High Short Interest Effect and Aggregate Volatility Risk

Alexander Barinov

Juan (Julie) Wu*

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* Alexander Barinov can be reached at 438 Brooks Hall, University of Georgia. Athens, GA 30602. Tel.: +1-706-542-3650. Fax: +1-706-542-9434. E-mail: abarinov@terry.uga.edu. Web: http://abarinov.myweb.uga.edu. Julie Wu can be reached at 433 Brooks Hall, University of Georgia. Athens, GA 30602. Tel.: +1-706-542-0934. Fax: +1-706-542-9434. E-mail: juliewu@terry.uga.edu. Web: http://juliewu.myweb.uga.edu/.

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Abstract

We propose a risk-based firm-type explanation on why stocks of firms with high relative short interest (RSI) have lower future returns. We argue that these firms have negative alphas because they are a hedge against expected aggregate volatility risk. Consistent with this argument, we show that these firms have high firm-specific uncertainty and option-like equity, and the ICAPM with the aggregate volatility risk factor can largely explain the high RSI effect. The key mechanism is that high RSI firms have abundant growth options and, all else equal, growth options become less sensitive to the underlying asset value and more valuable as idiosyncratic volatility goes up. Idiosyncratic volatility usually increases together with aggregate volatility, i.e., in recessions.

1. Introduction

It is well established that stocks of firms with high relative short interest (henceforth RSI) have low future returns (e.g., Asquith, Pathak, and Ritter, 2005). In our paper, we call this pricing anomaly the high RSI effect. Theoretical models that try to explain the high RSI effect build on seminal work by Miller (1977) and Diamond and Verrecchia (1987). Miller (1977) argues that the presence of short sales constraints keeps pessimistic investors out of the market, which leads to overvaluation, and subsequent corrections result in low returns (for empirical evidence see, e.g., Jones and Lamont (2002), Asquith, Pathak, and Ritter (2005), Boehme, Danielsen, and Sorescu (2006), and Boehme, Danielsen, Kumar, and Sorescu (2009)). Diamond and Verrecchia (1987) propose that short sellers are more likely to be informed because selling short is more expensive than long transactions. Among others, Dechow et al (2001) and Boehmer, Jones and Zhang (2008) argue that due to slow incorporation of the information short sellers have, highly shorted firms can have lower future returns.[1]

Both explanations for the high RSI effect, however, are not quite satisfactory for rational asset-pricing due to the assumption of some type of investors' irrationality. The Miller argument assumes that some optimists fall prey to the winner's curse again and again. Indeed, even if the short-sale constraints keep pessimists out of the market, the remaining optimists should not pay for the short-sale constrained stocks as much as they do when they are aware of the bad historical performance of such stocks.[2] The informed short sellers argument suggests not only that short sellers short "bad" shares, but also that other investors fail to correctly process the information in short interest even after it is revealed to them. It is not quite surprising that heavily shorted stocks do poorly after they are shorted, but it is surprising, if one believes in investors' rationality, that

[1] This last sentence takes a step outside of the Diamond and Verrecchia model, because in their model prices are unbiased.

[2] Duffie et al (2002) introduce bargaining power over lending fees and shows that, in a dynamic model and in the presence of irrational optimistic investors, some rational investors are willing to pay a very inflated price.

heavily shorted stocks continue to do poorly (several months into the future) even after everyone in the market learns that they are heavily shorted.

In this paper, we propose an alternative risk-based firm-type explanation on why high RSI firms have lower future returns. In contrast to the two theories above, this explanation does not require the assumption of investors' irrationality. We argue that high RSI firms have lower aggregate volatility risk, that is, they tend to beat the CAPM when expected aggregate volatility unexpectedly increases. The key reason, as shown later, is that high RSI firms turn out to be those with high firm-specific uncertainty and option-like equity[3]. Stocks of firms with high uncertainty and option-like equity are a good hedge against aggregate volatility risk because when aggregate volatility increases in recessions, firm-specific uncertainty also elevates. All else equal, higher idiosyncratic volatility during periods of high aggregate volatility means that option-like equity become less risky (as their delta declines) and more valuable.

Abnormally good performance during periods of increasing aggregate volatility is a desirable feature. Campbell (1993) creates a model where increasing aggregate volatility signals decreasing expected future consumption. For stocks whose value correlates positively with aggregate volatility news, investors would require a lower risk premium because these stocks provide additional consumption precisely when investors have to cut their current consumption for consumption-smoothing motives. Chen (2002) adds the precautionary savings motive to his model and shows that the positive correlation of asset returns with aggregate volatility changes is desirable, because such assets deliver additional consumption when investors have to consume less in order to boost precautionary savings. Ang, Hodrick, Xing, and Zhang (2006) confirm this prediction empirically and coin the notion of aggregate volatility risk. They show that stocks

[3] Equity can be option-like either because equity is a claim on option-like assets (growth options) or because equity itself is an option on the assets due to existence of risky debt.

with the most positive sensitivity to aggregate volatility increases have abnormally low expected returns.

In this paper, we use the previously established negative relation between firm-specific uncertainty and equity option-likeness, on the one hand, and aggregate volatility risk on the other, and argue that high RSI firms have low expected returns because they are a hedge against aggregate volatility risk due to having higher firm-specific uncertainty and more option-like equity.

The negative relation between aggregate volatility risk and various measures of firm-specific uncertainty and equity option-likeness has been empirically confirmed for the full cross-section of stocks in several prior studies: Barinov (2011a) shows that growth firms and high idiosyncratic volatility firms have low aggregate volatility risk. Barinov (2011b, 2013) demonstrates a similar relation between turnover and aggregate volatility risk and disagreement and aggregate volatility risk, respectively.

In empirical tests, we first examine whether high RSI firms have higher uncertainty and more option-like equity. Following Asquith, Pathak, and Ritter (2005), high RSI is benchmarked on either absolute cutoff percent (2.5% and 5% of shares outstanding) or relative cross-sectional percentiles (above the 90^{th} or 95^{th} percentiles of all stocks in each month). Uncertainty is proxied by idiosyncratic volatility (Ang et al, 2006), analyst dispersion on earnings forecast (Diether, Malloy, and Scherbina, 2002), and share turnover (Harris and Raviv, 1993). We use two proxies for equity option-likeness: a firm's market-to-book ratio (a measure of growth options) and the Standard and Poor's credit rating on a firm's long-term debt (a measure of the importance of the real option created by risky debt). We show that high RSI firms indeed have higher levels of firm-specific uncertainty and more option-like equity than low RSI firms or firms in the whole Compustat sample. Since all these measures of firm-specific uncertainty and equity option-likeness were shown to be negatively related to aggregate volatility risk in prior work, we conclude that high short interest firms are also likely to have low aggregate volatility risk.

We start our explanation of the high RSI effect by presenting anecdotal evidence from the most recent recession shows that high RSI firms experience much smaller losses than what is suggested by their market beta from CAPM, implying that high RSI firms behave like a hedge against aggregate volatility risk. We then examine whether the two-factor ICAPM with the market factor and the aggregate volatility risk factor (the FVIX factor) can explain the high RSI effect. The FVIX factor is a factor-mimicking portfolio that tracks daily changes in the VIX index, our proxy for expected aggregate volatility. The VIX index measures the implied volatility of the options on the S&P 100 index, and therefore can serve as a direct measure of the market expectation of aggregate volatility. Ang, Hodrick, Xing, and Zhang (2006) show that at daily frequency VIX has extremely high autocorrelation, which means that its change is a valid proxy for innovation in expected aggregate volatility, the variable of interest in the ICAPM context.

We first confirm the prior finding that high RSI firms have negative CAPM alphas (e.g., Asquith and Meulbroek, 1996, Asquith, Pathak, and Ritter, 2005, Boehme, Danielsen, and Sorescu, 2006). More interestingly, we show that the two-factor ICAPM can explain the negative alphas of high RSI firms. The main reason for this is that high RSI stocks have strong and positive loadings on the FVIX factor. By construction, the FVIX factor earns positive returns when aggregate volatility increases. Therefore, positive FVIX betas in the ICAPM indicate that high RSI firms beat the CAPM prediction when aggregate volatility increases, and thereby behave as a hedge against aggregate volatility risk.

To strengthen our argument that high RSI stocks are a hedge against aggregate volatility risk because they have high uncertainty and option-like equity, we propose several cross-sectional hypotheses: 1) high RSI firms earn negative CAPM alphas only when they have high uncertainty and option-like equity; 2) the difference in the alphas between high RSI firms with high and low uncertainty should shrink in the ICAPM with the FVIX factor; and 3) FVIX betas of high RSI firms should increase in uncertainty and measures of equity option-likeness. While several existing mispricing stories may also explain the first prediction (about the CAPM alphas), the other two predictions (about the ICAPM alphas and the FVIX betas) are new to the literature and enable us to discriminate between our argument and the existing mispricing explanations.

Consistent with these predictions, we find that high RSI stocks with low uncertainty have zero CAPM alphas. At the same time, the CAPM alphas of high RSI and high uncertainty firms are between -1% and -2% per month and highly significant. Most importantly, we add two new findings. First, the ICAPM with the FVIX factor shrinks significantly (by more than half and in many cases makes the alphas insignificant) the CAPM alphas of high RSI high uncertainty firms and their difference from the CAPM alphas of high RSI low uncertainty firms. Second, we also observe that the FVIX betas of the high RSI firms with high uncertainty are significantly more positive than those of the high RSI firms with low uncertainty. The FVIX betas suggest that the negative CAPM alphas of high RSI high uncertainty firms arise because these firms beat the CAPM during the periods of increasing aggregate volatility. These new cross-sectional findings provide more convincing evidence on our risk-based firm-type explanation.

The ICAPM with the FVIX factor is also able to explain why the high RSI effect is stronger among firms with low institutional ownership (Asquith, Pathak, and Ritter, 2005). Asquith, Pathak, and Ritter interpret institutional ownership (henceforth IO) as a measure of potential supply of shares to short sellers. They attribute the stronger high RSI effect for low IO firms to more binding short sale constraints (both high demand for and low supply of shares to short). We provide evidence that this pattern is related to the fact that institutions prefer to hold shares with lower uncertainty (see, e.g., Del Guercio, 1996, Falkenstein, 1996), and show that high RSI firms with low IO have higher uncertainty measures and more positive FVIX betas than high RSI firms with high IO.

Also consistent with our cross-sectional predictions, we find that high RSI firms earn negative CAPM alphas only if these firms have either high market-to-book or bad credit rating. This result is consistent with both our argument and the mispricing arguments. However, we further show that the ICAPM with FVIX factor materially reduces these alphas and in most cases makes them insignificant. This is important because it suggests that the ICAPM explanation goes beyond the mispricing stories. The primary reason for the dramatic reduction in alphas is again the strongly positive FVIX betas of the high RSI firms with option-like equity, versus the small to negative FVIX betas of the high RSI firms with less option-like equity.[4]

To further strengthen the argument that the negative alphas of high RSI firms are due to the fact that these firms have positive FVIX betas, we also study the source of the relation between RSI and FVIX betas. Using multivariate Fama-MacBeth regressions, we come to the conclusion that short sellers inadvertently load on FVIX while targeting firms with high uncertainty[5] and option-like equity. The positive relation between FVIX and RSI is subsumed by the positive relation between RSI and uncertainty/equity option-likeness, and the regressions of changes in RSI on changes in firm characteristics find that short sellers react to increases in firm-specific uncertainty and equity option-likeness by shorting more, but do not immediately react to changes in FVIX betas.

We show that high RSI firms beat the CAPM when aggregate volatility increases, but we note that this does not necessarily indicate that these firms gain value when aggregate volatility increases. Since the market return and aggregate volatility are strongly negatively correlated (the

[4] We also examine other growth option proxies such as sales growth, investment growth, and R&D-to-assets and obtain qualitatively similar results.
[5] To our knowledge, our paper is the first in the literature to document the positive relation between RSI and firm-specific uncertainty (suggesting that short sellers attempt to trade on the anomalies documented in Ang et al., 2006, and Diether et al., 2002).

monthly correlation between the market factor and the change in VIX is -0.69), a positive FVIX beta does not imply that the asset gains value when aggregate volatility increases. Any asset with a positive CAPM beta should lose when aggregate volatility increases, but an asset with a positive FVIX beta *loses less* than what the CAPM predicts. The positive loadings of high RSI stocks on the FVIX factor imply that when aggregate volatility increases, high RSI stocks lose value, but they lose much less than other stocks with similar market betas. In this sense, we call them a hedge against aggregate volatility risk.

