Short Sale Constraints, Differences of Opinion, and Overvaluation

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Abstract

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Miller (1977) hypothesizes that dispersion of investor opinion in the presence of short-sale constraints leads to stock price overvaluation. However, previous empirical tests of Miller's hypothesis have examined the valuation effects of only one of these two necessary conditions. We examine the valuation effects of the *interaction* between differences of opinion and short sale constraints. We find robust evidence of significant overvaluation for stocks that are subject to both conditions simultaneously. Stocks *are not* systematically overvalued when either one of these two conditions is not met.

I. Introduction

Miller (1977) theorizes that short-sale-constrained securities become overpriced when investors disagree about their value. In his model, overpricing develops because pessimists are restricted to owning zero shares when they actually wish to hold a negative quantity, and the price of the security is set by the beliefs of the most optimistic investors. However, as noted by Chen, Hong and Stein (2002), "in spite of its surface plausibility and intuitive appeal, the evidence for Miller's theory remains somewhat sparse, even after 25 years… [perhaps because] … empirical efforts in this area have tended to follow Figlewski (1981) who tests the theory by looking at the relationship between short interest and subsequent returns (p.172)."

Two necessary and sufficient conditions for Miller's overvaluation are that (1) the security is subject to short-sale constraints and (2) investors disagree about firm value. Indeed, in Miller's model, if a stock is subject to short-sale constraints but there is no disagreement about firm value, there are no optimists and pessimists in that market and the stock will not be overpriced. Likewise, if there is high dispersion of beliefs but no short sale constraint, both the optimists and pessimists will be able to trade (on opposite sides) and the market value will reflect the mean valuation over the cross-section of investors. On average, these stocks will also not be overvalued.

However, empirical tests of Miller have almost universally assumed that one of the necessary conditions holds and then examined the cross-sectional univariate effects of varying the other condition. Such tests have led, as Chen, Hong and Stein (2002) observed, to conflicting conclusions as to whether

Miller's overpricing exists, and perhaps underestimated the magnitude of the overpricing where it was actually observed.

We test Miller (1977) in a two-dimensional framework that accounts for both necessary overvaluation conditions simultaneously. The tests that we conduct suggest that neither the presence of short-sale constraints, nor a high dispersion of investor beliefs is independently sufficient to produce overpricing. When we control for both conditions simultaneously, we find that short-sale-constrained, high-dispersion firms underperform by as much as 21% per year relative to a standard four-factor risk-adjusted benchmark. In fact, controlling for both necessary conditions simultaneously allows us to identify a significant segment where the Miller-style overpricing is so severe that one-month *raw* returns for the group are as low as a *negative* 1.2% over the period 1988-2002. Thus, we show a level of underperformance that is significantly more severe than observed in any previous study.

This empirical outcome arises despite the use of a relatively liberal scheme to classify firms as having high dispersion-of-opinion or as highly short-sale-constrained. More aggressive parsing of the data may eventually reveal a subset of firms that are even more overpriced, and continued refinements of proxy construction by others may allow for better identification of firms with the requisite combination of overvaluation factors.

Our paper is organized as follows. Section II more fully describes the conflicting theoretical models and the results of empirical tests concerning overpricing in the presence of short-sale constraints. Section III explains the proxies we use to classify firms on the basis of (1) their level of short-sale constraint, and (2) the level of dispersion of investor beliefs. Section IV describes the econometric and measurement techniques employed. Sections V and VI present the empirical results of our tests. Section VII discusses whether trading strategy might have captured the abnormal returns in the study period, and Section VIII summarizes and concludes.

II. Literature Review

Miller (1977) suggests that short-sale constraints could prevent negative information from being impounded into stock prices. His analysis is based upon the existence of heterogeneous beliefs or information concerning the value of the security *and* the inability of pessimists to register their beliefs or information due either to prohibitions on or high costs of short selling. Miller concludes that stocks that are subject to short-sale constraints would be relatively overvalued.

Miller's theory has been quite controversial. For example, Jarrow (1980) points out that according to Miller (1977), market-wide short-sale constraints would lead to pervasive overpricing of the entire market. Diamond and Verrecchia (1987) note that in a rational framework short-sale constraints do not lead to overvaluation.[1]

Empirical tests attempting to discriminate between these competing paradigms were somewhat slow to develop and generally followed a rather limited methodological approach: although Miller's overvaluation occurs when <u>both</u> short-sale constraints <u>and</u> dispersion of opinion are relatively high, previous tests have typically focused on only one of the necessary conditions, independently. These uni-dimensional approaches are likely to reduce the power of the statistical tests and the magnitude of the measured overvaluation, and it is, therefore, perhaps unsurprising that much of the extant literature includes an array of inconclusive empirical results.

A. Studies that examine the effect of Short Sale Constraint on Overvaluation

Among the authors who investigated whether more short-sale constrained firms are overvalued, perhaps the first was Figlewski (1981). He proposed using observed short interest as a proxy for the level of short-sale constraints. Using a limited sample from 1973 to 1979, Figlewski finds some evidence that more

[1] More recently, Miller's conjecture has enjoyed greater appreciation with new theories incorporating Miller's insight in more formal and refined models. Chen, Hong and Stein (2002) develop a model where low breadth of ownership accompanies short-sale constraints. Duffie, Garleanu and Pedersen (2002) model high search costs as a short-sale friction that can produce prices above even the most optimistic shareholder's private valuation, and Danielsen and Sorescu (2001) develop a model where high return correlation with the broader market leads to a higher probability of short-sale constraints. Hong, Scheinkman, and Xiong

heavily shorted firms underperform less heavily shorted firms. These findings are weak in that while Figlewski's least shorted firms produced positive abnormal returns with high statistical significance, the most shorted deciles did not produce statistically significant negative abnormal returns.

Asquith and Meulbroek (1995) and Desai, Ramesh, Thiagarajan and Balachandran (2002) find statistically significant subsequent underperformance for heavily shorted firms.[2] The magnitude of the underperformance observed by Desai et al. (2002) over the subsequent year is approximately 8.8% after restricting the analysis to a subset of the most heavily shorted decile.[3]

Other papers that test Miller (1977) using short interest as a proxy for the severity of short-sale constraints find little or no relation between the level of short interest and subsequent returns. These papers include Woolridge and Dickson (1994), Brent, Morse and Stice (1990) and Figlewski and Webb (1993).

B. Studies that examine the effect of Dispersion of Opinion on Overvaluation

Turning our attention to papers that consider the effect of dispersion of opinion, we note that the most common proxy for dispersion of opinion is the standard deviation in analysts' forecasts. Diether, Malloy and Scherbina (2002) examine the valuation effect of the dispersion in analyst forecasts, and find evidence of a "Miller effect," in that the raw returns of stocks with higher dispersion of analysts' earnings forecasts earn lower future returns than control firms. The effect is more pronounced for small firms, high book-to- market firms, and low momentum firms.

The findings of Diether, Malloy and Scherbina (2002) are consistent with findings by Ackert and Athanassakos (1997) but at odds with those of Cragg and Malkiel (1982). Cragg and Malkiel (1982) report a positive relationship during the 1960's between dispersion in forecasts and future returns. However, Cragg

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(2004) model the opportunity to resell short-sale constrained securities to other optimistic investors at a later date as a put imbedded in the current market price of the stock.

[2] The methodologies used in these papers, however, were not designed to provide a test of Miller's theory. In fact, Miller (1977) is not cited in either paper.

[3] Desai, Ramesh, Thiagarajan and Balachandran (2002) find negative abnormal returns of –0.76% per month over the succeeding year using firms with short interest greater than 2.5%. In the universe of Nasdaq firms in their sample period, the 90th percentile of short interest was 2.09%. Thus, the cut-off for inclusion in the heavily shorted set is a subset of the top decile. [See Footnote 7 of Desai, Ramesh, Thiagarajan and Balachandran (2002).]

and Malkiel (1982) examine only 175 companies, and their results may be due to an error in the I/B/E/S analyst forecast data.[4]

Diether, Malloy and Scherbina (2002) report annualized abnormal returns of -9.1%, for the highest dispersion stocks.[5] However, subperiod analysis reveals that the Miller effect is much stronger in the 1980's than in the 1990's, during which time it almost disappears. Specifically, the difference in stock returns between high- and low-dispersion of opinion stocks in the 1992-2000 subperiod is statistically insignificant (t-statistic equals 0.86), while the difference in returns for the 1983-1991 subperiod achieves high statistical significance (t-statistic equals 4.63).[6]

In explaining the deteriorating performance of analyst forecasts as a predictor of returns, Diether, Malloy and Scherbina (2002) suggest that in the 1990's, trading costs have declined, investors have become better at valuing stocks, and firms have become more transparent. In other words, their findings suggest that Miller's theory, while true in the past, is of less relevance in modern security markets. On the other hand, recent accounting scandals at Enron, WorldCom, Tyco International and other large firms suggest that firms had not become as transparent during the 1990's as might have been previously believed.

Danielsen and Sorescu (2001), conduct tests using the standard deviation in analysts' forecasts and two additional proxies for dispersion of beliefs. They hypothesize that option introductions relax short-sale constraints and seek to cross-sectionally explain abnormal returns on the basis of dispersion of beliefs. Their empirical tests generally support Miller (1977), but the event-window negative abnormal returns associated with option introductions are relatively small, averaging less than 2%.

[4] Diether, Malloy and Scherbina (2002) note that historical prices in the regular I/B/E/S forecast files are adjusted for stock splits, and then rounded up to only two decimal digits. Thus if a stock had split by a factor of 10 over its lifetime, historical EPS estimates (by two different analysts) of 0.06 and 0.14 would both be reported as 0.01, giving the illusion that the standard deviation of these estimates is zero. Discovery of this data error casts doubt on almost all prior empirical research that uses the I/B/E/S dispersion of forecast as a proxy for dispersion of opinion.

[5] Deither, Malloy and Scherbina actually report abnormal returns of -0.79% monthly in the final column of Table II which they annualize as -9.48% (12 x-.79%). To facilitate comparison to results described in this paper and by others, we recompute the Diether, Malloy and Scherbina (2002) compounded annual return as $-9.1\% = (1-0.0079)^{12}-1$.

[6] See Diether, Malloy and Scherbina (2002) Table VIII. During 1983-1991, all size quintiles report statistically significant results, but in the sub-period 1992-2000, only the smallest firms continue to produce statistical significance.

C. Interacting the Dispersion of Opinion and the Short Sale Constraint dimensions

In examining these prior tests of Miller's theory, we note that the empirical results are mixed, perhaps because these tests have typically been constructed along only one of the two Miller dimensions. Some papers test the effect of cross-sectional differences in proxies for short-sale constraints, particularly observed levels of short interest, but do not distinguish between high- and low-dispersion-of-opinion firms. Others test for the correlation of various dispersion-of-belief proxies against ex-post returns while doing little to control for cross-sectional differences in the degree of the short-sale constraints.

Our methodology differs from previous tests of Miller in one fundamental respect: we interact the two Miller dimensions using proxies for both dispersion of opinion and differences in marginal costs of short selling. In doing so, we find robust evidence of Miller-style overpricing and obtain point-estimates of ex-post abnormal returns that are significantly more negative than previously reported, despite a less restrictive parsing of the data.

III. Proxies for Short-Sale Constraints and Dispersion of Opinion

Miller's theory proposes that firms which are *both* short-sale-constrained *and* subject to high dispersion of investor opinion are overvalued, but neither characteristic is independently sufficient to generate overvaluation. To test this conjecture, we create portfolios of firms grouped – independently – along both dimensions. We then compare the subsequent abnormal returns of these portfolios to determine whether firms in the most short-sale-constrained, highest-dispersion portfolio are ex-ante overvalued while firms that lack one of the necessary characteristics are not.

Because dispersion of opinion and the level of short-sale constraint cannot be directly observed, we utilize proxy variables for these factors. Caution requires that we acknowledge our tests assume that we have selected suitable proxies for dispersion of opinion and short-sale constraint levels. Our hypothesis is, in fact, a joint and multifaceted one: (a) Miller's theory is correct, (b) our proxies are suitable, and (c) our long-term performance models are appropriate.

We will describe the measures of overvaluation used in the next section, but first we describe here the proxies chosen to measure short-sale constraints and dispersion of opinion.

A. Short-sale constraint Proxies

Previous research suggests several proxies for the degree to which stocks are short-sale-constrained. These include the short stock rebate rate, the relative short interest level, and the presence of exchange trade options.

