Costly Arbitrage and Idiosyncratic Risk: Evidence from Short Sellers*

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Abstract

Previous studies have shown that high short interest stocks have low subsequent returns. We test whether the persistence of this effect is due to costs limiting arbitrage. The arbitrage cost that we focus on is idiosyncratic risk which, regardless of the arbitrageur's level of diversification, deters arbitrage activity. Consistent with costly arbitrage, we find that among high short interest stocks a one standard deviation increase in idiosyncratic risk predicts a more than 1% decline in monthly returns. Moreover, idiosyncratic risk does not predict returns across low short interest stocks, and short interest does not predict low returns across low idiosyncratic risk stocks. Our results are robust to commonly used proxies for both transaction costs and short sale constraints.

JEL classification: G11; G12; G14

Keywords: Short sellers; Short interest; Short sale constraints; Costly arbitrage; Idiosyncratic risk; Market efficiency

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1. Introduction

Papers by Asquith and Meulbroek (1995), Dechow, Hutton, Meulbroek, and Sloan (2001), Desai, Ramesh, Thiagarajan, and Balachandran (2002), and Asquith, Pathak, and Ritter (2005) show that highly shorted stocks have low subsequent returns. This finding represents an anomaly, as this source of return-predictability is currently unexplained by traditional asset pricing models. With any study of market anomalies, there are two different research questions that are of independent interest: (i) what is the source of the anomaly, i.e., what causes prices to move away from fundamental values? (ii) why are rational investors not arbitraging away the mispricing?[1]

There are several potential explanations for question (i), one of which is provided in Miller (1977). Miller hypothesizes that opinion divergence among investors coupled with short sale costs will create an upward bias in prices. Miller's model has found support in empirical studies such as Diether, Malloy, and Scherbina (2002), Asquith, Pathak, and Ritter (2005), Boehme, Danielsen, and Sorescu (2006), and Boehme, Danielsen, Kumar, and Sorescu (2008).

With respect to question (ii), it is puzzling that this mispricing is not arbitraged away by rational traders. Specifically, why do short sellers spend resources to find mispriced securities, but then not completely arbitrage the mispricing away? Moreover, why don't other investors, who can observe short interest, use short interest as an investment signal, and arbitrage the short interest anomaly away? It is unlikely that lending fees on shorted shares can fully explain the lack of arbitrage. Papers by D'Avolio (2002) and Boehme, Danielsen, and Sorescu (2006) estimate the average lending fee of a high short interest firm to be 0.15% and 0.17% per month, whereas the alphas of high short interest portfolios can exceed 1% per month. Hence, the existing literature has not yet answered question (ii), and this is where our paper comes in.

We test whether idiosyncratic risk plays a role in preventing short sellers from fully correcting the mispricing found in highly shorted stocks. We focus on idiosyncratic risk because Shleifer and Vishny

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[1] We follow Shleifer and Vishny (1997) and use the word arbitrage to describe: "trading based on knowledge that the price of an asset is different from its fundamental value."

(1997) and Pontiff (2006) identify it as the primary arbitrage holding cost. The larger the portfolio weight that an arbitrageur assigns to a stock, the more the stock's idiosyncratic variance affects the portfolio's variance. Hence, if an arbitrageur is risk averse, then all else equal, she will take a relatively small position in a high idiosyncratic risk stock (for both short and long positions). This result is shown in Treynor and Black (1973) and Pontiff (2006). This result does not depend on the arbitrageur's level of diversification; Treynor and Black (1973) and Pontiff (2006) show that idiosyncratic risk will limit arbitrage with equal effectiveness in portfolios containing many and few securities (more on this in Section 2). This framework suggests that if we observe a high short interest stock with high idiosyncratic risk, then we expect the stock to have a large alpha (in absolute value), or else short sellers would not keep the position open.

Evidence of arbitrageur risk aversion can be seen anecdotally among hedge funds. As an example, a loss bigger than 5% in a single month is considered disastrous in the hedge industry. During the "Quant Meltdown" in August 2007, many reputable hedge funds suffered losses of that order of magnitude, which made the front pages of the Wall Street Journal.[2] The average stock in our sample has a daily idiosyncratic return standard deviation of 3%; hence a risk-averse arbitrageur has an incentive to take only small positions, especially in high idiosyncratic risk stocks, so as to keep her portfolio variance minimal.

We find that idiosyncratic risk and abnormal returns are negatively correlated across high short interest stocks. Among high short interest stocks, the difference in abnormal returns between the highest and lowest idiosyncratic risk quintiles is a significant 1.24% per month. We also show that the negative relation between idiosyncratic risk and subsequent returns only exists across high short interest firms, indicating that our findings are not driven by a systematic relation between idiosyncratic risk and

[2] For example, on August 10, 2007, the Wall Street Journal reported on its front page A1 that "After the close of trading, Renaissance Technologies Corp., a hedge-fund company with one of the best records in recent years, told investors that a key fund has lost 8.7% so far in August and is down 7.4% in 2007. … The $1.8 billion publicly traded Highbridge Statistical Market Neutral Fund was down 5.2% for the month as of Wednesday..." (see Zuckerman, Hagerty, and Gauthier-Villars, 2007).

subsequent returns.[3] Our findings show that idiosyncratic risk is strongly correlated with short sellers' alphas, suggesting that it is a significant cost to short sellers. Thus our results provide an explanation for the persistence of the short interest anomaly.

There is a growing body of literature showing that anomalies are correlated to arbitrage costs. As examples, Pontiff (1996), Wurgler and Zhuravskaya (2002), Ali, Hwang, and Trombley (2003), Mashruwala, Rajgopal, and Shevlin (2006), Scruggs (2007), and McLean (2009) show that closed-end fund discounts, abnormal returns resulting from index inclusions, the book-to-market effect, the accrual anomaly, the mispricing of "Siamese twins" stocks, and long-term reversal are all related to arbitrage costs. The common conclusion in these studies is that costs prevent arbitrageurs from fully correcting mispricing; hence the persistence of the anomalies. Our study is unique, and can help to validate the common costly arbitrage conclusion in these other studies, in that we directly study the positions of the agents who are believed to be involved in the arbitrage process.

The remainder of this paper is organized as follows. Section 2 shows why idiosyncratic risk makes arbitrage costly. Section 3 describes our sample and provides preliminary results. Section 4 studies the impact of the interaction between short interest and idiosyncratic risk on subsequent stock returns, using both portfolio and regression tests. Section 5 contains the multivariate costly arbitrage results. Section 6 concludes.

2. Why Does Idiosyncratic Risk Make Arbitrage Costly?

Pontiff (2006) contends that there is confusion in the literature regarding why idiosyncratic risk makes arbitrage costly, as there is a tendency in the literature to incorrectly argue that idiosyncratic risk only deters arbitrage if arbitrageurs are undiversified. To show why idiosyncratic risk makes arbitrage

[3] Arnold, Butler, Crack, and Zhang (2005) find that short interest became more informative after the 1997 tax law changes, which made short selling against the box more costly. Their results are also broadly consistent with costly arbitrage.

costly, we briefly review the model studied in Treynor and Black (1973) and Pontiff (2006).[4] We also refer the interested reader to Pontiff's (2006) detailed analysis of the issue.