To provide further empirical validation to our main argument, we also perform two important robustness checks on our results. One traditional approach to measuring risk and changes in risk is the conditional CAPM. In the conditional CAPM, stocks with procyclical market betas (lower in recessions, higher in expansions) should have lower expected returns than what the CAPM implies. We show that high RSI firms have procyclical market betas, and the betas are even more procyclical for the high RSI stocks with high uncertainty, option-like equity, or low IO.

Second, we replace the FVIX factor by the variable it mimics – the change in the VIX index. We find that high RSI stocks load positively on the VIX change, which provides direct evidence that high RSI firms beat the CAPM when aggregate volatility increases. We also document that the loadings on the VIX change are significantly higher for the high RSI firms with high uncertainty, option-like equity, or low IO.

The main contribution of this paper is that we offer an alternative risk-based firm-type explanation for the high RSI effect. We demonstrate that a substantial part of the high RSI effect is explained by the ability of high RSI firms to hedge against aggregate volatility risk. This explanation complements the existing theories that focus on short sales constraints (Miller, 1977) and informed short sellers. We show that, once aggregate volatility risk is controlled for, these two arguments play a significantly smaller role in explaining the high RSI effect.

The rest of the paper is organized as follows. Section 2 presents data used in our analysis. Section 3 reports univariate results on high RSI stocks. Section 4 examines high RSI stocks in various cross-sections. Section 5 considers the conditional CAPM results, and Section 6 studies the determinants of short interest. Section 7 performs robustness checks on the main finding, and Section 8 concludes.

2. Data Sources

The level of short interest in individual stocks is reported to the exchanges by member firms on the 15th calendar day of every month (if it is a business day).[6] RSI is based on outstanding short position, divided by concurrent number of shares outstanding. It is available at monthly frequency for the period between January 1988 and December 2010.[7]

We obtain data on stock returns, price, share volume, shares outstanding from CRSP. All common domestic stocks (CRSP codes 10 and 11) listed on major exchanges are included. We use monthly cum-dividend returns from CRSP and complement them by the delisting returns from the CRSP events file.[8]

Measuring uncertainty and equity option-likeness can be challenging because they are not directly observable. Our strategy here is to adopt a number of proxies used in the literature so that our results are not proxy-specific. Motivated by prior literature, we use three proxies for firm-level uncertainty: idiosyncratic volatility (Ang et al., 2006), analyst disagreement on earnings (Diether et al., 2002, Barinov, 2012b), and share turnover (Harris and Raviv, 1993).

[6] Exchanges report short interest twice per month since September 2007. To be consistent with short interest data from earlier period, we keep the data at the monthly frequency.
[7] Nasdaq short interest data start from July 1988.
[8] Following Shumway (1997) and Shumway and Warther (1999), we set delisting returns to -30% for NYSE and AMEX firms (CRSP exchcd codes equal to 1, 2, 11, or 22) and to -55% for NASDAQ firms (CRSP exchcd codes equal to 3 or 33) if CRSP reports missing or zero delisting returns and delisting is for performance reasons. Our results are robust to setting missing delisting returns to -100% or using no correction for the delisting bias.

Idiosyncratic volatility is the standard deviation of the residuals from a Fama-French three factor model estimated for each firm-month using daily data. In the estimation, we require at least 15 daily returns to estimate the model and idiosyncratic volatility. The returns to the three Fama-French factors and the risk-free rate are from the website of Kenneth French at http://mba.tuck.dartmouth.edu/pages/faculty /ken.french/.

Analyst disagreement is a commonly used proxy for uncertainty. Analysts produce useful information to investors. The more uncertainty a firm's earnings are, the more analysts tend to disagree with each other. Disagreement is measured as the standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year scaled by the absolute value of the average outstanding earnings forecast. This measure excludes zero-mean forecasts and forecasts by only one analyst.

Share turnover also proxies for a firm's uncertainty. Harris and Raviv (1993) argue that investors trade more when they disagree about the asset value. Barinov (2011b) shows empirically that turnover is strongly related to several volatility and uncertainty measures. We define turnover as trading volume divided by shares outstanding (both from CRSP). To make comparisons across exchanges more meaningful, we adjust NASDAQ volume for the double counting following Gao and Ritter (2010).[9] In the paper, we use an annual measure of turnover, which is the average monthly turnover in the previous calendar year with at least 5 valid observations.

We adopt two proxies commonly used for equity option-likeness. The first proxy, market-to-book ratio, is used extensively in the literature to proxy for a firm's growth opportunities (e.g., Fama and French, 1993, 1996, 2008). It is computed from Compustat data as

[9] NASDAQ volume is divided by 2 for the period from 1983 to January 2001, by 1.8 for the rest of 2001, by 1.6 for 2002-2003, and is unchanged after that. A firm is classified as a NASDAQ firm if its CRSP events file listing indicator - exchcd - is equal to 3.

the market value at the fiscal year end (CSHO times PRCC from the new Compustat files) divided by the book value of equity (CEQ plus TXDB from the new Compustat files).[10]

Second, we use S&P credit rating to measure the importance of the real option created by the existence of risky debt (the firm's equity is a call option on its assets). S&P credit rating is the variable SPLTICRM from the Adsprate Compustat file. Following the literature, we transform the credit rating into numerical format (1=AAA, 2=AA+, 3=AA, ... , 21=C, 22=D), with higher value indicating lower credit quality. As a firm gets closer to being bankrupt (i.e., the shareholders are more likely to exercise the option created by leverage), the firm's equity is more option-like.[11]

We also use Thompson Financial 13F database to obtain data on institutional ownership (IO). IO is the sum of institutional holdings divided by the shares outstanding from CRSP. If a stock is in CRSP, but not in Thompson Financial 13F database, it is assumed to have zero IO if the stock's capitalization is above the 20th NYSE/AMEX percentile, otherwise its IO is assumed to be missing. Following Nagel (2005), we also look at residual IO to eliminate the high correlation between size and IO. Residual IO is the residual from the logistic regression of IO on log size and its squared value, where the regression is fitted to all firms within each separate quarter.

[10] We also use sales growth (defined as (sales(t)-sales(t-1))/sales(t-1)), investment growth (defined as (capex(t)-capex(t-1))/capex(t-1))) and R&D-to-assets ratio to proxy for growth opportunities. Results are qualitatively similar and thus not tabulated.

[11] A firm's leverage can be an alternative measure of the equity option-likeness created by debt, but we choose credit rating instead, because leverage is mechanically negatively correlated with market-to-book (the firm's market cap is both in the numerator of market-to-book and the denominator of leverage). In further tests, where we predict that the effect of RSI on future returns is stronger for the firms with option-like equity (high market-to-book or high leverage), it is inevitable that either market-to-book or leverage will not generate the predicted results because of the mechanical negative link between them. For example, if the negative RSI effect on future returns is stronger for high market-to-book firms, it has to be also stronger for low leverage firms, because low leverage firms have much higher market-to-book than high leverage firms. The correlation between credit rating and market-to-book is weaker than the correlation between market-to-book and leverage. Hence, sorts on credit rating are more likely to create a test independent of the results of the sorts on market-to-book.

3. Univariate analysis

3.1. High RSI and firm characteristics

The current literature on short selling is silent about aggregate volatility risk, yet investigating this potential risk is both theoretically and empirically motivated (Campbell, 1993, Ang et al., 2006, Barinov, 2011a). We argue that high RSI firms have low expected returns because they have lower aggregate volatility risk.

To examine whether aggregate volatility risk can explain the low expected returns to high RSI firms, we first check whether high RSI firms indeed have high uncertainty and option-like equity. We perform this step in this section with the only intent of showing that high RSI firms tend to be of the type that is the least exposed to aggregate volatility risk, as shown by existing research. We discuss why short sellers may want to short these firms in Section 6.

We define high RSI based on both absolute cutoff percent and relative cross-sectional percentiles, as in Asquith, Pathak, and Ritter (2005). The first approach defines firms with short interest greater than 2.5% and 5% of shares outstanding as high RSI firms. The second approach identifies stocks based on their short interest relative to other firms. This is important because RSI has increased substantially over time (Asquith, Pathak, and Ritter, 2005). We rank all firms according to RSI every month, and firms above the 90th (95th) percentiles are classified as high RSI firms. Because short interest information is collected in the middle of a calendar month and published close to the end of that month, we form monthly short interest portfolios on the basis of whether a firm's RSI is high during the previous month.[12] This timing is important: in an efficient market, informed short sellers should be making profits prior to the date when short interest is revealed to the public; but after short interest becomes publicly available, it should not predict abnormal returns.

[12] We also use 10% and 99th percentile in our analysis and find similar results. We do not report them due to small sample sizes.

Table 1 compares the median characteristics of high RSI firms to the medians of low RSI firms (with RSI below the 90th percentile) and firms in the Compustat universe.[13] We first look at the uncertainty measures. The idiosyncratic volatility in Table 1 is reported in percents per day: for example, 0.027 for the stocks with RSI above the 90th percentile means that, on average, these stocks have idiosyncratic volatility of 2.7% per day. The analyst disagreement of 0.061 for the same stocks means that the standard deviation of the EPS forecasts for these stocks is 6.1 cents for each dollar of EPS. For an average stock with RSI above the 90th percentile 15.8% of shares outstanding change hands each month.

Table 1 shows that high RSI firms indeed have significantly higher uncertainty than low RSI firms and Compustat firms. For example, the median analyst disagreement for high RSI firms is 28-38% higher than for low RSI firms and 15-25% higher than for all Compustat firms. Likewise, the turnover of a representative high RSI firm is more than twice higher than the turnover of the median low RSI firm or the turnover of the median Compustat firm. The higher analyst disagreement and higher idiosyncratic volatility of high RSI firms stand out despite the fact that high RSI firms are two-thirds larger than low RSI firms and Compustat firms.

It is interesting to note that in the high RSI sample all measures of uncertainty increase with RSI. Specifically, the median uncertainty of the stocks in the 95th percentile is higher than the median uncertainty of the stocks in the 90th percentile, and the same is true for absolute cut-offs.[14]

Proceeding to equity option-likeness, we find similar patterns. Specifically, high RSI firms have higher market-to-book and lower credit rating quality than low RSI firms or Compustat firms, which suggests that high RSI firms possess more option-like equity than low

[13] Inferences from comparisons are similar when low RSI is defined using alternative cut-offs (e.g. median RSI or RSI=2.5%).

[14] In fact, the uncertainty measures get even larger for 99th percentile or 10% cut-off, which we do not report due to smaller sample sizes.

RSI firms or Compustat firms. High RSI firms have median market-to-book ratio of around 2.5, compared to the median market-to-book ratio of around 2 for low RSI firms and Compustat firms. The credit rating of the representative firm in the high RSI sample is BB or BB-, worse than the credit rating of BBB+ (BBB) for the median low RSI firm (the median Compustat firm).

Table 1 also compares average raw returns of high RSI stocks to the average raw returns of other stocks. The monthly raw returns of high RSI stocks hover around 50 basis points. This is significantly different from the average return to all Compustat firms (around 0.9% per month) or to low RSI firms (around 1.2% per month). In untabulated results, we find that the average return of high RSI firms is statistically indistinguishable from the average risk-free rate (0.325% per month) in our sample period. It is striking that high RSI stocks earn only slightly more than the risk-free rate, suggesting that they should be a hedge against an important risk.

Taken collectively, Table 1 reveals that high RSI firms indeed have high uncertainty, option-like equity, and low expected returns. In the rest of the paper, we will show that the high uncertainty and option-like equity of high RSI firms are the main reason why these firms have low expected returns.

3.2. The aggregate volatility risk factor

The main asset pricing model we apply is the two-factor ICAPM with the market factor and the aggregate volatility risk factor (the FVIX factor). We describe the aggregate volatility risk factor in this section.