A.1. Short-Stock-Rebate Rates

Jones and Lamont (2002) argue that the short-stock-rebate rate is probably the best proxy for measuring the magnitude of short-sale constraints. However, because the stock-lending market is notoriously opaque, the use of rebate rates as a proxy presents serious limitations. Currently, there is no centralized, transparent market for borrowing shares. As a result, rebate rates (which often vary across borrowers of the same security) are not generally available to the public. Moreover, the time-series of data available, even from proprietary sources is generally limited to the past two or three years, which certainly limits its usefulness in long-term performance studies, such as this one. Nevertheless, in view of the importance of short-stock rebate data for measuring short-sale constraints, we use it in combination with other short-sale proxies to create a unified measure of short-sale constraint.

Our rebate data is obtained from a major broker and securities lender. It may be easiest to visualize this securities lender's market-making activities as borrowing stock from mutual funds and pension funds and re-lending them to hedge funds. The market maker earns a spread between the rebate rates on the two transactions. The rebate rates that we observe reflects only one side of the security lender's market-making activities, that between the mutual fund or pension fund and the market maker. We do not see the rebate rates on the transaction between the market maker and hedge funds, although the lender asserts that an extremely strong correlation exists between the two.

The data we have obtained covers the period March 2001 to December 2002, and includes daily short-stock rebate and "fee" data on several thousand stocks. For each stock, the fee calculated by the security lender nets the rebate rate against a market interest rate. In other words, the fee reflects both the prevailing short-term interest rates and the negotiated rebate rate on the security. Thus, the fee represents the opportunity cost that the short-seller pays to "rent" the security.

We use the fee data rather than the rebate rate data throughout our analysis because the fee properly adjusts for changing interest rate conditions that impact rebate rates. For most of the security loans, we observe an annual fee of 15 basis points, and 99% of the loans have annual fees of less than 500 basis points. However, the fees are occasionally much higher for some firms.

Because the fee data is available for only a limited time period, we use it primarily to validate other constraint proxies and to develop a "portmanteau" constraint metric. This is feasible because other constraint proxies are available for a much longer time period.

A.2. Relative Short Interest (RSI)

Short interest is the most common constraint proxy used in past studies. The standard practice when using short interest data is to scale each short interest observation by the number of shares outstanding. We follow this practice and refer to the metric as the *relative short interest* (RSI). Thus, RSI is the percentage of each firm's shares that are held short.

Short interest data have been obtained from the New York Stock Exchange (NYSE) and the NASD. Short interest data from both sources is available in digital form beginning in January of 1988. These data are collected monthly for transactions settling by the 15^{th} of each month. Using the ticker symbols shown in the short interest reports, we match each observation with CRSP data.

We observe that some firms for which trading data are available on CRSP are missing from the short interest reports. We do not include such "non-match" observations in our data. This decision is based on the fact that we cannot easily determine if these observations represent a zero level of short interest, or if short interest data are missing.[7]

Figlewski (1981) first proposed this proxy, hypothesizing that as the level of observed short sales increases, the unobserved demand to short the security probably rises as well. Thus, firms with high observed levels of short interest are the most difficult to short at the margin.

On the other hand, despite its use in numerous papers, one might argue that a stock with high levels of observed short interest must be relatively unconstrained rather than highly constrained. Indeed, a prohibition on short sales results in no observed short interest at all. To address this objection, we examine the empirical relation between RSI and the stock lending fees that we have obtained.

The average lending fee is computed by the securities lender each day as a weighted average of the fees on that day's borrowings in the security. We then average these daily fees to calculate a monthly fee value for each security. When the security lender borrowed no shares in the security during the month, but outstanding RSI is reported, a loan fee was imputed at a rate that reflects the normal fee that a mutual fund would be paid when no shares have previously been borrowed, 15 basis points.[8]

A.3. Options Status

We also use the presence of exchange-traded OPTIONS to distinguish between short-sale constrained and unconstrained firms. Firms with traded OPTIONS are presumed to be less short-sale constrained, consistent with findings by Figlewski and Webb (1993) and Danielsen and Sorescu (2001).

The intuition behind options relaxing short-sale constraints is that options allow investors to take short positions in securities without short selling directly. As previously noted, the securities lending market

[7] We cannot distinguish between zero and missing short interest data because the process of matching ticker symbols between the short-interest reports and CRSP files is not perfect. When CRSP ticker symbols fail to match a ticker symbol in the short-interest report, this is usually indicative that the short interest level is zero in both the current and prior month, but occasionally the failure to match is based upon some anomaly concerning the ticker in the short-interest report. For example, the ticker symbol might have changed on or around the report date. Moreover, both the trading venue and symbol may have changed near the report date.

[8] This imputation technique was suggested by the securities lender, and we note that it is in keeping with D'Avolio (2002) who finds the lowest fees associated with small, non-zero RSI.

is notoriously opaque so that the most active participants enjoy much better security-lending prices (lower fees) than less active participants. Investors who might short-sell at a relatively high cost can use options to synthetically short a security. Option market makers, as the counter-party to these synthetic short sales, are left with synthetic long positions, which they hedge by borrowing the stock and shorting it. As frequent participants in the short-selling market they face lower costs of executing and holding these positions. Competition among market makers allows these cost advantages to filter through to investors who therefore enjoy lower costs in establishing their synthetic short positions.[9]

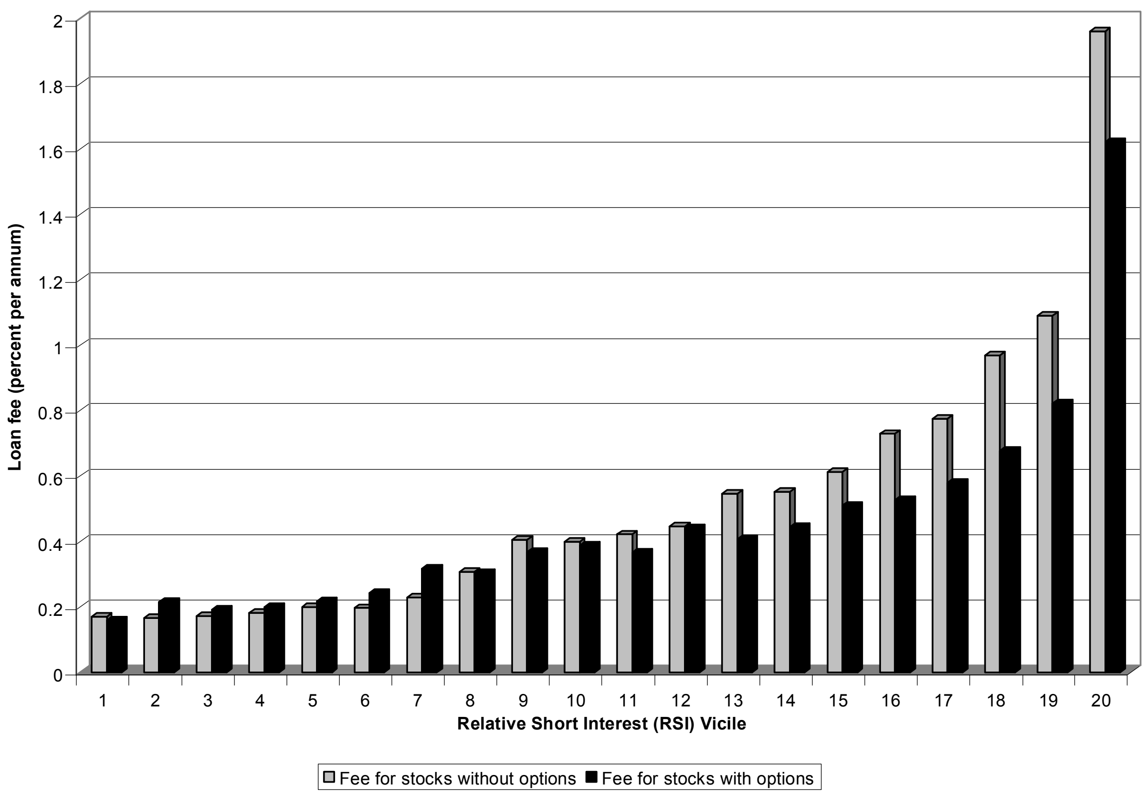

FIGURE 1: Short stock lending fee as a function of relative short interest

Figure 1 depicts the relation between average short-stock lending fees, relative short interest, and the stock's option status. The RSI variable depicted in the figure is constructed in the following manner. During

[9] For a more complete discussion of how options might reduce costs of short selling, see Danielsen and Sorescu (2001) and Evans, Geczy, Musto and Reed (2003)

each month we first sort firms on the basis of their RSI and place them into one of twenty ranked groups. We refer to the twenty equal sized groups as "*viciles.*"[10] Thus, each vicile contains 5% of the total number of observations. The Loan Fee in Figure 1 is the average loan fee for firms in each vicile.

Observe that the figure depicts a monotonically increasing, non-linear relation between security lending fees and the level of RSI. These results are similar to those observed by D'Avolio (2002) who also finds that high levels of short interest are associated with higher average costs of shorting the security. Our results differ slightly from those found by D'Avolio (2002) in that D'Avolio observes firms in the least shorted decile have slightly higher average fees than firms in the second decile of his data.

We speculate that our data does not mimic D'Avolio's data for the least shorted firms because we exclude firms with no data reported in the monthly short-interest files. We attempt to confirm this hypothesis by computing the average fee value for the firms that show up in our FEE data but are not in the reported RSI data. These firms had securities borrowed during the month, and they probably actually have zero short interest on the RSI reporting date. We observe that the average FEE for these firms is 25.4 basis points as compared to 16.9 basis points for firms in the lowest vicile in Figure 1. This is consistent with what we would expect if our differences with D'Avolio (2002) are driven by missing data for zero-short-interest firms.

Figure 1 also shows that firms with listed options have lower average FEE levels than non-optioned firms after controlling for RSI. This is consistent with the idea that options reduce the cost of short selling, as suggested by Danielsen and Sorescu (2001). However, Figure 1 also demonstrates that as an estimator of stocks borrowing fees, option status obviously is of secondary importance when compared to the Relative Short Interest level.

Overall, we conclude that the observed level of short interest is strongly correlated with, and monotonically increasing in, the short-stock lending fees during the period from March 2001 to December 2002, and this relation is somewhat stronger for stocks without options. For the highest levels of relative

[10] We created the word "viciles" based from Latin *vicies*, which means "twenty times," similar to the derivation of the word "deciles" from Latin *deciens,* which means "ten times."

short interest, the difference in fees between optioned and non-optioned stocks is the largest. The pattern depicted in Figure 1 gives comfort that RSI, interacted with option status, is indeed a reasonable proxy for short-sale constraint.

B. Proxies for Dispersion of Investor Opinions

We analyze three proxies for investor belief dispersion: (1) dispersion of analyst forecast obtained from I/B/E/S, (2) idiosyncratic volatility of stock returns (SIGMA), and (3) trading volume as a proportion of shares outstanding (TURNOVER).

B.1. I/B/E/S Analyst Forecast Dispersion

The first measure of dispersion of beliefs we use is the coefficient of variation for analysts' annual forecasts estimated from I/B/E/S data. The coefficient of variation is estimated by dividing the I/B/E/S reported standard deviation of analyst earnings/share forecasts for the current fiscal year end (I/B/E/S FY period "1") by the absolute value of the mean earnings/share forecast, as listed in the I/B/E/S Summary History file. This dispersion proxy is intuitively appealing, and was the principal proxy used by Diether, Malloy and Scherbina (2002).

As discussed earlier, the standard I/B/E/S forecast file contains an error related to rounding of historical split-adjusted values. Therefore, we obtained – upon special request from I/B/E/S – a separate file containing analyst forecasts that are unadjusted for historical stock splits, and therefore do not suffer from this potentially serious rounding error. We compute our coefficients of variation using this unadjusted file, which is the same as the one employed by Dither, Malloy and Scherbina (2002).

Unfortunately, as a proxy variable, I/B/E/S analyst dispersion data suffers from an important limitation. At least two analysts must report data to I/B/E/S before a dispersion value can be computed. As noted in Diether, Malloy and Scherbina (2002), only relatively large firms have two or more analysts providing forecasts. In fact, Danielsen and Sorescu (2001) report that among the firms that have sufficient liquidity for traded options to be introduced, nearly one third had fewer than two analysts per the I/B/E/S database. Thus, the most intuitively appealing proxy is of no direct value for many, if not most, small firms. And if small firm size happens to be correlated with either high levels of short sale constraints or high levels of dispersion of opinion, the use of I/B/E/S analyst dispersion in effect limits the sample to those firms where the Miller effect is less likely to be prevalent. This, in turns, can bias the results towards zero. For this reason, we consider two alternative proxies that can be computed for all CRSP firms, regardless of analyst coverage levels. We use the I/B/E/S dispersion measure primarily to validate these other proxies and to construct a single, unitary portmanteau proxy for dispersion of beliefs.