The arbitrageur's objective is to maximize utility, which is increasing in expected returns, and decreasing in variance. The arbitrageur must allocate her wealth among an active portfolio, the market portfolio, and a risk-free asset. The portfolio's alpha is the weighted sum of the individual stock alphas within the portfolio:

$$\alpha_p = \sum_{i=1}^{n} w_i \times \alpha_i \tag{1}$$

Equation (1) shows that alpha gives the arbitrageur an incentive to be undiversified. Equation (1) is maximized if the arbitrageur places all wealth in the highest alpha stock.

Treynor and Black assume that a security's variance can be decomposed into a systematic part, which can be completely explained by the firm's covariance with the market portfolio, and an uninsurable or idiosyncratic part that is unique to the firm. Market variance can be hedged by taking an offsetting position in the market portfolio, so in this part of the Treynor and Black analysis can be ignored. Idiosyncratic variance is assumed to be unique to the firm and is thus both unhedgeable and uncorrelated across firms. The variance of the active portfolio can therefore be written as:

$$\sigma_p^2 = \sum_{i=1}^{n} w_i^2 \times \sigma_{ie}^2 \tag{2}$$

Equation (2) shows that the arbitrageur also has an incentive to be diversified, as Equation (2) is minimized if the arbitrageur places an infinitesimally small weight on each position. Equation (1) shows that alpha keeps the arbitrageur from doing this. The arbitrageur has risk aversion of λ and solves for the optimal tradeoff of the incentives described in equations (1) and (2) with a portfolio optimization. The arbitrageur's utility function can be written as:

$$U = \sum_{i=1}^{N} w_i(\alpha_i + r_f) + w_m r_m + (1 - \sum_{i=1}^{N} w_i - w_m) r_f - \frac{1}{2}\lambda \sum_{i=1}^{N} w_i \sigma_{ie}^2 - \frac{1}{2}\lambda w_m^2 \sigma_m^2 \tag{3}$$

[4] The model in Pontiff (2006) is essentially the Treynor and Black (1973) model with a risk-free asset that can be either invested in, or shorted.

Where r_m is the return of the market portfolio, σ^2_m is the variance of the market portfolio, and r_f is the return of the risk free asset. The optimal weight for mispriced stock k that results from this portfolio optimization problem is:

$$w_k = \frac{\alpha_k}{\lambda \sigma_{ke}^2} \tag{4}$$

Equation (4) shows that each stock's weight bears a positive relation to its alpha, and a negative relation to its idiosyncratic risk. This relation does not depend on the arbitrageur's level of diversification, as it holds for any value of N, the number of securities in the arbitrageur's portfolio. This result predicts that all else equal high idiosyncratic risk stocks will get less arbitrage resources.

We elaborate on this issue in Equation (4) by examining the ratio of the portfolio weights of two securities k and j. The only two factors that determine the relative weights of securities k and j are the alphas and the idiosyncratic variances of the two stocks.[5]

$$\frac{w_k}{w_j} = \frac{\alpha_k / \sigma_{ke}^2}{\alpha_j / \sigma_{je}^2} \tag{5}$$

Pontiff (1996 and 2006) and Shleifer and Vishny (1997) reason that because idiosyncratic risk is a cost to the arbitrageur, arbitrageurs will push alphas towards zero, but do so less for high idiosyncratic risk stocks, as arbitrageurs take smaller positions in these stocks. Hence the largest mispricing should be found in the highest idiosyncratic risk stocks, as these stocks receive the least arbitrage resources. Put differently, arbitrageurs may take a large position in a high idiosyncratic risk stock, but only if that stock's alpha is very high. Such arbitrage activity will then push the stock's alpha towards zero, but arbitrageurs will only maintain a large position if the stock's alpha remains sufficiently high. Hence costly arbitrage predicts that idiosyncratic risk and abnormal returns will be negatively correlated across high short interest firms, as the most costly short positions should also be the most profitable.

[5] In this paper both equations 4 and 5 are derived in a mean-variance framework. However, these equations can be derived in a continuous time environment, in which the arbitrageur has constant relative risk aversion and faces constant investment opportunities. In this setting λ is the arbitrageur's coefficient of relative risk aversion. See Merton (1971). We thank George Pennacchi, the editor, for pointing this out to us.

3. Data, Definitions, and Preliminary Results

3.1. The Sample

Our sample consists of monthly short positions for NYSE stocks for the period January 1988 through December 2003, NASDAQ stocks for the period June 1988 through May 2003, and AMEX stocks for the period January 1995 through December 2003. [6] The exchanges collect the number of shares shorted for individual stocks on the fifteenth calendar day of each month. The data reflect shares shorted three to five days prior to the report date, as the member firms only report short interest positions resulting from settled trades. The exchanges share this information with news services, and the data are public information by the end of the month. The short positions of many firms are then reported in major periodicals such as the *Wall Street Journal* and on popular investing websites such as finance.yahoo.com.

We acquired quarterly data on institutional holdings from Thomson Financial. The 1978 Amendment to the Securities and Exchange Act of 1934 requires all institutions with more than $100 million under discretionary management to report their holdings to the SEC on what is now a quarterly basis on form 13F. All positions, which consist of more than 10,000 shares or $200,000 must be reported. If no institutional ownership is reported for a stock, then we assign it a value of zero. We obtained book values from Compustat and other stock information from CRSP.

All of the portfolio strategies that we study in this paper are implemented the month following the release of the information that we use to make our portfolios. For example, if short interest is reported in June, then we measure returns from July 1st forward. Investors could therefore have engaged in all of the strategies that we study in this paper by observing the same information that we do to form our portfolios.

[6] The NASDAQ does not have short interest data for the months of February 1990 and July 1990. Desai, Ramesh, Thiagarajan, and Balachandran (2002) who also use NASDAQ data report that these dates are missing from their data as well.

3.2. Arbitrage Cost Proxies

We use seven different arbitrage cost proxies. Following Pontiff (1996) we classify each cost as either a holding cost or a transaction cost. Holding costs occur in every period that a position is kept open, while transactions costs occur whenever a position is opened or closed.

3.2.1. Holding Costs Proxies

Our two holding cost measures are institutional ownership and idiosyncratic risk. We use institutional ownership as a proxy for short sale costs. The results in D'Avolio (2002) suggest that lending fees on shorted shares are closely related to institutional ownership, as it explains more than half of the variation in lending fees across firms. Asquith, Pathak, and Ritter (2005), Nagel (2005), and Boehme, Danielsen, Kumar, and Sorescu (2008) all contend that short sale costs are correlated with institutional ownership.

