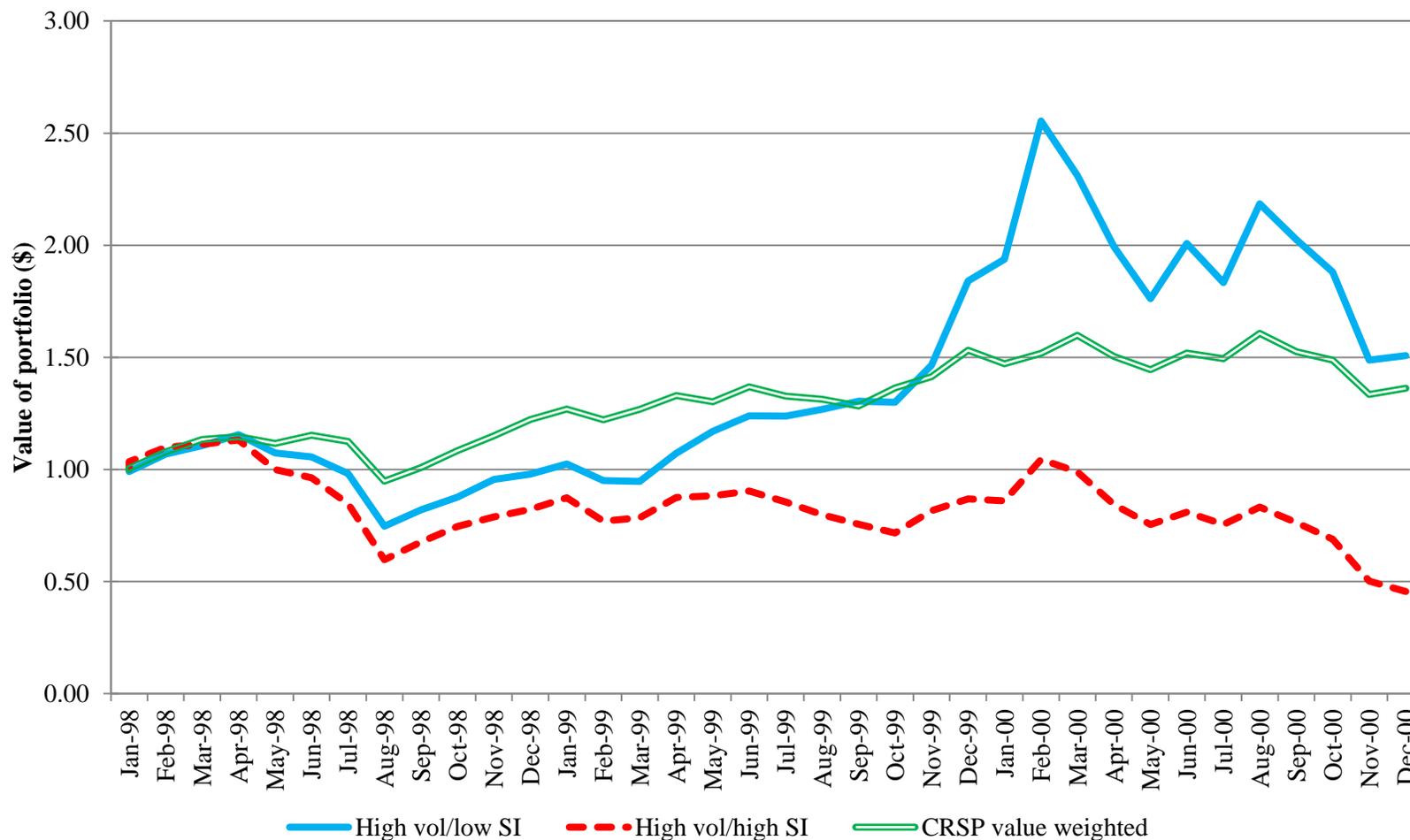
**Figure 2: The return on one dollar invested in low and high volatility stocks with low and high short interest**

This figure shows the value of a \$1 investment in equally weighted portfolios of low and high volatility stocks with low and high short interest from July 1991 through December 2012. A stock is considered low (high) volatility in month  $t$  if its idiosyncratic volatility in month  $t - 1$  falls within the lowest (highest) 20% among stocks in the sample. A stock is considered low (high) short interest in month  $t$  if its days to cover in month  $t - 1$  falls within the lowest (highest) 20% among stocks in the same volatility quintile. The value of the CRSP value weighted index is presented for comparison.