B.2. SIGMA and TURNOVER

The two supplementary dispersion proxies we consider are idiosyncratic firm volatility (SIGMA) and trading volume divided by the number of shares outstanding (TURNOVER). An attractive feature of SIGMA and TURNOVER is that each can be computed for all CRSP firms regardless of analyst coverage levels.

The first proxy, SIGMA is the standard deviation of the error terms from the Brown and Warner (1985) market model, estimated over the 100 days preceding the first day of the month for which the short interest data are reported.[11] Numerous authors present theoretical models correlating belief dispersion with asset time-series volatility. For example, Shalen (1993) and Harris and Raviv (1993) develop models that specifically investigate the role of belief dispersion (as opposed to asymmetric information) on trading volume, volatility, and other trading characteristics, and observe a positive empirical relationship between return volatility and the dispersion of I/B/E/S forecasts.

The second proxy, TURNOVER, is the trading volume over the same 100-day period preceding the first day of the month for which the short interest data are reported, scaled by shares outstanding.[12] Jones, Kaul and Lipson (1994) note "the apparent consensus even among academics that volume is related to

[11] Firms are excluded from our analysis in any month if more than 10 days of returns data or 75 days of volume data are identified as "missing" on CRSP in the prior 100 days or if the firm is missing RSI data. We also screen out all securities other than domestic common stocks.

[12] As per standard practice, Nasdaq trading volume is divided by two to reflect Nasdaq's dissimilarity to exchange-based trading.

volatility because it reflects the extent of disagreement about a security's value based on either differential information or differences of opinion."

In recent empirical studies Gebhardt, Lee and Swaminathan (2001), Danielsen and Sorescu (2001), and Diether, Malloy and Scherbina (2002) each use SIGMA and/or TURNOVER as proxies for dispersion of investor expectations.

C. Descriptive Statistics

Table 1 provides a description of the three dispersion proxies and three constraint proxies discussed in this section. We provide a snapshot of firms in our dataset at five-year intervals beginning with 1988, the first date for which short interest data is available in digital form. No clear pattern exists in the I/B/E/S analyst dispersion data or the volatility data. However, the average volume of trade has clearly risen over the sample period. The anomalous I/B/E/S mean for December 2002 is driven by one extreme outlier, which has a dispersion measure of 2000. Notice that the 99th percentile value is reasonable.

As previously discussed, we do not have stock-borrow FEE data for the earlier dates, and we provide a description of this proxy only for December 2002. The other constraint proxies, RSI and OPTIONS experience a clear increase in their mean values over the sample period.

For reasons that will become clear shortly, we wish to be more certain about whether the variables presented in Table 1 are stationary. Accordingly, for each variable we compute the average value each month and conduct a Dickey-Fuller test. The Dickey-Fuller test searches for unit roots so that failing to reject the unit root hypothesis is consistent with the series being non-stationary. These tests indicate that the I/B/E/S forecast dispersion metric is stationary (p=0.0203), but the other metrics are nonstationary.[13]

D. Construction of Unitary Constraint and Dispersion Proxies

Although we have identified multiple proxy variables for both necessary conditions described in Miller's model, for each condition we can identify one preferred proxy: the cost of short-selling is probably

[13] P-values for RSI, SIGMA, and TURNOVER are 0.97, 0.39, and 0.27, respectively.

best measured by the shorting FEE, and dispersion of beliefs is probably best represented by the dispersion of analysts' forecasts. These two proxies are undoubtedly the most intuitively appealing measures available. If they were available for the entire sample, we would probably want to use them alone and ignore the others.

However, limited data availability makes it impractical to pursue this approach. Indeed, FEE data is available to us only after March 2001, and I/B/E/S dispersion data is available only for firms with multiple analysts reporting earnings estimates, which represent less than half of the total sample.

Nevertheless, the most straightforward approach for testing Miller's theory would be to use a single unitary measure for each of the two necessary conditions. Therefore, we employ the available data on FEE and I/B/E/S dispersion to formulate a single composite measure for each attribute. This process is described in the next subsection.

D.1. A unitary CONSTRAINT proxy

Although we would prefer to use the FEE variable as the unique measure of short-sale constraint, this variable is only available for an unacceptably short time period. To overcome this limitation while simultaneously preserving the richness of the information provided by FEE, we construct, for each month over the period 1988 to 2002, a unitary "portmanteau" constraint variable, which recognizes the superiority of the FEE super-proxy measure and also employs information contained in the RSI and OPTIONS status variables.

Figure 1 suggests that the relationship between FEE and RSI is monotonically increasing at an increasing rate, but lower fees are observed when options are present, particularly when RSI is high. These insights help guide the construction of the unitary constraint proxy, which we now explain.

During each month for which we have FEE data, we sort firms on the basis of their RSI and place them into one of twenty ranked groups of equal size. Recall that we will refer to these groups as *viciles*. Thus, each vicile contains 5% of the total number of observations. By using these viciles each month, we control for the documented non-stationarity of the RSI variable. The calendar-time portfolio method described later will require a similar sorting and grouping of the data.

We then compute an average short stock FEE for each firm each month. After grouping the RSI data as described, we estimate the following cross-sectional regression:

$$
\begin{array}{lccccc}
FEE_{it} = & \alpha_0 & +\alpha_1 RSI_{it} & +\alpha_2\, RSI_{it}^{\,2} & +\alpha_3\, RSI_{it}^{\,3} & +\alpha_4 OPTIONS_{it} \\
& 0.07834 & 0.05438 & -0.00664 & 0.0003820 & -0.5908 \\
& \mathit{[4.40]} & \mathit{[6.69]} & \mathit{[-6.69]} & \mathit{[11.24]} & \mathit{[-10.20]} \\
& & +\alpha_5\, OPTIONS_{it}{*}RSI_{it} & +\alpha_6\, OPTIONS_{it}{*}RSI_{it}^{\,2} & +\alpha_7\, OPTIONS_{it}{*}RSI_{it}^{\,3} & +\varepsilon_{it} \\
& & 0.2587 & -0.02713 & 0.0007583 & \\
& & \mathit{[14.36]} & \mathit{[-15.40]} & \mathit{[14.36]} &
\end{array} \qquad (1)
$$

Number of Observations: 101651
$R^2 =$ 9.48%
t-statistics are shown in brackets.

where FEE is the continuous value of the average FEE discussed above, RSI is expressed as the firm's vicile classification, and OPTIONS is a dummy equal to one if the firm has exchange traded options trading prior to the first day of the month and zero otherwise. Firms with options introduced during the month are excluded from the regression.

Because borrowing fees are available only in 2001 and 2002, the above regression is estimated during that period only; however, we use the regression coefficients to estimate the fees for each stock and for every month back to 1988, the beginning of the short interest data.[14] We acknowledge that this method could systematically misestimate fees in the early years of the sample. Fitted FEE may systematically overstate or understate the unobservable FEE value from earlier periods. Fortunately, however, the tests that we perform later will control for this possibility in that they require only an appropriate rank-ordering of firms along the constructed variable. The monotonic relation between RSI and FEE, moderated by OPTIONS, (Figure 1)

[14] One possible concern with this approach is that we use regression coefficients based on observations that occur late in our sample period to estimate fitted values for FEE during the earlier years. Whether or not such approach is suitable depends upon the intended application. In this case, we assume that Equation (1) holds universally in all time periods but can only be measured in the most recent years, and therefore the estimated coefficients from Equation (1) will give a consistent cross-sectional rank-ordering of FEEs throughout the sample period.

provides us with confidence that the fitted values from Equation 1 will provide an appropriate rank-ordering in any given month.

The regression results for Equation (1) reinforce what we already have seen in Figure 1, namely that FEE is increasing in RSI at a non-linear rate, that FEEs are lower for stocks with OPTIONS, and that the effect of options is greater for the highest levels of short interest. In short, the results of the regression appear to justify the joint use of OPTIONS and RSI as proxies for the degree of short sale constrainedness.[15]

As stated previously, vicile groupings control for non-stationarity in the data. The selection of twenty equal groupings is arbitrary and was chosen to capture both subtleties in the data and precision in the point estimates.[16] Due to severe nonlinearities in the FEE-RSI relationship, inclusion of the cubed term significantly improves the proportion of fitted FEEs that are classified correctly.

Because we make use of fitted FEE extensively, it seems appropriate to ask whether the fitted values appear reasonable relative to the actual FEE data available. We find the rank correlation between the vector of fitted FEEs and the vector of actual FEEs to be 0.3977. We also focus on the highest quartiles of actual FEEs and fitted FEEs because it seems particularly important that the fitted values be reasonable proxies when short sale constraints actually exist. Likewise, it is desirable that the fitted proxy not misidentify firms as highly constrained when they actually are not. Accordingly, of all observations that have highest-quartile actual FEEs, 54% are in the highest fitted FEE quartile. Also, among the observations classified as being in the highest fitted FEE quartile, 56% come from the highest actual FEE quartile group.

Later in the paper, for robustness, we consider a variation on fitting Equation 1 using continuous values of RSI rather than the vicile rankings presented above. Using continuous values in Equation 1, the correlation between the vector of fitted and actual fees sorted in viciles is 0.3995, a value similar to the

[15] As noted previously, RSI has significantly greater explanatory power than OPTIONS. When fitted fees are constructed using RSI only, all of the findings in this paper continue to hold, although at modestly lower levels. In other words, OPTIONS improve the model's ability to identify short-sale constrained firms, but the overall results presented in this paper are not dependent upon inclusion of the OPTIONS variable in Equation 1.

[16] Fama and MacBeth (1973) analyse data grouped in an identical manner.

correlation value generated using the original specification for Equation 1. Thus, the continuous version of Equation 1 provides a similar overall goodness of fit.

D.2. A unitary DISPERSION proxy

While we would prefer to use the I/B/E/S analyst forecast dispersion as the sole measure of dispersion of beliefs, this would considerably reduce the sample size because less than half of the firms in our sample are followed by at least two analysts (Table 1). Therefore, we construct a unitary portmanteau DISPERSION variable using the same technique used to develop the CONSTRAINT proxy.

Specifically, for each dispersion proxy variable, we independently sort firms into viciles on a monthly basis. We then estimate the following regression:[17]

$$\begin{array}{lcccccccr} \text{IBES DISPERSION}_{it} = & \beta_0 & +\beta_1\text{SIGMA}_{it} & +\beta_2\text{SIGMA}^2_{it} & +\beta_3\text{ TURN}_{it} & +\beta_4\text{ TURN}^2_{it} & +\gamma_{it} & & (2) \\ & 6.5849 & 0.3440 & 0.00291 & 0.1291 & -0.00429 & & & \\ & \mathit{[170.0]} & \mathit{[57.44]} & \mathit{[9.35]} & \mathit{[20.53]} & \mathit{[-15.59]} & & & \end{array}$$

Number of Observations: 487664
$R^2 =$ 12.63%
t-statistics are shown in brackets.

Using the coefficient estimates from the above regression, we construct a dispersion variable for each firm-month observation beginning in 1988. We refer to this portmanteau proxy measure as "DISPERSION" in the empirical tests.

As an interesting tangential observation, we had expected that SIGMA and TURNOVER would be very highly correlated. However, the correlation coefficient between the viciles of these two measures was only 0.0607. Also, contrary to our expectations, SIGMA contributes far more than TURNOVER in explaining the cross-sectional variation in I/B/E/S dispersion estimates. When we exclude the SIGMA variables from the above regression, the R^2 is less than 2%.

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[17] Sorting by viciles controls for non-stationarity in the SIGMA and TURN variables. Because of the high degree of skewness in the I/B/E/S data, we also sort the analyst forecast data (IBES DISPERSION) into viciles.

The rank correlation between the vectors of fitted and actual I/B/E/S dispersion is 0.3272, and the model in Equation (2) correctly classifies approx 46% of the highest quartile actual observations into the highest quartile of fitted dispersion. Likewise, approximately 46% of the fitted I/B/E/S observations are from the highest quartile actual I/B/E/S dispersion metric.

As before for Equation 1, we also consider a continuous version of Equation 2. This alternative is later utilized in robustness checks presented in Section V. The I/B/E/S variable is highly skewed because it is scaled by the mean earnings estimate. Often, the mean estimate approaches zero. Using continuous values of the IBES DISPERSION variable results in a significant influence being exerted by outliers. Moreover, SIGMA and TURNOVER are also non-stationary. As a result, the correlation between fitted and actual values for the continuous model is 0.2712, significantly poorer than the vicile model correlation of 0.3272.