Treynor and Black (1973), Pontiff (1996, 2006), and Shleifer and Vishny (1997) predict that idiosyncratic risk should correlate with mispricing. We measure idiosyncratic risk by regressing the previous 100 days' returns of each stock on the daily realizations of a four-factor model. The factors include size, book-to-market, momentum, and the value-weighted market index minus the risk-free rate. To be included in our sample, each stock had to have at least 20 days of past return data. The standard deviation of the residuals from these regressions is our idiosyncratic risk measure.

As a robustness check we also computed idiosyncratic risk using monthly returns (over the previous 60 months) and obtained similar results. We found that idiosyncratic risk measures computed using 1, 3, 4, or 5-factor models (the fifth factor was an industry factor) are highly correlated and that each of these measures yields similar results. Other studies have also found that different idiosyncratic risk measures are highly correlated. For example Wurgler and Zhuravskaya (2002) use a matching firm method to calculate idiosyncratic risk. For each stock they form a portfolio of three firms that are of similar size and in the same industry. They then regress each stock's return on the matching portfolio's returns; the standard deviation of the residuals is their idiosyncratic risk measure. Wurgler and Zhuravskaya (2002) find that the correlation between this measure and a market-model measure is 0.98.

3.2.2. Transactions Costs Proxies

Our five transaction cost proxies include size, price, dollar volume, frequency of zero return days, and Amihud's (2002) illiquidity measure. Pontiff (1996) and Ali, Hwang, and Trombley (2003) both use size as a transaction cost proxy. Pontiff (2006) notes that smaller stocks are more illiquid, have higher bid ask spreads, and larger price impacts. Both Pontiff (2006) and Ali, Hwang, and Trombley (2003) include price as a transaction cost measure for similar reasons as market value.

We measure dollar volume as the average dollar volume traded each day over the previous month. Stocks with low dollar volume are less liquid and are therefore expected to yield larger price impacts when traded. Spiegel and Wang (2006) test whether several different measures of liquidity can predict the cross-section of stock returns. In multivariate tests that include idiosyncratic risk, Spiegel and Wang (2006) report that dollar volume is the only significant liquidity measure.

Amihud (2002) contends that the absolute value of daily returns divided by daily dollar volume can be used as a proxy for liquidity. Amihud (2002) shows that this measure bears a positive correlation to subsequent returns. Spiegel and Wang (2006) report that if dollar volume is excluded Amihud's (2002) measure can predict returns when in the presence of idiosyncratic risk. We use the average of this measure over the previous month.

We compute frequency of zero return days by computing the percentage of zero return days within the past month. Lesmond, Ogden, and Trzcinka (1999) contend that investors will not trade if transaction costs outweigh the value of their private information, thus frequency of zero return days are a measure of transaction costs.

3.3. Other Control Variables

In our multivariate tests we control for size, book-to-market, and momentum effects. Size serves a dual role of both a liquidity measure and a control variable. We obtained book values from the merged CSRP-Compustat data set. We use a stock's buy-and-hold return over the past six-months to measure momentum.

3.4. Forming Short Interest Portfolios

We use two different approaches to select stocks for our short interest portfolios. The first approach selects stocks by defining a cut-off in short interest (shares shorted /shares outstanding) as a criterion. Asquith and Meulbroek (1995), Desai, Ramesh, Thiagarajan, and Balachandran (2002), and Asquith, Pathak, and Ritter (2005) use similar criteria to form their short interest portfolios. Stocks with short interest that is greater than or equal to 10% go into our ≥ 10% portfolio, while those with short interest that is greater than or equal to 5%, but less than 10% go into our 5-10% portfolio.

The second approach selects stocks based on their short interest relative to the short interest of other stocks in the same cross-section. The stocks in the top percentile each month get assigned to our ≥ 99^{th} percentile portfolio, while those in 2^{nd} through 5^{th} percentiles comprise our 95^{th}-99^{th} percentile portfolio. A cross-sectional definition of high short interest is important, as the average firm short interest has increased over time (see Asquith, Pathak, and Ritter, 2005).

3.5. Summary Statistics

Table 1 compares the median characteristics of high and low short interest stocks. We calculate the median of each characteristic each month, and then take the time series average of each median. The first column displays the median short interest. The median short interest ranges from 6.7% to 23.3% in our different high short interest portfolios and is close to zero (either 0.2 or 0.3%) in our low short interest portfolios.

The second column reveals that stocks that are highly shorted tend to be larger than those that are not. For example, the stocks in the 95th-99th percentile portfolio have a median market value of \$275 million, while those in the low short interest portfolio have a median market value of \$124 million. This result is similar to those in Asquith, Pathak, and Ritter (2005) and Dechow, Hutton, Meulbroek, and Sloan (2001), both of whom find that short sellers target larger firms. This finding is also consistent with the results in D'Avolio (2002), who shows that the shares of larger firms are easier to borrow.

The third column reveals that highly shorted stocks tend to be growth stocks. The 95th-99th percentile portfolio has a median book-to-market ratio of 0.4, while the stocks in the < 95th percentile portfolio have a median book-to-market ratio of 0.57. These results are similar to those in Asquith, Pathak, and Ritter (2005) and Dechow, Hutton, Meulbroek, and Sloan (2001), both of whom find that highly shorted stocks have low book-to-market ratios. However the 99th percentile portfolio's book-to-market ratio is 0.89, while the stocks in the < 99th percentile portfolio have a median book-to-market ratio of 0.57. This suggests that the relation between short interest and book-to-market ratio seems to reverse for the extreme values of short interest. The stocks in the high short interest portfolios tend to have low past returns, and the median idiosyncratic risk is slightly higher in three of the four high short interest portfolios.

Table 1 shows that institutional ownership is substantially higher for high short interest stocks than for low short interest stocks. Dechow, Hutton, Meulbroek, and Sloan (2001) also find that institutional ownership is correlated with short interest. This highlights the problem of using short interest in isolation as a proxy for short sale costs. The institutional ownership values range from 33.1% to 36.4% in the high short interest portfolios, and only 12.4% to 13.6% in the low short interest portfolios. This difference suggests that the median high short interest stock may be less costly to borrow than is the median low short interest stock.

High short interest stocks tend to be more liquid than low short interest stocks. The median daily dollar volume ranges from \$2.8 million to \$3 million in the high short interest portfolio and is \$0.3 million in the low short interest portfolios. The percentage of zero return days ranges from 9.3% to 11%

in the high short interest portfolio and 18.9% to 19.5% in the low short interest portfolios. The Amihud (2002) illiquidity measure ranges from 2% to 3.1% in the high short interest portfolio and 23% to 25.3% in the low short interest portfolios (a high value of Amihud's (2002) measure suggests that the stock is illiquid).

3.6. Time Spent in High Short Interest Portfolios

Table 2 displays the average number of stocks in each of the high short interest portfolios, and how long stocks tend to remain in each of the portfolios. The $\geq 95^{th}$ percentile portfolio has on average 198 stocks in it each month. 34.8% of the stocks that entered this portfolio remained in the portfolio for one month, 22.7% remained for either 2 or 3 months, 15.7% remained for between 4 and 6 months, 12.0% for between 4 and 7 months, while 14.9% remained for more 13 months or more. The time spent in portfolio distributions are similar for the other short interest portfolios. These results are similar to those reported in Asquith, Pathak, and Ritter (2005).