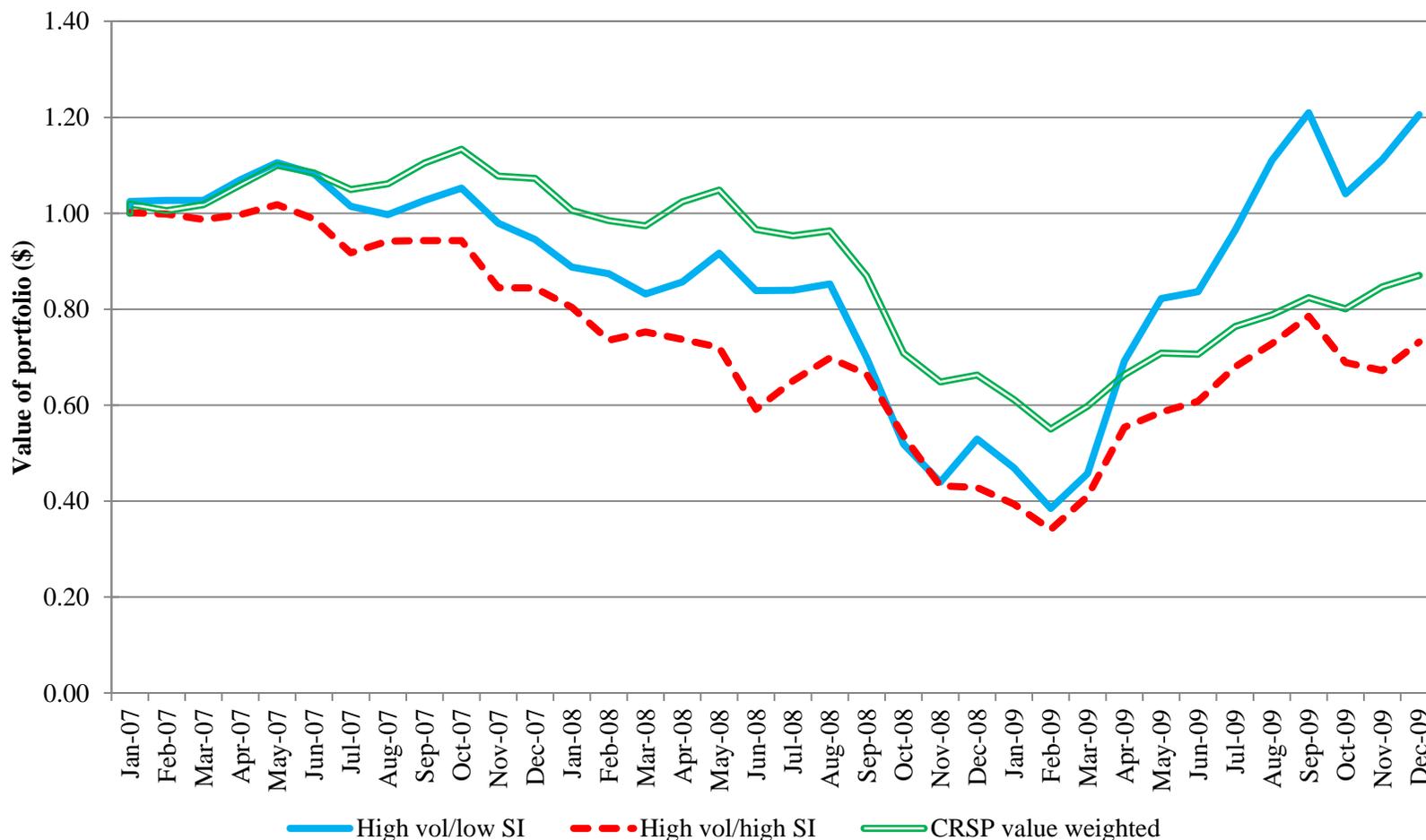
### Figure 3: The return on one dollar invested in high volatility stocks with low and high short interest – The “dot-com” bubble