We form the FVIX factor as the zero-investment portfolio that tracks daily changes in the VIX index. We regress daily changes in VIX on the daily excess returns to five quintiles sorted on the return sensitivity to changes in VIX. The sensitivity is the loading on the VIX change from the regression of daily stock returns in the past month on the market return and change in VIX.

The factor-mimicking regression uses all available data from January 1986 to December 2010. The FVIX factor is the fitted part of the regression less the constant. To obtain the monthly values of FVIX, we compound its daily returns. All results in the paper are robust to using other base assets instead of the VIX sensitivity quintiles, such as the 10 industry portfolios (from Fama and French, 1997) or the six size and book-to-market portfolios (from Fama and French, 1993).[15]

The factor-mimicking regression has rather high goodness-of-fit: its R-square is 49%. Consequentially, the correlation between change in VIX and FVIX returns is 0.69, suggesting that FVIX is a good factor-mimicking portfolio. We also find that, excluding the expectedly tight correlation between FVIX and MKT, FVIX is largely unrelated to other known priced factors, such as SMB, HML, and MOM. The highest correlation, 0.2, is between FVIX and HML, which is not surprising given the relation between growth options and aggregate volatility risk documented in Barinov (2011a). In untabulated results, we also look at the factor premium of FVIX. By construction, FVIX is a zero-investment portfolio that yields positive return when expected aggregate volatility increases. Hence, holding FVIX means having an insurance against increases in aggregate volatility. Therefore, FVIX has to earn significantly negative return even after other sources of risk have been controlled for. Consistent with that, the raw return to FVIX is -1.21% per month (t-statistic -3.4), and the CAPM alpha of FVIX is -48 bp per month (t-statistic -3.73).

Barinov (2012) uses the Gibbons et al. (1989) (GRS) test and finds that adding FVIX to the CAPM or Fama-French model significantly reduces pricing errors for several sets of

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[15] Ang et al (2006) use a very similar factor-mimicking portfolio. The only difference is that they perform the factor-mimicking regression of VIX changes on the excess returns to the base assets separately for each month. Clearly, the estimates of six or seven parameters using 22 data points are not too precise, and it is especially true about the constant, which varies considerably month to month. This variation adds noise to their version of FVIX, and the imprecise estimation of the constant makes the FVIX factor premium small and insignificant. In unreported results we find that the Ang et al (2006) version of FVIX is significantly correlated with our version of FVIX and produces the betas of the same sign. However, the use of the Ang, Hodrick, Xing, and Zhang (2006) version of FVIX in asset-pricing tests is problematic because of the noise in it and the small factor premium.

portfolios, such as industry portfolios, five-by-five size and market-to-book sorts, five-by-five size-momentum sorts, etc. In untabulated results, we also perform the GRS test for the sorts on RSI and find that FVIX is capable of reducing pricing errors for this portfolio set as well.

3.3. High RSI stocks during the recent recession

Before we conduct some formal tests with ICAPM model, we present some anecdotal evidence on high RSI firms from the most recent recession characterized by elevated aggregate volatility risk. Figure 1 shows the cumulative performance of the market (CumMKT), high RSI firms (CumHigh RSI), and the CAPM prediction of the performance of high RSI firms (CumMKT*Beta). All cumulative returns start at 1 on December 1, 2007.

The CAPM regression (untabulated) shows that the market beta of high RSI firms is 1.47. Hence, during the 18 recessionary months in the graph, when the market lost 35.6%, CAPM prediction suggests that high RSI firms should have lost much more, 49.75% (CumMKT*Beta). However, high RSI firms did not even lose as much as the market, despite their high beta. In fact, their cumulative returns (CumHigh RSI) stayed very close to the cumulative returns to the market (CumMKT), and by the end of the recession it turns out that high RSI firms lost only 33.7%.

The discrepancy between the realized returns to high RSI firms and the CAPM prediction is summarized by the cumulative abnormal return line (CAR). Beyond showing that cumulative abnormal return to high RSI firms are around 30% (≈(1-0.337)/(1-0.4975)-1) by the end of the recession, the CAR line also shows that the difference between the actual performance of high RSI firms and the CAPM prediction of their performance starts around June 2008, when the true market decline started. In fact, when we look at the period between June 2008 and March 2009, when almost all the market losses and high volatility episodes of the last recession happened, we find that out of the ten months, the abnormal return to high RSI firms are negative only once, and only slightly so. Even more, about 85% of the positive CAR to high RSI firms during the last recession (December 2007 – June 2009, 18 months) accrued during the ten months (June 2008 – March 2009) when all the action happened.

The analysis of the performance of high RSI firms during the recent crisis makes us cautiously optimistic about the ability of FVIX to explain the high RSI effect. Even though high RSI firms witness losses comparable to the losses of the market, and therefore seem risky, their losses are not nearly as large as their market beta would suggest. Hence, while it is unlikely that FVIX will completely explain why high RSI firms earn close to the risk-free rate in the last two decades, it is also clear that the CAPM overestimates the negative alphas of high RSI firms by over-adjusting their returns for risk.

3.4. High RSI firms in the two-factor ICAPM

We start our formal asset pricing tests by first checking whether high RSI stocks generate negative CAPM alphas in our sample. This is confirmed by the data. Panel A of Table 2 shows that high RSI portfolio has equal-weighted CAPM alphas ranging from -67 bp to -102 bp per month, with t-statistics ranging from -2.74 to -3.73. Using other models like the Fama-French model or the Carhart model also yields similar negative alphas.

A significant part of the alphas comes from the fact that the market betas of high RSI firms are quite high, around 1.5 (untabulated). That is, the CAPM estimates that high RSI firms are significantly riskier than average. However, their average raw returns, as we have seen from Table 1, are more like the returns of zero-beta firms. Therefore, high RSI firms behave as a hedge against an important risk.

Our key argument is that high RSI firms have negative CAPM alphas because they beat the CAPM when aggregate volatility increases. Their ability to be a hedge against aggregate volatility risk comes from their high firm-specific uncertainty and option-like equity (see Table

1). Given these firm features, we predict that in the ICAPM with the FVIX factor they should load positively on FVIX (the returns to the FVIX factor are positively correlated with VIX changes by construction) and their negative alphas should disappear in the ICAPM.

We estimate the two-factor ICAPM in Panel B. The alphas of high RSI firms indeed decline by more than half from their CAPM values and become insignificant at the 5% level. The key reason for the success of the ICAPM is the FVIX betas. The FVIX betas in Panel C are strongly positive in all cases, suggesting that high RSI firms beat the CAPM when aggregate volatility increases and therefore are hedges against aggregate volatility risk.[16]

Taken together, the above results strongly suggest that a significant part of the alphas of high RSI firms comes from the fact that the CAPM (and other asset pricing models) overestimates their risk. According to the CAPM, high RSI stocks should have disastrous performance when the market goes down, which makes the average returns to high RSI stocks (around the risk-free rate) hard to understand. The ICAPM with the FVIX factor points out that the performance of high RSI firms during market downturns is far from being that bad, since their value gets a boost from the impact of higher idiosyncratic volatility in downturns on their option-like equity. Therefore, the total risk of high RSI firms is below average, and one cannot conclude definitely that their average return is an insufficient reward for its risk (though point estimates seem to indicate that it is more likely to be insufficient than not).[17]

Prior research (see, e.g., Boehmer et al., 2008) also suggests a low RSI effect of positive alpha of low RSI firms. While studying the low RSI effect is beyond the scope of the paper, it is interesting to gauge whether FVIX can help explaining it. In untabulated results, we find, somewhat contrary to our expectations, that low RSI firms (with RSI in the bottom RSI quintile)

[16] In unreported results, we repeat the tests in this section using value-weighted returns. We find that the high RSI effect is expectedly weaker, though still significant, in value-weighted returns (the alphas of high RSI are between -30 bp and -60 bp per month). We also find that the aggregate volatility risk explanation of high RSI effect is even stronger in value-weighted returns, since the FVIX betas of high RSI firms are larger, have higher t-statistics, and the ICAPM alphas of high RSI firms are within 6 basis points of zero.

are even more volatile than high RSI firms, despite having lower market-to-book and same credit rating as high RSI firms. We do not expect therefore that low RSI firms will have significantly negative FVIX beta that would explain their positive alpha. This is what we find when we look at quintile RSI portfolios. The low RSI effect of Boehmer et al. (2008) exists only in equal-weighted returns, and FVIX is unable to explain it: in equal-weighted returns, dominated by small volatile firms, the FVIX beta of low RSI firms is still positive, though smaller than the FVIX beta of high RSI firms. In value-weighted returns, we do find a significantly negative FVIX beta of low RSI firms, but it is not helpful either because of the lack of the low RSI effect in value-weighted returns.

4. High RSI effect in the cross-section

In the previous section, we have shown that high RSI firms have negative CAPM alphas because they are a hedge against aggregate volatility risk. This argument is supported by the evidence that high RSI firms have high firm-specific uncertainty and option-like equity. This further leads to the prediction that the high RSI effect and, most importantly, the aggregate volatility risk explanation should be stronger for the firms with higher levels of uncertainty and/or more option-like equity. In this section, we perform single sorts on the uncertainty measures and measures of equity option-likeness in the high RSI sample. We refrain from performing double sorts of high RSI stocks on both uncertainty and equity option-likeness, because the high RSI subsample consists of only several hundred stocks, and any sensible double sorts (e.g., three-by-three, nine groups) produce underdiversified portfolios with the number of stocks in low double digits.

Extending our main hypothesis, we make the following cross sectional predictions:

- The CAPM alphas of high RSI firms with low uncertainty measures or non-option-like equity measures are zero.

- The CAPM alphas of high RSI firms significantly increase in uncertainty and real option measures
- The ICAPM alphas of high RSI firms are significantly reduced in all uncertainty and equity option-likeness groups and do not depend on either uncertainty measures or measures of equity option-likeness
- FVIX betas of high RSI firms significantly increase in uncertainty and real option measures

We note that although existing mispricing theories may also explain the first two predictions, the last two predictions are not discussed in the previous literature and allow us to differentiate between our risk-based explanation and existing mispricing arguments.

4.1. High RSI effect and uncertainty sorts

In this section, we examine high RSI effect sorted on proxies for uncertainty. Our basic sorting procedure is the same. Every month, we sort the high RSI stocks into terciles according to one proxy for uncertainty at month t-1 and report their equal-weighted CAPM alphas, equal-weighted ICAPM alphas, and FVIX betas at month t.[18]

4.1.1. High RSI effect and idiosyncratic volatility

We first examine the sorts of high RSI stocks on idiosyncratic volatility. In the left part of Panel A of Table 3, we observe that high RSI stocks with low idiosyncratic volatility have zero CAPM alphas, consistent with the first prediction. At the same time, the CAPM alphas of high

[18] In unreported results, we repeat the tests in this and subsequent sections using value-weighted returns and reach the same conclusions as in the previous sections. In value-weighted returns, the CAPM alphas of high RSI firms are uniformly smaller, though they still routinely top -1% per month for high uncertainty firms, firms with option-like equity, and firms with low institutional ownership. The aggregate volatility risk explanation of the high RSI effect is even stronger in value-weighted returns, since value-weighted FVIX betas of high RSI firms are generally larger and more significant, and value-weighted ICAPM alphas of high RSI firms are closer to zero.

RSI stocks with high idiosyncratic volatility range from -1.57% to -2.03% per month and are highly significant, consistent with the second prediction. The magnitudes of the CAPM alphas of high volatility high RSI stocks are extreme, but they are comparable with previous studies.

The next two sections of Panel A present the test that discriminates between our story and the mispricing story in the literature based on Miller (1997). In the middle section of Panel A, the patterns of the ICAPM alphas are largely consistent with our third prediction. Specifically, the ICAPM with the FVIX factor reduces the alphas of high RSI stocks with medium idiosyncratic volatility from about more than 50 bp per month and statistically significant, to almost zero and insignificant. Noticeably, the ICAPM also reduces by about 80 bp per month (about half) the huge CAPM alphas of high RSI firms with high idiosyncratic volatility and their difference with the CAPM alphas of high RSI firms with low idiosyncratic volatility.