On a cumulative basis, 57.5% of the firms that enter the $\geq 95^{th}$ percentile portfolio remain in the portfolio for 3 months or less, while 73.2% remain for 6 months or less. The results here suggest that short sellers keep their positions open for relatively short periods of time. This makes sense, as lending fees and idiosyncratic risk make open short positions costly.

3.7. Short Interest and Abnormal Returns

In this Section we measure the abnormal returns of our short interest portfolios. We use DGTW benchmark-adjusted returns as our measure of abnormal returns. Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW) developed the benchmark returns. The DGTW adjustment accounts for size, book-to-market, and momentum effects. To create the DGTW adjustment, stocks are first sorted on market values, then on book-to-market values, and finally on past returns. This results in 125 different portfolios, for which monthly returns are calculated.[7] [8]

Table 3 reports annualized DGTW benchmark-adjusted returns for the four different equally weighted short interest portfolios at 1, 3, 6, and 12-month horizons. We adjust each monthly stock return by subtracting the return of the matching DGTW portfolio during that month. We use the method of Newey and West (1987) to adjust our *t-statistics* for autocorrelation when appropriate.

The results displayed in Table 3 suggest that high short interest portends low returns. The annualized abnormal returns for the 95^{th}-99^{th} percentile portfolio are –4.38% (*t-statistic* = –1.63), –4.78% (*t-statistic* = –2.44), –4.37% (*t-statistic* = –2.92) and –3.06% (*t-statistic* = –2.58) at the 1, 3, 6, and 12-month horizons. The 5-10% short interest portfolio has abnormally low returns of similar magnitude and significance at each of the four horizons as well.

The 99^{th} percentile portfolio has the lowest returns at each horizon. The annualized abnormal returns range from –14.70% to –9.08%. All of the *t-statistics* are greater than 3. The abnormal returns of the ≥ 10% short interest portfolio are similar to those of the 99^{th} percentile portfolio, but smaller in magnitude. The results here are similar to those reported in Asquith and Meulbroek (1995), Dechow, Hutton, Meulbroek, and Sloan (2001), Desai, Ramesh, Thiagarajan, and Balachandran (2002), and Asquith, Pathak, and Ritter (2005).

4. Short Interest, Idiosyncratic Risk, and Subsequent Stock Returns

4.1. Portfolio Tests

In this subsection we cross-sort our high short interest portfolios into idiosyncratic risk quintiles. We collapse our four short interest portfolios into two for the sake of brevity. We first form our short interest portfolios and then within the portfolios we sort on idiosyncratic risk. Portfolio 5 is the high

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[7] The benchmark data are available at Russ Wermer's web page. We thank Russ Wermers for making the data available to us. For more details on the construction of these portfolios see DGTW.

[8] As a robustness check we redid Tables 3 and 4 using a 4-factor model and got similar results to those obtained using DGTW returns.

idiosyncratic risk portfolio and portfolio 1 the low idiosyncratic risk portfolio. We study the ≥ 5% short interest portfolio and the ≥ 95th percentile portfolio. The results are similar across the two portfolios, so we focus our discussions on those of the ≥ 95th percentile portfolio. We report results for the 1 and 3 month horizons, for in Table 2 we note that more than half of the firms that entered our high short interest portfolios remained in the portfolios for 3 months or less.

In Table 4 the high short interest portfolios are cross-sorted into 5 different idiosyncratic risk (IR) portfolios. The results are also displayed in Figure 1. Arbitrage should be the most costly among high IR firms, so we predict that returns will be the lowest in the highest IR portfolio. The pattern of abnormal returns across the five portfolios is monotonic at both return horizons; the alphas increase with costs. The two lowest IR portfolios do not have significantly low returns at either horizon. The high IR ≥ 95th percentile portfolio's annualized returns are –17.42% (*t-statistic* = –2.65) and –12.50% (*t-statistic* = –2.70) at the 1 and 3-month horizons. The differences between the highest and lowest IR portfolios are –14.90% (*t-statistic* = –2.10) and –10.64% (*t-statistic* = –2.13) at the 1 and 3-month horizons. The fact that the abnormal returns are not significant in the low IR portfolios suggests that when IR is low arbitrage is effective and mispricing is corrected.

4.2. Regression Tests

In this subsection, we run regressions to study the impact of the interaction between short interest and idiosyncratic risk on subsequent stock returns across all sample stocks. The results are reported in Table 5. The dependent variable in each regression is annualized raw returns over either 1 or 3-month horizons, in percentages. The regressions are Fama and MacBeth (1973) style regressions in that we perform a cross-sectional regression each month and then take a time series average of the cross-sectional coefficients. The *t-statistics* are adjusted for autocorrelation using the method of Newey and West (1987) when appropriate.

In Panel A of Table 5 we use a continuous measure of short interest, while in Panel B we use a dummy variable (High SI Dummy) that is equal to one if a firm's short interest places it in the ≥ 95th percentile portfolio, and zero otherwise. We include IR (idiosyncratic risk) in the regressions along with an interaction between IR and the short interest variables in two of the regressions. We hypothesize that the interaction should be negative and significant, in that high SI and high IR should lead to low subsequent returns. All of the regressions include the log of market value (LOGSIZE), book-to-market ratio (BK/MKT), and past six-month returns (MOM) as control variables.

In all of the regressions in both panels the relation between idiosyncratic risk and subsequent returns is insignificant. Ang, Hodrick, Xing, and Zhang (2006) measure idiosyncratic risk using daily returns over the past month, and subsequent returns over the next month, and find a negative systematic relation between idiosyncratic risk and subsequent returns. Bali and Cakici (2008) contend that Ang et al.'s findings are isolated to their measurement horizon, and our findings support this conjecture.

In regressions 1 and 3 of Panel A the SI coefficient is negative and significant, showing that high short interest stocks have low subsequent returns. In regressions 2 and 4 the IR * SI interaction term is included. In both regressions the interaction term is negative and significant, showing that stocks with high short interest that also have high idiosyncratic risk have especially low subsequent returns. Moreover, in both regressions 2 and 4 the SI coefficient is now positive and significant, showing that short interest only predicts low subsequent returns when idiosyncratic risk is high.

In Panel B short interest is replaced with a high short interest dummy variable (High SI Dummy). The dummy variable takes on a coefficient of -9.19 and -9.86 in regressions 1 and 3, showing that if a stock is in the high short interest portfolio, then its subsequent return is lower by about 9% per year. As in Panel A, once the IR * High SI Dummy interaction term is included, the coefficient on High SI Dummy becomes positive and significant, while the interaction term is negative and significant. These findings show that the short interest anomaly is limited to high idiosyncratic risk stocks.