D.3. Endogeneity of Dispersion and Constraint

While this paper examines the interaction of short-sale constraints and dispersion of beliefs, one might reasonably be concerned that the predeliction of a security to be short-sale constrained might be, at least partially, endogenous, and perhaps determined by dispersion of opinion concerning the security. To address this concern, we orthogonalize the constraint and dispersion-of-opinion variables by regressing fitted constraint on fitted dispersion. The residuals from this regression capture the independent effect of constraint. However, the adjusted R-square in this regression is only 0.0037, consistent with the two variables capturing different information.[18]

As confirmation that the two variables are not highly correlated, we also examine the rank correlation between the fitted fee viciles and the fitted dispersion viciles. We observe that the correlation is actually slightly negative: -0.0612 ($p<0.0001$). This means that each of the two vectors proxies for something else, and an adjustment for multicollinearity is not critical.

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[18] In later robustness checks, we also utilize the independent effect of the dispersion variable defined as the residuals obtained after regressing fitted dispersion on constraint.

IV. Measures of Overvaluation

Having identified proxy variables for short-sale constraints and dispersion of beliefs, we must next construct a metric for overvaluation. Following Diether, Malloy and Scherbina (2002) we measure overvaluation primarily as the ex-post calendar time abnormal returns of various test portfolios. If overvaluation is indeed associated with the interaction of high shorting costs and high dispersion of beliefs, this overvaluation should disappear through time, either because the dispersion of beliefs is subsequently diminished (such as when investors observe a more accurate signal of the security's true value), or because the short-sale constraints are subsequently reduced. Thus, we expect firms that are both subject to high short-sale constraints and high dispersion of opinion to produce negative abnormal returns following their inclusion in the test portfolio. We will refer to this time period as the "post-selection horizon."

A. The Calendar Time Methodology

We measure long-term abnormal returns using the *calendar time* methodology analyzed by Mitchell and Stafford (2000) as implemented by Boehme and Sorescu (2002). Mitchell and Stafford (2000) note that this methodology is preferred because Buy-and-Hold Abnormal Returns (BHARs) and Cumulative Abnormal Returns (CARs) are highly vulnerable to the problems of cross-sectional dependence among firms and may exacerbate the effects of a potentially misspecified asset-pricing model. Failing to control for cross-sectional correlation among firms can yield overstated t-statistics in both BHARs and CARs.

Cross-sectional dependence is of paramount concern in this study since a firm may be included in our test portfolios for many consecutive months, causing the sample to be significantly clustered in calendar time and the post-selection horizons to be severely overlapping. Treating each month as a separate event -- as is common with the BHAR (or CAR) methodology -- would lead to downward biased standard errors and significantly inflated t-statistics. BHARs also exacerbate the misspecified model problem. Spurious abnormal returns near the beginning of the measurement window are compounded by the BHAR measure. Thus, significant biases can be introduced over longer horizons.

In contrast, with the calendar time methodology "monthly returns are less susceptible to the [misspecified] model problem," and "cross-correlations of event-firm abnormal returns are automatically accounted for in the portfolio variance" (Mitchell and Stafford, 2000, page 288).[19]

The calendar time methodology requires that we construct test portfolios of firms for which abnormal returns are then measured. To construct the portfolios, we first categorize firms on the basis of various groupings of CONSTRAINT and DISPERSION portmanteau proxies described in the pervious section. A typical categorization consists of 16 portfolios formed by intersecting 4 CONSTRAINT quartiles with 4 DISPERSION quartiles. Portfolio returns are measured for both a one-month and a one-year horizon. In the one-month horizon measurement procedure, each firm is assigned to one of the 16 portfolios based on its CONSTRAINT and DISPERSION rankings in the previous month. We then calculate the return on both an equal-weighted and a value-weighted basis. For one-year horizon portfolios, the procedure is similar except that firms are retained in the portfolio for 12 months, but returns are reported on a monthly basis. Notice that a single firm can be a component of multiple portfolios when one-year horizons are considered, but every firm is unique to a portfolio for the one-month horizon. Calendar time portfolios are rebalanced on the first day of each month to reflect the changing portfolio composition.

Throughout the paper, we present both equal-weighted and value-weighted portfolio returns. As discussed in Fama (1998), many previous studies that report significant abnormal returns using equally weighted portfolios lack robustness when reexamined with value-weighted methods

Moreover, of particular concern to our study, Fama posits that small firms are the most susceptible to the misspecified model problem. Therefore, if a sample is overpopulated with small firms, empirical results based on equally weighted portfolios are more likely to be driven by a misspecified model. Value weighting mitigates the problem by giving higher weight to larger firms. Value weighting is also considered more representative of the wealth generating attributes of any long-term abnormal performance.

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[19] The difference between the BHAR and calendar time methodologies is illustrated in Boehme and Sorescu (2002), where BHAR t-statistics are shown to be about twice the magnitude of the corresponding calendar time t-statistics.

B. The Four-Factor Asset Pricing Model

We estimate the following four-factor regression model for both the one-month and one-year horizons:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t}, \tag{3}$$

where $R_{p,t}$ represents the calendar time portfolio of short-sale constrained securities, and $R_{f,t}$ is the return of the one-month Treasury Bill. The four independent variables are the excess return on the market portfolio ($R_{m,t}$-$R_{f,t}$), the difference between the returns of value-weighted portfolios of small and big firm stocks (SMB_t), the difference in returns of value-weighted portfolios of high and low book-to-market stocks (HML_t), and the difference in returns of value-weighted portfolios of firms with high and low prior momentum (UMD_t, or "up" minus "down"). The first three factors are proposed by Fama and French (1993), and the momentum factor is proposed by Carhart (1997).[20] This fourth factor is necessary because Fama and French (1996) and Carhart (1997) document a momentum bias for the "traditional" three-factor model. Indeed, the three-factor model does not completely explain the cross section of stock returns when firms are subject to unusually high or low returns prior to their inclusion in the calendar time portfolio. The intercept, α_p, from Equation (3) is interpreted as the mean monthly abnormal return of the calendar time portfolio. Because the portfolio in any given month may contain from one to several hundred firms, we estimate this regression using both ordinary (OLS) and weighted least squares (WLS) procedures.

Some of our tests involve comparisons between the calendar time portfolio of stocks that are expected to be the most overvalued (those that are both hard to short and subject to high dispersion of opinion), and various control portfolios of stocks for which there should be no overvaluation because one of the necessary conditions is not satisfied. In order to perform such comparisons, we construct, for each calendar month, a hedge portfolio consisting of long positions in the overvalued stocks and short positions in one of the various control portfolios. The returns of the hedge portfolio are regressed on the four factors:

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[20] The four factors are made available by Kenneth French on his website at Dartmouth College.

$$R_{p,t}-R_{control,t} = \alpha_p + \beta_p(R_{m,t}-R_{f,t}) + s_pSMB_t + h_pHML_t + u_pUMD_t + e_{p,t}, \quad (4)$$

The "hedge" intercept obtained in this manner (α_p) represents a measure of the relative long-term abnormal performance of hard-to-short, high-dispersion firms vis-à-vis various control sets that are not expected to be overvalued.[21]

C. Alternative pricing models examined for robustness

Since the true asset-pricing model is unknown, we employ additional methods to establish robustness. Specifically, we compute calendar time abnormal returns using the three-factor model proposed by Fama and French (1993), and the CAPM. The three-factor Fama-French model contains the first three independent variables of Equation (3) but omits the momentum factor, UMD. The CAPM considers only the ($R_{m,t}-R_{f,t}$) independent variable. We also examine the raw returns of the calendar time portfolios, which are computed as the intertemporal average of the calendar time portfolio returns without any risk adjustment.

V. Results

In the two previous sections, we devise unitary portmanteau measures of both dispersion of beliefs and short-sale constraints, and we establish the calendar-time portfolio approach for measuring long-term abnormal returns and, by inference, ex-ante mispricing. We now present the main empirical tests of Miller (1977). Specifically, we inquire if <u>both</u> dispersion of beliefs <u>and</u> short-sale constraints are necessary for securities to become overvalued.

A. Independent Effects of CONSTRAINT and DISPERSION on Abnormal Returns

The first step in this process is to search for evidence of Miller-style mispricing when one necessary condition exists, without regard to the other. This gives us a baseline against which to compare tests when both conditions are present.

[21] Equation (4) follows a procedure similar to that proposed by Mitchell and Stafford (2000).

Table 2 presents an analysis of calendar-time portfolios grouped on the basis of CONSTRAINT, the short-sale constraint portmanteau proxy. Deciles are assigned each month (beginning with January 1988) by sorting all NYSE and Nasdaq firms on this CONSTRAINT measure, with decile 10 representing the most constrained stocks.

We construct both equal- and value-weighted calendar time portfolios and regress the excess returns ($R_{p,t}$-$R_{f,t}$) of these portfolios on the four Fama-French and Carhart factors of Equation (3). Two different investment horizons are examined: one month and 12-months. In each case, we estimate both OLS and WLS regressions, where the WLS method weights the returns in a given month by the square root of the number of firms in that month. Each column in the table corresponds to a different portfolio construction method: equal- or value-weightings, OLS or WLS regressions, one-month or one-year horizons.

The intercept term shown for each regression represents the abnormal return corresponding to that particular asset-pricing model. T-statistics are computed from the intertemporal variation in the monthly portfolio returns, and are reported in brackets under each intercept. As we increase short-sale CONSTRAINT, we generally observe a decrease in the abnormal returns, as predicted by Miller (1977). However, the results are not completely robust because the stocks that are most heavily constrained (Decile 10) are not overpriced in a statistically significant sense when using the value-weighted methodology over a one-year horizon.

Table 3 presents a similar analysis for portfolios constructed using the portmanteau DISPERSION proxy. DISPERSION deciles are assigned for each month (beginning with January 1988) based on the population of NYSE and Nasdaq firms, where decile 10 represents firms with the highest DISPERSION.

As we increase DISPERSION, we generally obtain more negative abnormal returns, although this relation appears to hold primarily for the one-month horizon using the value-weighted methodology and lacks robustness when the calendar time portfolios are equally weighted. In fact, the point estimate for abnormal returns in Decile 10 portfolios are actually positive in three of the eight models presented.

In the aggregate, the results presented in Table 3 must be viewed as only weakly supportive of dispersion of beliefs being related to overpricing. This is consistent with Diether, Malloy and Scherbina (2002), who found equally weak evidence of this same relation during the 1990s.

Taken as a whole, we conclude that analyzing the impacts of short-sale constraints and dispersion of beliefs independent of one another leads to weak inferences that are not robust across alternative measurement methods.

B. The Interactive Effect of CONSTRAINT and DISPERSION on Abnormal Returns

Miller's theory requires that both dispersion of beliefs and short-sale constraints exist *simultaneously* in order for firms to become overvalued. Therefore, each factor should have an effect on security returns, conditional on the presence of the other. We now examine the relation between overvaluation and the interaction of CONSTRAINT and DISPERSION.

B.1. The Price Effect of CONSTRAINT when Dispersion of Beliefs is High

We begin by ranking all firms on the basis of CONSTRAINT and DISPRESION. These rankings are conducted independently from each other, at the beginning of each month. We then use these variables jointly to assign firms to portfolios at the beginning of each month.

Because we are creating portfolios on the basis of two independently sorted variables, the remainder of our analysis will focus on portfolios formed on the basis of quartiles (as opposed to deciles). Indeed, decile groupings along each independent dimension would create 100 portfolios each month, some of which would contain a relatively small number of firms. Using quartile groupings for each dimension we obtain a more manageable number of 16 different monthly portfolios. For robustness purposes, however, we confirm the validity of our results using two-dimensional decile groupings (not shown). In this case, the pattern of returns closely resembles the one obtained with quartile groupings, and the magnitude of the overvaluation is more dramatic for the portfolio containing the highest CONSTRAINT and DISPERSION deciles, compared to the one formed with the highest quartiles.

Table 4 presents the valuation effect of CONSTRAINT for firms in the highest quartile of DISPERSION each month. The format in Panel A is identical to that presented in Tables 2 and 3, except that we now use quartiles instead of deciles. In Panels B and C we assess robustness using alternative proxy construction methods and alternative long-term performance measurement models. Notice that in the presence of high DISPERSION, abnormal returns in Panel A are decreasing in CONSTRAINT and that the relationship is highly robust across portfolio weighting methods (equal or value weighted), calendar-time horizons (a month or a year), and regression methodologies (OLS or WLS).

Miller's theory (1977) suggests that we should focus our attention on CONSTRAINT Quartile 4 where both necessary conditions for overpricing are present. The one-month abnormal returns for this portfolio ranges from -1.334% to -1.642% per month, which corresponds to an annualized abnormal return of between -14.8% and -18%. The one-year holding period returns range from -0.706% to -0.927% per month, or -8.1% to -10.6% per year.