This figure shows the value of a \$1 investment in equally weighted portfolios of high volatility stocks with low and high short interest from January 1998 through December 2000. A stock is considered high volatility in month  $t$  if its idiosyncratic volatility in month  $t - 1$  falls within the highest 20% among stocks in the sample. A stock is considered high volatility and low (high) short interest in month  $t$  if its days to cover in month  $t - 1$  falls within the lowest (highest) 20% among high volatility stocks. The value of the CRSP value weighted index is presented for comparison.



**Figure 4: The return on one dollar invested in high volatility stocks with low and high short interest – The financial crisis**

This figure shows the value of a \$1 investment in equally weighted portfolios of high volatility stocks with low and high short interest from January 2007 through December 2009. A stock is considered high volatility in month  $t$  if its idiosyncratic volatility in month  $t - 1$  falls within the highest 20% among stocks in the sample. A stock is considered high volatility and low (high) short interest in month  $t$  if its days to cover in month  $t - 1$  falls within the lowest (highest) 20% among high volatility stocks. The value of the CRSP value weighted index is presented for comparison.



**Table 1: The return on low and high volatility stocks**

This table shows the return on portfolios of low and high volatility stocks from July 1991 through December 2012. A stock is considered low (high) volatility in month  $t$  if its idiosyncratic volatility in month  $t - 1$  falls within the lowest (highest) 20% among stocks in the sample. We present results for the portfolios using both equal and value weighting. The value weighted portfolios weight stocks by their market capitalization at the end of month  $t - 1$ . We present results for the CRSP value weighted index for comparison. Average return is the annualized mean monthly return. Geometric return is the annualized monthly compound return. Median return is the annualized median monthly return. Standard deviation is the annualized standard deviation of monthly returns. Sharpe (Treynor) ratio is the annualized average of the monthly returns less the risk-free rate divided by the annualized standard deviation of monthly returns (CAPM beta).

	CRSP value	Equally weighted		Value weighted	
		Low volatility	High volatility	Low volatility	High volatility
Average return	9.8%	12.8%	12.8%	11.5%	10.4%
Geometric return	8.6%	12.1%	7.9%	10.7%	5.9%
Median return	16.1%	19.0%	14.0%	16.9%	12.4%
Standard deviation	15.4%	12.2%	31.9%	12.5%	29.8%
Sharpe ratio	0.44	0.80	0.31	0.68	0.25
Treynor ratio	0.07	0.15	0.06	0.11	0.04

**Table 2: The return on low and high volatility stocks with low and high short interest**

This table shows the return on portfolios of low and high volatility stocks with low and high short interest from July 1991 through December 2012. A stock is considered low (high) volatility in month  $t$  if its idiosyncratic volatility in month  $t - 1$  falls within the lowest (highest) 20% among stocks in the sample. A stock is considered low (high) short interest in month  $t$  if its days to cover in month  $t - 1$  falls within the lowest (highest) 20% among stocks in the same volatility quintile. We present results for equally weighted portfolios in Panel A and value weighted portfolios in Panel B. The value weighted portfolios weight stocks by their market capitalization at the end of month  $t - 1$ . Average return is the annualized mean monthly return. Geometric return is the annualized monthly compound return. Median return is the annualized median monthly return. Standard deviation is the annualized standard deviation of monthly returns. Sharpe (Treynor) ratio is the annualized average of the monthly returns less the risk-free rate divided by the annualized standard deviation of monthly returns (CAPM beta).