5. Multivariate Analyses: Comparing the Effects of Different Costly Arbitrage Proxies

In this Section we compare the effects that the different costly arbitrage proxies have on the underperformance of high short interest stocks. For the sake of brevity, we limit our analysis to the $\geq 95^{th}$

percentile definition of high short interest, although in unreported results we find that the ≥ 5% short interest portfolio produces similar results. Our dependent variable in each regression is annualized raw returns over either 1 or 3-month horizons. The regressions are Fama and MacBeth (1973) style regressions in that we perform a cross-sectional regression each month and then take a time series average of the cross-sectional coefficients. The *t-statistics* are adjusted for autocorrelation using the method of Newey and West (1987) when appropriate.

In Table 6 the regressions are done using two separate samples; stocks within our high short interest ≥ 95^{th} percentile portfolio and stocks in the low short interest < 95^{th} percentile portfolio. Regressions 1-5 are done in the high short interest sample, while Regressions 6-10 are done in the low short interest sample. We perform the regressions in high and low short interest samples separately to test whether systematic effects have caused our results. Costly arbitrage predicts that we should only find a negative relation in our high short interest sample, whereas if there is a systematic relation between idiosyncratic risk and returns, like that found in Ang, Hodrick, Xing, and Zhang (2006), then the idiosyncratic risk coefficient ought to be similar in both the low and high short interest samples regressions.

In Panel A the dependent variable is annualized 1-month returns, in Panel B the dependent variable is annualized 3-month returns, both in percentages. All of the regressions include the log of market value (LOGSIZE), book-to-market ratio (BK/MKT), and past six-month returns (MOM) as control variables. As discussed earlier, LOGSIZE could also be interpreted as a costly arbitrage proxy.

Idiosyncratic risk has been used as a proxy for opinion divergence, so in Regressions 3-5 and 8-10 we include dispersion in analysts' forecasts (DISP) as a control variable for opinion divergence. We follow Diether, Malloy, and Scherbina (2002) and measure dispersion in analysts' forecasts as the standard deviation of next quarter's earnings forecasts, scaled by the mean value of the earnings forecasts. In unreported tests we also used trading volume as a measure of opinion divergence and obtained similar results.

In order to have this measure, a firm must have at least two analysts' earnings estimates. Within our sample only 26% of our total observations and 40% of our high short interest observations have a dispersion value. In order to maintain a reasonably large and representative sample, we create a dummy variable (DISP Dummy) that is equal to one if the observation has a dispersion value, and zero if it does not. If the observation is missing a dispersion value, then we assign it a dispersion value of zero. This framework allows us to maintain our sample size, without affecting inference on the dispersion slope coefficient. Pontiff and Woodgate (2008) and McLean, Pontiff, and Watanabe (2008) use this method to include firms with missing book-to-market values.

In Regression 1 of Panel A (high short interest sample) idiosyncratic risk (IR) is the only arbitrage cost variable along with the log of firm size. The IR coefficient takes on a value of –468.71 (*t-statistic* = –3.29), which is consistent with the costly arbitrage hypothesis. IR has a standard deviation of 0.031, so a one standard deviation increase in IR leads to a 14.53% reduction in subsequent annual returns. Regression 6 is similar to Regression 1, only Regression 6 uses the low short interest sample and the IR coefficient now takes on a value of 40.98 (*t-statistic* = 0.47). The results again show that IR only predicts returns across high short interest firms, suggesting that our findings are not driven by a systematic relation between idiosyncratic risk and subsequent returns.[9] [10]

Regression 2 includes IO as a control variable. In Regression 2 IR's *t-statistic* is –3.16, while IO's is 1.98, so both cost proxies are important, but IR seems to be more important. In Regressions 3 and 4 dispersion in analysts' forecasts (DISP) is added as a control variable. The DISP coefficient is insignificant, while the IR coefficient remains virtually unchanged. Hence, IR's relation with subsequent returns across high short interest firms does not seem to be driven by opinion divergence, as the

[9] We also do not find a relation between idiosyncratic risk and returns in the full sample (Table 5). This result is consistent with Bali and Cakici (2008) who argue that there is no robust relation between idiosyncratic risk and subsequent returns.

[10] In unreported robustness tests, we also used 6-month and 12-month returns as dependent variables. The 6-month results are similar, whereas the 12-month results are in the same direction but mostly insignificant. As reported in Table 2, 73.2% of the stocks that enter the ⩾ 95th percentile portfolio remain in the portfolio for 6 months or less.

significance of the IR coefficient (–3.29 in Regression 1, –3.16 in Regression 2, –3.31 in Regression 3, and –3.60 in Regression 4) remains virtually unchanged.

None of the transaction cost measures in regressions 4 and 5 are both correctly signed and consistently significant in either of the panels. Amihud's (2002) measure and frequency of zero return days do not serve as costly arbitrage proxies (although Amihud's (2002) measure did in unreported univariate tests), for among the high short interest firms both measures have positive coefficients, which is consistent with the notion that liquidity is priced in the cross-section. Across high short interest firms, the transaction cost measures are not very highly correlated, so issues with multicollinearity are likely not driving our results in the high SI regressions. Moreover, we also estimated regressions using each transaction cost measure separately along with IR and IO, and the results are similar (not reported).[11]

In Regression 5, we add an interaction term, IR * (1 – IO), to see if there is any interactive effect between IR and our proxy for short sale constraints: IO. We use (1 – IO) to interact with IR because short sale constraints should be high when IO is low, or when (1 – IO) is high. If the predictive power of IR for low subsequent returns among high short interest stocks depends on short sale constraints, then we would expect the coefficient of this interaction term to be negative and significant. However, the coefficient is insignificant (*t-statistic* is –0.33). Our model, as specified in equation (4) in Section 2, does not predict an interactive effect between idiosyncratic risk and short sale constraints. So the lack of significance here is not surprising. Also, it made the IR and IO coefficients insignificant, though the magnitude of the IR coefficient remains similar, at –452.84. The results in Panel B are similar to those in Panel A.

[11] Diether, Lee, and Werner (2008) find that a portfolio strategy based on daily short interest, with turnover of 400% per month, does not exceed its transaction costs. Arbitrageurs who trade at such high frequencies are probably more concerned with transaction costs than with holding costs, while arbitrageurs who hold stocks for longer periods may be more concerned with holding costs, such as idiosyncratic risk and lending fees. The turnover in our monthly high short interest portfolio is only 30% per month. Taken together, the results in these two papers suggest that over different horizons, different costs can matter more or less.

6. Conclusion

Previous studies have shown that highly shorted stocks have low subsequent returns. In this paper we study why this short interest effect is not arbitraged away. Our findings suggest that this effect persists because idiosyncratic risk limits arbitrage among short sellers. Our results are consistent with observations in other studies, which have noted that the apparent lack of short selling in some instances could not be explained by short sale costs alone. For example, Jones and Lamont (2002) find that during the period 1926-1933 stocks with high lending fees had low subsequent returns, although the underperformance of some of these stocks was too great to be justified by lending fees alone. Ofek and Richardson (2003) study the role that short sale costs played in the DotCom bubble. They conclude that short sale costs were one important factor, but note that their analysis "ignores the relative volatility spread between Internet and non-Internet stocks" and conclude "The magnitude of this volatility needs to be incorporated into a full explanation of the Internet rise and fall."