By contrast, the first quartile portfolio, composed of firms with highest DISPERSION but lowest CONSTRAINT, shows no evidence of overvaluation. Indeed, many of the point estimates for each model are in fact positive, suggesting that dispersion of opinion alone is not sufficient to produce overvaluation. The presence of short-sale constraints is also needed. This evidence is consistent with Miller's theoretical argument: stocks that are not short-sale constrained are unlikely to become overvalued, even when the cross-section of investors' opinion is diverse. Without short-sale constraints, the pessimists' beliefs will be reflected as short positions that drive asset prices towards equilibrium.

The evidence presented in Panel A supports the hypothesis that stocks with both high dispersion of beliefs and high short-sale constraints are significantly overvalued, but this conclusion rests upon an assumption that the four-factor model reasonably represents the true pricing model. Because the true asset-pricing model is unknown, it is conceivable that the negative abnormal returns could result from a misspecified model rather than overvaluation (Fama (1998)). We address this possibility by considering alternative asset-pricing models including (1) the CAPM, (2) the "traditional" Fama-French three factor-model (which does not include Carhart's momentum factor), and (3) the intertemporal average of *raw* returns. All results are qualitatively similar to those presented in Panel A. Thus, for conciseness, we present only the raw return results in Panel B of Table 4. The raw returns are all negative for firms in the highest CONSTRAINT quartile, which is remarkable given the overall strong performance of the stock market during the 1988-2002 period.

In Panel C we repeat the analysis using an alternative proxy construction method. Panel C presents results generated when we adopt the continuous-value method for fitting FEEs and IBES. The results are qualitatively identical to Panel A with Quartile 4 abnormal returns at least as negative as in those in Panel A, and Quartile 1 returns often positive.

To ensure that we are examining the effects of CONSTRIANT wholly independent of DISPERSION, we orthogonalize the fitted FEE vicile vector against the fitted IBES vicile vector, and use the residuals as the CONSTRAINT dimension (not shown). The results do not change.

We repeat the analysis in Table 4 using decile groupings (not shown), as opposed to quartiles. The portfolio composed of firms in the highest DISPERSION *and* highest CONSTRAINT deciles reports abnormal returns that are even more negative than the corresponding quartile results. Moreover, we find no evidence of overvaluation for firms that lie at the intersection of the highest DISPERSION and lowest CONSTRAINT deciles.

In summary, the results in Table 4 and the related robustness checks strongly suggest that overvaluation occurs only when stocks are both subject to high short-sale CONSTRAINTs and high DISPERSION of opinion. When DISPERSION is high but the CONSTRAINT is low, we find no evidence of overvaluation.

B.2. The Price Effect of DISPERSION when Short-Sale Constraints are Present

Table 5 presents the abnormal returns for stocks belonging to the highest CONSTRAINT quartile. Within this group, we examine the impact of dispersion of beliefs. The format follows that in Table 4, with Panel A depicting four-factor abnormal returns for portfolios that are short-sale constrained but which differ in dispersion of beliefs, as measured by the DISPERSION proxy.

Notice that all coefficients and t-statistics for DISPERSION Quartile 4 of Table 5 are identical to those shown in Quartile 4 of Table 4. Obviously, the results are identical because the portfolios are identical. This portfolio is in the highest quartile of both CONSTRAINT and DISPERSION. Table 5 illustrates a near monotonicity of returns for portfolios ranked on DISPERSION, conditional on short-sale CONSTRAINTs being present. Quartile 4 reports the most negative abnormal returns regardless of the methodology selected, and Quartile 3 has the next lowest returns.

Quartiles 1 and 2 earn higher returns than either Quartiles 3 or 4, and they are not negative in a statistically significant sense. Each of these results is consistent with Miller's theory that both necessary conditions must be present for overpricing to occur.

Panel B presents raw returns for robustness, and the qualitative results are the same as in Panel A. Alternative pricing model specifications including the Fama-French three factor model and the CAPM model (neither shown) also produce very similar results to that depicted in Panel A.

Panel C presents results generated when we adopt the continuous-value method for fitting FEEs and IBES. Once again, the results are qualitatively identical to Panel A with Quartile 4 abnormal returns at least as negative as in those in Panel A, and Quartile 1 returns often positive.

When we examine the partial DISPERSION dimension estimated as the residual from an OLS regression of the Fitted IBES vicile vector on the fitted FEE vicile vector the results do not change (results not shown).

We repeat the analysis in Table 5 using decile groupings (not shown). Again, abnormal returns are almost monotonically decreasing as one increases DISPERSION for stocks belonging to the 10th

CONSTRAINT decile, and the results are robust across the asset pricing and regression models employed. Furthermore, we find no evidence of overvaluation for firms in the 10th CONSTRAINT decile when dispersion of opinion is low (lowest DISPERSION deciles), again supporting Miller's argument that both high CONSTRAINT and high DISPERSION are required to produce overvaluation.

As an additional robustness check, we have reconstructed both Tables 4 and 5 using the original coefficient of variation of analyst forecast from I/B/E/S, rather than the portmanteau DISPERSION proxy (not shown). The shortcoming of the I/B/E/S measure relative to DISPERSION is that smaller firms, which intuitively might be most likely to become overvalued, are absent from the analysis when analyst coverage is insufficient. Indeed, the sample size in this case is less than half of the original sample. Nevertheless, repeating the tests using only the firms for which the I/B/E/S measure is available produces results that are not qualitatively distinguished from those depicted in Tables 4 and 5.

B.3. Analysis of Partial Effects using Hedge Portfolios

The results in Tables 4 and 5 suggest that neither high DISPERSION nor high CONSTRAINT is independently sufficient to generate Miller's overvaluation. In addition, in the presence of one condition, overvaluation is a monotonically increasing function in the other variable. That is, abnormal returns appear to decrease for high CONSTRAINT firms as we increase DISPERSION. Likewise, abnormal returns appear to decrease for high DISPERSION firms as we increase CONSTRAINT. To test for the statistical significance of these two relations, we employ the hedge portfolio methodology, which is designed to compare abnormal returns between two separate calendar-time portfolios (Mitchell and Stafford (2000), Boehme and Sorescu (2002)). Table 6 presents the results for the benchmark case in which constraint and dispersion are measured using fitted values from vicile regressions (1) and (2). Panel A of Table 6 examines the impact of short-sale constraints conditional on firms in the highest DISPERSION quartile. The intercepts reported are for hedge portfolios that take long positions in high CONSTRAINT firms (4th quartile of Table 4) and short positions in low CONSTRAINT firms (1st quartile of Table 4). Consistent with our conjecture, these hedge-portfolio intercepts are negative, statistically significant, economically substantial, and methodologically robust.

It is worth noting that because the long and short legs of the hedge portfolios in Panel A differ in the CONSTRAINT quartile but not in the DISPERSION quartile, the abnormal returns reported reflect the partial effect of CONSTRAINT when DISPERSION is high.

Panel B repeats the analysis with firms that belong to the highest CONSTRAINT quartile. The intercepts presented pertain to hedge-portfolios that take long positions in high DISPERSION firms (4th quartile of Table 5) and short positions in low DISPERSION firms (1st quartile of Table 5). Accordingly, the intercept values reported reflect the partial effect of DISPERSION when CONSTRAINT is high. Again, the intercepts are negative, statistically significant, economically substantial, and methodologically robust.

We repeat the analysis in Table 6 using deciles. As expected, the results are consistent with those presented for quartiles. We also repeat the analysis in Table 6 using the continuous variable variations on Equations (1) and (2), as in Panel C of Tables 4 and 5. For each specification, we also construct perfectly orthogonalized portmanteau proxies to ensure that the marginal contribution of each variable is important. All of these results are very similar. (Results not shown.)

C. Other Robustness Checks

We perform several other robustness checks and the results confirm the insights already presented. Of particular importance, we consider whether the negative abnormal returns observed might be caused by contemporaneous increases in the cost of equity. Indeed, if the portfolio composed of stocks that are both costly to short and subject to high dispersion of beliefs experiences an unexpected one-time increase in the cost of equity during the measurement horizon period, the observed price declines would result from investors' use of a higher discount rate rather than a correction of overvaluation. We examine this hypothesis by measuring the cost of equity for this portfolio every month during the period beginning 36 month prior to each stock's inclusion in the portfolio, and ending 36 months after that inclusion. We then estimate a switching means model as in Sorescu (2000) to detect if there is a sudden increase in the cost of equity during the month that follows the stocks' inclusion in the portfolio (not shown). Our results confirm that there is no switch towards a higher cost of equity immediately after stocks are included in this portfolio. In fact, the cost of equity is not reliably different during the post-inclusion period compared to the pre-inclusion period. These results support the hypothesis that the negative raw and abnormal returns are driven by the correction of overvaluation, rather than by an unexpected increase in the cost of equity.

We also limit our analysis to firms that enter this most overvalued portfolio for the first time, and the results do not change.

VI. Firm-Specific Time Series Results

An implication of Miller's theory is that for each firm, we would expect overvaluation to become less severe (i.e. abnormal returns to be negative) as the stock experiences a contemporaneous transition towards lower dispersion or constraint measures. Alternatively, we would expect to observe an increase in valuation (i.e. positive abnormal returns) for stocks that contemporaneously move towards higher dispersion or constraint measures.[22] We test this implication by estimating, for each firm in our sample, the following time-series regression:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t}-R_{f,t}) + s_i SMB_t + h_i HML_t + u_i UMD_t + d_i \Delta DV_{it} + c_i \Delta CV_{it,} + e_{p,t}. \qquad (5)$$

This regression is conducted on a firm-by-firm basis over the full 1988-2002 period. For each firm we estimate a separate regression over the entire period for which the firm reports valid return data on CRSP, but we require at least twelve months of valid return data on CRSP. The right-hand-side explanatory variables consist of the four standard Fama-French-Carhart factors and two additional factors reflecting the change in dispersion or short-sale constrainedness during the month. The notations "ΔDV" and "ΔCV" stand for contemporaneous "change in Dispersion Vicile" and "change in Constraint Vicile" respectively.

[22] We wish to thank an anonymous referee for drawing our attention to this insight.

The ΔDV variable is constructed by rank ordering each firm, each month, on the basis of DISPERSION. Each firm is then assigned to one of twenty vicile groups each month, on the basis this rank ordering. This procedure adjusts the dispersion measure for market-wide intertemporal changes. ΔDV is the change in the DISPERSION vicile firm rank from the beginning of the month to the end of the month. The ΔCV variable is constructed in an identical manner, but using CONSTRAINT rather than DISPERSION in the rank-ordering process.

The coefficient estimates d_i and c_i reflect the correlation between changes in CONSTRAINT or DISPERSION viciles and the contemporaneous risk-adjusted returns. If Miller is correct, the coefficient estimates on these variables should be positive. Indeed, if during a given month a firm moves towards higher CONSTRAINT and DISPERSION viciles, it becomes more short-sale constrained and suffers from increased dispersion of opinion. The firm will have a higher valuation at the end of the month compared to the beginning of the month so the contemporaneous abnormal returns measured during that month should be positive. Likewise, if the firm moves towards lower CONSTRAINT and DISPERSION viciles, it becomes less short-sale constrained and is subject to less dispersion of investor's opinion, suggesting that its overvaluation will be less significant at the end of the month compared to the beginning of the month. In this case, the contemporaneous abnormal returns measured during that month should be negative. Either way, contemporaneous abnormal returns are expected to move in the same direction as contemporaneous transitions among the CONSTRAINT and DISPERSION viciles, suggesting that the coefficient estimates c_i and d_i should be positive.

In order to test whether coefficients c_i and d_i are generally positive across the population of firms, we estimate the cross-sectional mean and median values obtained from firm-level regressions. Table 7 reports the results for the 10762 firms in our sample. Also reported is the number of positive and negative coefficient estimates produced. The t-statistic of the mean value shows that the coefficient estimates are positive with statistical significance better than the 1% level. The p-values for the sign rank and sign tests of the median are significant at extremely high statistical levels. If ΔDV and ΔCV had no impact on contemporaneous returns, we would expect, by pure chance, to observe an equal number of positive and negative c_i and d_i coefficients in cross-section. However, the number of positive coefficients is much larger, and the binomial test confirms that the probability of this result being generated by pure chance is a near impossibility.

Overall, the results in Table 7 provide strong support for a rather subtle, yet important, implication of Miller's theory: the positive contemporaneous relation between firm-specific returns and migration along the CONSTRAINT and DISPERSION dimensions.