The right portion of Panel A also presents further evidence in support of the last prediction: among the high RSI stocks, the FVIX betas start at zero for stocks with low idiosyncratic volatility and increase monotonically and significantly with idiosyncratic volatility. The FVIX betas suggest that the ability of high RSI firms to hedge against aggregate volatility is absent for high RSI stocks with low idiosyncratic volatility and increases with idiosyncratic volatility.

The evidence in the middle and right sections of Panel A is consistent with the aggregate volatility risk explanation of the high RSI effect, but not with its mispricing explanation. First, by definition, the part of the CAPM alpha that is explained by covariance with an additional risk factor is not mispricing. Second, the mispricing theories of the high RSI effect make no prediction about the covariance of returns to high RSI firms and innovations to aggregate volatility. Indeed, it is hard to imagine why the absence of pessimistic traders in the market due to short-sale constraints (the Miller (1977) explanation of the high RSI effect) should make the returns covary more with changes in VIX.

4.1.2. High RSI effect and analyst disagreement

Panel B of Table 3 reports the CAPM alphas, ICAPM alphas and FVIX betas of high RSI portfolios sorted on analyst forecast dispersion. In the left part of Panel B, we observe, consistent with our first prediction, high RSI stocks with low dispersion have zero CAPM alphas. In line with the second prediction, the CAPM alphas of high RSI stocks increase with analyst disagreement. The CAPM alphas of high RSI, high disagreement stocks range between -0.79% to -1.15% per month, with t-statistics between -2.6 and -3.35. The difference in the CAPM alphas between high RSI, high disagreement stocks and high RSI, low disagreement stocks is highly statistically significant.

When controlling for aggregate volatility risk (the middle part of Panel B), the ICAPM reduces by more than 50 bp per month (more than half) the CAPM alphas of high RSI firms with high analyst disagreement and their difference with the CAPM alphas of the high RSI firms with low analyst disagreement, and in most cases the ICAPM alphas are statistically insignificant. These changes in alphas support the third prediction.

The reason for the reduction in alphas becomes clearer if one looks at the FVIX betas in the right part of Panel B. The FVIX betas of the high RSI stocks with high analyst forecast dispersion are significantly more positive than those of the high RSI, low dispersion stocks, consistent with the fourth prediction. The patterns of FVIX betas suggest that high RSI stocks with high analyst forecast dispersion react less negatively to increases in aggregate volatility than high RSI stocks with low analyst forecast dispersion.

4.1.3. High RSI effect and share turnover

Lastly, we examine share turnover. The more investors disagree about the firm value, the greater is their incentive to trade and the higher the turnover is (Harris and Raviv, 1993). The left part of Panel C in Table 3 shows that the CAPM alphas are not significant in three out of four cases among high RSI stocks with low turnover. In sharp contrast, the CAPM alphas are highly significant for high RSI stocks with high turnover. This is generally consistent with our view that high RSI predicts low returns because high RSI, on average, means more disagreement. If the disagreement is fairly low, high RSI does not predict lower returns.

The two-factor ICAPM with FVIX significantly reduces the alpha of high RSI firms with medium and high turnover. The magnitude of the reduction in the alphas is 38 to 70 bp, which is more than half of their CAPM values. After controlling for FVIX, the difference in the alphas between high RSI stocks with high turnover and low turnover decreases from about -90 bp per month, to less than -50 bp.

We again find evidence in support of the prediction on the FVIX betas. The FVIX betas of the high RSI firms with high turnover are strongly positive, in contrast to the ones of the high RSI firms with low turnover, which are significantly lower and sometimes insignificant. The difference in FVIX betas between high RSI firms with low and high turnover indicates that the higher CAPM alphas of these firms can be at least partly explained by the fact that these stocks react less negatively to increasing aggregate volatility.

4.1.4. Aggregate volatility risk and the Miller (1977) story

Miller (1977) also predicts that the alphas of high RSI, high disagreement stocks will be more negative than the alphas of high RSI stocks with low disagreement. Under the Miller (1977) story, higher costs of shorting keep the pessimistic traders out of the market, and the market price represents the average valuation of the optimists. With larger disagreement, the average valuation of optimists is also higher, i.e., the stock is more overpriced and will have lower returns going forward as the price is corrected.

Our analysis in this section points to an alternative explanation of why high RSI stocks with higher disagreement have more negative alphas. The discriminating test is the ICAPM with FVIX: we show that high RSI, high disagreement stocks are the best hedges against aggregate volatility risk, which can explain from one-third to half of what would otherwise be interpreted as mispricing and, in several cases, can leave the rest insignificant. The decline in the alphas after FVIX is controlled for is consistent with our explanation, but not the Miller (1977) explanation for two reasons. First, Miller (1977) predicts that heavily shorted stocks are mispriced, but the part of the CAPM alphas that can be explained by an additional risk factor, by definition, is not mispricing. Second, it is unlikely that the high shorting fees of short-sale constrained (heavily shorted) stocks will make their returns covary more positively with changes in VIX and produce positive FVIX betas.

Despite the clear distinction between the parts of the high RSI effect that can be explain by the Miller story and the aggregate volatility risk story, these two explanations of the high RSI effect are not mutually exclusive in the sense that they can be both at work and can both be explaining a part of the high RSI effect. Rather, our results suggest that both stories are likely to coexist – 40-75% of what is believed to be the overpricing of high RSI, high disagreement firms is in fact a reward for their lower aggregate volatility risk, but the rest may be due to mispricing, as Miller (1977) predicts.

4.2. High RSI effect and institutional ownership

Asquith, Pathak, and Ritter (2005) find that the high RSI effect is stronger for firms with low institutional ownership (IO). Viewing RSI as demand for and IO as a potential supply of shares to short sellers, they argue that high RSI, low IO stocks face more binding short sales constraints, and therefore have more negative CAPM alphas. Their interpretation is the Miller (1977) story: higher costs of short sale mean overpricing, and the costs of short sale are the highest if both demand (RSI) is high and supply (IO) is low. As will be shown next, this may not be the whole story and aggregate volatility risk also plays a role.

In the left part of Panel A of Table 4, we confirm the results in Asquith, Pathak, and Ritter (2005) for our time period. We sort high RSI stocks into terciles according to their IO in the previous quarter. The CAPM alphas for high RSI, low IO stocks range from -0.94% to -1.3% per month, while the alphas for high RSI and high IO are not significantly different from zero.

Shleifer and Vishny (1997) show that institutions should prefer to hold stocks with low levels of volatility or uncertainty. Their argument is two-fold: first, portfolio managers feel underdiversified, because their personal wealth largely depends on the performance of the portfolio they manage, and they therefore want to avoid idiosyncratic volatility as much as possible. Second, higher idiosyncratic volatility means a higher probability that even the correct bets on mispriced stocks will have to be called off due to margin calls and cash outflows. Del Guercio (1996) and Falkenstein (1996) confirm empirically that IO is negatively related to idiosyncratic volatility.

We also find that in the high RSI sample, stocks with low IO indeed have higher idiosyncratic volatility and higher analyst disagreement (untabulated). The difference between low and high IO is substantial: the median analyst forecast dispersion of high RSI firms with low IO is three times higher than that of high RSI firms with high IO. This implies that in the high RSI sample sorting on IO is similar to sorting on uncertainty (in reverse order). High RSI, low IO stocks provide a good hedge against aggregate volatility risk, just as high RSI, high uncertainty stocks do.

In the middle part of Panel A of Table 4, we report the ICAPM alphas, which provide a discriminating test between our story and the story in Asquith, Pathak, and Ritter (2005). If IO is related to the RSI effect because of the relation between IO and idiosyncratic volatility/disagreement and the consequent relation between IO and aggregate volatility risk, we will see the dependence of the RSI effect on IO significantly reduced in the ICAPM alphas.

This is what we observe in Panel A: the alphas of high RSI, low IO stocks diminish to about half of the respective CAPM alphas. The difference in the alphas between high RSI, low IO stocks and high RSI, high IO stocks also declines from about 80 bp per month in the CAPM to about 40 bp per month in the ICAPM.

The right portion of Panel A reports the FVIX betas. We observe large and positive FVIX betas of high RSI, low IO stocks. This is the key reason why ICAPM can explain the negative CAPM alphas. The large positive FVIX betas of high RSI, low IO stocks indicate that these stocks beat the CAPM by a wide margin when aggregate volatility increases, and therefore have much lower risk than what the CAPM estimates. This contrasts with the small and insignificant FVIX betas of high RSI, high IO stocks.

One may be concerned that institutional ownership is highly correlated with size, and what we observe in Panel A of Table 4 could be driven by size/liquidity effect. To address this concern, we follow Nagel (2005) and compute residual IO, which is orthogonal to size (see more details in the data section). Panel B of Table 4 replaces the IO with the residual IO. We observe nearly identical results in Panel B. Controlling for FVIX materially reduces not only the alphas of high RSI stocks with low residual IO but also the difference of these alphas with the alphas of high RSI stocks with high residual IO. The FVIX betas start small and marginally significant for high RSI stocks with high residual IO, and increase strongly and monotonically as residual IO decreases.

Taken together, the ICAPM can offer another explanation for the low returns of high RSI, low IO firms documented in Asquith, Pathak, and Ritter (2005). Compared to high RSI, high IO firms, firms with high RSI and low IO have more negative CAPM alphas because they have higher uncertainty and therefore lower aggregate volatility risk. We find that about half of the results in Asquith, Pathak, and Ritter (2005) can be attributed to aggregate volatility risk.

The arguments in Section 4.1.4 apply to this section as well. Both the Asquith et al. explanation and the aggregate volatility explanation can be driving the relation between the high RSI effect and IO. However, the parts of this relation they explain are clearly different. The part of the relation in the CAPM alphas (the left part of Table 4) that is explained by controlling for FVIX is due to aggregate volatility risk, not mispricing, because mispricing, by definition, is the part of the expected return unexplained by covariance with a risk factor.

4.3. High RSI effect and option-like equity

We now test our predictions with respect to equity option-likeness. The first measure of equity option-likeness we consider is market-to-book ratio. Market-to-book ratio is commonly used to proxy for a firm's growth options. The higher is the market-to-book ratio, the more growth options the firm has. We then use the Standard and Poor's credit rating on a firm's long-term debt to proxy for equity option-likeness created by the existence of risky debt. Worse credit rating means higher probability of bankruptcy and higher probability of the forced or voluntary exercise of the call option on assets represented by equity. For firms with good credit rating the probability of bankruptcy is fairly low, and for these firms the fact that their equity is a call option on the assets is relatively unimportant. For firms with poor credit rating, the equity is more option-like.

4.3.1. High RSI effect and market-to-book

In Panel A of Table 5, we sort the high RSI stocks into terciles according to their market-to-book ratios from the previous year, and work with equally-weighted portfolio returns in the next month. The left part of Panel A shows that high RSI firms with high market-to-book earn significantly negative CAPM alphas in the range of -0.77% and -0.97% per month, with t-statistics from -2.69 to -3.15, depending on the RSI cut-off used. Consistent with our first two predictions, these alphas are significantly different from the CAPM alphas of the high RSI, low market-to-book stocks (close to zero).

The main contribution of our research design lies in the ICAPM alphas and FVIX betas. Importantly, the ICAPM alphas are all insignificant. As predicted, the alphas of high RSI, high market-to-book firms decline the most, by more than 50% the CAPM alphas. Moreover, the high RSI firms with high market-to-book ratio load more positively on the FVIX factor than the high RSI, low market-to-book firms. The difference in the FVIX betas is large and statistically significant, supporting our prediction that the high RSI firms with high market-to-book have more negative CAPM alphas because they beat the CAPM by a wider margin when aggregate volatility increases.

4.3.2. High RSI effect and credit rating

In Panel B of Table 5, we sort high RSI stocks into three groups, those with good credit rating (normally BBB+ and above), medium rating, and bad rating (normally B+ and below) in the previous year. Consistent with the first prediction, high RSI firms with good rating do not earn negative CAPM alphas. In contrast, high RSI firms with bad rating earn strong and negative CAPM alphas of -0.88% to -1.25% per month. This supports the second prediction and is consistent with our argument that worse credit rating means that the firm's equity is more option-like.