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Table 1. Summary Statistics

This table reports summary statistics for high and low short interest stocks. Our sample period is from January 1988 to December 2003. We have NYSE short interest data from January 1988 to December 2003, NASDAQ short interest data from June 1988 to May 2003 (NASDAQ data for February 1990 and July 1990 are not available), and AMEX short interest data from January 1995 to December 2003. At the end of each month, stocks are classified as either high or low short interest stocks, either based on relative cutoffs using percentiles of short interest or based on absolute cutoffs using percentages of short interest. At the end of each month, the median of each variable is computed across stocks. Then the mean of the medians over the 192 sample months is reported. Definitions of variables are as follows. SI (short interest) is shares shorted divided by shares outstanding. SIZE is the market value of equity ($ million). BK/MKT is the book-to-market value ratio. Since book values are from COMPUSTAT quarterly, we use the data from the beginning of each quarter for all three months in the quarter. MOM (momentum) is the previous six-month return with a one-month gap, i.e., the return from lag month 7 to lag month 1. IR (idiosyncratic risk) is the standard deviation of the residuals from the Fama-French-Carhart four-factor model (market, size, book-to-market, and momentum) over the previous 100 trading days of each month. IO (institutional ownership) is shares held by institutions divided by shares outstanding. Since shares held by institutions are reported quarterly, we use the data from the beginning of each quarter for all three months in the quarter. PRC is the stock price at the end of the month ($). VOLD is the average daily trading volume in dollars during the month ($ million). ZFREQ is the frequency of zero daily returns during the month. A_ILLIQ is the illiquidity measure suggested by Amihud (2002). For each month, A_ILLIQ is the average daily ratio of the absolute value of daily return divided by the daily trading volume in millions of dollars. T-statistics, which are in parentheses, are adjusted for serial correlation using Newey-West standard errors.

	SI	SIZE	BK/MKT	MOM	IR	IO	PRC	VOLD	ZFREQ	A_ILLIQ
High SI (95-99th %ile)	8.6%	275	0.40	0.2%	3.2%	33.6%	17.0	2.8	11.0%	2.9%
Low SI (< 95th %ile)	0.2%	124	0.57	2.0%	2.9%	13.0%	11.7	0.3	19.4%	25.3%
Difference		151	–0.17	–1.7%	0.3%	20.7%	5.4	2.5	–8.4%	–22.4%
		(3.41)	(–8.98)	(–1.33)	(2.36)	(6.59)	(6.63)	(3.69)	(–8.73)	(–3.50)
High SI (≥ 99th %ile)	23.3%	185	0.89	0.3%	2.9%	36.4%	21.4	2.9	9.4%	2.2%
Low SI (< 99th %ile)	0.3%	127	0.57	1.9%	2.9%	13.6%	11.9	0.3	18.9%	22.4%
Difference		58	0.32	–1.6%	–0.1%	22.8%	9.5	2.6	–9.5%	–20.2%
		(1.99)	(1.15)	(–1.84)	(–0.45)	(7.78)	(4.38)	(5.08)	(–6.72)	(–3.31)
High SI (5-10%)	6.7%	318	0.40	0.3%	3.2%	33.1%	16.8	2.8	11.0%	3.1%
Low SI (< 5%)	0.2%	118	0.58	2.0%	2.9%	12.4%	11.6	0.3	19.5%	25.3%
Difference		200	–0.18	–1.7%	0.3%	20.7%	5.2	2.5	–8.5%	–22.2%
		(3.27)	(–11.83)	(–1.21)	(2.33)	(6.17)	(5.84)	(3.47)	(–9.87)	(–3.89)
High SI (≥ 10%)	14.5%	243	0.48	0.6%	3.1%	36.1%	18.8	3.0	9.3%	2.0%
Low SI (< 10%)	0.2%	125	0.57	1.9%	2.9%	13.2%	11.8	0.3	19.1%	23.0%
Difference		118	–0.09	–1.3%	0.2%	22.9%	7.0	2.7	–9.7%	–21.0%
		(3.76)	(–1.08)	(–1.25)	(3.51)	(8.39)	(9.93)	(4.96)	(–7.14)	(–3.46)

Table 2. High Short Interest Stocks Categorized by Persistence and Median Months in Portfolio

This table reports the distribution of the length of time that a stock spends continuously in the high short interest portfolios once it enters. SI (short interest) is shares shorted divided by shares outstanding. Our sample period is from January 1988 to December 2003. At the end of each month, stocks are classified as either high or low short interest stocks, either based on relative cutoffs using percentiles of short interest or based on absolute cutoffs using percentages of short interest. The high short interest portfolios are formed at the end of each month. A stock that re-enters a high short interest portfolio after falling out is treated as a new observation. If no short interest is reported for a stock in a given month, it is counted as being out of the high short interest portfolio. Note that lengths may be truncated toward the end of the sample. For example, a stock, which enters a portfolio in November 2003, will have a length of at most two months. Average number of stocks is computed by taking the time series average of numbers of stocks in each monthly high short interest portfolios over the 192 sample months.

	Distribution of the length of time spent in a portfolio once entering						
Portfolio	1 month	2-3 months	4-6 months	7-12 months	≥ 13 months	Median months	Average number of stocks
High SI, ≥ 95th %ile	34.8%	22.7%	15.7%	12.0%	14.9%	3	198
High SI, ≥ 99th %ile	38.1%	26.3%	14.5%	12.1%	9.0%	2	40
High SI, ≥ 5%	31.6%	23.1%	15.9%	12.7%	16.7%	3	286
High SI, ≥ 10%	34.4%	23.8%	15.2%	12.8%	13.7%	3	98

Table 3. High Short Interest and Annualized DGTW-Adjusted Returns

This table presents equal-weighted annualized DGTW-adjusted buy-and-hold returns (%) on various stock portfolios formed based on short interest. SI (short interest) is shares shorted divided by shares outstanding. Our sample period is from January 1988 to December 2003. At the end of each month, stocks are classified as either high or low short interest stocks, either based on relative cutoffs using percentiles of short interest or based on absolute cutoffs using percentages of short interest. The DGTW-adjusted return is the raw return minus the return on the matching DGTW characteristic portfolio during the holding period. The matching DGTW portfolios are developed by Daniel, Grinblatt, Titman, and Wermers (1997). All returns are annualized and reported in percentages. T-statistics, which are in parentheses, are adjusted for serial correlation using Newey-West standard errors when appropriate ((n–1) lags for n-month returns).