VII. Trading Rule Profitability

Having documented abnormal returns for firms that are both short-sale constrained and subject to differences of opinion, an obvious question is whether a trading rule exists that can capture these abnormal returns. We identify three important factors that are likely to hamper an investor's ability to capture these returns. First, short positions must cover the associated borrowing FEE costs. Second, microstructure liquidity constraints (including trading and execution costs) could make it difficult to implement the strategy without moving the price of the underlying stock. Third, if leverage is used, the portfolio returns must be reasonably stable through time so that short-term fluctuations in returns do not force liquidation of the portfolio before the long-term results can be captured.

Because we have data on FEEs for the period March 2001 to December 2002, we can use this period to estimate the costs of implementing a hedge portfolio strategy that captures the abnormal returns. In keeping with the methods already presented, we construct hedge portfolios that are rebalanced on the first of each month. Over this 22 month period, a zero-investment hedge portfolio that is long the CRSP value-weighted return index and short the "Miller" portfolio (CONSTRAINT quartile 4 intersected with

DISPERSION quartile 4) earns a raw return of 1.95% per month on the notional value, meaning the value of each leg.[23] This is consistent with the results previously presented over the full sample period.

To address whether an actual trading strategy is feasible, we first impose a series of screens designed to constrain the portfolio to a set of reasonably liquid firms. These screens were suggested by the trading desk of the security lender which supplied the FEE data we have used. They are summarized as follows:

- the share price of each included security must be greater than or equal to $5.00;
- the position size in each firm cannot exceed 2% of the prior month's trading volume;
- a position limit of one million dollars maximum is imposed on each security.

The "2% rule" and the million-dollar position limit are imposed because the portfolios rebalance on a single day each month. Larger trades would be difficult to execute without impacting share prices.

After imposing these rules, the raw return on the hedge portfolio declines from 1.95% to 0.84%, a surprisingly large decline of 1.11%. This decline reveals that relatively illiquid short-sale constrained firms are responsible for much of the "Miller" effect.

We next consider the cost of lending FEE on the short side of the portfolio. For this, we calculate the average FEE for each firm at the time the portfolio is constructed. Because the FEEs we observe are paid by the security lender to mutual funds and other institutions, these are not the FEEs that a hedge fund could obtain. Hedge funds cannot borrow directly from mutual funds because hedge funds have poor credit ratings. Instead, the market for borrowing and lending shares is intermediated by parties such as our data provider who, understandably, has not provided us with the data on the spreads they earn. We have been informed that during the 1980's and 1990's the spread might be reasonably estimated to average 0.75% annually. Current spreads are smaller as the new volume generated by the proliferation of hedge funds has led to greater competition in intermediating security lending.

[23] Because the size of each leg in the portfolio changes from month-to month, we estimate the mean using ordinary least squares on monthly value-weighted calendar-time portfolios.

We assume the cost to hedge funds to be the annual FEE provided by the security lender plus 0.75%. On this basis, the fees paid for the short positions in the portfolio reduce the monthly returns to 0.67% per month.

Our discussions with hedge fund managers suggest that an important attribute of a trading strategy is consistency of returns from month to month. A strategy that generates non-negative returns 2/3 of the time has good potential to be implemented. After applying the microstructure screens and FEE costs, the strategy, while earning positive returns of 0.67% per month, loses money in 9 of the 22 months or 41% of the time. This suggests that the risks associated with earning the abnormal returns may be unacceptably high.

The hypothetical portfolio averages approximately $100 million in notional amount each month, and monthly turnover is approximately 50% of the short leg. Using the 0.67% average monthly return results in annual revenues of approximately $8 million dollars per year before trading, execution and management costs. After these costs are considered, the dollar profit, while large for an individual, is probably much smaller than many opportunities currently pursued by hedge funds.

In summary, because we have data for a 22-month period in 2001 and 2002, it is possible to estimate costs of selling short the Miller portfolio. However, we should be cautious about extending these findings to the earlier periods, since we have no evidence of shorting costs prior to 2001. Assuming that the 22-month period is representative, after adjusting for liquidity limitations and after applying a reasonable spread for intermediated FEEs, returns on the notional value reduce to 0.67% per month. However, the volatility of returns would have made efforts to capture the observed abnormal returns relatively risky, particularly in a leveraged portfolio. Additional transaction, execution or management costs in excess of the 0.67% would exhaust the returns. Transaction and management costs of lesser amounts would reduce the available returns and increase the risk as measured by the percentage of "winning" months.

VIII. Summary and Conclusion

Our research indicates that firms subject to both high short-sale constraints and high dispersion of investors' opinions are likely to be overvalued. This overvaluation is significant in both statistical and economic terms. Over the period 1988-2002, a period of significant appreciation in the market, the annualized *raw* returns of the most short-sale-constrained, high-dispersion stocks are between –9.1% and –13% for one-month holding periods. Using the various standard benchmarks we have reported, annualized monthly holding period abnormal returns over the same period are between –14.8% and –20.7% depending on the method used. This conclusion appears to be robust across model specifications and portfolio construction methods.

In contrast to the above findings, we also find that portfolios of firms that possess one of Miller's necessary conditions, but not the other, do not appear to be overvalued. Accordingly, an important contribution of this paper is to highlight the importance of the interaction of short-sale constraints with dispersion of beliefs. High dispersion of investor opinion does not result in overpricing unless the marginal cost of short selling has also become relatively high. Likewise, short-sale constraints alone do not create overpricing.

Although the observed overpricing could be viewed as an anomaly that violates the efficient markets framework, our analysis suggests that it cannot be fully arbitraged away. Firms that are subject to high dispersion of opinion and are short-sale constrained are often illiquid. Borrowing fees and other transaction costs must be covered. There also are fixed costs to operating a hedge fund, and the notional size of a liquid portfolio is relatively small. Finally, the returns may be too volatile to be attractive.

However, if short sellers exist who can borrow/trade at unusually low costs and have high risk tolerance, these parties should be able to capture some of the observed overpricing in short-sale-constrained securities, but we believe that much of the mispricing probably cannot be arbitraged. Nevertheless, short-sale-constrained stocks with high dispersion of investor opinion would seem to be stocks that most investors should want to avoid.

This paper also offers guidance for improved long-term performance methodologies. Considering the predictable impact of short-sale constraints and dispersion of beliefs on security prices, new asset pricing models might be needed that explicitly control for these factors.

Given the economic magnitude of the overpricing observed in this study, certain public policy changes may be warranted. Specifically, one might argue that efforts should be made to lower the costs of short selling. Current regulatory policy imposes greater burdens on short selling than on establishing long positions. Ostensibly, the impetus for this regulatory bias is to limit manipulation of security prices by short sellers who might spread misinformation about firm quality. However, it seems improbable that short sellers are in a more powerful position to misrepresent firm value than is management who might benefit from inflating a firm's share price. History is replete with incidents in which managers have selectively disclosed, and occasionally even misrepresented, information concerning a firm's quality or prospects. Policies that allow negative sentiment to be more fully reflected in share prices might serve to counterbalance incentives of others to inflate share prices.

Consider, for example, the well-documented absence of "sell" recommendations by investment advisors. The bias against sell recommendations apparently arises, in part, from brokerage houses' inability to generate trading activity from these recommendations. Short-sale constraints probably limit the trading activity that "sell" recommendations would otherwise generate. Relaxation of the regulatory constraints might alter the incentive structure for brokerage houses and analysts, resulting in more even-handed analysis of the firms covered.

An example of a specific public policy action that might be appropriate is to encourage redevelopment of a transparent centralized market for the lending and borrowing of shares. While we have been able to utilize a proprietary database for this study, as Jones and Lamont (2002) observe, the quality of public information on short-sale costs was better in the 1920s than it is today. Although small individual investors are in a poor competitive position to short overvalued securities, they can sell long positions that are overpriced. More transparent security lending markets would put these investors on notice that certain high-volume, high-volatility securities may have become overvalued because they have become costly to short.

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Table 1: Descriptive Statistics

A description of each proxy variable is provided for four different calendar dates: January 1988, January 1993, January 1998, and December 2002. Proxies are estimated for all U.S.-domiciled common stocks listed on the NYSE and Nasdaq. For each calendar date the *Analyst Forecast Dispersion* is the I/B/E/S standard deviation of the next fiscal-year-end earnings per share forecast, scaled by the forecast mean. The *Standard Deviation of Abnormal Returns* (*SIGMA*) is the standard deviation of the error term obtained from the market model computed over the prior 100 days. The *Volume of Trade (TURNOVER)* equals to the average of the daily ratios of the number of shares traded to the total number of shares. The *Equity Loan FEE* is the mean annualized equity lender's loan fee for shares borrowed for short sales. The *Relative Short Interest (RSI)* is measured as the short interest divided by the number of outstanding shares. The *OPTIONS* status reports the total number of firms in our sample and the proportion of firms with exchange-traded options.

Dependent Variable	Date	N. Obs.	Mean	First Percentile	First Quartile	Median	Third Quartile	99^{th} Percentile
I/B/E/S	198801	2153	1.6912	0.0000	0.0289	0.0593	0.1556	5.0000
Analyst forecast	199301	2506	1.3904	0.0000	0.0194	0.0417	0.1059	3.1000
dispersion	199801	3867	1.6841	0.0000	0.0133	0.0290	0.0756	2.2143
	200212	2566	4.4104	0.0000	0.0095	0.0233	0.0660	2.6667
Std. Deviation of	198801	5437	0.0468	0.0094	0.0277	0.0407	0.0584	0.4983
Abnormal Returns:	199301	5027	0.0471	0.0072	0.0216	0.0355	0.0577	0.2104
SIGMA	199801	6547	0.0389	0.0010	0.0211	0.0317	0.0465	0.1506
	200212	4677	0.0428	0.0095	0.0208	0.0330	0.0547	0.1608
Volume of Trade:	198801	4962	0.0022	0.0000	0.0010	0.0017	0.0028	0.0087
TURNOVER	199301	4653	0.0028	0.0003	0.0012	0.0020	0.0035	0.0128
	199801	6377	0.0036	0.0003	0.0014	0.0024	0.0043	0.0176
	200212	4522	0.0037	0.0002	0.0009	0.0021	0.0048	0.0214
Equity Loan FEE	200212	4568	0.0044	0.0008	0.0014	0.0015	0.0020	0.0500
Relative Short	198801	1145	0.0083	0.0000	0.0009	0.0026	0.0071	0.0981
Interest (%):	199301	4166	0.0105	0.0000	0.0006	0.0023	0.0086	0.1236
RSI	199801	6111	0.0157	0.0000	0.0005	0.0038	0.0163	0.1605
	200212	4413	0.0266	0.0000	0.0013	0.0096	0.0213	0.2333
OPTIONS Status:	198801	5478	0.0785					
(1 if optioned,	199301	5068	0.1689					
0 otherwise)	199801	6665	0.2825					
	200212	4809	0.4999					

Table 2: Overvaluation as a function of short-sale CONSTRAINT only

One-month and one-year calendar-time abnormal returns are shown as a function of the short sale constraint proxy (CONSTRAINT). CONSTRAINT deciles are assigned for each month (beginning with January 1988) by sorting all NYSE and Nasdaq firms on CONSTRAINT, with decile 10 being the highest CONSTRAINT. Firms are then assigned to and enter a designated calendar-time portfolio for each month based on the previous month-ending CONSTRAINT ranking.

The abnormal returns are computed by forming both equally and value weighted calendar-time portfolios and regressing the excess portfolio returns ($R_{p,t}$-$R_{f,t}$) on the three Fama and French (1993) risk factors (R_m-R_f, SMB, and HML) and the Carhart (1997) momentum factor (UMD). Calendar-time portfolios are re-balanced each month, and include only firms that entered the portfolio during the previous month (one-month horizon) or 12 months (one-year horizon). The estimation method is both ordinary (OLS) and weighted (WLS) least squares; the WLS method weights the monthly excess returns by the square root of the number of firms in the portfolio each month. The abnormal return for each sub-sample is the intercept (α_p) from the following regression:

$$R_{p,t}\text{-}R_{f,t} = \alpha_p + \beta_p(R_{m,t}\text{-}R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t}.$$

Abnormal returns are expressed in *percentage* per month. All t-statistics are computed from the intertemporal variation in the monthly calendar-time portfolio returns and are shown in brackets under each parameter.