The ICAPM with the FVIX factor substantially reduces the alphas of high RSI, poor credit rating firms. The alphas decrease by an average of 50 bp per month, or 40-55% of the CAPM values, and become statistically insignificant. The difference in the alphas between the high RSI, bad credit rating firms and high RSI, good credit rating firms, sees a larger reduction by roughly 70 bp per month, or about two thirds of the CAPM alphas. The difference becomes insignificant.

The explanation could be found in the difference in FVIX betas: the strongly positive FVIX betas of stocks with high RSI and bad credit rating, versus the negative FVIX betas of stocks with high RSI and good credit rating. The FVIX betas confirm that a significant part of the difference in the CAPM alphas of the top and bottom portfolios can be attributed to the difference in equity option-likeness and the consequent difference in aggregate volatility risk.

4.3.3. Aggregate volatility risk and the informed short sellers story

Lakonishok, Shleifer, and Vishny (1994) argue that high market-to-book firms are overvalued. Avramov et al. (2009) argue the same about the stocks with bad credit rating. Dechow et al. (2001) and Desai et al (2006) show that short sellers use overvaluation proxies, such as market-to-book, to choose stocks to short, and the use of these proxies generates more profit for short sellers. To the extent that short sellers trade on public signals such as market-to-book and credit rating and other investors do not use the information in RSI, high RSI firms with either highest market-to-book or bad credit rating will have the most negative CAPM alphas. The CAPM alphas observed in Table 5 seem to support the informed short sellers story.

However, the fact that, after controlling for aggregate volatility risk, the alphas decline by 40-55% and become statistically insignificant cannot be explained by the informed short sellers story. The part of the expected return explained by a risk factor is, by definition, not mispricing, but rather a fair compensation for risk. Hence, this part has nothing to do with short sellers targeting overpriced growth or distressed firms. If the only reason heavily shorted firms with high market-to-book or bad credit rating earn low expected returns is their loading on FVIX (and we cannot reject this hypothesis in the middle part of Table 5), then short sellers that short such firms are not really informed, as they are not receiving any abnormal gains from shorting these firms, only expected returns for bearing aggregate volatility risk.

Also, the positive FVIX betas of heavily shorted firms with high market-to-book or bad credit rating cannot be explained by the informed short sellers story. Targeting low-risk firms can be an unintended consequence of targeting overpriced firms, but cannot be a way of earning abnormal gains.

5. High RSI effect in the Conditional CAPM

One traditional approach to measuring risk and changes in risk is the conditional CAPM. In the conditional CAPM, a stock with procyclical market beta (lower in recessions, higher in expansions) should have lower expected returns than what the static CAPM predicts. Barinov (2011a) shows that, as both aggregate volatility and idiosyncratic volatility increase in recession, the value of growth options becomes less sensitive to the value of the underlying asset, and the growth options, therefore, become less risky when risks are high. This effect is more pronounced for more volatile firms and growth firms. Since high RSI stocks have high levels of uncertainty and option-like equity (see Table 1), high RSI firms should have procyclical market betas. The betas of high RSI firms should be more procyclical if these firms have high uncertainty or option-like equity.

To estimate the conditional CAPM, we employ four commonly used conditioning variables: the dividend yield, the default premium, the risk-free rate, and the term premium.[19] The conditional CAPM assumes that the market beta is a linear function of the four conditioning variables above.

[19] We define the dividend yield, DIV, as the sum of dividend payments to all CRSP stocks over the previous 12 months, divided by the current value of the CRSP value-weighted index. The default spread, DEF, is the yield spread between Moody's Baa and Aaa corporate bonds. The risk-free rate is the one-month Treasury bill rate, TB. The term spread, TERM, is the yield spread between ten-year and one-year Treasury bond. The data on the dividend yield and the risk-free rate are from CRSP. The data on the default spread and the term spread are from FRED database at the Federal Reserve Bank at St. Louis.

Table 6 presents the difference in the market betas between recession and expansion for various high RSI portfolios. Recession is defined as the months when the expected market risk premium is above its average value, and expansion takes the rest of the sample. The expected market risk premium is the forecasted excess market return from the regression of realized excess market returns on the previous month values of the four conditioning variables above.

Panel A shows that high RSI firms have procyclical market betas, consistent with the conditional CAPM explanation. The numbers in Table 6 are recession minus expansion beta differentials. A negative number means that the beta of the portfolio in question is lower in recession, that is, the beta is procyclical and the portfolio is less risky than what the static CAPM estimates. Depending on the RSI cut-off we use, we find that in recessions the beta of high RSI firms decreases by 0.10-0.14 (t-statistics are 3 and above).

Compared to other studies that use the conditional CAPM, the change in the beta of high RSI firms is large. For example, Petkova and Zhang (2005) find that the beta of the HML portfolio in 1963-2001 increases by only 0.05 from similarly defined expansion to similarly defined recession. However, even this change is insufficient to explain the negative CAPM alphas of high RSI firms. Assuming that the maximum possible difference in the market risk premium between expansion and recession is 1% per month, the change of 0.14 in the market beta of high RSI firms suggests that the conditional CAPM can diminish the alphas of high RSI firms by at most 14 bp per month, as compared to the CAPM alphas between 0.67% and 1.02% per month (see Table 2). In untabulated results, we look at the alphas of high RSI firms in the conditional CAPM and find that the alphas indeed decline by only 10 bp from their CAPM values and remain highly significant. Hence, it is essential to add the FVIX factor in order to explain the performance of high RSI firms. Yet, the conditional CAPM produces betas that qualitatively support our claim that high RSI firms weather downturns better than what the static CAPM would suggest.

Panel B of Table 6 examines the arbitrage portfolios that buy high RSI, high uncertainty stocks and short high RSI, low uncertainty stocks. These portfolios earn negative CAPM alphas, because, as Table 3 shows, high RSI, high uncertainty firms have more negative CAPM alphas than high RSI, low uncertainty firms. Therefore, we expect that in the conditional CAPM these arbitrage portfolios will have procyclical betas.

The betas in Panel B come out extremely procyclical. Their decrease in recessions varies from close to 0.4 for turnover-based portfolios (long in high RSI high turnover, short in high RSI low turnover) to about 0.5 for idiosyncratic volatility based portfolios (long in high RSI high volatility firms, short in high RSI low volatility firms). Therefore, Panel B provides strong support for the conjecture that high RSI, high uncertainty stocks weather downturns significantly better than high RSI, low uncertainty stocks with similar average market betas.

In Panel C, we look at the change in betas for the portfolios long in high RSI stocks with option-like equity (high market-to-book or bad credit rating) and short in high RSI stocks with non-option-like equity (low market-to-book or good credit rating). We find that the betas of the portfolio that buys high RSI, bad credit rating or high M/B firms and shorts high RSI, good credit rating or low M/B firms are extremely procyclical (the betas drop by about 0.3 in recessions). The evidence in Panel C is largely consistent with our prediction that high RSI firms perform better in market downturns than what the static CAPM predicts only if these firms have option-like equity.

Panel D presents similar portfolios formed using IO. It turns out that the betas of high RSI, low IO firms decrease in recessions by a significantly greater amount than the betas of high RSI, high IO firms. The same conclusion holds if IO is replaced by residual IO. Hence, just as the FVIX betas suggest, during downturns high RSI, low IO firms perform better than high RSI, high IO firms with similar market betas from the static CAPM.

6. Why Short Sellers Short Firms with Positive FVIX Betas?

Our aggregate volatility risk explanation of the high RSI effect is based on two facts that are both empirically and theoretically motivated. First, we use the fact that short-sellers are targeting growth firms and distressed firms (see, e.g., Dechow et al., 2001). This is to be expected, since growth firms and distressed firms are known to have low future returns (see, e.g., Fama and French, 1993, Avramov et al., 2009) and are believed to be overpriced. Similarly, we hypothesize (and confirm in this section) that short sellers are targeting high uncertainty firms, potentially for the same reasons.

Second, we use the fact that high uncertainty firms with option-like equity have positive FVIX betas (and hence, negative exposure to aggregate volatility risk). Barinov (2011a, 2013) shows that this is the case and offers a theoretical explanation: when both aggregate volatility and firm-specific uncertainty increase during recessions, high-uncertainty, option-like firms perform relatively well, because, first, option value increases in volatility, holding everything else fixed, and, second, because the beta of the option decreases in firm-specific uncertainty (see Johnson, 2004, for the formal proof of the latter statement).

The question that remains is why short sellers end up targeting firms with positive FVIX betas, as the analysis in the previous sections shows. Do they act on the (possibly erroneous) belief that option-like firms with high uncertainty are overpriced and inadvertently load on FVIX in an effort to target such firms? Or do they consciously choose to short firms with positive FVIX betas, thereby exposing themselves to aggregate volatility risk, in an effort to increase the expected return to the short position? Both explanations seem plausible. The tests in this section aim to differentiate between these two explanations.

Panel A of Table 7 performs Fama-MacBeth regressions (in logs) of RSI on a list of characteristics that has been previously shown to be related to short interest, plus FVIX beta and firm-specific uncertainty measures.[20] All firm characteristics, including the FVIX beta, are measured one period prior to recording RSI and are therefore known to the short sellers when they choose whether to short the stock or not and for how much.

The first three rows suggest that short sellers are cost-conscious: consistent with prior research, they tend to short stocks of larger firms, firms with higher stock price and higher institutional ownership. The next three rows show that short-sellers are momentum traders (they tend to short losers), that short sellers (somewhat unexpectedly) target firms with high market betas, and that short sellers do not take into account the short-term reversal of Jegadeesh (1990) in their trades.

The first column of Panel A shows that, consistent with our previous analysis, short sellers target firms with positive FVIX betas. However, the coefficient becomes weaker as we control for measures of firm-specific uncertainty (idiosyncratic volatility, analyst disagreement, and turnover) and for measures of equity option-likeness (market-to-book and credit rating). In the last four columns, the slope on FVIX beta flips its sign and becomes significantly negative (with the exception of column six), which suggests that, controlling for firm-specific uncertainty and equity option-likeness, short sellers target firms with negative FVIX betas, not positive FVIX betas.[21] (The evidence in columns three to eight that short sellers target high-uncertainty firms is, to our knowledge, new to the literature).

The evidence in Panel A seems more consistent with the idea that short sellers inadvertently load on FVIX while targeting allegedly overpriced stocks with high uncertainty and option-like equity. They seem to make no effort to target stocks with positive FVIX betas

[20] We also experiment with a probit regression of the dummy for high RSI firms (defined either of the four ways we used in Sections 3-5) on the firm characteristics from Table 7. The results are very similar, suggesting that the relation between short interest and the firm characteristics stays qualitatively the same even for the firms with extremely high RSI.

[21] While controlling for all measures of firm-specific uncertainty and equity option-likeness materially reduces the initially positive link between FVIX beta and short interest, turnover and credit rating seem to be of particular importance.

outside of this group, and they do not lean towards stocks with more positive FVIX betas in this group either.[22] The result that the positive relation between FVIX betas and RSI is subsumed by the measures of firm-specific uncertainty and equity option-likeness is also consistent with evidence in Section 4 that the high RSI effect exists only if firm-specific uncertainty is high and/or equity is option-like.

In unreported regression of changes in RSI on the changes in the explanatory variables, we find that while RSI does respond positively to increases in firm-specific uncertainty and equity option-likeness, there is no apparent link between changes in RSI and changes in FVIX betas. This evidence suggests again that short sellers do not target firms with positive FVIX betas. Rather, the tendency of high RSI firms to have positive FVIX betas is a by-product of their effort to short firms with high uncertainty and option-like equity.

The decision of short sellers to target firms with high uncertainty and option-like equity is not necessarily ill-informed. First, we do not observe the precise shorting date, and cannot exclude the possibility that informed short sellers make significant profits between the shorting date and the date when short interest is revealed to the public, as should be the case in a (semi-strongly) efficient market.