Panel A: Equally weighted portfolios

	Low volatility		High volatility	
	Low SI	High SI	Low SI	High SI
Average return	16.1%	9.9%	22.0%	1.3%
Geometric return	15.5%	9.0%	17.0%	-3.8%
Median return	21.2%	13.4%	21.8%	1.5%
Standard deviation	11.4%	13.6%	32.5%	32.0%
Sharpe ratio	1.15	0.50	0.58	-0.06
Treynor ratio	0.22	0.10	0.12	-0.01

Panel B: Value weighted portfolios

	Low volatility		High volatility	
	Low SI	High SI	Low SI	High SI
Average return	11.5%	10.8%	17.1%	5.4%
Geometric return	10.5%	9.8%	12.0%	0.4%
Median return	19.3%	13.1%	23.8%	5.9%
Standard deviation	14.4%	14.5%	31.6%	31.4%
Sharpe ratio	0.59	0.54	0.44	0.07
Treynor ratio	0.12	0.10	0.08	0.01

**Table 3: Do high volatility stocks with low and high short interest have alpha?**

This table shows the results from regressing monthly percentage returns on portfolios of high volatility stocks with low and high short interest against the Fama-French four-factor model augmented with the Pastor and Stambaugh (2003) liquidity factor. A stock is considered high volatility in month  $t$  if its idiosyncratic volatility in month  $t - 1$  falls within the highest 20% among stocks in the sample. A stock is considered low (high) short interest in month  $t$  if its days to cover in month  $t - 1$  falls within the lowest (highest) 20% among high volatility stocks. We present results for the portfolios using both equal and value weighting. The value weighted portfolios weight stocks by their market capitalization at the end of month  $t - 1$ . The time period used is July 1991 through December 2012.  $p$ -values from robust standard errors are reported below the coefficients in brackets. \*, \*\*, and \*\*\* represent statistical significance at the 10%, 5%, and 1% levels.

	Equally weighted			Value weighted		
	Low SI	High SI	Low - High	Low SI	High SI	Low - High
Beta	1.24*** [0.000]	1.22*** [0.000]	0.02 [0.772]	1.32*** [0.000]	1.29*** [0.000]	0.03 [0.794]
SMB	1.33*** [0.000]	1.21*** [0.000]	0.12 [0.262]	0.95*** [0.000]	0.98*** [0.000]	-0.03 [0.884]
HML	-0.08 [0.377]	-0.13 [0.181]	0.05 [0.612]	-0.40*** [0.001]	-0.21** [0.043]	-0.19 [0.198]
UMD	-0.53*** [0.000]	-0.61*** [0.000]	0.08 [0.445]	-0.34*** [0.000]	-0.47*** [0.000]	0.13 [0.166]
PS Liq	-0.06 [0.287]	0.01 [0.856]	-0.07 [0.318]	-0.03 [0.656]	-0.03 [0.686]	-0.00 [0.970]
Alpha	0.95*** [0.000]	-0.71*** [0.005]	1.67*** [0.000]	0.56** [0.038]	-0.40 [0.135]	0.96** [0.011]
Observations	258	258	258	258	258	258
$r^2$	0.87	0.88	0.02	0.82	0.82	0.03

**Table 4: How do high volatility stocks with low and high short interest differ?**

This table shows mean and median characteristics for high volatility stocks with low and high short interest. We measure each characteristic for each stock each month from July 1991 through December 2012. A stock is considered high volatility in month  $t$  if its idiosyncratic volatility in month  $t - 1$  falls within the highest 20% among stocks in the sample. A stock is considered low (high) short interest in month  $t$  if its days to cover in month  $t - 1$  falls within the lowest (highest) 20% among high volatility stocks. The results for the full sample of all stocks are presented for comparison. Days to cover is the last reported value of short interest in month  $t - 1$  divided by the average daily trading volume in month  $t - 1$ . Short interest ratio is the last reported value of short interest in month  $t - 1$  divided by shares outstanding at the end of month  $t - 1$ . Idiosyncratic volatility is standard deviation of the residuals from regressing month  $t - 1$  daily returns against the Fama-French four-factor model. Beta, size, and book-to-market are measured following Fama and French (1992). Size is reported in millions of dollars. Size decile is determined using the NYSE breakpoints. 12-month return is the return from month  $t - 13$  to month  $t - 1$ . Amihud illiquidity is the average of the absolute daily return divided the dollar trading volume measured from month  $t - 13$  through month  $t - 1$ . The resulting value is multiplied by one million. Share turnover is the average daily trading volume in month  $t - 1$  divided by shares outstanding at the end of month  $t - 1$ . Institutional holdings is the percentage of outstanding stock held by institutions in the last available series of 13F reports.