	Horizon							
	One-month (Number of calendar months = 179)				One-year (Number of calendar months = 179)			
CONSTRAINT decile	Equally-weighted		Value-weighted		Equally-weighted		Value-weighted	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
1	0.579	0.590	0.508	0.538	0.438	0.462	0.292	0.315
	*[4.52]****	*[4.51]****	*[3.55]****	*[3.66]****	*[4.03]****	*[4.20]****	*[2.80]****	*[3.00]****
2	0.442	0.427	0.458	0.429	0.411	0.422	0.193	0.201
	*[3.75]****	*[3.57]****	*[2.77]****	*[2.58]****	*[4.13]****	*[4.21]****	*[1.48]*	*[1.53]*
3	0.294	0.299	0.261	0.275	0.275	0.277	0.188	0.195
	*[2.90]****	*[3.00]****	*[2.04]***	*[2.15]***	*[3.14]****	*[3.27]****	*[1.51]*	*[1.56]*
4	0.209	0.227	0.096	0.093	0.222	0.239	-0.041	-0.039
	*[2.08]***	*[2.22]***	*[0.82]*	*[0.79]*	*[2.50]***	*[2.70]****	*[-0.43]*	*[-0.40]*
5	0.140	0.156	0.104	0.104	0.127	0.135	0.027	0.024
	[1.59]	*[1.80]**	*[1.11]*	*[1.08]*	*[1.56]*	*[1.71]**	*[0.39]*	*[0.34]*
6	0.218	0.229	0.121	0.128	0.223	0.230	0.157	0.176
	*[1.90]**	*[2.07]***	*[1.66]**	*[1.69]**	*[2.02]***	*[2.18]***	*[2.61]****	*[2.87]****
7	0.101	0.117	0.186	0.224	0.113	0.118	0.069	0.086
	[0.89]	*[1.03]*	*[2.07]***	*[2.42]***	*[1.21]*	*[1.29]*	*[0.93]*	*[1.13]*
8	-0.174	-0.158	-0.121	-0.111	0.010	0.014	0.029	0.040
	[-1.45]	*[-1.29]*	*[-1.17]*	*[-1.05]*	*[0.09]*	*[0.13]*	*[0.36]*	*[0.49]*
9	-0.558	-0.548	-0.203	-0.194	-0.255	-0.252	-0.069	-0.070
	*[-5.05]****	*[-5.03]****	*[-1.76]**	*[-1.73]**	*[-2.59]****	*[-2.57]***	*[-0.70]*	*[-0.71]*
10	-0.990	-0.954	-0.267	-0.278	-0.696	-0.676	-0.180	-0.195
	*[-7.22]****	*[-7.11]****	*[-1.70]**	*[-1.76]**	*[-5.72]****	*[-5.78]****	*[-1.30]*	*[-1.40]*

***, **, * Significantly different from zero at the 1%, 5%, and 10% levels, respectively. Two tail tests are used.

Table 3: Overvaluation as a function of DISPERSION of opinion only

One-month and one-year abnormal calendar-time returns are shown as a function of the dispersion of opinion proxy (DISPERSION). DISPERSION deciles are assigned for each month (beginning with January 1988) by sorting all NYSE and Nasdaq firms on DISPERSION, with decile 10 being the highest DISPERSION. Firms are then assigned to and enter a designated calendar-time portfolio each month based on the previous month-ending DISPERSION ranking.

The abnormal returns are computed by forming both equally and value weighted calendar-time portfolios and regressing the excess portfolio returns ($R_{p,t}$-$R_{f,t}$) on the three Fama and French (1993) risk factors (R_m-R_f, SMB, and HML) and the Carhart (1997) momentum factor (UMD). Calendar-time portfolios are re-balanced each month, and include only firms that entered the portfolio during the previous month (one-month horizon) or 12 months (one-year horizon). The estimation method is both ordinary (OLS) and weighted (WLS) least squares; the WLS method weights the monthly excess returns by the square root of the number of firms in the portfolio each month. The abnormal return for each sub-sample is the intercept (α_p) from the following regression:

$$R_{p,t}-R_{f,t} = \alpha_p + \beta_p(R_{m,t}-R_{f,t}) + s_pSMB_t + h_pHML_t + u_pUMD_t + e_{p,t}.$$

Abnormal returns are expressed in *percentage* per month. All t-statistics are computed from the intertemporal variation in the monthly calendar-time portfolio returns and are shown in brackets under each parameter.

	Horizon							
	One-month (Number of calendar months = 179)				One-year (Number of calendar months = 179)			
DISPERSION decile	Equally-weighted		Value-weighted		Equally-weighted		Value-weighted	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
1	0.213	0.253	0.069	0.075	0.194	0.216	0.078	0.087
	[1.31]	*[1.54]*	*[0.75]*	*[0.80]*	*[1.16]*	*[1.27]*	*[0.79]*	*[0.85]*
2	0.170	0.197	-0.041	-0.015	0.136	0.129	0.019	0.053
	[0.93]	*[1.07]*	*[-0.40]*	*[-0.15]*	*[0.76]*	*[0.72]*	*[0.21]*	*[0.58]*
3	0.204	0.212	0.078	0.090	0.084	0.085	0.081	0.119
	[1.13]	*[1.18]*	*[0.60]*	*[0.68]*	*[0.48]*	*[0.49]*	*[0.84]*	*[1.21]*
4	0.188	0.184	0.329	0.343	0.085	0.057	0.224	0.245
	[1.09]	*[1.08]*	*[2.34]***	*[2.39]***	*[0.52]*	*[0.35]*	*[1.87]**	*[1.98]***
5	0.124	0.101	0.245	0.277	0.020	-0.013	0.109	0.126
	[0.81]	*[0.66]*	*[1.42]*	*[1.58]*	*[0.14]*	*[-0.09]*	*[0.72]*	*[0.80]*
6	-0.020	-0.021	-0.163	-0.175	0.008	-0.003	0.040	0.023
	[-0.17]	*[-0.17]*	*[-0.78]*	*[-0.83]*	*[0.08]*	*[-0.03]*	*[0.22]*	*[0.12]*
7	-0.124	-0.163	-0.304	-0.318	-0.047	-0.086	-0.120	-0.115
	[-1.35]	*[-1.79]**	*[-1.23]*	*[-1.27]*	*[-0.59]*	*[-1.10]*	*[-0.51]*	*[-0.48]*
8	-0.171	-0.228	-0.449	-0.456	0.004	-0.044	-0.217	-0.250
	[-1.34]	*[-1.82]**	*[-1.51]*	*[-1.52]*	*[0.03]*	*[-0.33]*	*[-0.79]*	*[-0.91]*
9	-0.327	-0.306	-0.891	-0.996	0.072	0.124	-0.283	-0.305
	[-1.43]	*[-1.30]*	*[-2.46]***	*[-2.70]****	*[0.32]*	*[0.52]*	*[-0.84]*	*[-0.88]*
10	-0.101	0.052	-1.268	-1.205	0.320	0.527	-0.667	-0.666
	[-0.21]	*[0.11]*	*[-2.60]****	*[-2.44]***	*[0.71]*	*[1.14]*	*[-1.69]**	*[-1.69]**

***, **, * Significantly different from zero at the 1%, 5%, and 10% levels, respectively. Two tail tests are used.

Table 4: Overvaluation for highest DISPERSION stocks as a function of CONSTRAINT

One-month and one-year calendar-time abnormal returns are shown for high DISPERSION stocks (4th quartile) as a function of the short-sale-CONSTRAINT proxy. DISPERSION and CONSTRAINT quartiles are assigned each month (beginning with January 1988) by sorting all NYSE and Nasdaq firms on DISPERSION and CONSTRAINT, with Quartile 4 being the highest. Firms are assigned to and enter a designated calendar-time portfolio each month based on the previous month ending DISPERSION and CONSTRAINT ranking. The analysis shown below categorizes stocks in DISPERSION quartile four (highest DISPERSION), as a function of the CONSTRAINT level.

The abnormal returns shown in Panel A are computed by forming both equally and value weighted calendar-time portfolios and regressing the excess portfolio returns ($R_{p,t}$-$R_{f,t}$) on the three Fama and French (1993) risk factors (R_m-R_f, SMB, and HML) and the Carhart (1997) momentum factor (UMD). Calendar-time portfolios are re-balanced each month, and include only firms that entered the portfolio during the previous month (one-month horizon) or 12 months (one-year horizon). The estimation method is both ordinary (OLS) and weighted (WLS) least squares; the WLS method weights the monthly excess returns by the square root of the number of firms in each month. The abnormal return for each sub-sample is the intercept (α_p) from the following four-factor regression:

$$R_{p,t}-R_{f,t} = \alpha_p + \beta_p(R_{m,t}-R_{f,t}) + s_pSMB_t + h_pHML_t + u_pUMD_t + e_{p,t}.$$

Panel B reports the mean raw returns of the calendar-time portfolios. All returns are expressed in *percentages* per month. T-statistics are computed from the intertemporal variation in the monthly calendar-time portfolio returns and are shown in brackets under each parameter.

Panel C reports four-factor model intercepts where the monthly CONSTRAINT and DISPERSION portmanteau proxies are fitted using coefficients from *continuous* (as opposed to *vicile*-grouped) variable versions of Equations (1) and (2) in the body of this paper. Both the dependent and independent variables are in continuous form in the fitting regressions.

Panel A: Four-factor model intercepts with constraint and dispersion estimated from vicile-based models

	Horizon							
	One-month (Number of calendar months = 179)				One-year (Number of calendar months = 179)			
CONSTRAINT quartile	Equally-weighted		Value-weighted		Equally-weighted		Value-weighted	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
1	0.495	0.496	0.008	-0.039	0.641	0.710	0.256	0.213
	[1.53]	*[1.46]*	*[0.03]*	*[-0.12]*	*[2.14]***	*[2.27]***	*[0.91]*	*[0.72]*
2	0.233	0.238	-0.422	-0.402	0.437	0.515	-0.232	-0.249
	[0.67]	*[0.67]*	*[-1.24]*	*[-1.20]*	*[1.38]*	*[1.58]*	*[-0.80]*	*[-0.87]*
3	-0.130	-0.009	-0.237	-0.289	0.259	0.371	-0.099	-0.193
	[-0.39]	*[-0.03]*	*[-0.62]*	*[-0.76]*	*[0.81]*	*[1.13]*	*[-0.30]*	*[-0.59]*
4	-1.642	-1.550	-1.334	-1.352	-0.927	-0.822	-0.711	-0.706
	*[-5.08]****	*[-4.77]****	*[-3.32]****	*[-3.20]****	*[-2.95]****	*[-2.58]****	*[-1.93]**	*[-1.85]**

***, **, * Significantly different from zero at the 1%, 5%, and 10% levels, respectively. Two tail tests are used.

Panel B: Raw returns with constraint and dispersion estimated from vicile-based models

CONSTRAINT quartile	Horizon: One-month (Number of calendar months = 179) Equally-weighted OLS	Equally-weighted WLS	Value-weighted OLS	Value-weighted WLS	One-year (Number of calendar months = 179) Equally-weighted OLS	Equally-weighted WLS	Value-weighted OLS	Value-weighted WLS
1	1.630	1.675	0.560	0.530	1.938	1.965	1.072	0.987
	*[2.38]***	*[2.43]***	*[0.91]*	*[0.85]*	*[2.94]****	*[2.94]****	*[1.74]**	*[1.56]*
2	1.237	1.269	0.177	0.223	1.529	1.511	0.599	0.534
	[1.49]	*[1.50]*	*[0.23]*	*[0.28]*	*[1.96]***	*[1.87]**	*[0.78]*	*[0.67]*
3	0.806	0.612	0.449	0.125	1.261	1.065	0.668	0.340
	[0.88]	*[0.62]*	*[0.49]*	*[0.13]*	*[1.44]*	*[1.13]*	*[0.79]*	*[0.37]*
4	-0.794	-0.860	-1.003	-1.155	-0.013	-0.023	-0.074	-0.190
	[-0.86]	*[-0.86]*	*[-1.07]*	*[-1.14]*	*[-0.02]*	*[-0.02]*	*[-0.09]*	*[-0.20]*

***, **, * Significantly different from zero at the 1%, 5%, and 10% levels, respectively. Two tail tests are used.

Panel C: Four-factor model intercepts with constraint and dispersion estimated from continuous-value models

CONSTRAINT quartile	Horizon: One-month (Number of calendar months = 179) Equally-weighted OLS	Equally-weighted WLS	Value-weighted OLS	Value-weighted WLS	One-year (Number of calendar months = 179) Equally-weighted OLS	Equally-weighted WLS	Value-weighted OLS	Value-weighted WLS
1	0.675	0.637	-0.019	-0.028	0.734	0.753	0.167	0.118
	*[2.23]***	*[2.01]***	*[-0.06]*	*[-0.09]*	*[2.71]****	*[2.65]****	*[0.63]*	*[0.44]*
2	0.398	0.372	-0.174	-0.164	0.522	0.593	-0.100	-0.084
	[1.18]	*[1.08]*	*[-0.50]*	*[-0.46]*	*[1.68]**	*[1.86]**	*[-0.35]*	*[-0.30]*
3	-0.264	-0.295	-0.920	-1.052	0.188	0.256	-0.437	-0.496
	[-0.74]	*[-0.84]*	*[-2.46]***	*[-2.82]****	*[0.55]*	*[0.74]*	*[-1.33]*	*[-1.53]*
4	-1.700	-1.595	-1.784	-1.800	-0.918	-0.821	-1.034	-1.093
	*[-4.60]****	*[-4.23]****	*[-4.25]****	*[-4.16]****	*[-2.56]***	*[-2.23]***	*[-2.84]****	*[-2.96]****

***, **, * Significantly different from zero at the 1%, 5%, and 10% levels, respectively. Two tail tests are used.

Table 5: Overvaluation for highest CONSTRAINT stocks as a function of DISPERSION

One-month and one-year calendar-time abnormal returns are shown for high CONSTRAINT stocks (4th quartile) as a function of the DISPERSION of opinion proxy. DISPERSION and CONSTRAINT quartiles are assigned each month (beginning with January 1988) by sorting all NYSE and Nasdaq firms on DISPERSION and CONSTRAINT, with Quartile 4 being the and highest. Firms are assigned to and enter a designated calendar-time portfolio each month based on the previous month-ending DISPERSION and CONSTRAINT ranking. The analysis shown below categorizes stocks in CONSTRAINT quartile four (highest CONSTRAINT), as a function of DISPERSION level.