Second, the evidence in Section 4 shows that while in many cases we cannot reject the hypothesis that, after the short interest becomes publicly available, heavily shorted firms with high uncertainty and option-like equity are fairly priced (i.e., their alphas are insignificantly negative), the alphas of these firms are uniformly negative and often economically large, not to mention the cases in which they remain significant. Hence, even after controlling for FVIX, we see no evidence that short sellers hurt their trading profit by shorting firms with high uncertainty and option-like equity, and it is quite possible that our tests just lack power to elicit the

[22] The latter conclusion is further confirmed by unreported regressions that use interaction variables for FVIX betas, on the one hand, and measures of firm-specific uncertainty and equity option-likeness on the other.

profitability of their strategies. The point of our paper is not that heavily shorted firms do not underperform at all (though the majority of our results are consistent with this view), the point of our paper is that this apparent underperformance is substantially reduced after controlling for aggregate volatility risk.

One alternative of why the regressions in Panel A do not find that, controlling for other determinants of short interest, short sellers target firms with positive FVIX betas, is the market timing hypothesis. If short sellers are able to predict the movements of market volatility, they may positively (negatively) load on FVIX before volatility increases (decreases), and overall in the whole sample the relation between short interest and FVIX betas will be weak and can have either sign.[23]

Panels B and C of Table 7 test this hypothesis by regressing the time series of the select coefficients from the Fama-MacBeth regression in the eighth column of Panel A on the next-month returns to the market and FVIX. Panel B performs these regressions using the market return and FVIX return separately, Panel C uses them both in the same regression.

We find no evidence that short sellers are able to time the market volatility and load more on FVIX just before FVIX posts positive returns or just before the market loses (which is often synonymous to increased volatility). In fact, it seems like short sellers have weak tendency to load more on FVIX just before the market goes up (and hence, FVIX loses due to its negative market beta). Likewise, it does not seem that the decision of short sellers to target firms with high uncertainty and option-like equity is driven by market timing or volatility timing, or that short sellers time the market or market volatility while deciding on what the market beta of shorted stocks has to be (see the last column of Panels B and C). We conclude that the lack of evidence that, controlling for other determinants of short interest, short sellers target firms with

[23] We do not have strong priors on whether short sellers time the market or not. While short sellers are widely believed to be informed, they are usually believed to be informed about individual stocks, and not necessarily about the whole market.

positive FVIX betas is not due to their market/volatility timing effort, because short sellers do not seem to be timing either market or volatility. The latter result that short sellers do not time either market or volatility and accept the consequences that they inadvertently load on some risk factors while choosing the stocks to short, is, to our knowledge, new to the literature.

7. Robustness Checks

7.1 Tradable FVIX

The FVIX factor used in the paper is constructed using the factor-mimicking regression for the full sample. This is a standard practice in constructing the factor-mimicking portfolios since at least Breeden et al. (1989). The benefit of doing the regression using the full sample rather than an expanding estimation window that uses only the information available to the econometrician in each period of time is the increased precision of estimates. The drawback is the potential look-ahead bias from assuming that investors knew the coefficients from the factor-mimicking regression run in 1986-2010 back in the early 1990s. [24]

In this subsection, we briefly describe the results of replacing FVIX by the version of FVIX free from the potential look-ahead bias, henceforth referred to as FVIXT. FVIXT is constructed running the same factor-mimicking regression as the one used to construct FVIX, but using only the data available in period t. For example, in January 1992 the regression is estimated using data from January 1986 to December 1991, and then the coefficients are multiplied by the values of the returns to the base assets in January 1992 to obtain the value of FVIXT return in January 1992. Then in February 1992 the regression is re-run using the data from January 1986 to January 1992, etc.

[24] This assumption is not as extreme as one may think, since while the econometrician does not observe expected market volatility before 1986 due to availability of VIX, investors probably had at least some idea about what expected market volatility was and how to hedge against its changes long before VIX was made available.

FVIXT starts in January 1991, because we use the first five years of VIX values as the learning sample. Results (untabulated) show that in this shorter sample both FVIX and the alphas of high RSI firms are similar to full-sample results. The factor risk premium of FVIXT though is higher than that of FVIX, at -76 bp per month (t-statistic =-2.41). When FVIXT is used to explain the alphas of high RSI firms and the difference in the alphas of high RSI firms between the subsamples described in Tables 3-5 (value firms vs. growth firms, volatile firms vs. low volatility firms, low IO firms vs. high IO firms, and distressed firms vs. healthy firms), we find that in the vast majority of cases the alphas from the ICAPM with FVIXT and the ICAPM with the usual FVIX differ by at most 10 bp per month. We also find that FVIXT betas of all portfolios we consider are still statistically significant, though numerically somewhat smaller than FVIX betas due to the higher factor risk premium of FVIXT. We thus conclude that our main results do not change when FVIX is replaced by fully tradable FVIXT and that the version of FVIX we used in the paper does not suffer from look-ahead bias.

7.2. Replacing FVIX with the change in VIX

In previous sections, we present evidence that in the ICAPM with the market factor and the FVIX factor high RSI firms have positive FVIX betas. Because, by construction, the FVIX factor is strongly positively correlated with increases in expected aggregate volatility (as proxied for by the change in the VIX index), the positive FVIX betas imply that the reaction of high RSI stocks to increases in expected aggregate volatility is less negative than what the CAPM predicts.

In this subsection, we present more direct evidence that high RSI firms indeed beat the CAPM when aggregate volatility increases. We replace the FVIX factor with the VIX change and test if high RSI firms have positive loadings on the VIX change, and if the loadings become more positive for high FVIX firms with high uncertainty and option-like equity.

In unreported results, we regress on the market return and the change in VIX the returns to high RSI firms and the difference in the returns of high RSI firms between the subsamples described in Tables 3-5 (value firms vs. growth firms, volatile firms vs. low volatility firms, low IO firms vs. high IO firms, and distressed firms vs. healthy firms). We perform the regressions at the daily frequency, because at the daily frequency the change in VIX is closer to innovation in VIX.

We find that the change in VIX is positive and significant in all regressions. The magnitude of its slopes suggests that when VIX increases, high RSI firms witness losses that are 50% lower than those predicted by the CAPM. Likewise, the slopes on the VIX change imply that the arbitrage portfolios that buy high RSI firms with high market-to-book (bad credit rating, low IO, high volatility) and short high RSI firms with low market-to-book (good credit rating, high IO, low volatility) tend to witness gains comparable in the magnitude to the losses predicted by the CAPM when VIX increases.

7.3. High RSI Effect in Event-Time

Previous studies document that the high RSI effect is relatively short-lived and lasts from 2 to 12 months (Asquith, Pathak, and Ritter, 2005). In unreported results, we also study the behavior of the CAPM and ICAPM alphas of high RSI firms in event-time and check whether FVIX betas exhibit a similar pattern. If the high RSI effect indeed lasts at most 12 months, we expect FVIX betas of high RSI firms to also decline fast in event time, though they might stay significant longer than CAPM alphas, because risk is likely to be persistent.

We examine the CAPM alphas of high RSI firms 3, 6, 9, 12, and 18 months after the portfolio formation and find that the high RSI effect remains visible for up to a year, but the larger part of it dissipates in 18 months. FVIX betas exhibit a very similar, though somewhat muted pattern. They are close to being flat in the first year after portfolio formation, decline significantly in the second year, but still remain visible even after two years. We thus conclude that the event time behavior of the high RSI effect is largely consistent with FVIX being the explanation for at least a significant part of the high RSI effect.

8. Conclusion

The existing short selling literature has focused on short sales constraints or asymmetric information between short sellers and other traders to explain why high RSI stocks have negative future abnormal returns. Motivated by the aggregate volatility risk literature, this study offers an alternative risk-based firm-type explanation using a two-factor ICAPM with an aggregate volatility risk factor.

The main difference between the existing explanations of the low returns to high RSI stocks and our explanation is that the existing explanations have to assume investors' irrationality, while our explanation points out a low risk of high RSI stocks. This is not only a methodological difference. If the low returns to high RSI stocks are due to investors' irrationality, a rational investor has to short or at least ignore such stocks. We question this investment recommendation: our analysis shows that, controlling for aggregate volatility risk, there are little significant abnormal gains to be earned from shorting or ignoring high RSI firms.

We show that high RSI firms beat the CAPM when expected aggregate volatility increases. The main reason is that high RSI stocks have high levels of firm-specific uncertainty and option-like equity. Firm-specific uncertainty tends to increase when aggregate volatility increases. This increase in uncertainty makes option-like equity less sensitive to the value of the underlying asset and, all else equal, less risky and more valuable. Also, holding everything else equal, higher uncertainty means higher value of option-like equity because of the options' convexity in the value of the underlying asset.

We find that the alphas of high RSI firms drop by about a half and become insignificant after we control for the aggregate volatility risk factor (the FVIX factor). The loadings of high RSI firms on the FVIX factor strongly support our prediction that high RSI firms beat the CAPM when aggregate volatility increases.

Consistent with our hypothesis that high RSI firms have negative CAPM alphas because of their high uncertainty and option-like equity, we document that high RSI firms earn negative CAPM alphas only if these firms have high uncertainty or option-like equity. While several mispricing stories in the literature offer a similar prediction, we come up with further cross-sectional predictions that differentiate our explanation from the rest of the literature. We predict and find that the negative CAPM alphas of high RSI firms with high uncertainty or option-like equity decline substantially, and in many cases, disappear in the ICAPM with the FVIX factor. The loadings on FVIX also show, as predicted, that the ability to beat the CAPM in the periods of increasing aggregate volatility is confined to the high RSI firms with substantial uncertainty or option-like equity.

We also show that high RSI firms with low IO have higher uncertainty measures and therefore beat the CAPM by a wider margin when aggregate volatility increases than high RSI firms with high IO. We thus provide a complementary story to explain the result in Asquith, Pathak, and Ritter (2005) that high RSI, low IO firms have the most negative CAPM alphas.

Further supporting the aggregate volatility risk explanation, high RSI firms have procyclical (i.e., lower in recessions) market betas, and this procyclicality is strongest among high RSI stocks with high uncertainty and option-like equity. Also, we show high RSI stocks load positively on the VIX change, and that the loadings on the VIX change are significantly higher for the high RSI firms with high uncertainty and option-like equity.

We also analyze the motives that make short sellers short firms with positive FVIX betas. Our tests suggest that short sellers do not directly target firms with positive FVIX betas, whether in an effort to increase the expected return of the short position (a positive FVIX beta suggests that the asset is a hedge against aggregate volatility risk) or in an effort to time changes in aggregate volatility. Rather, short sellers just inadvertently load on the FVIX factor while trying to short the firms that they perceive as overpriced (high uncertainty firms, growth firms, and distressed firms). While in many cases, after controlling for aggregate volatility risk, we cannot reject the hypothesis such firms, even if targeted by short sellers, are not overpriced, the point estimates of the alphas are always positive and in many cases economically large, implying that the short sellers clearly do not harm themselves, and might even be earning abnormal returns by shorting these firms, even if the shorting comes together with loading up on the FVIX factor.

Our analysis points out that once aggregate volatility risk is controlled for, the evidence in favor of mispricing driven by either short sales constraints or information asymmetry becomes less pronounced. Overall, we conclude that at least one-half of the high RSI effect is not mispricing, but rather is explained by low aggregate volatility risk of heavily shorted firms. This conclusion holds both in the full sample and in several subsamples, in which the high RSI effect is believed to be the strongest.

Our results also speak to recent world-wide regulatory actions that restrict short sellers in various forms. The finding that heavily shorted firms earn low future returns primarily because they have lower aggregate volatility risk should help ease the concern that many practitioners, regulators, and public commentators have about potential destabilizing effects of short selling.