Portfolio	1-month	3-month	6-month	1-year
High SI, 95-99th %ile	–4.38	–4.78	–4.37	–3.06
	(–1.63)	(–2.44)	(–2.92)	(–2.58)
High SI, ≥ 99th %ile	–14.70	–12.68	–11.41	–9.08
	(–3.87)	(–4.33)	(–4.50)	(–4.33)
High SI, 5-10%	–4.21	–4.32	–4.24	–1.88
	(–1.83)	(–2.42)	(–2.94)	(–1.47)
High SI, ≥ 10%	–8.54	–8.01	–7.51	–6.74
	(–2.52)	(–3.34)	(–3.92)	(–4.53)

Table 4. High Short Interest Stocks Partitioned by Idiosyncratic Risk Quintiles, Annualized DGTW-Adjusted Returns

This table presents equal-weighted annualized DGTW-adjusted buy-and-hold returns (%) of various stock portfolios formed based on short interest and idiosyncratic risk. Our sample period is from January 1988 to December 2003. At the end of each month, stocks are classified as either high or low short interest stocks, either based on relative cutoffs using percentiles of short interest or based on absolute cutoffs using percentages of short interest. We further rank the high short interest stocks (either ≥ 95^{th} %ile or ≥ 5%) based on idiosyncratic risk at the end of each month and assign the high short interest stocks to five quintile portfolios. Combined is the portfolio that includes all high short interest stocks in each month. Definitions of variables are as follows. SI (short interest) is shares shorted divided by shares outstanding. IR (idiosyncratic risk) is the standard deviation of the residuals from the Fama-French-Carhart four-factor model (market, size, book-to-market, and momentum) over the previous 100 trading days of each month. The DGTW-adjusted return is the raw return minus the return on the matching DGTW characteristic portfolio during the holding period. The matching DGTW portfolios are developed by Daniel, Grinblatt, Titman, and Wermers (1997). All returns are annualized and reported in percentages. T-statistics, which are in parentheses, are adjusted for serial correlation using Newey-West standard errors when appropriate ((n–1) lags for n-month returns).

	High SI, ≥ 95^{th} %ile		High SI, ≥ 5%	
Portfolio	1-month	3-month	1-month	3-month
Quintile 5 (Highest IR)	–17.42	–12.50	–12.74	–12.08
	(–2.65)	(–2.70)	(–2.01)	(–2.65)
Quintile 4	–7.86	–10.00	–10.82	–9.51
	(–1.69)	(–3.09)	(–2.56)	(–2.93)
Quintile 3	–2.48	–5.63	–2.16	–2.89
	(–0.76)	(–2.01)	(–0.68)	(–0.96)
Quintile 2	–2.06	–2.08	–1.53	–1.99
	(–0.84)	(–1.16)	(–0.68)	(–1.20)
Quintile 1 (Lowest IR)	–2.52	–1.86	–2.08	–1.80
	(–1.45)	(–1.29)	(–1.11)	(–1.36)
Combined	–6.43	–6.36	–5.77	–5.61
	(–2.40)	(–3.23)	(–2.39)	(–3.07)
Highest - Lowest IR	–14.90	–10.64	–10.66	–10.29
	(–2.10)	(–2.13)	(–1.51)	(–2.07)

Table 5. Fama-MacBeth Regressions: Short Interest and Idiosyncratic Risk Interactions

This table reports monthly Fama-MacBeth regression results across all sample stocks. Our sample period is from January 1988 to December 2003. The dependent variable in each regression is annualized raw returns (%) over either 1 or 3-month horizons. Definitions of independent variables are as follows. Short interest (SI) is the number of shares shorted divided by the number of shares outstanding. In Panel A we use a continuous measure of short interest, while in Panel B we use a dummy variable (High SI Dummy) that is equal to one if a firm's short interest places it in the ≥ 95th percentile portfolio, and zero otherwise. IR (idiosyncratic risk) is the standard deviation of the residuals from the Fama-French-Carhart four-factor model (market, size, book-to-market, and momentum) over the previous 100 trading days of each month. LOGSIZE is the natural logarithm of SIZE, which is the market value of equity in millions of dollars. BK/MKT is the book-to-market value ratio. Since book values are from COMPUSTAT quarterly, we use the data from the beginning of each quarter for all three months in the quarter. MOM (momentum) is the previous six-month return with a one-month gap, i.e., the return from lag month 7 to lag month 1. T-statistics, which are in parentheses, are adjusted for serial correlation using Newey-West standard errors when appropriate ((n–1) lags for n-month returns).

Panel A. Continuous Short Interest Variable

	Annualized 1-Month Raw Return (%)		Annualized 3-Month Raw Return (%)	
	(1)	(2)	(3)	(4)
IR	32.14	63.87	73.31	100.73
	(0.37)	(0.75)	(0.84)	(1.16)
SI	–76.51	115.27	–75.43	103.47
	(–3.76)	(3.92)	(–4.08)	(4.59)
IR * SI		–5660.36		–5364.66
		(–5.82)		(–6.47)
LOGSIZE	–2.49	–2.56	–1.90	–1.97
	(–3.72)	(–3.83)	(–3.23)	(–3.40)
BK/MKT	0.86	0.81	0.48	0.42
	(2.81)	(2.64)	(4.02)	(3.79)
MOM	4.02	4.05	4.31	4.33
	(1.17)	(1.19)	(2.17)	(2.21)
Constant	28.12	27.19	24.02	23.35
	(6.22)	(6.07)	(4.64)	(4.56)
# of months	192	192	192	192

Panel B. Dummy Variable for High Short Interest

	Annualized 1-Month Raw Return (%)		Annualized 3-Month Raw Return (%)	
	(1)	(2)	(3)	(4)
IR	28.62	41.72	70.75	81.02
	(0.33)	(0.48)	(0.80)	(0.90)
High SI Dummy	–9.19	8.97	–9.86	7.07
	(–3.70)	(2.40)	(–5.13)	(2.12)
IR * High SI Dummy		–533.43		–499.89
		(–5.21)		(–6.00)
LOGSIZE	–2.62	–2.61	–2.02	–2.02
	(–3.85)	(–3.85)	(–3.41)	(–3.43)
BK/MKT	0.83	0.80	0.45	0.43
	(2.74)	(2.66)	(3.89)	(3.78)
MOM	4.04	4.03	4.34	4.37
	(1.17)	(1.17)	(2.17)	(2.20)
Constant	28.42	27.88	24.29	23.96
	(6.28)	(6.17)	(4.68)	(4.62)
# of months	192	192	192	192