The abnormal returns shown in Panel A are computed by forming both equally and value weighted calendar-time portfolios and regressing the excess portfolio returns ($R_{p,t}$-$R_{f,t}$) on the three Fama and French (1993) risk factors (R_m-R_f, SMB, and HML) and the Carhart (1997) momentum factor (UMD). Calendar-time portfolios are re-balanced each month, and include only firms that entered the portfolio during the previous month (one-month horizon) or 12 months (one-year horizon). The estimation method is both ordinary (OLS) and weighted (WLS) least squares; the WLS method weights the monthly excess returns by the square root of the number of firms in each month. The abnormal return for each sub-sample is the intercept (α_p) from the following four-factor regression:

$$R_{p,t}-R_{f,t} = \alpha_p + \beta_p(R_{m,t}-R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t}.$$

Panel B reports the mean raw returns of the calendar-time portfolios. All returns are expressed in *percentages* per month. T-statistics are computed from the intertemporal variation in the monthly calendar-time portfolio returns and are shown in brackets under each parameter.

Panel C reports four-factor model intercepts where the monthly CONSTRAINT and DISPERSION portmanteau proxies are fitted using coefficients from *continuous* (as opposed to *vicile*-grouped) variable versions of Equations (1) and (2) in the body of this paper. Both the dependent and independent variables are in continuous form in the fitting regressions.

Panel A: Four-factor model intercepts with constraint and dispersion estimated from vicile-based models

	Horizon							
	One-month (Number of calendar months = 179)				One-year (Number of calendar months = 179)			
DISPERSION quartile	Equally-weighted		Value-weighted		Equally-weighted		Value-weighted	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
1	-0.099	-0.026	-0.118	-0.065	-0.094	-0.080	-0.074	-0.054
	[-0.51]	*[-0.14]*	*[-0.94]*	*[-0.55]*	*[-0.50]*	*[-0.43]*	*[-0.76]*	*[-0.59]*
2	-0.232	-0.228	0.053	0.075	-0.178	-0.230	0.096	0.108
	[-1.07]	*[-1.05]*	*[0.33]*	*[0.46]*	*[-0.88]*	*[-1.14]*	*[0.61]*	*[0.66]*
3	-0.717	-0.766	-0.608	-0.626	-0.458	-0.486	-0.152	-0.178
	*[-4.59]****	*[-4.82]****	*[-2.44]***	*[-2.41]***	*[-3.31]****	*[-3.48]****	*[-0.68]*	*[-0.76]*
4	-1.642	-1.550	-1.334	-1.352	-0.927	-0.822	-0.711	-0.706
	*[-5.08]****	*[-4.77]****	*[-3.32]****	*[-3.20]****	*[-2.95]****	*[-2.58]****	*[-1.93]**	*[-1.85]**

***, **, * Significantly different from zero at the 1%, 5%, and 10% levels, respectively. Two tail tests are used.

Panel B: Raw returns with constraint and dispersion estimated from vicile-based models

DISPERSION quartile	Horizon: One-month (Number of calendar months = 179)				One-year (Number of calendar months = 179)			
	Equally-weighted		Value-weighted		Equally-weighted		Value-weighted	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
1	1.040	1.205	1.035	1.291	1.027	1.112	0.990	1.152
	*[3.66]****	*[4.38]****	*[3.42]****	*[4.37]****	*[3.59]****	*[3.88]****	*[3.41]****	*[3.95]****
2	0.905	0.972	1.053	1.174	0.902	0.863	1.105	1.126
	*[2.11]***	*[2.29]***	*[2.23]***	*[2.48]***	*[2.07]***	*[1.96]***	*[2.34]***	*[2.34]***
3	0.251	0.202	0.123	0.096	0.437	0.356	0.590	0.497
	[0.39]	*[0.30]*	*[0.17]*	*[0.13]*	*[0.68]*	*[0.53]*	*[0.84]*	*[0.66]*
4	-0.794	-0.860	-1.003	-1.155	-0.013	-0.023	-0.074	-0.190
	[-0.86]	*[-0.86]*	*[-1.07]*	*[-1.14]*	*[-0.02]*	*[-0.02]*	*[-0.09]*	*[-0.20]*

***, **, * Significantly different from zero at the 1%, 5%, and 10% levels, respectively. Two tail tests are used.

Panel C: Four-factor model intercepts with constraint and dispersion estimated from continuous-value models

DISPERSION quartile	Horizon: One-month (Number of calendar months = 179)				One-year (Number of calendar months = 179)			
	Equally-weighted		Value-weighted		Equally-weighted		Value-weighted	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
1	-0.121	-0.071	-0.023	-0.002	-0.066	-0.085	0.029	0.064
	[-0.58]	*[-0.35]*	*[-0.20]*	*[-0.02]*	*[-0.33]*	*[-0.43]*	*[0.32]*	*[0.77]*
2	-0.231	-0.246	-0.189	-0.197	-0.126	-0.168	-0.081	-0.100
	[-1.12]	*[-1.18]*	*[-1.27]*	*[-1.32]*	*[-0.66]*	*[-0.88]*	*[-0.59]*	*[-0.72]*
3	-0.881	-0.933	-0.730	-0.793	-0.570	-0.598	-0.392	-0.396
	*[-5.61]****	*[-5.90]****	*[-2.75]****	*[-2.94]****	*[-4.15]****	*[-4.36]****	*[-1.60]*	*[-1.56]*
4	-1.700	-1.595	-1.784	-1.800	-0.918	-0.821	-1.034	-1.093
	*[-4.60]****	*[-4.23]****	*[-4.25]****	*[-4.16]****	*[-2.56]***	*[-2.23]***	*[-2.84]****	*[-2.96]****

***, **, * Significantly different from zero at the 1%, 5%, and 10% levels, respectively. Two tail tests are used.

Table 6: Analysis of partial effects using hedge portfolios

One-month and one-year calendar-time abnormal returns are shown for hedge (zero-investment) portfolios that take long positions in the high-CONSTRAINT-quartile, high-DISPERSION-quartile stocks, and short positions in stocks that are either in the low-CONSTRAINT, high-DISPERSION quartiles (Panel A), or high-CONSTRAINT, low-DISPERSION quartiles (Panel B). DISPERSION and CONSTRAINT quartiles are assigned for each month (beginning with January 1988) by sorting all NYSE and Nasdaq firms on DISPERSION and CONSTRAINT, with Quartile 4 being the highest. Firms are assigned to and enter a designated calendar-time portfolio each month based on the previous month ending DISPERSION and CONSTRAINT ranking. The four-factor hedge portfolio abnormal returns are computed by forming both equally and value weighted calendar-time portfolios and regressing the difference in portfolio returns ($R_{long,t}$-$R_{short,t}$) on the three Fama-French risk factors (R_m-R_f, SMB, HML) and the Carhart (1997) momentum factor (UMD). The raw calendar-time returns are also shown. Calendar-time portfolios are re-balanced each month, and include only firms that entered the portfolio during the previous month (one-month horizon) or 12 months (one-year horizon). The estimation method is both ordinary (OLS) and weighted least squares (WLS); the WLS method weights the monthly excess returns by the square root of the number of firms in each month. For the four-factor model, abnormal returns are calculated as the intercept (α_p) from the relevant regression:

$$R_{long,t}-R_{short,t} = \alpha_p + \beta_p(R_{m,t}-R_{f,t}) + s_pSMB_t + h_pHML_t + u_pUMD_t + e_{p,t}. \quad \text{(Fama-French-Carhart Four Factor Model)}$$

Abnormal returns are expressed in *percentage* per month. T-statistics are computed from the intertemporal variation in the monthly calendar-time hedge portfolio returns and are shown in brackets under each parameter.

Panel A: Highest constraint/highest dispersion portfolio *minus* lowest constraint/highest dispersion portfolio

	Horizon							
	One-month (Number of calendar months = 179)				One-year (Number of calendar months = 179)			
Model estimated	Equally-weighted		Value-weighted		Equally-weighted		Value-weighted	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
4-factor	-2.137	-2.086	-1.342	-1.300	-1.569	-1.559	-0.967	-0.894
	*[-6.41]****	*[-6.17]****	*[-2.93]****	*[-2.68]****	*[-5.85]****	*[-5.82]****	*[-2.62]****	*[-2.30]***
Raw returns	-2.424	-2.395	-1.563	-1.494	-1.952	-1.990	-1.147	-1.050
	*[-5.83]****	*[-5.58]****	*[-2.82]****	*[-2.56]***	*[-5.11]****	*[-5.04]****	*[-2.49]***	*[-2.15]***

***, **, * Significantly different from zero at the 1%, 5%, and 10% levels, respectively. One-tail tests are used for hedge portfolios.

Panel B: Highest constraint/highest dispersion portfolio *minus* highest constraint/lowest dispersion portfolio

	Horizon							
	One-month (Number of calendar months = 179)				One-year (Number of calendar months = 179)			
Model estimated	Equally-weighted		Value-weighted		Equally-weighted		Value-weighted	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
4-factor	-1.543	-1.546	-1.216	-1.276	-0.833	-0.793	-0.637	-0.665
	*[-3.29]****	*[-3.30]****	*[-2.70]****	*[-2.79]****	*[-1.78]**	*[-1.67]**	*[-1.59]*	*[-1.64]*
Raw returns	-1.834	-1.878	-2.039	-2.114	-1.040	-1.091	-1.064	-1.120
	*[-2.14]***	*[-2.15]***	*[-2.46]***	*[-2.50]***	*[-1.25]*	*[-1.27]*	*[-1.43]*	*[-1.45]*

***, **, * Significantly different from zero at the 1%, 5%, and 10% levels, respectively. One-tail tests are used for hedge portfolios.

Table 7: Time-series price effects of changes in DISPERSION and CONSTRAINT

Time series price effects of changes in DISPERSION or CONSTRAINT are examined by estimating the following firm-specific time-series model:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t}-R_{f,t}) + s_i SMB_t + h_i HML_t + u_i UMD_t + d_i \Delta DV_{it} + c_i \Delta CV_{it,} + e_{p,t}.$$

The model augments the standard Fama-French-Carhart model with two variables that capture the effect of contemporaneous changes in DISPERSION ("ΔDV") and CONSTRAINT ("ΔCV") for each firm. At least 12 monthly observations are required for each firm.

The ΔDV variable is constructed by rank ordering each firm, each month, on the basis of DISPERSION. Each firm is then assigned to one of twenty groups of equal size (vicile) each month on the basis this rank ordering. ΔDV is the change in the vicile for the firm from the beginning of the month to the end of the month. The ΔCV variable is constructed in an identical manner using CONSTRAINT rather than DISPERSION in the rank-ordering process.

Each regression is estimated during the period from February 1988 to December 2002, for every NYSE and Nasdaq firm having valid DISPERSION and CONSTRAINT estimates.

Reported below are the cross-sectional mean and median estimates of the time-series regression coefficients d_i and c_i. T-statistics are shown in brackets under the mean. Also reported are p-values for the sign rank and sign tests of the median and total number of positive and negative coefficients, respectively.

	Mean and median regression coefficients of monthly changes in dispersion and constraint	
	d_i	c_i
Mean	0.00893	0.00397
t-statistic	*[17.30]* ***	*[13.57]* ***
Median	0.00625	0.00299
p-value	<0.0001	<0.0001
No. positive	7083	6658
Total observations	10762	10762
Percent positive	68.5%	61.9%
p-value	<0.0001	<0.0001

*** Significantly different from zero at the 1% level.