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Table 1. Summary statistics

This table compares median stock characteristics of high RSI stocks to the median stock characteristics of low RSI stocks and the Compustat universe. Size is monthly market capitalization. IVol refers to idiosyncratic volatility and is the standard deviation of the Fama-French model residuals. The Fama-French model is fitted to daily returns in each firm-month. Dispersion is the standard deviation of earnings forecasts divided by the average forecast. Turnover is average monthly share turnover over the past year. M/B is market-to-book ratio. Credit rating is a firm's S&P credit rating score. The comparison on returns is between average monthly raw returns. High RSI is defined as short interest that is above 2.5%, 5%, 90th percentile, and 95th percentile, respectively. Low RSI is defined as below 90th percentile. The sample period is from 1988 to 2010.

		high RSI-low RSI	high RSI - compustat universe		high RSI-low RSI	high RSI - compustat universe		high RSI-low RSI	high RSI - compustat universe		high RSI-low RSI	high RSI - compustat universe
high RSI=	**>2.5%**	**>2.5%**	**>2.5%**	**>5%**	**>5%**	**>5%**	**>90%ile**	**>90%ile**	**>90%ile**	**>95%ile**	**>95%ile**	**>95%ile**
IVol	0.026	0.000	0.003	0.026	0.001	0.003	0.027	0.001	0.004	0.027	0.002	0.004
t-stat		*0.81*	*6.22*		*1.99*	*6.78*		*2.52*	*7.75*		*3.87*	*9.62*
Dispersion	0.056	0.014	0.006	0.062	0.020	0.012	0.061	0.018	0.011	0.066	0.023	0.016
t-stat		*5.11*	*2.21*		*5.54*	*3.29*		*9.15*	*5.20*		*7.77*	*5.00*
Turnover	0.123	0.666	0.062	0.144	0.088	0.084	0.158	0.102	0.097	0.179	0.123	0.118
t-stat		*14.0*	*16.6*		*12.7*	*14.3*		*7.20*	*7.53*		*7.36*	*7.65*
M/B	2.440	0.569	0.542	2.574	0.702	0.675	2.547	0.676	0.648	2.639	0.765	0.738
t-stat		*8.53*	*8.32*		*10.5*	*10.3*		*11.4*	*11.8*		*13.4*	*13.7*
Rating	11.973	2.856	2.631	12.653	3.536	3.311	12.611	3.495	3.269	12.951	3.835	3.609
t-stat		*8.9*	*11.9*		*12.4*	*18.3*		*16.9*	*29.8*		*16.0*	*26.8*
Return(%)	0.623	-0.595	-0.514	0.485	-0.734	-0.652	0.462	-0.756	-0.675	0.430	-0.789	-0.707
t-stat	*1.60*	*-4.89*	*-4.33*	*1.24*	*-5.07*	*-5.19*	*1.13*	*-5.27*	*-5.27*	*1.08*	*-5.21*	*-5.02*
Size	0.469	0.332	0.329	0.473	0.336	0.333	0.458	0.321	0.319	0.433	0.295	0.293
t-stat		*10.5*	*12.1*		*10.4*	*12.0*		*10.7*	*12.4*		*11.5*	*13.5*

Table 2. univariate results

This table reports equally-weighted CAPM alphas, ICAPM alphas and FVIX betas of high RSI stocks. Panel A reports CAPM alphas. Panel B reports ICAPM alphas. Panel C reports FVIX betas. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from 1988 to 2010.

high RSI=	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**
Panel A. CAPM alpha				
CAPM alpha	-0.668	-0.843	-0.852	-1.020
t-stat	*-2.74*	*-3.17*	*-3.35*	*-3.73*
Panel B. ICAPM alpha				
ICAPM alpha	-0.245	-0.374	-0.376	-0.517
t-stat	*-0.88*	*-1.23*	*-1.28*	*-1.61*
Panel C. FVIX beta				
FVIX beta	0.890	0.987	1.000	1.058
t-stat	*2.98*	*2.91*	*3.24*	*2.90*

Table 3. High RSI and firm-specific uncertainty

This table reports equally-weighted CAPM alphas, ICAPM alphas and FVIX betas of high RSI stocks sorted on idiosyncratic volatility (Panel A), analyst dispersion (Panel B), and turnover (Panel C). IVol refers to idiosyncratic volatility and is the standard deviation of the Fama-French model residuals. The Fama-French model is fitted to daily returns in each firm-month. Dispersion is the standard deviation of earnings forecasts divided by the average forecast. Turnover is average monthly share turnover over the past year. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from 1988 to 2010.

Panel A. High RSI and idiosyncratic volatility

	CAPM alpha				ICAPM alpha				FVIX beta			
high RSI=	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**
Low	0.126	-0.004	0.014	-0.056	0.064	0.053	0.063	0.129	-0.129	0.122	0.103	0.388
t-stat	*0.72*	*-0.02*	*0.07*	*-0.25*	*0.38*	*0.23*	*0.31*	*0.52*	*-1.12*	*1.34*	*0.83*	*3.44*
Medium	-0.372	-0.514	-0.566	-0.705	0.013	-0.061	-0.143	-0.234	0.809	0.953	0.889	0.991
t-stat	*-1.50*	*-1.95*	*-2.25*	*-2.40*	*0.05*	*-0.19*	*-0.48*	*-0.67*	*2.57*	*2.48*	*2.63*	*2.22*
High	-1.573	-1.862	-1.747	-2.031	-0.683	-1.005	-0.838	-1.191	1.871	1.802	1.912	1.766
t-stat	*-3.65*	*-4.18*	*-4.04*	*-4.50*	*-1.47*	*-2.11*	*-1.75*	*-2.40*	*3.13*	*3.14*	*3.15*	*2.93*
H-L	-1.699	-1.858	-1.762	-1.975	-0.747	-1.059	-0.902	-1.320	2.000	1.680	1.809	1.378
t-stat	*-4.13*	*-4.77*	*-4.61*	*-5.08*	*-1.88*	*-2.87*	*-2.41*	*-3.50*	*3.01*	*3.08*	*2.73*	*2.38*

Panel B. High RSI and analyst dispersion

	CAPM alpha				ICAPM alpha				FVIX beta			
high RSI=	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**
Low	-0.138	-0.205	-0.232	-0.281	-0.059	-0.076	-0.063	-0.078	0.166	0.271	0.357	0.427
t-stat	*-0.70*	*-0.82*	*-1.01*	*-1.02*	*-0.28*	*-0.28*	*-0.24*	*-0.25*	*1.39*	*1.65*	*2.47*	*2.37*
Medium	-0.203	-0.512	-0.435	-0.730	0.103	-0.132	-0.065	-0.268	0.642	0.798	0.778	0.971
t-stat	*-0.87*	*-1.82*	*-1.70*	*-2.46*	*0.41*	*-0.43*	*-0.23*	*-0.76*	*2.39*	*2.26*	*2.48*	*2.21*
High	-0.796	-1.043	-0.982	-1.150	-0.206	-0.437	-0.415	-0.614	1.239	1.275	1.193	1.127
t-stat	*-2.56*	*-3.29*	*-3.14*	*-3.35*	*-0.58*	*-1.25*	*-1.19*	*-1.69*	*3.54*	*3.62*	*3.56*	*3.04*
H-L	-0.658	-0.839	-0.750	-0.869	-0.148	-0.361	-0.352	-0.536	1.073	1.004	0.836	0.700
t-stat	*-2.67*	*-2.98*	*-2.69*	*-2.85*	*-0.53*	*-1.23*	*-1.12*	*-1.67*	*3.73*	*3.91*	*2.83*	*2.49*

Panel C. high RSI and turnover

	CAPM alpha				ICAPM alpha				FVIX beta			
high RSI=	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**
Low	-0.270	-0.381	-0.420	-0.515	-0.079	-0.139	-0.145	-0.201	0.401	0.510	0.577	0.660
t-stat	*-1.09*	*-1.46*	*-1.55*	*-1.84*	*-0.28*	*-0.47*	*-0.47*	*-0.62*	*2.37*	*2.52*	*2.81*	*2.54*
Medium	-0.609	-0.828	-0.778	-1.054	-0.223	-0.383	-0.342	-0.552	0.813	0.937	0.919	1.055
t-stat	*-2.40*	*-2.90*	*-2.98*	*-3.50*	*-0.75*	*-1.15*	*-1.12*	*-1.50*	*2.83*	*2.72*	*3.15*	*2.89*
High	-1.048	-1.275	-1.287	-1.444	-0.396	-0.577	-0.604	-0.760	1.372	1.468	1.437	1.439
t-stat	*-3.30*	*-3.91*	*-4.03*	*-4.51*	*-1.23*	*-1.73*	*-1.84*	*-2.19*	*3.08*	*3.03*	*3.22*	*2.99*
H-L	-0.779	-0.894	-0.868	-0.930	-0.317	-0.439	-0.459	-0.559	0.971	0.958	0.860	0.779
t-stat	*-2.69*	*-3.13*	*-2.95*	*-3.53*	*-1.40*	*-1.89*	*-2.03*	*-2.22*	*2.88*	*2.78*	*2.61*	*2.89*

Table 4. High RSI and institutional ownership

This table reports equally-weighted CAPM alphas, ICAPM alphas and FVIX betas of high RSI stocks sorted on institutional ownership (IO) (Panel A) and residual IO (Panel B). IO is defined as shares owned by institutions as a percent of total shares outstanding. Residual IO is the residual from the logistic regression of IO on log size and its square. The regression is fitted to all firms within each separate quarter. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from 1988 to 2010.

Panel A. High RSI and IO

	CAPM alpha				ICAPM alpha				FVIX beta			
high RSI=	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**
Low	-0.944	-1.162	-1.125	-1.306	-0.435	-0.641	-0.545	-0.728	1.070	1.094	1.219	1.215
t-stat	*-3.54*	*-4.03*	*-4.01*	*-4.27*	*-1.55*	*-2.10*	*-1.84*	*-2.22*	*2.53*	*2.41*	*2.75*	*2.39*
Medium	-0.271	-0.411	-0.439	-0.636	0.076	0.044	-0.033	-0.181	0.730	0.958	0.855	0.956
t-stat	*-1.31*	*-1.70*	*-1.97*	*-2.30*	*0.31*	*0.15*	*-0.13*	*-0.55*	*3.13*	*3.12*	*3.51*	*3.08*
High	-0.144	-0.313	-0.275	-0.426	-0.029	-0.172	-0.168	-0.168	0.245	0.337	0.296	0.652
t-stat	*-0.62*	*-1.15*	*-0.98*	*-1.30*	*-0.12*	*-0.60*	*-0.57*	*-0.46*	*2.05*	*2.26*	*1.76*	*3.33*
H-L	0.797	0.867	0.908	1.078	0.401	0.462	0.329	0.570	-0.838	-0.967	-1.594	-1.286
t-stat	*3.33*	*3.26*	*3.08*	*3.56*	*2.03*	*2.02*	*1.49*	*2.16*	*-2.19*	*-2.65*	*-5.63*	*-4.28*

Panel B. High RSI and residual IO

	CAPM alpha				ICAPM alpha				FVIX beta			
high RSI=	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**
Low	-0.929	-1.128	-1.010	-1.080	-0.473	-0.634	-0.462	-0.505	0.959	1.037	1.154	1.209
t-stat	*-3.81*	*-4.06*	*-3.80*	*-3.63*	*-1.88*	*-2.19*	*-1.69*	*-1.61*	*2.29*	*2.27*	*2.72*	*2.40*
Medium	-0.394	-0.576	-0.613	-0.773	-0.012	-0.115	-0.197	-0.303	0.804	0.970	0.877	0.989
t-stat	*-1.87*	*-2.35*	*-2.68*	*-2.86*	*-0.05*	*-0.39*	*-0.75*	*-0.95*	*3.09*	*3.07*	*3.04*	*2.80*
High	-0.143	-0.231	-0.310	-0.566	0.050	-0.061	-0.122	-0.377	0.406	0.359	0.395	0.398
t-stat	*-0.53*	*-0.78*	*-1.11*	*-1.75*	*0.17*	*-0.19*	*-0.40*	*-1.06*	*2.87*	*2.30*	*2.97*	*2.52*
H-L	0.786	0.896	0.700	0.514	0.523	0.574	0.339	0.128	-0.553	-0.678	-0.759	-0.812
t-stat	*3.04*	*3.29*	*2.57*	*1.67*	*2.46*	*2.44*	*1.57*	*0.44*	*-1.57*	*-1.78*	*-1.92*	*-1.80*

Table 5. High RSI and real options

This table reports equally-weighted CAPM alphas, ICAPM alphas and FVIX betas of high RSI stocks sorted on market-to-book (Panel A) and credit rating (Panel B). Credit rating is a firm's S&P credit rating score. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from 1988 to 2010.