Table 6. Fama-MacBeth Regressions for High and Low Short Interest Stocks

This table reports monthly Fama-MacBeth regression results for high short interest stocks (≥ 95th %ile) and low short interest stocks (< 95th %ile) separately. SI (short interest) is shares shorted divided by shares outstanding. Our sample period is from January 1988 to December 2003. At the end of each month, stocks are classified as either high or low short interest stocks based on a relative cutoff using the 95th percentile of short interest. For Panel A, the dependent variable is the annualized 1-month raw return in percentages. For Panel B, the dependent variable is the annualized 3-month raw return in percentages. Definitions of independent variables are as follows. IR (idiosyncratic risk) is the standard deviation of the residuals from the Fama-French-Carhart four-factor model (market, size, book-to-market, and momentum) over the previous 100 trading days of each month. IO (institutional ownership) is shares held by institutions divided by shares outstanding. Since shares held by institutions are reported quarterly, we use the data from the beginning of each quarter for all three months in the quarter. DISP (dispersion in analysts' forecasts) is the standard deviation of next quarter's earnings forecasts, scaled by the mean value of the earnings forecasts. DISP Dummy is equal to one if the observation has a dispersion value, and zero if it does not. PRC is the stock price at the end of the month ($). VOLD is the average daily trading volume in dollars during the month ($ million). ZFREQ is the frequency of zero daily returns during the month. A_ILLIQ is the illiquidity measure suggested by Amihud (2002). For each month, A_ILLIQ is the average daily ratio of the absolute value of daily return divided by the daily trading volume in millions of dollars. LOGSIZE is the natural logarithm of SIZE, which is the market value of equity in millions of dollars. BK/MKT is the book-to-market value ratio. Since book values are from COMPUSTAT quarterly, we use the data from the beginning of each quarter for all three months in the quarter. MOM (momentum) is the previous six-month return with a one-month gap, i.e., the return from lag month 7 to lag month 1. T-statistics, which are in parentheses, are adjusted for serial correlation using Newey-West standard errors when appropriate ((n–1) lags for n-month returns).

Panel A. Annualized 1-Month Raw Return (%)

	High SI, ≥ 95th %ile					Low SI, < 95th %ile				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IR	–468.71	–445.83	–465.73	–487.87	–452.84	40.98	48.29	42.82	–18.60	–224.48
	(–3.29)	(–3.16)	(–3.31)	(–3.60)	(–1.52)	(0.47)	(0.56)	(0.50)	(–0.22)	(–1.23)
IO		6.49	5.85	4.30	0.69		11.43	9.55	8.38	13.77
		(1.98)	(1.80)	(1.26)	(0.08)		(4.82)	(4.27)	(3.78)	(2.85)
DISP			7.77	8.68	7.31			–0.33	–0.29	–0.26
			(1.02)	(1.26)	(1.05)			(–0.34)	(–0.30)	(–0.27)
DISP Dummy			6.47	7.46	7.42			7.51	7.36	7.35
			(2.37)	(2.72)	(2.72)			(5.26)	(5.39)	(5.47)
IR * (1 - IO)					–109.83					200.70
					(–0.33)					(1.26)
PRC				0.10	0.09				0.06	0.06
				(0.75)	(0.73)				(1.95)	(1.91)
VOLD				0.12	0.14				0.15	0.15
				(0.81)	(0.91)				(5.07)	(5.15)
ZFREQ				47.72	46.91				0.92	0.90
				(1.95)	(1.96)				(0.13)	(0.13)
A_ILLIQ				2.13	2.33				–0.11	–0.11
				(0.72)	(0.78)				(–0.99)	(–0.99)
LOGSIZE	–1.48	–1.74	–2.43	–1.87	–1.99	–2.66	–3.29	–4.02	–5.07	–5.19
	(–1.11)	(–1.32)	(–1.90)	(–1.30)	(–1.40)	(–3.91)	(–5.28)	(–6.61)	(–7.58)	(–7.76)
BK/MKT	0.60	0.59	0.63	0.69	0.78	0.83	0.79	0.80	0.72	0.72
	(0.86)	(0.83)	(0.87)	(0.87)	(0.98)	(3.80)	(3.63)	(3.66)	(3.24)	(3.23)
MOM	10.08	10.07	10.23	12.07	12.20	3.80	4.01	4.41	5.09	5.14
	(2.01)	(2.00)	(2.06)	(2.58)	(2.64)	(1.11)	(1.18)	(1.32)	(1.55)	(1.58)
Constant	28.50	26.96	30.38	21.41	24.85	28.14	28.22	30.17	36.32	37.15
	(2.98)	(2.80)	(3.20)	(1.93)	(2.16)	(6.24)	(6.28)	(6.67)	(6.48)	(6.75)
# of months	192	192	192	192	192	192	192	192	192	192

Panel B. Annualized 3-Month Raw Return (%)

	High SI, ≥ 95th %ile					Low SI, < 95th %ile				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IR	–383.42 (–3.24)	–363.56 (–3.10)	–382.61 (–3.30)	–400.93 (–3.61)	–339.86 (–1.59)	79.67 (0.89)	86.73 (0.98)	83.10 (0.95)	41.66 (0.49)	–103.83 (–0.64)
IO		7.38 (2.93)	6.43 (2.60)	4.89 (1.76)	0.14 (0.02)		9.69 (4.70)	8.11 (4.21)	7.49 (3.95)	11.11 (2.82)
DISP			–5.14 (–1.00)	–4.59 (–0.90)	–3.82 (–0.75)			–0.69 (–1.19)	–0.68 (–1.18)	–0.65 (–1.13)
DISP Dummy			5.84 (2.70)	5.70 (2.77)	5.27 (2.54)			5.93 (5.03)	5.78 (5.11)	5.73 (5.15)
IR * (1 - IO)					–151.95 (–0.71)					140.13 (1.11)
PRC				0.13 (1.35)	0.14 (1.42)				0.07 (2.46)	0.07 (2.54)
VOLD				0.03 (0.40)	0.03 (0.33)				0.11 (3.95)	0.11 (4.01)
ZFREQ				36.25 (2.62)	34.97 (2.49)				8.36 (1.39)	8.30 (1.40)
A_ILLIQ				4.53 (2.83)	5.00 (3.11)				–0.01 (–0.16)	–0.01 (–0.12)
LOGSIZE	–0.54 (–0.58)	–0.84 (–0.90)	–1.50 (–1.58)	–0.72 (–0.72)	–0.66 (–0.66)	–2.07 (–3.46)	–2.62 (–4.45)	–3.23 (–5.50)	–3.76 (–6.66)	–3.83 (–6.84)
BK/MKT	0.20 (0.48)	0.17 (0.40)	0.20 (0.47)	0.21 (0.46)	0.26 (0.57)	0.55 (3.54)	0.53 (3.37)	0.52 (3.39)	0.45 (3.14)	0.45 (3.13)
MOM	13.22 (4.21)	13.29 (4.24)	13.24 (4.28)	14.07 (5.28)	14.28 (5.32)	3.84 (1.93)	4.05 (2.05)	4.33 (2.24)	4.86 (2.57)	4.85 (2.55)
Constant	20.34 (2.75)	18.68 (2.56)	21.37 (2.88)	11.49 (1.39)	14.26 (1.68)	24.15 (4.62)	24.24 (4.65)	25.80 (4.89)	27.06 (4.66)	27.65 (4.82)
# of months	192	192	192	192	192	192	192	192	192	192

Figure 1. High Short Interest Stocks Partitioned by Idiosyncratic Risk Quintiles

This figure plots equal-weighted annualized DGTW-adjusted buy-and-hold returns (%) of high short interest (≥ 95th %ile) stocks further partitioned into quintile portfolios based on idiosyncratic risk. This figure corresponds to the results in Table 4 for ≥ 95th %ile short interest stocks (results for ≥ 5% short interest stocks are similar, and are not plotted here to save space). See Table 4 for detailed variable definitions.