	Low SI n = 21,610		High SI n = 21,417		Full sample n = 538,256	
	Mean	Median	Mean	Median	Mean	Median
Days to cover	0.82	0.46	13.17	11.19	5.57	3.55
Short interest ratio	2.0%	0.5%	9.3%	7.4%	3.7%	1.9%
Idiosyncratic volatility	4.2%	3.8%	3.8%	3.5%	2.1%	1.7%
Beta	1.43	1.42	1.47	1.45	1.23	1.17
Size	2005	301	556	338	3427	712
Size decile	3.8	3.0	3.1	2.0	4.9	4.0
Book-to-market	0.53	0.43	0.41	0.30	0.50	0.44
12-month return	29.8%	10.5%	0.6%	-14.0%	18.6%	10.7%
Amihud illiquidity	0.30	0.03	0.14	0.02	0.10	0.01
Share turnover	1.6%	1.2%	0.9%	0.6%	0.8%	0.5%
Institutional holdings	50.3%	49.7%	48.3%	44.8%	57.5%	59.6%

**Table 5: What is the simultaneous effect of high volatility and short interest?**

This table presents results from equation (1) in the paper:

$$\text{Return}_{i,t} = \text{FF Controls}_{i,t-1} + \text{Idio Vars}_{i,t-1} + \text{Short Interest Vars}_{i,t-1} + \text{Time FE} + \varepsilon_{i,t}$$

The dependent variable is the percentage stock return for stock  $i$  in month  $t$ . We include four FF Controls $_{i,t-1}$ . Beta, ln(size), and book-to-market are measured following Fama and French (1992). 12-month return is the return for stock  $i$  from month  $t - 13$  to month  $t - 1$ . We include two Idio Vars $_{i,t-1}$ . Idio vol is the standard deviation of the residuals from regressing month  $t - 1$  daily returns for stock  $i$  against the Fama-French four-factor model. High vol dummy equals one if the idio vol of stock  $i$  in month  $t - 1$  falls within the highest 20% among stocks in the sample, zero otherwise. We include three Short Interest Vars $_{i,t-1}$ . Days to cover is the last reported value of short interest for stock  $i$  in month  $t - 1$  divided by average daily trading volume for stock  $i$  in month  $t - 1$ . Low (high) DTC dummy is equal to one if days to cover for stock  $i$  in month  $t - 1$  falls within the lowest (highest) 20% among stocks in the month  $t - 1$  volatility quintile of stock  $i$ , zero otherwise. We interact the high vol dummy and the two DTC dummy variables in some models. All right-hand-side variables, except beta and the dummy variables, are  $z$ -scored (demeaned and divided by standard deviation) within each month. Before  $z$ -scoring, we winsorize all variables, except beta and the dummy variables, at 1% and 99%. We include monthly time fixed effects in all models and cluster standard errors on time. \*, \*\*, and \*\*\* represent statistical significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Beta	-0.07 [0.851]	0.13 [0.669]	-0.10 [0.784]	0.12 [0.682]	0.13 [0.653]	0.14 [0.641]
ln(size)	0.02 [0.835]	-0.06 [0.455]	-0.02 [0.778]	-0.11 [0.152]	-0.11 [0.174]	-0.11 [0.165]
Book-to-market	0.19*** [0.010]	0.16** [0.018]	0.18** [0.017]	0.14** [0.040]	0.13* [0.051]	0.13* [0.057]
12-month return	0.13 [0.311]	0.12 [0.337]	0.11 [0.399]	0.10 [0.452]	0.10 [0.459]	0.09 [0.491]
Idio vol		-0.26*** [0.010]		-0.30*** [0.003]	-0.26*** [0.008]	-0.27*** [0.005]
Days to cover			-0.23*** [0.000]	-0.26*** [0.000]	-0.15*** [0.001]	-0.17*** [0.000]
High vol dummy					-0.13 [0.159]	-0.04 [0.684]
Low DTC dummy					0.31*** [0.000]	0.25*** [0.003]
High DTC dummy					-0.20** [0.013]	-0.05 [0.511]
High vol * Low DTC						0.28** [0.045]
High vol * High DTC						-0.62*** [0.000]