Panel A. High RSI and M/B

	CAPM alpha				ICAPM alpha				FVIX beta			
high RSI=	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**
Low	0.087	0.092	-0.053	-0.350	0.135	0.160	0.017	-0.228	0.617	0.749	0.593	0.619
t-stat	*0.25*	*0.24*	*-0.13*	*-0.78*	*0.34*	*0.36*	*0.04*	*-0.44*	*2.60*	*2.96*	*2.28*	*2.68*
Medium	-0.171	-0.422	-0.381	-0.548	0.015	-0.202	-0.172	-0.360	0.778	0.925	0.862	0.982
t-stat	*-0.70*	*-1.57*	*-1.52*	*-1.86*	*0.06*	*-0.70*	*-0.62*	*-1.13*	*4.01*	*5.20*	*4.65*	*5.60*
High	-0.770	-0.906	-0.866	-0.974	-0.364	-0.497	-0.464	-0.575	1.525	1.521	1.507	1.558
t-stat	*-2.69*	*-2.98*	*-2.84*	*-3.15*	*-1.40*	*-1.72*	*-1.60*	*-1.89*	*6.14*	*5.55*	*5.82*	*5.50*
H-L	-0.856	-0.997	-0.812	-0.624	-0.500	-0.657	-0.481	-0.347	0.908	0.772	0.914	0.940
t-stat	*-2.31*	*-2.45*	*-1.91*	*-1.30*	*-1.38*	*-1.59*	*-1.14*	*-0.71*	*2.57*	*1.84*	*2.25*	*2.30*

Panel B. high RSI and credit rating

	CAPM alpha				ICAPM alpha				FVIX beta			
high RSI=	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**
Low(Good)	0.015	-0.310	-0.134	-0.446	-0.209	-0.502	-0.266	-0.590	-0.471	-0.405	-0.277	-0.303
t-stat	*0.06*	*-0.95*	*-0.43*	*-1.18*	*-0.89*	*-1.63*	*-0.83*	*-1.52*	*-2.03*	*-1.57*	*-0.79*	*-0.88*
Medium	0.089	0.090	-0.150	-0.357	0.129	0.282	0.006	-0.094	0.085	0.405	0.328	0.555
t-stat	*0.33*	*0.30*	*-0.47*	*-1.09*	*0.46*	*0.89*	*0.02*	*-0.27*	*0.33*	*1.99*	*1.22*	*2.54*
High(Bad)	-0.886	-1.350	-1.124	-1.248	-0.406	-0.770	-0.571	-0.751	1.000	1.206	1.162	1.035
t-stat	*-2.21*	*-2.65*	*-2.85*	*-2.18*	*-0.91*	*-1.33*	*-1.25*	*-1.16*	*4.22*	*4.03*	*3.62*	*2.35*
H-L	-0.887	-1.043	-0.990	-0.784	-0.177	-0.266	-0.305	-0.137	1.478	1.615	1.439	1.347
t-stat	*-2.53*	*-2.16*	*-2.35*	*-1.31*	*-0.49*	*-0.55*	*-0.75*	*-0.22*	*4.29*	*4.17*	*2.76*	*2.17*

Table 6. Conditional CAPM

The table presents the difference in market betas between recession and expansion for various portfolios. The beta is a linear function of the four conditioning variables - the dividend yield, the default premium, the risk-free rate, and the term premium. Recession is defined as the months when the expected market risk premium is above its average value, and expansion takes the rest of the sample. The expected market risk premium is the forecasted excess market return from the regression of realized excess market returns on the previous month values of the four conditioning variables. Panel A includes the high RSI portfolio (Table 2). Panel B includes the arbitrage portfolios buying high RSI stocks with high value of idiosyncratic volatility, dispersion, or turnover, and shorting the high RSI stocks with low value of idiosyncratic volatility, dispersion, or turnover. Panel C includes the arbitrage portfolios buying high RSI stocks with high value of M/B, bad credit rating, and shorting high RSI stocks with low value of M/B, or good credit rating. Panel D reports the arbitrage portfolios buying high RSI firms with low value of IO or residual IO and shorting high RSI firms with high value of IO or residual IO. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation.

high RSI=	**>2.5%**	**>5%**	**>90%ile**	**>95%ile**
Panel A. High RSI portfolio				
high RSI	-0.126	-0.142	-0.144	-0.104
t-stat	*-7.26*	*-6.03*	*-6.09*	*-3.26*
Panel B. High RSI and firm specifc uncertainty				
Idiosyncratic volatility	-0.505	-0.441	-0.465	-0.548
t-stat	*-8.18*	*-5.28*	*-7.65*	*-7.73*
Dispersion	-0.236	-0.359	-0.328	-0.397
t-stat	*-3.69*	*-3.58*	*-3.79*	*-4.83*
Turnover	-0.389	-0.378	-0.340	-0.276
t-stat	*-6.68*	*-4.98*	*-5.11*	*-4.93*
Panel C. High RSI and real option				
M/B	-0.335	-0.203	-0.232	-0.368
t-stat	*-3.93*	*-2.22*	*-2.75*	*-4.52*
Credit Rating	-0.322	-0.169	-0.275	0.009
t-stat	*-5.62*	*-3.15*	*-4.08*	*0.19*
Panel D. High RSI and IO				
IO	-0.310	-0.324	-0.287	-0.213
t-stat	*-7.32*	*-6.77*	*-3.78*	*-2.37*
Residual IO	-0.241	-0.408	-0.280	-0.204
t-stat	*-6.09*	*-7.89*	*-5.23*	*-5.11*

Table 7.Why Do Short Sellers Short Firms with Positive FVIX Betas?

Panel A reports Fama-MacBeth regression of log (RSI) on FVIX and measures of uncertainty and option-likeness controlling for price, size, institutional ownership, market beta, momentum and return reversal. Panel B (C) regresses coefficients from Model 8 in Panel A on next-month returns to the market and FVIX, seperately (in the same model). Price is log of stock price. Size is log of monthly market capitalization. IO is log of shares owned by institutions as a percent of total shares outstanding. Market Beta is beta from CAPM model. Momentum is the return between month t-12 and month t-2. Reversal is the past month return. FVIX is FVIX beta. M/B is log of market-to-book ratio. IVol refers to log of idiosyncratic volatility, which is the standard deviation of the Fama-French model residuals. The Fama-French model is fitted to daily returns in each firm-month. Dispersion is log of the standard deviation of earnings forecasts divided by the average forecast. Turnover is log of average monthly share turnover over the past year. Credit rating is a firm's S&P credit rating score (AAA=1, AA+=2, ... D=22).

Panel A: Fama-MacBeth regression

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Price	-11.64	15.24	23.47	25.05	14.62	37.68	24.71	20.44
t-stat	*-4.91*	*6.68*	*10.4*	*13.9*	*11.7*	*13.6*	*17.9*	*11.7*
Size	33.09	17.10	20.38	1.706	1.214	9.424	-2.909	-8.447
t-stat	*10.1*	*6.29*	*7.29*	*0.63*	*0.48*	*6.80*	*-1.15*	*-5.49*
IO	8.153	6.823	12.30	63.16	1.383	7.896	10.51	12.66
t-stat	*3.60*	*2.99*	*4.38*	*19.0*	*1.90*	*3.27*	*4.40*	*4.62*
Market Beta	65.31	57.36	52.96	46.53	11.54	39.43	12.50	10.29
t-stat	*15.8*	*14.6*	*13.7*	*12.9*	*7.21*	*12.1*	*6.16*	*4.97*
Momentum	-0.119	-4.590	-7.956	-0.366	-25.15	-22.11	-22.04	-19.11
t-stat	*-0.05*	*-1.98*	*-3.32*	*-0.15*	*-13.7*	*-7.15*	*-11.7*	*-7.45*
Reversal	-0.298	-0.262	-0.183	-0.175	-0.011	-0.107	0.011	0.111
t-stat	*-6.62*	*-6.58*	*-5.24*	*-4.74*	*-0.41*	*-2.10*	*0.36*	*2.32*
FVIX	2.012	1.432	0.863	1.006	-0.889	-0.231	-1.125	-1.045
t-stat	*3.89*	*4.16*	*2.71*	*2.28*	*-2.87*	*-0.40*	*-3.91*	*-2.69*
M/B		29.57	26.74	31.79	22.91	5.039	20.95	12.17
t-stat		*18.5*	*18.6*	*16.4*	*15.2*	*3.62*	*14.4*	*8.27*
IVol			46.90				4.110	2.919
t-stat			*20.8*				*4.05*	*1.88*
Dispersion				19.29			11.22	4.527
t-stat				*13.3*			*11.3*	*8.63*
Turnover					106.95		94.64	82.53
t-stat					*74.9*		*56.4*	*47.7*
Rating						16.88		5.379
t-stat						*44.7*		*15.9*
AdjRsq	18.42	17.24	19.90	22.42	45.65	19.86	42.62	43.00

Panel B: Regress coefficients from Model 8 in Panel A on next-month market return and FVIX, seperately.

Coef=	FVIX	M/B	IVol	Dispersion	Turnover	Rating	Market Beta
MKT	0.112	0.147	0.086	-0.037	-0.281	0.026	0.395
t-stat	*2.04*	*0.90*	*0.33*	*-0.42*	*-1.43*	*0.87*	*1.26*
FVIX	-0.079	-0.081	-0.099	0.032	0.226	-0.017	-0.288
t-stat	*-0.68*	*-2.12*	*-0.51*	*0.48*	*1.65*	*-0.83*	*-1.34*

Panel C: Regress coefficients from Model 8 in Panel A on next-month marketreturn and FVIX.

Coef=	FVIX	M/B	IVol	Dispersion	Turnover	Rating	Market Beta
MKT	0.180	0.264	0.322	-0.115	-0.562	0.057	0.634
t-stat	*2.36*	*1.17*	*0.93*	*-0.90*	*-1.59*	*1.08*	*1.50*
FVIX	0.359	-0.021	-0.533	0.087	0.371	0.016	-0.106
t-stat	*1.00*	*-0.12*	*-0.71*	*0.43*	*0.55*	*0.18*	*-0.15*

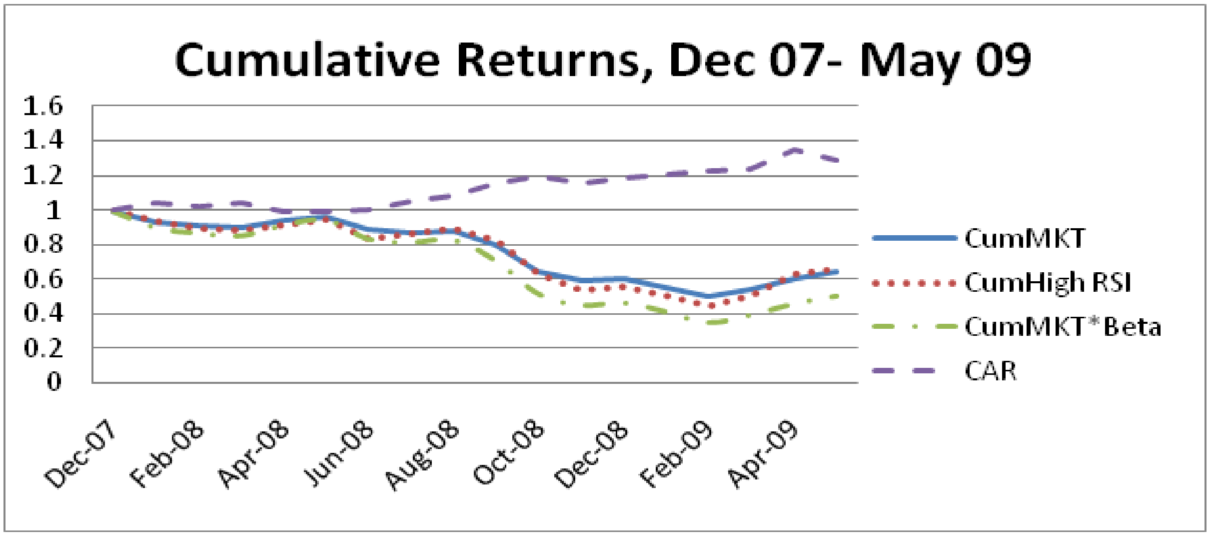

Figure 1. Cumulative returns in recent recession