**Table 6: Do execution costs prevent the realization of the high volatility portfolio returns?**

This table shows the results from regressing monthly percentage returns on varying portfolios of high volatility stocks with low and high short interest against the Fama-French four-factor model augmented with the Pastor and Stambaugh (2003) liquidity factor. A stock is considered high volatility in month  $t$  if its idiosyncratic volatility in month  $t - 1$  falls within the highest 20% among stocks in the sample. A stock is considered low (high) short interest in month  $t$  if its days to cover in month  $t - 1$  falls within the lowest (highest) 20% among high volatility stocks. After those sorts are complete, we sort stocks within those groups into terciles each month based on one of three different variables measured as of  $t - 1$ : Amihud illiquidity, share turnover, and institutional holdings. Each of those variables is measured as described in Table 4. We use the stocks within each resulting tercile to form equally weighted portfolios. Panel A presents monthly alphas for those portfolios after sorting on Amihud illiquidity. Panel B presents monthly alphas for those portfolios after sorting on share turnover. Panel C presents monthly alphas for those portfolios after sorting on institutional holdings. The time period used is July 1991 through December 2012.  $p$ -values from robust standard errors are reported below the coefficients in brackets. \*, \*\*, and \*\*\* represent statistical significance at the 10%, 5%, and 1% levels.

Panel A: Amihud illiquidity

	Low SI	High SI	Low SI - High SI
High illiquidity	0.80** [0.033]	-1.21*** [0.001]	2.00*** [0.000]
Mid illiquidity	1.39*** [0.000]	-0.61* [0.050]	2.00*** [0.000]
Low illiquidity	0.69*** [0.007]	-0.33 [0.306]	1.02*** [0.007]
High illiquidity - Low illiquidity	0.11 [0.764]	-0.87** [0.031]	0.98* [0.070]

Panel B: Share turnover

	Low SI	High SI	Low SI - High SI
High turnover	0.94*** [0.007]	-0.53 [0.142]	1.48*** [0.001]
Mid turnover	1.29*** [0.000]	-0.58* [0.051]	1.86*** [0.000]
Low turnover	0.64** [0.024]	-1.02*** [0.001]	1.67*** [0.000]
High turnover - Low turnover	0.30 [0.411]	0.49 [0.175]	-0.19 [0.702]

Panel C: Institutional holdings

	Low SI	High SI	Low SI - High SI
High holdings	0.79*** [0.004]	-0.41 [0.151]	1.20*** [0.002]
Mid holdings	1.19*** [0.000]	-0.88*** [0.006]	2.07*** [0.000]
Low holdings	0.88** [0.035]	-0.85** [0.022]	1.73*** [0.000]
High holdings - Low holdings	-0.09 [0.832]	0.45 [0.250]	-0.54 [0.313]

**Table 7: Are the high volatility portfolio returns driven by a momentum strategy?**

This table shows the results from regressing monthly percentage returns on varying portfolios of high volatility stocks with low and high short interest against the Fama-French four-factor model augmented with the Pastor and Stambaugh (2003) liquidity factor. A stock is considered high volatility in month  $t$  if its idiosyncratic volatility in month  $t - 1$  falls within the highest 20% among stocks in the sample. A stock is considered low (high) short interest in month  $t$  if its days to cover in month  $t - 1$  falls within the lowest (highest) 20% among high volatility stocks. After those sorts are complete, we sort stocks within those groups into terciles each month based on one of two different variables: prior year return and prior year alpha. Prior year return is the return for a stock from month  $t - 13$  to month  $t - 1$ . Prior year alpha is the alpha for a stock from month  $t - 13$  to month  $t - 1$  measured using the Fama-French four-factor model augmented with the Pastor and Stambaugh (2003) liquidity factor. We use the stocks within each resulting tercile to form equally weighted portfolios. Panel A presents monthly alphas for those portfolios after sorting on prior year return. Panel B presents monthly alphas for those portfolios after sorting on prior year alpha. The time period used is July 1991 through December 2012.  $p$ -values from robust standard errors are reported below the coefficients in brackets. \*, \*\*, and \*\*\* represent statistical significance at the 10%, 5%, and 1% levels.

## Panel A: Prior year return

	Low SI	High SI	Low SI - High SI
High prior return	0.59** [0.034]	-0.55** [0.042]	1.14*** [0.003]
Mid prior return	0.89*** [0.001]	-0.63** [0.020]	1.52*** [0.000]
Low prior return	1.37*** [0.002]	-0.95** [0.030]	2.32*** [0.000]
High prior return - Low prior return	-0.78* [0.079]	0.40 [0.337]	-1.18** [0.019]

## Panel B: Prior Year Alpha

	Low SI	High SI	Low SI - High SI
High prior alpha	0.87*** [0.003]	-0.31 [0.326]	1.18*** [0.002]
Mid prior alpha	0.86*** [0.004]	-0.91*** [0.001]	1.78*** [0.000]
Low prior alpha	1.13*** [0.001]	-0.92** [0.023]	2.05*** [0.000]
High prior alpha - Low prior alpha	-0.26 [0.422]	0.61 [0.145]	-0.87* [0.081]

**Table 8: High volatility stocks with low and high short interest during turbulent markets**

This table shows the return on portfolios of high volatility stocks with low and high short interest. Panel A shows results from January 1998 through December 2000. Panel B shows results from January 2007 through December 2009. A stock is considered high volatility in month  $t$  if its idiosyncratic volatility in month  $t - 1$  falls within the highest 20% among stocks in the sample. A stock is considered low (high) short interest in month  $t$  if its days to cover in month  $t - 1$  falls within the lowest (highest) 20% among high volatility stocks. We present results for the portfolios using both equal and value weighting. The value weighted portfolios weight stocks by their market capitalization at the end of month  $t - 1$ . We present the CRSP value weighted index for comparison. Average return is the annualized mean monthly return. Geometric return is the annualized monthly compound return. Median return is the annualized median monthly return. Standard deviation is the annualized standard deviation of monthly returns. Sharpe (Treynor) ratio is the annualized average of the monthly returns less the risk-free rate divided by the annualized standard deviation of monthly returns (CAPM beta).

Panel A: "Dot-com" bubble (1998-2000)

	CRSP value	Equally weighted		Value weighted	
		Low SI	High SI	Low SI	High SI
Average return	12.2%	21.5%	-18.5%	29.1%	-6.4%
Geometric return	10.3%	13.8%	-25.9%	19.3%	-14.5%
Median return	31.3%	29.6%	-2.0%	43.2%	10.9%
Standard deviation	19.1%	40.2%	37.7%	44.5%	39.6%
Sharpe ratio	0.37	0.41	-0.62	0.54	-0.29
Treynor ratio	0.07	0.11	-0.15	0.14	-0.07

Panel B: Financial crisis (2007-2009)

	CRSP value	Equally weighted		Value weighted	
		Low SI	High SI	Low SI	High SI
Average return	-2.4%	16.4%	-4.0%	0.7%	0.5%
Geometric return	-4.6%	6.2%	-10.4%	-7.5%	-5.1%
Median return	13.3%	10.6%	-2.1%	10.0%	1.5%
Standard deviation	21.1%	47.4%	36.9%	40.0%	35.0%
Sharpe ratio	-0.21	0.30	-0.16	-0.04	-0.04
Treynor ratio	-0.04	0.07	-0.04	-0.01	-0.01